NANYANG TECHNOLOGICAL UNIVERSITY

MODELLING AND SIMULATION OF SUPPLY CHAIN RESILIENCE USING COMPLEX SYSTEM APPROACHES

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

2020

MODELLING AND SIMULATION OF SUPPLY CHAIN RESILIENCE USING COMPLEX SYSTEM APPROACHES

by

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A thesis submitted to the
School of Computer Science and Engineering
in partial fulfilment of the
requirements for the degree of
Doctor of Philosophy

School of Computer Science and Engineering
Nanyang Technological University

February 2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

19 August 2019

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

19 August 2019	
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Authorship Attribution Statement

This thesis contains material from 4 papers published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as Wen Jun Tan, Zhengping Li, and Wentong Cai. Design of supply chain topology to mitigate demand and supply risks. In *Proceedings of the 2015 Winter Simulation Conference*, pages 230–241, 2015.
DOI: 10.1109/WSC.2015.7408167.

The contributions of the co-authors are as follows:

- Dr. Li provided the initial project direction.
- I conducted literature review, developed the agent-based model, designed and conducted all the experiments, and analyzed and interpreted experimental results, with guidance of Prof. Cai and Dr. Li.
- I wrote the manuscript drafts. The manuscript was revised by Prof. Cai and Dr. Li.

Chapter 4 is published as Wen Jun Tan, Wentong Cai, and Allan NengSheng Zhang. Integration design of supply chain hybrid simulation. In *Proceedings of the 2017 Winter Simulation Conference*, pages 493–504, December 2017.
DOI: 10.1109/WSC.2017.8247810.

The contributions of the co-authors are as follows:

- Prof. Cai gave the initial direction.
- I conducted literature survey, developed hybrid model, designed and conducted all the experiments, analyzed and interpreted experimental results, with guidance of Prof. Cai and Dr. Zhang.
- I wrote the manuscript drafts. The manuscript was revised by Prof. Cai and Dr. Zhang.

Chapter 5 is published as Wen Jun Tan, Allan NengSheng Zhang, and Wentong Cai. A graph-based model to measure structural redundancy for supply chain resilience.

International Journal of Production Research, 57(20):6385–6404, 2019. ISSN 0020-7543. DOI: 10.1080/00207543.2019.1566666.

The contributions of the co-authors are as follows:

- Dr Zhang gave the initial direction.
- I conducted literature review, developed the graph model and supply chain resilience measure, conducted all computational experiments, and analyzed and interpreted the experimental results, with guidance of Prof. Cai and Dr. Zhang.
- I wrote the manuscript drafts. The manuscript was revised by Prof Cai and Dr Zhang.

Chapter 6 is published as Wen Jun Tan, Wentong Cai, and Allan NengSheng Zhang. Structural-aware supply chain network simulation approach for building supply chain resilience. International Journal of Production Research, pages 1–28, 2020. doi: 10.1080/00207543.2019.1705421.

The contributions of the co-authors are as follows:

- Prof. Cai gave the initial direction.
- I conducted literature survey, developed simulation model, designed and conducted all the experiments, analyzed and interpreted experimental results, with guidance of Prof. Cai and Dr. Zhang.
- I wrote the manuscript drafts. The manuscript was revised by Prof. Cai and Dr. Zhang.

21st February 2020

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Abstract

Due to the globalization and increased collaboration between firms, supply chains (SCs) are evolving into supply chain networks (SCNs). The dynamic business environment and growing complexity of global SCNs lead to increasing vulnerabilities in the SCNs to disruptions. Supply chain resilience (SCRES) offers an approach to build an SCN such that it can mitigate the impact of disruptions and provide effective response to recover from the disruptions in a timely manner. However, due to their complexities, it is a challenge to design resilient SCNs. An SCN can be generally characterized into *microscopic* behaviours and *macroscopic* properties. In this thesis, macroscopic properties of an SCN are modelled using graphs or system dynamics (SD) models; the microscopic behaviours of the SC operations are modelled using agent-based model (ABMs).

Firstly, a top-down approach is proposed to design SCN topologies for hierarchical networks based on SC strategies. A bottom-up approach using ABM is proposed to evaluate the operational performance of the SCN topologies. An SCN is modelled as a hierarchical network and an ABM is developed to model individual SC operations for each entity in the SCN. Through simulation-based analysis, effective SCN topology can be identified to mitigate a particular risk scenario.

Secondly, to study the external effects on its internal operations, a firm often needs to construct an SCN model. The firm may have sufficient data to build a detailed model of its operational processes. However, it is difficult to construct the rest of the SCN model at the same level of details since the firm has no control or visibility over the external entities. Hence, a hybrid model of the SCN using integration design is proposed to model the whole SCN using SD and the focal firm using ABM. This hybrid model is, therefore, able to capture different levels of details of the same system. Trade-offs between mitigation and contingency strategies and between backorder cost and ordering cost are analysed through simulation of the hybrid model.

Thirdly, hierarchical networks with the same type of material flow between stages

limit the applicability of the SCN model on complex multi-stage SCNs. To overcome this limitation, a top-down approach to model an SCN using graph theory is proposed. The proposed model is capable of representing the structural redundancy for strategic planning. Based on the structural analysis of an SCN, all the SCs in the SCN can be identified. An approach to assess SCRES is proposed to measure the structural redundancy using the number of SCs in an SCN. The vulnerability of an SCN can also be assessed by identifying critical plants. To evaluate the proactive mitigation strategy, random disruptions are simulated using real-world SCNs, and it shows that the SCRES can be improved by adding redundant plants. Contingency strategy is also developed to response reactively to the criticality of the disrupted plant.

Finally, using structural analysis alone cannot capture the dynamics of recovery of SCN during the disruption. To consider the dynamics of disruption-recovery behaviours, a simulation model is developed by combining the graph model with ABM of SC operational behaviours. Based on structural analysis, mitigation strategies are designed to build redundancy. Contingency strategies are analysed to prioritise recovery on affected SCN. New SCRES indexes are proposed by evaluating the SC performance measures for disruptions of each plant and aggregating the measures based on the criticality of plants in the SCN. Simulation results show that these strategies can be used to build resilience by enabling the SCN to recover faster after disruptions. In addition, mitigation strategies are suitable for long-term disruptions while contingency strategies are more effective for short-term disruptions.

In summary, the contributions of this thesis to the current state-of-the-art are: (1) modelling SCN using complex system approaches and (2) building a resilient SCN. SCN models have been developed to represent the complexities in real-world SCNs. These models are used to design a wide variety of different SCRES strategies: proactive mitigation strategies to improve resilient against disruptions and reactive contingency strategies to recover the SCN from the impact of disruptions. Through analysis of SCRES, this enables decision makers to build a more resilient SCN.

Acknowledgements

First and foremost, I would like to express my earnest and deepest gratitude to my PhD supervisor Professor Cai Wentong and my co-supervisors Dr Li Zhengping and Dr Allan Zhang NengSheng. Their expertise and invaluable advice have left a profound impact on my work, especially in the way of critical thinking and problem solving. Special thanks to Professor Cai for his remarkable guidance, constant help and support, and lots of caring and patience in the past five years. He is a mentor of a lifetime to me, and I am honoured to be his student. Although Dr Li is no longer around, I will always remember his teachings in the beginning two years of my PhD. Dr Zhang's immense knowledge and passion in research also help me in completing the remaining three years of my PhD.

At this point, I would also like to thank A*STAR for funding my scholarship and Professor Cai for keeping me funded after my scholarship ended. Special thanks should be given to Ms. Irene Ng-Goh Siew Lai for her support and kind encouragements throughout the years. In addition, my friends at Singapore Institute of Manufacturing Technology (SIMTech) and colleagues of Parallel and Distributed Computing Laboratory (PDCL) for their patient help along the way.

Most importantly, I would like to thank both my parents and sisters for their strong support and consistent help. Last, but not least, thanks to everyone else who also helped me in one way or another along my PhD journey.

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Notations

$\mathcal{C}_p$	Production capacity of plant p.
c_b	Backorder cost per unit material.
c_m	Inventory holding cost per unit material.
c_o	Ordering cost per unit order.
c_p	Production cost per unit material.
c_r	Redundant capacity cost per unit material.
$\mathbf{C}(p)$	Total cost when plant p is disrupted.
C_b	Total backorder cost.
C_I	Investment cost for strategy s.
C_m	Total inventory holding cost.
C_o	Total ordering cost.
C_p	Total production cost.
C_r	Total redundant capacity cost.
d_m	Demand for material m.
d^{in}	Incoming demand.
d^{out}	Out-going demand.
D^{out}	Total outgoing demand.
E	Set of edges in an SC G.
E_H	Set of edges in an SCN H.
E_I	Set of directed edges from material m to plant p in an SC G.
E_O	Set of directed edges from plant p to material m in an SC G.
$\mathcal{E}$	Set of entities.
$\mathcal{E}_x^{in}$	Set of downstream entities for entity ε_x.
$\mathcal{E}_x^{out}$	Set of outstream entities for entity ε_x.
$\mathcal{F}_p^b$	Backup capacity factor.

$\mathcal{F}^r_p$	Redundant capacity factor.
f_m	Order fulfilment of material m.
G	A graph of SC.
$\mathbb{G}$	A set of SC in an SCN.
$\mathbb{G}(p)$	A set of SC in an SCN that contains plant p, where $\mathbb{G}(p) \subseteq \mathbb{G}$.
H	A graph of SCN.
i_m	Inventory at material m.
i^F_p	Finished product at plant p.
i^M	Material inventory.
i^P	Product inventory.
i^W	Work-in-progress Inventory.
i^W_p	Work-in-progress inventory for plant p.
$\mathcal{L}^O$	Order lot size.
$\mathcal{L}^S$	Shipment lot size.
m_o	End product.
m^-	Output material for a plant.
M	Set of materials in an SC G.
M_H	Set of materials in an SCN H.
$M^+(p)$	Set of input material for plant p, where $m^+ \in M^+(p)$.
n_{scn}	Number of SCs in an SCN H.
$n_{scn}(p)$	Number of SCs in an SCN H that contains p.
$o_{p,m}$	Order from plant p upstream to material m.
$o_{m,p}$	Order from material m upstream to plant p.
o_p	Production orders for plant p.
$\mathcal{O}_{m_o}$	Order quantity for end product m_o.
P	Set of plants in an SC G.
P_{crit}	Set of critical plants in an SCN H.
P_H	Set of plants in an SCN H.
$P^+(m)$	Set of upstream plants producing material m.
$P^-(m)$	Set of downstream plants that require material m as input.

P_{nr}	Set of non-redundant plants in an SCN H.
r_p	Capacitated production rate for plant p.
$\mathcal{R}_c$	Aggregated SCRES index for total cost.
$\mathcal{R}_t$	Aggregated SCRES index for TTR.
s^{in}	Incoming supply.
s^{out}	Out-going supply.
S^{out}	Total outgoing supply.
$S_{m,p}$	Cycke stock at material m for plant p.
$\mathcal{T}^D_{p,m}$	Delivery lead time from plant p to material m.
$\mathcal{T}^W$	Time window length to average the demand.
$\mathcal{T}^O$	Order lead time.
$\mathcal{T}^P_p$	Production lead time for plant p.
$\mathcal{T}^S$	Shipment lead time.
$t_r(p)$	Time-to-recover when plant p is disrupted.

Acronyms

ABM	Agent-based Model.
CSL	Customer Service Level.
DC	Distribution Centre.
SC	Supply Chain.
SCM	Supply Chain Management.
SCN	Supply Chain Network.
SCRES	Supply Chain Resilience.
SD	System Dynamic.
TTR	Time-To-Recover.
VA	Value-added.

Chapter 1

Introduction

In the introduction, we outline fundamentals for supply chain, supply chain network and supply chain resilience, as well as introducing complex systems. Based on these preliminaries, we discuss the objectives and contributions of this thesis.

1.1 Background

1.1.1 Supply Chain & Supply Chain Network

A supply chain (SC) describes an integrated system of firms involved in the upstream and downstream flows of finances, information, and products from suppliers to customers [124]. It contains a set of firms, e.g., suppliers, manufacturers, distributors, and retailers, for the purpose of managing the inventory, production, purchasing, and distribution. An SC can also be generally categorised into two types: distribution or manufacturing. A distribution SC distributes the product from the suppliers to the retailers; a manufacturing SC processes the raw materials into end products. However, most real-world SCs are combination of both types.

An SC is initially modelled as a sequential set of connections between firms [63]. Different connection types, such as SC contracts between the entities or various types of

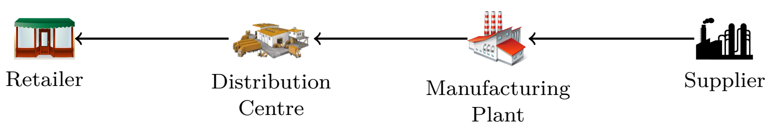


Figure 1.1: An example of SC model, where arrows represent material flows.

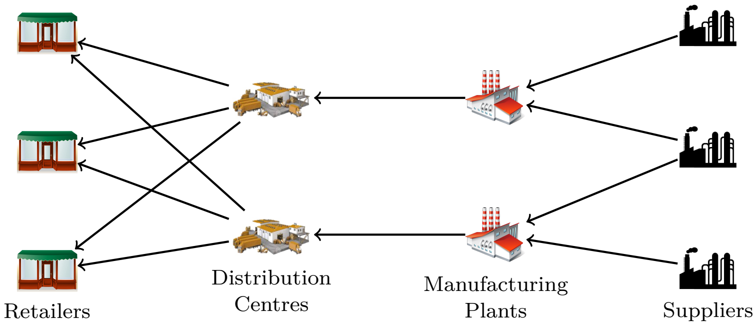


Figure 1.2: An example of a multi-stage SCN model.

flows (material, financial and information flows), represent the interdependent relationships between firms. Material flows refer to the logistic transfer of physical products; financial flows refer to the exchange of cash during the transactions; information flows refer to coordination of data and orders. Figure 1.1 shows an example of an SC model which connects entities of different types. This SC has four stages: supplier, manufacturing plant, distribution centre (DC), and retailer. The supplier provides the raw materials to the manufacturing plant to be processed into end products. The end products are sent to DC before distributing to the retailer. The type of material process at each stage can be different (e.g., processing from raw materials to end products at the manufacturing plant and DC only handles the distribution of the end products).

Many SC operations are still designed based on these overly simplified and highly linear models [21]. However, these linear models of SC do not reflect the realities of modern SCs. They are unable to consider the complex interdependent relationships between firms, where a firm can be connected to multiple upstream or downstream firms [28]. Hence, to capture this complex relationships, a supply chain network (SCN) is used, which comprises of multiple SCs [63]. Figure 1.2 shows an example of a multi-stage SCN, which has a complex interconnect structure. For instance, there is more than one supplier connected to each manufacturing plant and the DCs distribute the end products to more than one retailer.

Supply chain management (SCM) is the management of upstream and downstream relationships from suppliers to customers in order to deliver superior customer value at less cost to the whole SC [32]. SCM can be generally divided into two levels: strategic and operational [155]. Primary objectives of SCM at strategic level include long-term planning to determine the most cost-effective location of facilities (e.g., plants or DCs), the flow of products throughout the SCN, and assignment of customers to the retailers. On the other hand, operational planning usually involves short-term planning to determine the optimal safety stock level for each product at each firm, the lot size and frequency of the orders to be placed, the delivery and production lead times, and the customer service levels.

1.1.2 Supply Chain Resilience

In 2015, the explosion at the Port of Tianjin resulted in insurance cost of USD$1.5 billion, with uninsured costs several times higher [75]. While the daily operations resumed after a month, the customers and port operations continued to be affected by the incident. While such events are rare, SC disruptions often have significant impacts [197]. In recent decades, globalisation and lean production unintentionally have caused an increase in SC risks. To lower manufacturing costs, firms often source materials and components from around the world, and also keep lower inventories and buffer stocks, improve agility in response to market shifts, and simplify quality costs. At the same time, many firms do not have enough visibility of their SCs. They do not always have the information regarding the transportation routes of their suppliers, or the sources of their suppliers. These issues increase the likelihood of disruptions in SCs and allow the effects of disruptions to ripple throughout the whole SCN [40, 162, 191].

Supply chain resilience (SCRES) provides an approach to manage these risks. SCRES is emphasized in managing SC risks and uncertainties as it enables firms to provide an effective response during disruptions and recover from the disruptions quickly. Resilient firms can be less vulnerable to disruptions and are more capable of handling disruptions when they do occur [140, 144]. Due to the more fragile SCs and the awareness of the impacts of the disruptions [35, 114], firms have reported that resilience in an SC to mitigate disruption has become a top priority [202]. Thus, SCRES has become a major topic in SCM research and practice recently.

The research on SCRES became popular since the early 2000s, with some early definitions of SCRES from [33, 153]. SCRES is defined as "the adaptive capability of an SC to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the SC to a robust state of operations" [91]. Although substantial research has been carried out on SCRES, there are still research gaps in building a resilient SC:

1. Although SCRES literature has identified many strategies for improving resilience, there are few studies on the development or implementation of these strategies [17] and on the effectiveness of these strategies to mitigate the impact of disruptions.

2. For long-term recovery from disruptions, the experts have agreed that the SC performance should undergo a period of loss, then a period of increased performance to assist in the recovery before restoring to the original level [27]. Although existing approaches consider the recovery process, it is still an open research issue of developing operational plans to reflect this recovery behaviour, e.g., contingency plans to activate backup plants.

3. The literature in SCRES is sparse on how the SCRES can be measured and analysed; only a few articles discussed SCRES assessment [91]. Without understanding the existing SCRES in an SC, it would be difficult to assess the response and reaction of the SC during disruptions.

1.1.3 Complex Systems

Due to the complexities of SCNs, there are increasing research studies on analysing SCNs by using complex systems approaches in recent years. A complex system is composed of interconnected parts that exhibit emergent properties that are not obvious from the behaviours of individual parts [125]. An SCN can be generally characterized by *microscopic* behaviours and *macroscopic* properties.

Microscopic behaviours, describing the internal behaviour of a complex system, are the building blocks of the system [71]. To characterize these microscopic behaviours, models representing the low-level processes are simulated to generate aggregated system properties [3]. The essential properties defining a complex system includes *heterogeneity* and *local interactions* [69, 92]. A complex system consists of heterogeneous parts which differ in their characteristics. This heterogeneity also presents in an SCN, which comprises many agents (suppliers, plants, etc.) with different operational behaviours. There are local interactions and interdependencies between firms in an SCN. For example, a plant depends on its suppliers for the supply of parts and manufactures products that are delivered to retailers.

A suitable modelling paradigm for microscopic system properties is agent-based model (ABM). It is a bottom-up approach which simulates behaviours of low-level processes to evaluate the mechanisms that are most influential in producing the emergent properties. In ABM, the focus is on modelling individual entities within the system as agents and the interactions between them [15]. It can capture the micro-level behaviours of SCs by modelling the complexity of heterogeneous agents and their interactions. Hence, it has been used to study global SCNs where the complexity, uncertainty and potential of emergent properties are highly prevalent. As ABM can be used to model the operational behaviours, SCM often utilizes ABM to evaluate the SC operations, such as production scheduling and distribution scheduling [76].

The macroscopic properties in a complex system emerge from the behaviours of individual parts and their interactions [70]. A complex system shows macroscopic properties such as *emergence* and *self-organization*, which describes the relation between microscopic behaviours of the system and system-level properties. For example, the delivery performance of an SC is not only dependent on a single entity within the SC, but also the result of interactions between entities in the system. Self-organization is an emergent property that arises without any external influence and is the result of interactions of local autonomous decision makers [48]. However, SCs are not yet a hundred percent self-organizing – they still rely on human initiative and depend on operational frameworks designed by people [204]. In terms of decision-making, a *top-down* approach is where an executive decision maker makes the decisions on how something should be done [177]. Hence, strategic decisions in an SC are usually taken by the higher authority or the senior management; whereas self-organization in SCs is mostly realised by decentralized decision-making, such as the operational planning in individual firms within the SC.

Top-down models (e.g., network or graph models) are usually used to represent system-level properties [3]. Network models are usually used to represent real-world systems which describe the relationships of interacting agents. Graph theory provides mathematical structures to represent these relationships between agents as nodes and edges. The SCNs modelled using network or graph are frequently used for strategic planning such as the determination of the optimal location of facilities and underlying principles of splitting production across sites, etc. [76].

Although various model/approaches have been used for SCN modelling, there are still research gaps in modelling the complexities of SCN for SCRES analysis:

4. An SCN can contain various entities representing different operational behaviours. Different entities in an SC are interconnected by material and information flows.

Hence, it is important to model heterogeneity in a complex multi-stage SCN.

5. Existing graph models are unable to analyse the dependencies across multi-stages in an SCN, where vulnerabilities in the upstream stages of the SCN can have a significant impact downstream. The complex interdependencies in an SCN can contain redundancies that reduce these vulnerabilities. To analyse these dependencies across a multi-stage SCN, a new graph model is required to model the structural redundancy.

6. It is not a simple task to identify cause and effect relationships in a disruption, which is commonly used in risk analysis. The impact of disruptions can propagate throughout an SCN, causing large scale failures in the SC operations. Moreover, structural analysis on graph models is unable to capture the dynamics of recovery of SCN during the disruption. A simulation model is needed to model the dynamic response of an SCN during disruption that considers recovery operations.

7. ABM is commonly used in operational-planning, but the lack of information limits the applicability of this model. On the other hand, the SD model lacks accuracy in modelling the operational behaviours. A combination of these models can represent both the microscopic behaviours and macroscopic properties in an SCN.

1.2 Objectives

The research described in this thesis aims to address the challenges by developing new approaches to analyse and evaluate SCRES. To meet these challenges, the research reported in this thesis mainly focuses on the following two aspects: (1) building a resilient SC and (2) modelling SC using complex system approaches.

1.2.1 Building a Resilient Supply Chain

Due to the high impact of disruptions, it is important to build a resilient SC. There are two main approaches to improve SCRES: (i) proactive efforts of mitigation, and (ii) reactive capabilities of recovery. Proactive strategies plan and design SCN for anticipating unexpected disruptions [143]. By identifying vulnerabilities of SCN at the strategic design and planning stages, SCN can be designed to be more resilient to disruptive events through building redundancy and flexibility on the vulnerable components in the network [9, 17, 38, 39].

Focusing only on proactive mitigation in the SC is insufficient; the recovery of SC performance is also an important factor in a disruption. Reactive contingency strategies focus on the ability to identify the risk sources and impacts and to adapt to the impact of disruption and change accordingly to recover quickly and efficiently. During disruptions, contingency plans must be implemented quickly to expedite stabilisation and recovery in order to ensure the continuous supply of products and avoid long-term impact [81].

Enterprises are interested in evaluating the resilience of their existing SCNs and the implications of new strategies on their SCRES. Several surveys have highlighted the importance of quantitative methods to study SC disruption risks [44, 68, 172] and quantitative analysis of SCRES [142]. This research will propose new approaches to evaluate the SCRES using models to provide quantifiable measures for comparisons and contrasts amongst the implementations of SCRES strategies.

1.2.2 Modelling SC Using Complex System Approaches

Complex system theory provides approaches to model the complexity of SCN at different levels: (i) microscopic behaviours of individual entities and their interactions within an SCN, and (ii) macroscopic properties of the whole SCN. The macroscopic level focuses on mitigation strategies to build resilient in SCNs to withstand the impact of disruptions. At the microscopic level, contingency strategies are evaluated to determine SC's response and recovery from disruptions. It is still open research to model the complexity of SCN, design SCRES strategies, and evaluate their effects on the overall SCRES.

Network models will be proposed to model the macroscopic properties of SCN. The network models will consider the heterogeneity of SCN, where nodes represent entities in the SCN (e.g., suppliers, plants and retailers) and connections between the nodes represent relationships between entities. An SCN can be modelled as a hierarchical network where each hierarchy in the network represents a stage. There is only a single edge between two nodes and the edges only connect nodes between adjacent stages. For example in Figure 1.2, there is only a single edge between a supplier and manufacturing plant. The supplier does not connect to the assembly plant directly. However, for a more complex real-world SCN, a graph model of an SCN is required to generalise the hierarchical network structure, which can consider the complex interdependencies within the SCN. Through graph theoretical analysis, structural characteristics of SCNs can provide summarised statistics regarding the SCRES. In addition, system dynamics (SD) model can also be used to represent the system properties of an SCN.

At microscopic level, ABM will be used to model the operational behaviours of individual SC entities. ABM can consider the dynamic response of SCN during disruption to model recovery behaviour. Hence, the key performance indicators in terms of SC operational performance and financial metrics can be used to quantitatively assess the SCRES.

To enable the analysis of the system and its components across different levels of details, a hybrid model using ABM and SD will be also proposed to model SCN. An example of hybrid model is shown in Figure 1.3. The hybrid model will make it possible to capture both microscopic behaviours and macroscopic properties with limited information regarding the SC operations.

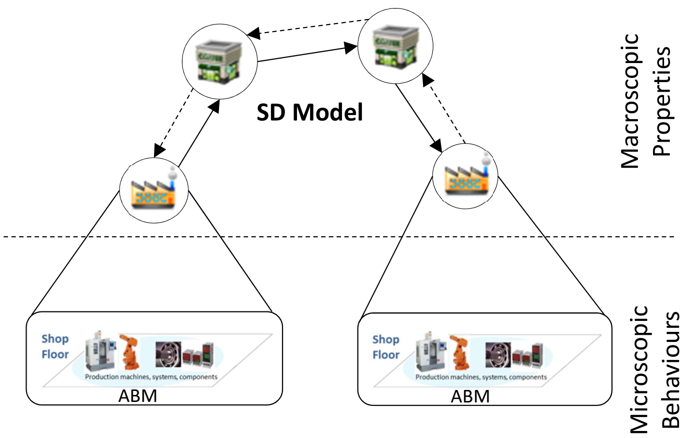


Figure 1.3: An example of a hybrid model of SCN, where macroscopic properties are modelled as SD (e.g. demand and supply flows) and microscopic behaviours (e.g. detailed operational processes at shop floor) are modelled as ABMs.

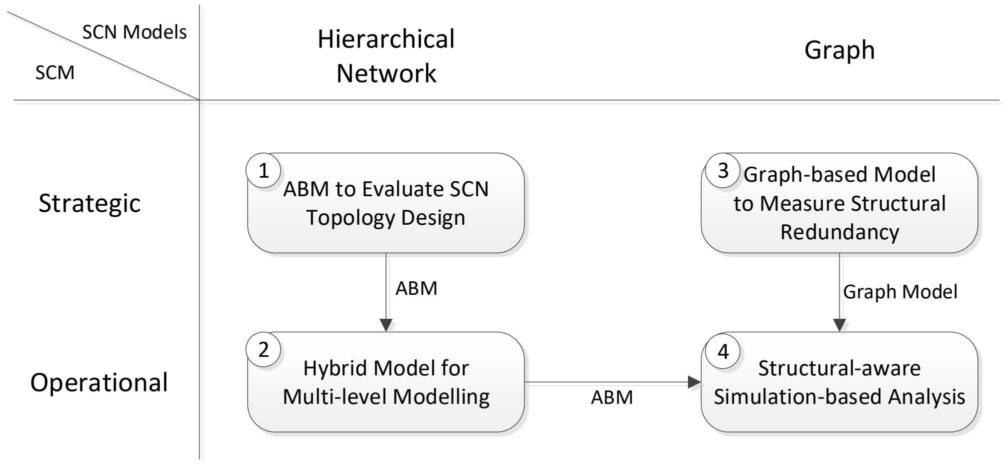


Figure 1.4: Categorization of four pieces of work.

1.3 Contributions

In this thesis, four pieces of work are accomplished to analyse and evaluate SCRES. Figure 1.4 shows the overall structure of this thesis. To keep the SCN model tractable, it is common to model an SCN as a hierarchical network. However, to enable an analysis of more complex real-world SCN, it is necessary to represent the SCN using a graph model. As described in Section 1.1.1 earlier, there are two levels to SCM – strategic and operational planning. Each work focuses on a different aspect of the modelling and SCM issues. Contributions of this thesis are summarized as follows:

1) Agent-based Model to Evaluate SCN Topology Design: A top-down approach for strategic planning is proposed to design SCN topologies for hierarchical networks based on SC strategies. A bottom-up approach using ABM is proposed to evaluate the operational performance of the SCN topologies. A distribution SCN is modelled as a hierarchical network and an ABM is developed to model individual SC operations for each entity in the SCN. Through simulation-based analysis, effective SCN topology can be identified to mitigate a particular risk scenario. This research addresses the challenges 1, 3, and 4.

2) Hybrid Model for Multi-level Modelling: To study the external effects on its internal operations, a firm often needs to construct an SCN model. The firm may have sufficient data to build a detailed model of its operational processes. However, it is difficult to construct the rest of the SCN model at the same level of details since the firm has no control or visibility over the external entities. An integration design approach is used to create a hybrid model of an SCN: the whole SCN is modelled using SD and the focal firm is modelled using ABM. This hybrid model is, therefore, able to capture different levels of details of the same system. An ABM is developed by extending the one developed in the first piece of work to consider SC operations in a manufacturing SCN. The SD model can be used for strategic planning and ABM can be used for operational planning. To evaluate SCRES strategies, trade-offs between mitigation and contingency strategies and between backorder cost and ordering cost are analysed on different disruption scenarios. This research addresses the challenges 1–4, 6, and 7.

3) Graph-based Model to Measure Structural Redundancy: Hierarchical networks with the same type of material flow between stages limit the applicability of the SCN model on complex multi-stage SCNs. To model the complex interdependencies across SCN and overcome the limitations of the hierarchical network, a top-down approach to model an SCN using graph theory is proposed. The proposed model is capable of representing the structural redundancy for strategic planning. The model considers both materials and plants in an SCN and captures two essential relationships between the materials and plants (that is, *material-to-product relationship* and *inter-plant relationship*). The two relationships form the basic building blocks for constructing a multi-stage SCN. Hence, heterogeneous material flows between the stages can be represented using these relationships. Based on the structural analysis of an SCN, all the SCs in an SCN can be identified. A new approach to assess SCRES is proposed to measure the structural redundancy using the number of SCs in an SCN. The vulnerability of an SCN can also be assessed by identifying critical plants. Case studies are used to illustrate the contingency response to disruptions. To evaluate the proactive mitigation strategy, random disruptions are simulated using real-world SCNs, and it shows that the SCRES can be improved by adding redundant plants. Contingency strategy is also developed to response reactively to the criticality of the disrupted plant. This research addresses the challenges 1–5.

4) Structural-aware Simulation-based Analysis: Structural analysis alone cannot capture the dynamics of recovery of an SCN during the disruption. To consider the dynamics of disruption-recovery behaviours, a simulation model is developed by combining the graph model with ABM of SC operational behaviours. This simulation model includes information and material flows and considers the inventory-production system with backorders. Based on structural analysis, mitigation strategies are designed to build redundancy. Contingency strategies are analysed to prioritise recovery on affected SCN. New SCRES indexes are proposed by evaluating the SC performance for disruptions of each plant and aggregating the measures based on the criticality of plants in the SCN. These indexes avoid the need for predictions about rare disruptive events and measure the response to disruptions that might occur within the SCN. Simulation results show that these strategies can be used to build resilience by enabling SCN to recover faster after disruptions. In addition, mitigation strategies are more suitable for long-term disruptions while contingency strategies are more effective for short-term disruptions. This research addresses the challenges 1–6.

1.4 Outline

This thesis is organized into seven chapters.

- Chapter 2 provides a review of SCRES (definitions, strategies and assessment approaches) and modelling paradigms for SCs. Details regarding the research gaps are further elaborated based on the review.
- In Chapter 3, the design of SCN topologies for hierarchical networks and the details of the ABM is presented. A three-stage distribution SCN is used as the case study to identify effective SCN topology to mitigate different risk scenarios. This chapter is based on the work published in Winter Simulation 2015 (see List of Publications [1]).
- In Chapter 4, the details of the hybrid model of SCN that combines SD and ABM is presented. A real-world manufacturing SCN is used to assess the cost-effectiveness of mitigation and contingency strategies under various disruption scenarios of varying frequency and duration. This work has been published in Winter Simulation 2017 (see List of Publications [3]).
- In Chapter 5, a graph model of an SCN is presented. A new SCRES measurement is proposed based on the structural redundancy of SCN. Case studies based on two real-world manufacturing SCNs are discussed to illustrate the applicability of the graph model. The content of this chapter is based on the work published in International Journal of Production Research 2019 (see List of Publications [4]).

- In Chapter 6, a simulation model which extends the previous graph model with agent behaviours is presented. Mitigation and contingency strategies are designed based on the structural analysis of an SCN. These SCRES strategies are evaluated using the proposed SCRES indexes on a real-world manufacturing SCN for different disruption scenarios.
- Finally, Chapter 7 concludes this thesis with a summary of the research and pointers for further work.

Chapter 2

Literature Review

This chapter provides a review of the literature on the research problems addressed in this thesis: the concept of resilience in the context of SC and the characteristics of SCRES. Existing SC strategies to build resilience and assessment approaches to measure SCRES are also reviewed. After identifying the scope and characteristics of SCRES, different paradigms for modelling SC are discussed with their limitations for analysing SCRES. Finally, the research gaps are identified, which serve as the basis for the following chapters.

2.1 Supply Chain Resilience

2.1.1 Resilience

Constant market changes caused by technological innovations and customers' needs increase the demand volatility in SCs. The effort to identify and mitigate SC risks has traditionally focused on operational risks, e.g., demand risks. Although disruptions have a low probability of occurrence, they may cause a significant business impact when occurred [160, 168]. One of the major focuses of SCM is on building a robust SC that can sustain its operation during and after the disruption [181]. However, building a robust SC that encompasses every point of possible failure and delivers reliable performance throughout the entire disruptive event is difficult. Since it is not possible to avoid such events, SCRES provides an approach to handle these disruptions.

The diverse notions of SCRES have highlighted the issue that there is a lack of consensus in the definition of SCRES [123, 174]. The various definitions of SCRES from existing literature are listed in Appendix A. Since researchers have a different perspective on the concept of SCRES, the elements of these definitions have been extracted and summarised in Table 2.1:

Resistance the ability of an SC to minimise the impact of a disruption;

Response the ability of an SC to react early to the occurrence of a disruption;

Recovery the ability of an SC to return to a steady state of operational capacity after a disruption;

Adaptation the ability of an SC to change to suit the different condition of disruption; and

Speed the speed of recovery of an SC after a disruption.

After disruption, an SC can recover back to the **original state** or grow to a **better state**. The number of papers that discussed these concepts is also tabulated.

By considering the main elements discussed by these definitions, the top four key characteristics of SCRES can be determined: (i) resistance, (ii) response, (iii) recovery, and (iv) original state. One of the most comprehensive definitions of SCRES is defined as "the adaptive capability of an SC to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the SC to a robust state of operations" [91]. Some authors proposed an adaptation to a better state after disruption such that the SCN can be more resistance to future disruptions. However, both adaptation and growth are not commonly considered as the key elements of SCRES. Although recovery speed is also not the main consideration, extensive downtime of a disrupted SC may lead to the lost of business. Since recovery is a key characteristic of SCRES, timely recovery should also be considered. In addition, these SCRES definitions do not appear to consider cost-effectiveness. Tukamuhabwa et al. [188] argued that it is important to consider cost in the definition of the resilience of an economic system. The impact minimization of SC disruptions should be cost effective [105, 192]. Hence, cost-effectiveness should also be another key consideration for developing a resilient SC.

In summary, a resilient SC needs to have the resistance capacity to mitigate the impact of unexpected disruption. When a disruption occurs, the SC needs be able to response to the disruption and recover in a timely manner back to the original state. The

Table 2.1: Elements in SCRES.

Authors	Resistance	Response	Recovery	Adaptation	Speed	Original State	Better State
Barroso et al. [11]	✓	✓				✓	
Blackhurst et al. [17]	✓		✓		✓	✓	✓
Brandon-Jones et al. [20]		✓	✓		✓	✓	
Carvalho et al. [25]		✓					
Christopher and Peck [33], Peck [138]		✓	✓			✓	✓
Falasca et al. [45]	✓		✓		✓	✓	
Fiksel [47]	✓			✓			
Gaonkar and Viswanadham [53]	✓	✓	✓				
Guoping and Xinqiu [58]			✓			✓	
Hearnshaw and Wilson [65]	✓						
Jüttner and Maklan [89]			✓				
Kamalahmadi and Parast [91]	✓	✓	✓	✓	✓		
Kim et al. [95]	✓						
Klibi et al. [98]	✓	✓	✓	✓	✓		
Kumar and Sosnoski [100]	✓	✓	✓				
Longo and Ören [113]		✓	✓		✓	✓	
Melnyk [121]	✓	✓	✓				
Pereira et al. [139]		✓	✓		✓	✓	✓
Pettit et al. [141]	✓			✓			✓
Ponis and Koronis [143]	✓	✓		✓		✓	✓
Ponomarov and Holcomb [144]	✓	✓	✓	✓			
Priya Datta et al. [145]	✓	✓		✓			
Rice and Caniato [153]		✓	✓			✓	
Sarathy [158]			✓		✓		
Sawik [160]	✓			✓			
Schmitt and Singh [165]	✓		✓		✓		
Sheffi and Rice Jr [169]			✓		✓	✓	
Shuai et al. [170]		✓	✓		✓	✓	
Xiao et al. [206]			✓	✓		✓	
Yao and Meurier [209]		✓	✓	✓		✓	
Zsidisin and Wagner [212]		✓	✓	✓			
No. of Papers	16	17	22	11	11	13	5

SC also needs to manage the disruption in a more cost-effective way to gain a competitive advantage over its competitor[60, 209]. It is still an open research issue to design strategies that encompass these characteristics and operational plans to implement these strategies.

2.1.2 SCRES Strategies

Corresponding to key characteristics of SCRES, there are two broad categories of SC strategies to improve SCRES: **proactive mitigation** and **reactive contingency** strategies. Proactive strategies plan and design an SCN for anticipating unexpected disruptions [143]. However, managers may be reluctant to implement proactive strategies since it becomes difficult to justify investments that mitigate potentially disruptive events which may not ultimately occur [188]. On the other hand, reactive strategies focus on the ability to identify the risk sources and impacts, and to react to the impact of disruption and change accordingly to recover quickly and efficiently. During disruptions, contingency plans must be implemented quickly to expedite stabilisation and recovery in order to ensure continuity of supply and avoid long-term impact [81]. In general, SCRES strategies can be grouped as described below.

Agility

Agility is the ability of an SC to "respond quickly to unpredictable changes in demand or supply" [33]. An agile SC is more resilient by being responsive to the random and targeted disruptions [118]. The agility of the SC is also related to capabilities such as *velocity* and *visibility* [33].

Velocity refers to "the rate which an SC recovers from disturbance" [89], which also represents the rate of flexible adaptations [176]. Velocity focuses on reducing the lead-time in the SC [8, 55, 122, 198]. At the planning stage, reducing the product development time will reduce the overall planning life cycle [93]. At the manufacturing stage, the production batch size can be reduced [55, 199]. The transportation time can be reduced by improving logistics [37, 93, 97]. Shorter lead-time leads to better responsiveness to disruption within an SC.

Visibility implies "the ability to see through the entire SC, have a clear view of upstream and downstream inventories, demand and supply conditions, and production and purchasing schedules" [33]. Within an SC, visibility can be improved by investing in information technology [110], including better inventory tracking systems [203]. This enables better monitoring of the SC [42]. Between firms within the SC, increasing visibility can be achieved by improving communications between the stakeholders in the SC [42, 189, 200]. It ensures that the firms share important information with each other, especially regarding the effects of the disruptions [156]. This enables the firms to identify potential vulnerabilities and the sources of disruption quickly.

Flexibility

Flexibility involves building capabilities of change within an SC [89]. This makes the SC more resilient through the flexibility of change in response to disruptions. The flexible strategies can be implemented at various stages of an SC.

At the supplier level, flexible sourcing strategies can be introduced to allow switching of suppliers promptly during disruption [8, 55, 118, 148, 199]. This is also known as contingent re-routing, where backup plants (at a higher price) are used to maintain the production process during the disruption [29, 36, 185]. These backup plants allow SCN to continue working during the disruption by providing the alternative source of production capacity. Option contracts are usually used to reserve capacity from backup plants at a pre-negotiated price for a reservation fee. This contract stipulates that the plant has to use the reserve capacity for production during disruptions and the buyer will incur penalty costs for the reserved capacity even if the capacity is not utilized [156]. Other than that, flexible supplier contracts (e.g., long term and short term contracts) also allow the change in production quantities or pricing in order to minimize shortages during disruptions [148, 180, 189, 199].

At the manufacturer level, flexible manufacturing processes utilize postponement to fulfill uncertain demands [87, 148, 180], by delaying the actual commitment of resources [23]. Hence, postponement enhances resilience during a crisis by deferring demand fulfillment to a future period, e.g., after the disruption [181]. In addition, smaller production unit allows flexibility on altering the production as required [199]. This allows production on demand according to the current global and local information, instead of fixing to a monthly schedule [145]. Therefore, changes in the production schedule can be applied easily during disruptions.

At the distribution level, flexible transportation enables firms to switch transportation routes or modes quickly, bypassing the impact zone of disruptions [8, 26, 34, 55, 118, 148, 189]. This flexibility enables the continuity of the logistics operations in the midst of disruptions.

At the demand level, flexibility can be used to influence customer choices, such as dynamic pricing, assortment planning, and silent product rollovers. Dynamic pricing allows changing the price to meet the current demand, such as an increase in price to handle shortages [87, 148]. Assortment planning is a process whereby products are selected and planned according to the available supplies [99]. Silent product roll-over or product switch allows flexibility on order fulfillment by replacing the product with similar alternatives [55, 87, 148, 189]. This allows the products and services to be managed according to the uncertainties in the customer demand [55].

Collaboration

SC collaboration refers to the ability to work effectively with other firms in an SC for mutual benefit [141]. Collaboration between firms mainly involves the exchange of information to reduce uncertainties and improve accuracy in forecasting [33]. It allows the firms to align their efforts in the midst of a disruption [144], thereby improving the resilient of the SC. Suppliers can also collaborate to improve the market position and financial strength in the SC by pooling their resources to ensure better survivability during disruptions [102, 199].

Integration

Vertical integration increases the control the enterprise has over the whole SC [117]. Acquisition is also a powerful tool to bring necessary firms under the control in the same enterprise, decreasing the dependence on outsourcing [42]. Through increasing control over an SC, contingency plans can be executed efficiently with minimum delays to mitigate disruptions. However, additional control also ties up capital, and indirectly constraints the SC flexibility.

An SC can either integrate upstream (supplier) or downstream (retailers). Upstream integration focuses on integration with the suppliers [122], which builds stronger and better relationships with suppliers [93]. By fortifying the suppliers, it increases the suppliers' resilience to disruptions [187]. In contrast, coordination with downstream partners allows more control over the market demand, such as price or product coordination [8].

Redundancy

Redundancy is also proposed as a strategy to mitigate disruptions [7, 91, 113, 139, 188]. For instance, there are several approaches to build redundancy in SC.

Redundancy can be built in an SCN structure, e.g., by having multiple production plants for a product or a component. SCN redundancy duplicates the facilities in order to continue to serve customers while rebuilding and repairing the affected plants after disruptions [98]. These redundancies are designed to help the SC avoid the significant waste of time, effort and money involved in the disruption by providing the capabilities of responding to these sudden changes [35, 212]. Multiple plants diversify risks by decreasing the likelihood that disruption to a single plant significantly affects the SC. The redundant plants also allow an SCN to maintain the production process even if one of the plants is down during disruption [185].

Redundant capacity is a mitigation strategy that is commonly used, as it is effective because it is the quickest type of capacity to bring online. Redundant capacity means that the production lines or facilities maintain in excess of capacity in order to have the capacity to response to disruption [153]. It enables an SCN to meet customers' demand and fulfil the backorders during recovery. If there are sufficient spare capacity and inventory, the final assembly downstream can continue to operate [72]. Hence, the consequences of the disruption will not be felt beyond the disrupted plant. Even if the redundant capacity does not entirely isolate the disruption, it can serve to shorten the disruption duration felt by customers.

Hedging

Hedging can help to distribute the disruption risks and prevent a single point of failure during disruption, which improves the overall resilience of SCs. However, hedging requires significant investments because it involves multiple options for decision variables, each of which incurs addition costs [117].

At the suppliers and manufacturers, a globally dispersed portfolio of suppliers and facilities improves SCRES such that a localized disruption event will not affect all the entities at the same time or in the same magnitude [117]. Hedging can also be applied at the logistic level, which diversifies the transportation by splitting the shipment flow [77]. Disruption in one of the route will not disrupt the whole SCN. Aggregation or pooling demand [148] allows the creation of a balanced portfolio of products so that the supply

Table 2.2: Proactive mitigation strategies.

Strategies	Descriptions
Agility	• Visibility – The ability to see through the entire SC (all nodes and links), which helps to identify vulnerabilities [33, 42].
Flexibility	• Long-term and short-term contracts that can enable flexibility in supply to minimize shortages [148, 180, 189, 199].
Collaboration	• Exchange of information with other firms in an SC to reduce uncertainties and improve accuracy in forecasting [33, 141]. • Horizontal integration to pool resources in order to ensure better survivability during disruptions [199].
Integration	• Vertical integration – Increasing control over the upstream suppliers and downstream retailers [93, 117, 122].
Redundancy	• Structural redundancy – Facilities are duplicated in order to continue to serve customers while rebuilding and repairing the affected plants after disruptions [98]. • Redundancy capacity – Production lines or facilities maintain in excess of capacity in order to have the capacity to response to disruption [153].
Hedging	• Supplier selection – Dispersing portfolio of suppliers and facilities globally to minimize disruptions and their impact [117]. • Diversify transportation – Splitting shipment flow [77] • Portfolio diversification – Indulging in different products to reduce dependence on particular products and suppliers [93, 148] .

Table 2.3: Reactive contingency strategies.

Strategies	Descriptions
Agility	• Velocity – Shorter lead-time increases speed of flexible adaptations that determines the recovery speed of an SC from a disruption [8, 55, 89, 122, 176, 198]. • Visibility – Identifying the sources of disruption quickly [156].
Flexibility	• Contingent re-routing – switching to alternative suppliers during disruptions [8, 55, 118, 148, 199]. • Postponement – deferring demand to a future period after disruption [181]. • Flexible transportation – switching transportation routes or modes quickly to avoid disrupted region [8, 26, 34, 55, 118, 148, 189]. • Flexible demand – Influencing customer choices through, e.g., dynamic pricing, assortment planning and silent product rollovers [55, 87, 99, 148, 189].
Collaboration	• Sharing necessary information and resources for response and recovery with other firms in an SC [33, 141, 144].

disruption of a single product does not impact the whole SCN [93]. Customers can select another product from the portfolio when one of the products is disrupted.

In summary, some particular strategies can be either proactive or reactive depending on the scope of the implementation [188]. A summary of proactive mitigation strategies and reactive contingency strategies from literature is shown in Table 2.2 and Table 2.3 respectively. These strategies describe the strategic plans from a high-level. Concrete operational plans still need to be designed in order to apply these strategies to real-world SCNs.

2.1.3 SCRES Assessment Models

To measure the effectiveness of SC strategies, a quantitative assessment of SCRES is required. There are research works that proposed conceptual models to measure SCRES.

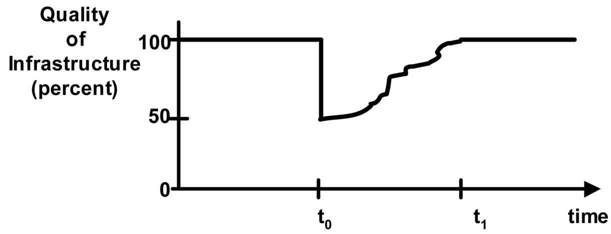


Figure 2.1: Resilience triangle [22].

Resilience triangle is the first model considering the impact of disruptive events from a disaster management perspective (Figure 2.1). It represents different factors such as the initial performance level, loss of functionality and recovery time [22]. It can be used to model the loss of performance over time due to disruptions and recovery behaviours in the system. The disruption occurs at time t_0 and the system eventually recovers from the impact of the disruption at time t_1. System performance at time t is denoted with $Q(t)$. Hence, resilience is measured by:

$$\mathcal{R} = \int_{t_0}^{t_1} [100 - Q(t)]dt$$

Tukamuhabwa et al. [188] proposed a concept of adaptive resilience. Figure 2.2 illustrates the adaptation of an SC to the disruption such that it becomes more resilient to similar disruptions. Period A refers to the first disruption, where the impact of disruption is large; while Period B refers to the second disruption with a smaller loss. SCRES

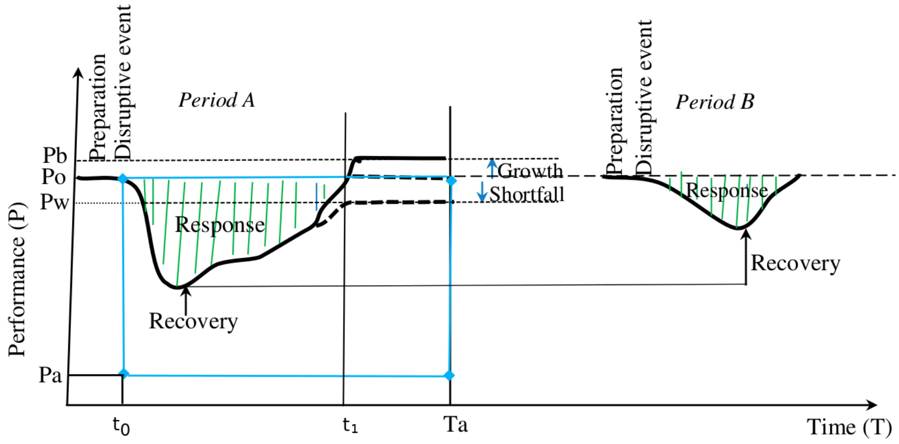


Figure 2.2: Adaptive resilience [188].

measures performance loss after a disruption till recovery, by calculating the area above the curve as the shaded area in Period A. p_0 refers to the initial performance level before the disruption and p_a is the minimum acceptable performance level. An SC will be totally disrupted when its performance is below p_a. The best and worst performance after recovery are p_b and p_w respectively. The maximum acceptable recovery time denoted as T_a. This approach provides a comparative measurement for SCRES, which can be used to assess the adaptive capabilities and/or the growth of the SC after the initial disruption event.

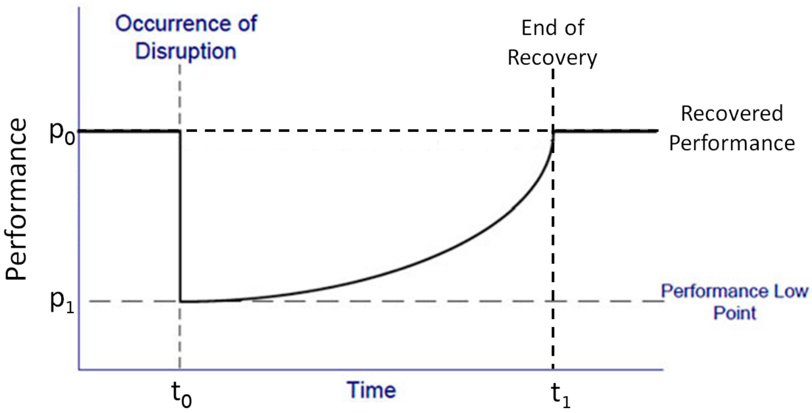


Figure 2.3: Performance profile disruption behaviour [129].

Munoz and Dunbar [129] proposed a more detailed approach to quantitatively evaluate resilience across multi-dimensions, which is shown in Figure 2.3. At the occurrence of disruption, there is a sharp drop in performance to the lowest point. The performance recovers over time to an acceptable performance range. To capture multiple transient response dimensions, five resilience metrics are employed to measure the performance of an SC in terms of delivery lead time:

Recovery $\mathcal{R}_r$ measures the duration of recovery from the start of disruption t_0 to the end of recovery t_1:

$$\mathcal{R}_r = t_1 - t_0$$

Impact $\mathcal{R}_i$, assesses the impact of disruption by measuring the difference in the performance level before disruption p_0 and at the full impact of disruption p_1:

$$\mathcal{R}_i = p_0 - p_1$$

Profile length $\mathcal{R}_l$, measures the length of the recovery curve:

$$\mathcal{R}_l = \int_{t_0}^{t_1} \sqrt{1 + (\frac{\delta Q(t)}{\delta t})^2 \delta t}$$

Performance loss $\mathcal{R}_p$, is the area above the performance curve during the period of disruption:

$$\mathcal{R}_p = (t_1 - t_0) \times p_0 - \int_{t_0}^{t_1} Q(t) \delta t$$

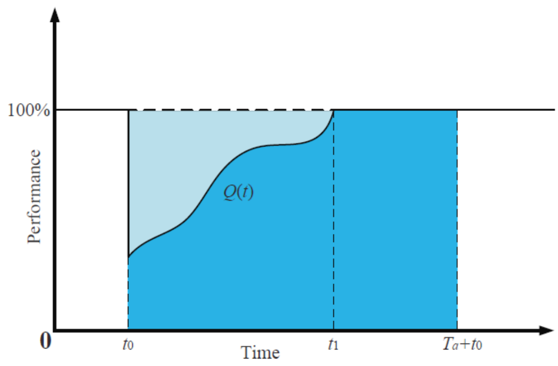
Weighted-sum $\mathcal{R}_w$, measures the time-dependent deviation from a linear recovery $g(a_i)$ to the actual recovery performance $Q(a_i)$, where $a_1 = t_0$ and $a_n = t_1$:

$$\mathcal{R}_w = \sum_{i=1}^{n} a_i [g(a_i) - Q(a_i)]$$

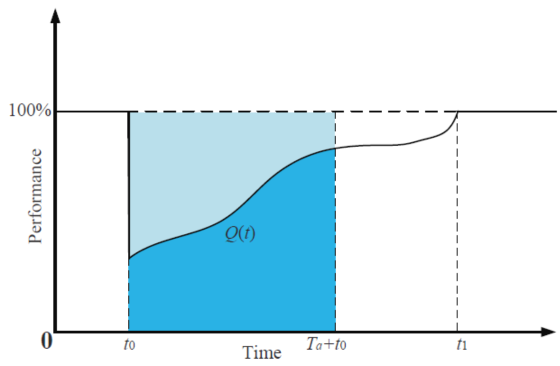
A resilience index is generated by aggregating the five resilience metrics:

$$\mathcal{R} = w_1 \times \mathcal{R}_r + w_2 \times \mathcal{R}_i + w_3 \times \mathcal{R}_p + w_4 \times \mathcal{R}_l + w_5 \times \mathcal{R}_w$$

Li et al. [111] proposed a new measurement approach to SCRES by considering only the maximum allowable recovery time determined by users (i.e., T_a). Figure 2.4 shows two scenarios where (a) the system performance returns to its original level within the allocated recovery time, i.e., $T_a + t_0 \geq t_1$, and (b) the system performance has not



(a) Recovery within maximum allowable recovery time



(b) Recovery after maximum allowable recovery time

Figure 2.4: Measuring performance in maximum recovery time in two scenarios [111].

recovered back to its original level within the allocated recovery time, i.e., $T_a + t_0 < t_1$. The resilience is determined by:

$$\mathcal{R} = \frac{\int_{t_0}^{T_a+t_0} Q(t)\delta t}{T_a}$$

This relative measure can be used to compare SCRES of different SCN.

In summary, current approaches for SCRES assessment only considers the recovery of SC performance back to its original level after the disruption. However, for long-term recovery from disruptions, experts have agreed that SC performance should undergo similar behaviour as shown in Figure 2.5 [27]. Tomlin and Wang [186] also identified one of the primary drivers for the recovery time is the additional capacity after a disruption. To be able to fully recover from the performance loss, this requires an SCN to have the capacity to absorb and bounce back after a disruption. During disruption when SCN is unable to fulfil orders, these orders will be retained as backorders. To recover after disruption, SCN needs to have the additional capacity to fulfil the backorders. This additional capacity for recovery is often not represented in the existing SCRES models as described earlier.

2.2 Complex Systems

Decision-making in SCNs is complex, which requires appropriate models. Different models can be used to represent the complexities of SCNs. Graph and SD are common modelling approaches for SCNs at the macroscopic level. At the microscopic level, ABM

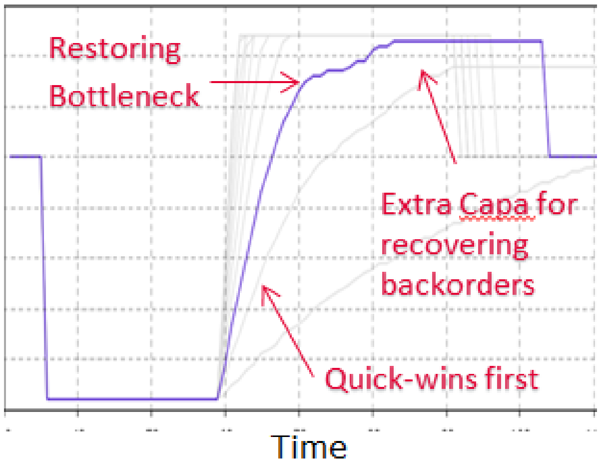


Figure 2.5: Additional capacity for recovery [27].

is frequently used to represent the operational behaviours of the individual entity in the SCN. To model a complex system with different level of details, hybrid modelling can be used to combine different models.

2.2.1 Graph

An SCN can be represented as a *network*. Hierarchical network is typically used to model SCN, where each hierarchy in the network represents a stage. There is only a single edge between two nodes and the edges only connect nodes between adjacent stages. An SCN can also be modelled mathematically as a *graph* $G = (V, E)$, where V is the set of nodes and E is the set of edges. The nodes represent the firms and edges represent the set of connections that link these firms together. Directed edges can be used to represent the direction of flows (e.g., material or information flows). In a production process of a manufacturing SCN, the relationship from the input material to the output product is also known as the *material-to-product* relationship.

SC disruption can be modelled by removing a node or edge from the SCN. A disruption in the graph occurs when there is no path between the source node and the sink node due to the disruption in the nodes or edges. When the graph is disconnected, it disrupts the flow in the graph, which causes a loss in the function of the SCN.

Network analysis can be used to study the existing SCN to determine characteristics of the graph (e.g., identification of critical nodes in the graph). By analysing topological characteristics of SCNs, it can provide summarised statistics for describing particular features. This is particularly useful since the analysis of topological characteristics of the interconnection structure in an SCN enables managers to analyse various aspects of the SCN. In addition, many real-world complex networks (e.g., SCN) can contain a significant amount of structural redundancy, in which multiple vertices play identical topological roles [116].

Another key benefit of using a graph model is that it only requires relational data and allows for detailed analysis and comparison with other networks [120]. Hence, to perform topological (or structural) analysis of an SCN, only the information regarding the relationships between firms in the SCN is required; detailed information regarding the SC operations is not needed.

Supply Chain Network Topology

Random and scale-free networks are common complex network topologies that are used to model complex systems. Random networks are networks with Poisson degree distribution, where links between nodes are placed at random. Erdős Rényi model is one of the earliest random network models that generate networks using the random attachment (RA) [43]. Scale-free networks are widely observed in natural and human-made systems, whose degree distribution follows a power law. Barabási-Albert model generates scale-free networks using the preferential attachment (PA) [10]. PA determines that a new node has a higher probability of connecting to high-degree nodes. These high degree nodes are also known as hub nodes [10].

Many theoretical modelling efforts of SCNs have been focusing on variants of PA or RA to generate network topologies for analysis [14, 46, 103, 131, 195]. They mostly analysed the SCN topology from the perspective of evolutionary dynamics, where the SCN structure evolves over time. There are several research works that applied the PA at each stage in the hierarchical network [118, 183, 210, 211]. However, they only analyse the SCN topology from the system perspective, which is difficult to apply practically to the strategic design of real-world SCN.

In addition, most SCNs focusing on a single enterprise are not large compared to scale-free network, such as online social networks which consist of millions of nodes. Kim et al. [94] analysed the supply network topology of three case studies of automotive supply networks, where the largest network consists of 34 firms. Kito et al. [96] also found that Toyota SCN topology is not scale-free even for a network size of 3,109 firms. Hence, the small size of SCN cannot represent the emergent network topological properties, such as the resilient of a scale-free network.

Graph Analysis of SCRES

Table 2.4 summarizes the existing graph models of SCN based on a topical search of 'SCRES', 'Redundancy' and 'Graph' from the *Web of Science*. The type of graphs is described, along with the representations of nodes and edges. The number of stages that the model can represent is also shown. The last column shows the measure used in the model.

A number of studies have been proposed to assess SCRES using qualitative indicators, e.g., for redundancy and flexibility [30, 85, 154, 173, 190, 192]. The indicators are usually collected through surveys of the experts. Dependencies between qualitative indicators are then modelled using a graph, and an aggregated index is used to assess the overall SCRES. However, these studies do not model the actual SCN, which is the structural representation of the physical material flows and production processes in the SCN.

Much of the current literature on SC redundancy focused on optimizing redundancy in an SCN with only a few stages using analytical models [7, 16, 90, 134, 136]. Optimizing redundancy for multi-stage SCN quickly becomes intractable due to the complexities of the problem.

There are existing models on SCRES that consider redundancy only between two stages in an SCN. Wang and Ip [193] quantified the resilience of logistic networks considering redundancy between the demand and supply. Salehi Sadghiani et al. [157] proposed a deterministic multiple set-covering model to design resilient SCNs under operational and disruption risks. Redundant supplier is assigned to each demand node in the SCN. These approaches are unable to analyse the dependencies across multi-stages in the SCN, where vulnerabilities in the upstream stages of the SCN can have a significant impact downstream.

To consider redundancy across multiple stages in an SC, existing research works on multi-stage SCNs assumed that all plants within the SCN or at the same stage play the equivalent role, or that the type of material flows between stages are the same. Graves and Tomlin [56] considered a SCN where all the plants in a stage can process any products. The redundancy is measured by the total capacity of the plants that can fulfil the corresponding product demand. Redundancies can be measured by the excessive capacity between two stages. Xu et al. [207] developed an assessment approach

Table 2.4: Review of existing graph models of SCN.

Reference	Graph	Nodes	Edges	Stages	Measure
Graves and Tomlin [56]	Bipartite graph	Plants & materials	Material-plant links	Multi	Process flexibility
Wang and Ip [193]	Undirected bipartite graph	Demand & supply	Delivery lines	2	Weighted sum of node resilience
Adenso-Díaz et al. [1] Adenso-Díaz et al. [2]	Directed graph	Suppliers, plants, wholesalers & customers	Product flows	Multi	Network reliability & robustness
Mizgier et al. [126]	Directed graph	Suppliers, focal firms & customers	Purchasing relationships	Multi	Total average loss
Ma et al. [115]	Undirected graph	Manufacturers, suppliers, retailers & customers	Trading relationships	Multi	Node centrality
Xu et al. [207]	Directed graph	Firms	Demand-supply relations	Multi	Customer satisfaction
Kim et al. [95]	Directed graph	Physical locations	Transportation links	Multi	Ratio of redundant nodes to total nodes
Mari et al. [118]	Directed graph	Suppliers, manufacturers & retailers	Material flows	3	Supply availability, size of LFN, clustering coefficient, supply path length in LFN
Reyes Levalle and Nof [152]	Directed graph	Firms	Material flows	Multi	Total cost of flow and total quality of service
Salehi Sadghiani et al. [157]	Bipartite graph	Demand & supply	Material flows	2	Supplier setup costs & transportation costs
Han and Shin [61]	Undirected graph	Risk factors	SC relations	Multi	Average probability of disruption per risk
Wang and Xiao [196]	Undirected graph	Suppliers, manufacturers, distributors & retailers	Production relations	4	SFZ-based index of structure, fixation, efficiency & flexibility
Li et al. [111]	Directed graph	Suppliers, manufacturers, distribution centres & retailers	Materials or product deliveries	4	Recovery time
Nakatani et al. [132]	Directed graph	Materials	Material-to-product links	Multi	Market concentration

of SCRES based on demand satisfaction, where the redundant resources can be used to fulfil the demand during disruptions. The demand at each stage can only be satisfied by the upstream stage. Kim et al. [95] considered SCRES as a network-level attribute to withstand disruptions of nodes in the SCN. SCRES is defined as the ratio of the redundant nodes to the total number of nodes. Mari et al. [118] proposed various resilience metrics for SCs that measure the largest functional SCN (LFN), which is the remaining SCN after disruption, assuming that the demand can be satisfied through the remaining supply nodes. Li et al. [111] proposed a new measure of resilience which measured the average system performance, considering recovery time with a strict upper bound. Nodes with the same function are grouped as one stage, e.g., suppliers, manufacturers, distributors, retailers, etc.

In the context of SCRES, there are also related works that use graph theoretical approaches for disruption analysis and vulnerability assessment of SCNs. Adenso-Díaz et al. [1] considered the impact of network factors (e.g., source criticality) on the reliability of supply networks. The authors also analysed the robustness of the supply networks under targeted attacks or random disruptions [2]. Mizgier et al. [126] measured SCRES using vulnerability in terms of average loss at each firm due to disruptions. Ma et al. [115] proposed that resilience can be achieved either through redundancy to the key suppliers or by keeping a high level of collaboration amongst the key suppliers. The key node can be identified by the critical path analysis. Reyes Levalle and Nof [152] analysed the impact of SCN design on SCRES, which is measured using the total cost of flow and total quality of service in the SCN. Han and Shin [61] assessed the structural robustness of an SC considering disruption propagation, which is measured by the average probability of disruption per risk at each node. Wang and Xiao [196] considered SC recovery under cascading failures. When a node fails, it increases the loads of its upstream and downstream nodes. Based on the load at each node, SCRES is measured using spatial fidelity zones (SFZ) in terms of the structure, fixation, efficiency, and flexibility of the SCN. Nakatani et al. [132] used a graph model representing the material-to-product relationships to assess an SC's vulnerability to disruption risks. SC vulnerability indicators are proposed based on the market concentration of domestic and imported commodities.

In summary, some graph models are limited to a few stages in SCN and unable to analyse complex multi-stage SCN. Other graph models did not differentiate the production process of each type of material and assumed that all plants, either in the whole

SCN or within the same stage, are equivalent. This limited structure complexity makes it difficult to model the in-depth dependencies among the plants and materials. Hence, many of these models are unable to capture both material-to-product and inter-plant relationships in a multi-stage SCN.

2.2.2 System Dynamics

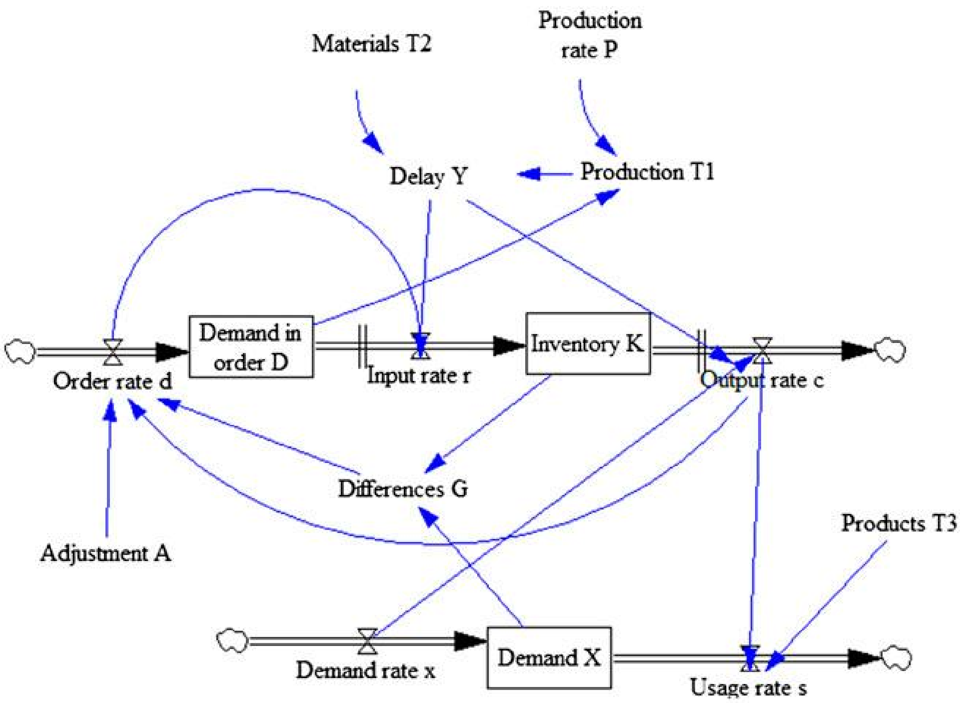


Figure 2.6: An example of SD model of a spare parts SC [112].

System dynamics (SD) is an approach to understand the non-linear behaviour of complex systems over time using stocks, flows, internal feedback loops, table functions and time delays [50, 51]. There are two aspects of SD theory: 'system' represents the structure of the system and the concept of feedback effect; whereas 'dynamics' reflects the changes in the behaviour of the system components over time. In a causal loop diagram, the assumed interactions between the variables are formalised to demonstrate the interdependence within the system boundaries. A closed chain of causal relations is defined as the feedback loop, which could be positive or negative [107]. The positive loop is unstable and oscillated that triggers systems to grow, evolve, and collapse; whereas the negative loop moves the system towards a stable situation. For example, Figure 2.6

shows a stock-and-flow diagram of a spare parts SC. There are two flows: order flow and demand flow of the spare parts. Three stocks represent the demand for spare parts (X), current orders for spare parts (D), and inventory of spare parts (K).

SD modelling has been used for disruption and SCRES analysis. Bukowski et al. [24] modelled a steel production system with three suppliers using SD modelling to assess the impact of disruption to the system. By simulating supplier disruptions of different durations, the degree of loss and resilience can be measured. Li et al. [109] modelled a three-stage SCN with dual suppliers using SD modelling. Individual SC entity is modelled as an SD model and connected through the material flows between the entities. The model is used to assess the SCRES with different level of information sharing when disruption occurs to a sub-supplier. They also used SD modelling to describe the connections between the disruption risks and their associated changes of system behaviour in an SC [108]. SD models are used to represent the inventory system, transportation capacity and disruptive event. By increasing either transportation capacity or equipment number, the improvement in transportation capacity enhanced SCRES by reducing the impact of disruption.

Since SD is often used to model SC from the system perspective, where it models SC as a rigid structure. It is difficult to use SD to represent structural dynamics in an SCN. For example, to model contingency strategies, the SCN structure can change to activate backup plants.

2.2.3 Agent-based Model

An SC can be represented using ABM, where each agent is a firm within the SC and agents interact with each other within an environment [54]. An agent is designed with a set of properties and rules which guides the interaction between the agents and the environment. ABM can be used to model the heterogeneity in the SC where it comprises heterogeneous entities (e.g., suppliers, manufacturers, and retailers) with different interaction behaviours (material and information flows).

This bottom-up approach simulates the underlying processes responsible for global patterns and allows us to evaluate the mechanism that is most influential in producing emergent patterns. Through the local changes at the microscopic level, it can bring about emergent patterns at the macroscopic level.

The agents are usually executed in a simulation with discrete time and each agent

Table 2.5: Summary of existing SCRES simulations.

Reference	SCN	Disruption	Mitigation Strategy	Contingency Strategy	SC Performance	SCRES Index
Carvalho et al. [26]	4 stages	Scenarios	Inventory buffer	Transshipment	Lead time & Cost	-
Schmitt and Singh [164]	3 stages	Scenarios	Inventory buffer	Backup plant	Fill Rate	-
Schmitt [163]	3 stages	Scenarios	Inventory buffer	Backup plant	Service Level & Cost	-
Schmitt and Singh [165]	3 stages	Risk Profile	Inventory buffer	Backup plant	Fill Rate	-
Schmitt et al. [166]	4 stages	Scenarios	Inventory Buffer	Expedite Orders	Fill Rate & Cost	-
Barroso et al. [12]	3 stages	Scenarios	Inventory Buffer	-	Fulfilment Rate	Aggregated Performance Loss
Chen [27]	3 stages	Scenarios	-	Backup Plant	Fill Rate & Cost	-
Li et al. [111]	4 stages	Scenarios	-	Flexible sourcing	Fulfilment Quantity & Delivery Distance	Average Performance within recovery time
Ledwoch et al. [103]	Complex network	Random & Targeted	Inventory buffer	Backup plant	Fill rate & Cost	-
Nguyen [133]	Hierarchical network	Stochastic disruption length	Inventory buffer	-	Tardiness & TTR	Sampled average SC performance

performs actions for every time step. To be able to develop an accurate model for analysing SCN, this requires extensive information regarding the demand and supply in the SC, the operational processes of each firm (such as the inventory policies or the production schedule) and the detailed operational behaviours between firms within the SC.

Simulation-based Analysis of SCRES

Since ABM is such a promising research area, it has been used in various SC studies. ABMs for evaluating SCRES are summarized in Table 2.5. The table shows (i) the complexity of the SCN model, (ii) the disruption model, (iii) mitigation and (iv) contingency strategies, (v) SC performance metric, and (vi) SCRES index.

ABMs enable a more realistic analysis of real-world SCN by considering more than two stages that are difficult to represent in analytical models. Three-stage SCNs have been used in case studies in [12, 27, 163–165], while four-stage SCN in [26, 27, 166]. Nguyen [133] proposed a network model that can represent complex multi-stage SCNs. Ledwoch et al. [103] modelled SCNs as complex networks (e.g., random and scale-free networks).

Snyder et al. [172] provided an extensive review of disruption models used in SC risk management. Disruption is typically modelled as a disturbance causing a production flow interruption of fixed duration, and this approach was adopted in many case studies [12, 26, 111, 163, 164, 166]. Schmitt and Singh [165] used risk profiles of disruption inter-arrival times for each plant in SCN. The varying impact of the disruption has also been considered, where the capacity of the facilities decreases instead of a full disruption of the capacity [27, 111]. Ledwoch et al. [103] considered random and targeted disruptions on SCN. Stochastic disruption lengths are used in [133].

There are research works that considered mitigation strategies, such as using inventory buffer [26, 103, 133, 163]. Different contingency strategies are also evaluated – transshipments [26], flexible sourcing [111], re-routing to alternative sites or backup facilities [27, 103, 164], or expediting orders [166]. These works showed that contingency strategies are necessary to recover SC performance back to the normal operational state.

Different SC performance measures have been used to quantify the impact of disruptions in terms of time, cost and operational performance. Since disruption delays the fulfilment of orders, various time measures have been used – lead time ratio measures the ratio between actual and promised lead time [26], tardiness measures the delay in time, and recovery time measures the time taken for recovery [133]. The delivery distance can also be used to measure delay indirectly [111]. Since the financial impact of disruption is another important consideration, the total cost is another common performance measure [26, 27, 103, 163, 166]. For operational performance, fill rate is commonly used, which measures the fraction of customer demand that is met through immediate stock availability, without backorders or lost sales [27, 103, 164–166]. Similar operational measures, such as fulfilment rate [12] or service level [163] which measures the percentage of orders fulfilled, and fulfilment quantity [111] which measures the amount of product fulfilled, are also used. These measures enable decision-makers to understand the SC performance due to the disruption dynamics.

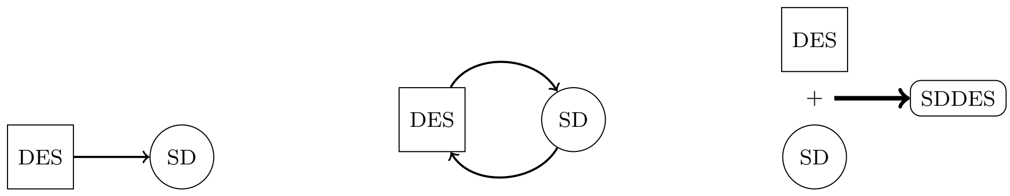
SCRES indexes are proposed to aggregate the SC performance measures across the whole SCN, instead of just focusing on a particular part of the SCN. These indexes help to understand how certain strategies improve SCRES and identify improvements to reduce the impact of disruptions. Barroso et al. [12] quantified SCRES by aggregating the performance loss due to the drop in fill rate using four different aggregation approaches. Li et al. [111] measured SCRES using the average performance within the maximum allowable recovery time. This enables the comparison of different SCN on the same relative scale. Instead of aggregating SC performance using a weighted average of the likelihood of disruptions determined by the decision-makers, Nguyen [133] proposed a sampling approach to determine the probability of these events.

In summary, most of the existing ABMs do not consider the structural properties of an SCN to build a more resilient SCN. As reviewed earlier, structural analysis of an SCN can give a theoretical insight into the vulnerabilities in the SCN. Based on this knowledge, more effective approaches to manage the disruptive events can be proposed, e.g., by designing mitigation strategies to protect the vulnerabilities and contingency strategies to prioritise the recovery. To evaluate the effectiveness of the SCRES strategies, the recovery of SCN during disruption can be analysed through simulation-based analysis.

2.2.4 Hybrid Model

Previous research focuses on using different methods for modelling different level of details in a complex system, e.g., SD at the macroscopic level or ABM at the microscopic level [179]. In order to model a complex system, a more generic and holistic strategy is required, which should allow combining different models to enable the analysis of the system and its components across different levels of details. Hybrid modelling was first proposed in the context of mixing different modelling methods by Shanthikumar and Sargent [167]. Morgan et al. [128] proposed various approaches for combining discrete event simulation (DES) and SD as described in the details below. Three types of hybrid designs are illustrated in Figure 2.7.

Sequential design first uses the SD model to capture the whole system under study, and then the DES model is used to focus on a specific process of the system. There is usually a linear and unidirectional relationship between the models, where the output of one model is used as the input for the other model. In Figure 2.7a, the output from DES model is used as input for the SD model. For example, Reiner [151] proposed a combined usage of SD and DES: order fulfilment process is simulated using DES and the



(a) Sequential (b) Interaction (c) Integration

Figure 2.7: Toolkit of hybrid designs.

performance indicators obtained from DES are used in the customer-orientated process evaluation using SD.

Interaction design is frequently used to capture the operational processes and interactive influences acting upon them. Compared to sequential design, interaction design has bi-directional feedback between the models. In Figure 2.7b, there is an exchange of results between DES and SD models. For instance, Wang et al. [194] proposed a hybrid model using interaction design. SD is used to predict the production output and adjust the production rate based on the input from the sale department (agent), DES simulates the assembling process based on the production rates from the production planning (SD model), and the assembled products are input to the sale department (agent) to be sold to customers.

Integration design combines DES and SD in the same model, taking the same view of the system. The two methods are inseparable and need to function together as a single model. This gives a concise and coherent view of the model, instead of separate results from each model to end-users, as shown in Figure 2.7c. For example, Helal et al. [66] proposed to integrate DES and SD to simulate a manufacturing enterprise. An overall SD is built for the enterprise system, where the model is decomposed into functional modules. A number of DES models are developed for the selected functional modules in the system as dictated by analysis needs. This reduces the development time required for building a large DES model to represent the entire functionality of the system.

Existing works using integration design for hybrid modelling have been reviewed. A case study was done using a hybrid model for management policy design and testing of a real manufacturing system [135]. SD model of an SC is built to represent the strategic level in addition to the financial and accounting aspects; whereas DES model represents the operational level for the production process at the shop floor level. The main goal of using a hybrid model is to improve the communications between the shop floor managers and the operations manager by synchronising the data between the operational and strategic levels. Jovanoski et al. [88] proposed a hybrid model for production management which combines an SD model of sales and an DES model of the production. Using hybrid model reduces the inaccuracy of modelling production system using SD-only approach and also reduces the complexity of modelling an overall enterprise model using a DES-only approach.

An extensive survey of the existing hybrid models was done by Brailsford et al. [19]. They have highlighted that a critical aspect of hybrid model development is how the different models are integrated. To integrate different models, Helal et al. [66] utilize functional decomposition to divide the system into smaller functional modules which can be modelled by DES. However, as SCN can be modelled using a network that connects the SC entities through material and information flows, an entity-oriented decomposition of an SCN would be more applicable for hybrid modelling.

2.3 Research Gaps

The definitions of resilience in the context of SC are discussed and the existing SC strategies that have been proposed to improve SCRES are summarized. To achieve SCRES, strategies can be designed from two perspectives: proactive mitigation before the disruption and reactive contingency plans during the disruption. The conceptual models to assess SCRES are also reviewed.

The focus of SCN analysis determines the choice of the modelling paradigm. For strategic planning, the macroscopic characteristics of SCN can be modelled as a graph or SD model. For operational planning, ABM can be used to represent the micro-level characteristics of individual behaviour in an SC.

Based on the reviews in this chapter, several key research gaps have been identified, which serve as the basis for research in this thesis. These gaps are also the challenges of this thesis. The research gaps are mainly categorised in terms of (1) building a resilient SC; and (2) modelling SC using complex system approaches.

2.3.1 Building a Resilient Supply Chain

1) Resistance against Disruptions

Although there are many strategies for improving resilience in SCRES literature, there are few studies on the development or implementation of these strategies [17] and on the assessment of the effectiveness of these strategies to mitigate the impact of disruptions. To address this research gap, a design of SCN topologies representing different strategies is proposed in Chapter 3 and a graph model to represent structural redundancy in an SCN is proposed in Chapter 5. To improve the resistance against disruptions, different mitigation strategies are designed and evaluated in Chapters 4 and 6.

2) Recovery from Disruptions

Although existing approaches consider the recovery process, developing operational plans to reflect this recovery behaviour is still an open research issue. SC performance is not a binary behaviour that drops immediately during the disruption (w.r.t., the resilience triangle) and recovers to the original level immediately when the contingency plans are activated. Future studies are required to design and implement reactive contingency strategies to enable effective and efficient recovery of SCN after disruptions.

In addition, the existing approaches to model SCRES often assume that the system performance would be back to the original level after recovery. SCN needs to have the capacity to absorb the loss and recover this loss in order to fully recover from the impact of disruption. The loss is typically modelled as backorders and the recovery includes clearing the backorders.

Contingency strategies, considering backorders, are designed and evaluated in Chapters 4 and 6. Specifically, contingency strategies are developed to improve the recovery time after disruptions in Chapter 5.

3) Assessment of SCRES

The literature in SCM is sparse on how the SCRES can be measured and analysed; only a few articles discussed SCRES assessment [91]. Without understanding the existing SCRES in an SC, it would be difficult to assess the response and reaction of an SC during disruptions. The assessment approaches are also dependent on the model used to represent the SCN. Therefore, after designing strategies to improve resilient of SCN, quantitative assessment approaches for SCRES are required for a statistical comparison between the strategies.

Moreover, it is obvious that one key performance measurement of an SC is whether it creates economic value for the shareholders [150]. Therefore, financial measurements such as the cost, revenue, and value-added (VA) are the key performance indicators in an SC. Investments in SC strategies directly decrease net profits while actual recovery costs are yet to be assessed. Hence, cost-effectiveness is an important consideration for designing SCRES strategies [188].

In this thesis, quantitative SCRES measures are proposed (e.g., customer-service level in Chapter 3, backorder quantities in Chapter 4 and recovery time in Chapter 6). A new resilience measurement to measure structural redundancy is proposed in Chapter 5. New SCRES indexes, to aggregate SC performance measurements for disruptions of each plant in the SCN, are proposed in Chapter 6. In addition, the financial impact is also measured using VA in Chapter 3, backorder and ordering costs in Chapter 4, and total operational costs in Chapter 6.

2.3.2 Modelling SC using Complex System Approaches

4) Modelling Heterogeneity in SCN

One of the key research gaps in SCN modelling is that heterogeneity in an SCN is often not considered. To enable analytical tractability and simplify the problem, many complex network models usually consider homogeneous network, that is all the nodes have the same behaviour and so do the edges. However, entities within an SCN (e.g., suppliers, manufacturers, and retailers) may have different operational behaviours. Moreover, hierarchical network models in the literature usually assume the same type of flow between stages. However, the edges in an SCN can represent different flows, such as material and information flows. In Chapter 3, a distribution SCN is modelled as a hierarchical network. An ABM of a distribution SCN is developed to model the heterogeneity of real-world SCNs. This is extended to model a manufacturing SCN in Chapters 4 and 6, considering production operations.

Existing research works assume that either all plants within an SCN are equivalent or plants in the same stage are equivalent [56, 95, 111, 118, 207]. This implies the existing models in the literature do not differentiate the production processes of different type of materials in an SCN. This is unrealistic as there are significant cost and time for each plant to set up the same production capabilities within the same stage. Most enterprises are small and medium-sized in an SCN, they are highly specialised and the labour division is sophisticated [196]. In the fierce market competition, they would not voluntarily change their competitive business activities. To address this research gap, a graph model is proposed in Chapter 5 to consider the heterogeneous dependencies across a whole SCN.

5) Modelling Structural Redundancy

Redundant network structure in an SCN contains multiple plants that can provide redundant capabilities to mitigate disruptions. Most literature on SC disruption analysis focuses on a single plant or connection between the stages in an SCN, even though disruptions can have long and lasting effects throughout the SC [165]. However, disruptions in the production of vital upstream materials can propagate and affect the production processes downstream [132]. The current models from the literature (as reviewed in Section 2.2.1) are unable to analyse the dependencies across multi-stages in an SCN, where vulnerabilities in the upstream stages of the SCN can have a significant impact downstream. Given the above draw-backs, in order to assess SCRES, the graph model proposed in Chapter 5 considers structural redundancy.

6) Modelling Dynamic Response during Disruptions

There are research works that use analytical models to optimize contingency strategies in the disruption-recovery period for single-stage production and inventory [5, 41, 52, 67, 146, 205, 208] and two-stage SCNs [6, 137, 159]. However, many of these models are analytically intractable on multi-stage SCN due to the complexity of the problem [171].

Using graph analysis alone cannot capture the dynamics of recovery of SCN during the disruption [27]. Graph analysis of SCN does not consider detailed SC operations, e.g., capacities and lead time. Simulation has the advantage that it can handle complex scenarios and analyse disruption-recovery behaviour over time [79].

Hence, a hybrid model is proposed in Chapter 4, analysing system-level properties of the SCN using SD and the focal firms using ABM. The hybrid model enables modelling of the focal firms with more detailed operational behaviours, such as the dynamic response to disruptions. Furthermore, in Chapter 6, the graph model from Chapter 5 is extended with operational behaviour of ABM from Chapter 4 to model the response to disruptions.

7) Modelling Different Level of Details

SD is frequently used in high level strategic modelling of SC for long-term decision-making [101]. Since SD focuses on the macro-level details in an SC, aggregated data is sufficient to calibrate the model. Typically, for public-listed firms, their annual account reports regarding the total sales and production volume are publicly available. Hence, parameters for simulation of SCN using SD could be calibrated easily based on publicly available data.

On the other hand, ABM is often used in short-term operational planning, due to the advantage of modularity in modelling SC processes [101]. However, the complexity of ABM increases exponentially with the size of the simulated system [147]. In addition, a firm may not have visibility and control over the whole of SCN. Detailed operational behaviours of all SC entities are not available, e.g., inventory or procurement policies of a business entity are not revealed to its business partners. Building an ABM for an entire SCN is difficult without all the operational behaviours and parameters.

Due to the limitations of the SD model and ABM, a hybrid model is proposed in Chapter 4 to combine both models using the integration design approach. An entity-oriented decomposition of an SCN is used to divide up the SCN such that each entity can be represented at a different level of details. Th macroscopic properties of the whole SCN are modelled using SD and microscopic behaviours of the focal firms are modelled using ABM.

Chapter 3

An Agent-based Model to Evaluate Supply Chain Network Topology Design

Operational risks (e.g., demand and supply) are the inherent uncertainties in an SCN. To reduce the negative effects of the demand and supply risks, the SCN needs to be well-designed to manage the uncertainties in the business environment [105]. This chapter proposes a top-down approach to design SCN topologies for hierarchical networks based on SC strategies and a bottom-up approach using ABM to evaluate the operational performance of these SCN topologies. The SCN topologies are designed in Section 3.1. Section 3.2 develops an ABM for a typical distribution SCN. Through experimental analysis with different SCN topologies and risk scenarios, Section 3.3 investigates the performance of the SCN and attempts to determine the suitability of the SCN topology for a particular risk scenario.

3.1 Supply Chain Network Topology Design

It is a challenge to identify the right strategy for handling a particular SC risk scenario. Using the appropriate strategy can either reduce the likelihood of occurrence of disruption or reduce the negative implication of the disruption [180]. Some research works have been done on defining suitable strategies for various risk scenarios in order to mitigate the risks and improve the performance of the SCN.

Lee [104] proposed an *Uncertainty Framework* and classified the SC strategies into four main types: efficient, responsive, risk-hedging and agile strategy. The framework selects SC strategy based on uncertainties in demand and supply. An analysis of different SC strategies was conducted through a survey to evaluate the uncertainty framework based on profile deviation approach [178]. However, they provide no quantitative evaluation on the effectiveness of the SC strategies on handling the demand and supply uncertainties.

An *efficient strategy* focuses on achieving cost efficiency by eliminating redundant operations [49]. This can be done by reducing the connections between SC entities in order to ensure a smooth flow of product across the SCN. By using only a single supplier, the firm can negotiate for better deals for the products, such as more discounts for larger order quantities. Similarly, each DC only serves a single retailer. This help to decrease the operating cost and simplify the SCN structure.

A *responsive strategy* is flexible and responsive to the changing needs of the customer [49]. This strategy can be customized to the specific requirements of the customer. Using this strategy, the firms increase the number of DCs to distribute the uncertainties of customer demand among the DCs.

A *risk-hedging strategy* focuses on sharing the supply risk among the suppliers. This strategy introduces flexibility by having multiple suppliers [175]. When there is supply disruption on one of the suppliers, the firm can still fulfil part of the orders through the remaining suppliers. Hence there is still partial fulfilment of the orders, not a total disruption to its customer.

An *agile strategy* implements flexibility in handling both the demand and supply risks [31]. Similar to the risk-hedging strategy, one of the ways of achieving flexibility is by having multiple suppliers in an SCN. The firm can also increase the links between the DCs and the retailers to handle the demand risks. However, there is always an additional cost involved in maintaining multiple suppliers and additional connections between the DCs and the retailer. Hence, the firm needs to determine whether the cost of implementing the strategy outweighs the benefits of mitigating the risks.

Figure 3.1 shows the three-stage SCNs modelled as hierarchical networks. The agents in each stage (from right to left) are the *suppliers* (s_1 to s_4), *DCs* (dc_1 to dc_4) and *retailers* (r_1 to r_4). The connections between the agents indicate material flows between the stages. The direction in the connection shows the flow of the products from the supplier to the retailer. The materials do not flow directly across stages, e.g., from the supplier to the

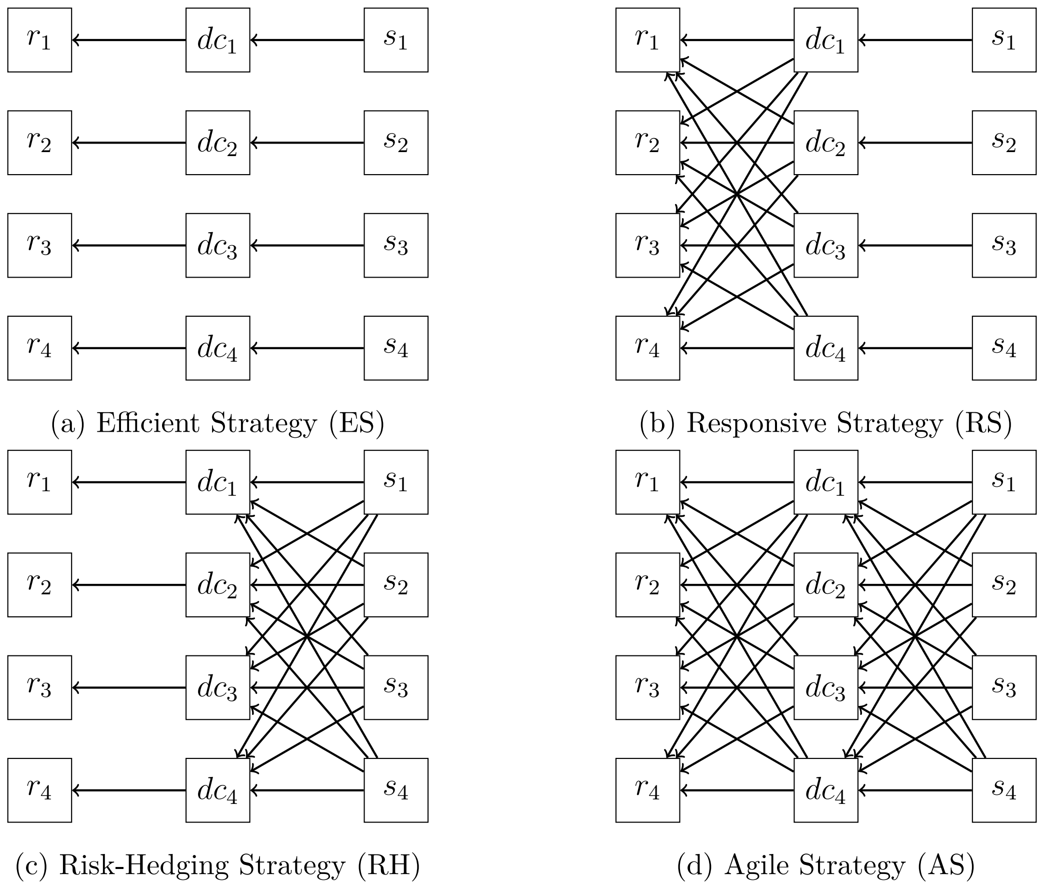


Figure 3.1: Three-stage SCNs modelled as hierarchical networks.

retailer directly. The opposite direction represents the flow of the orders, from the retailer to the supplier. When an agent has more than one supplier, the order quantity is split evenly according to the number of suppliers available.

Based on the SC strategies described in this section, we design four different SCN topologies, as shown in Figure 3.1. An efficient strategy (ES) seeks to reduce redundant operations, by maintaining a single connection from the suppliers to the retailers. Therefore, we design a network topology with only one connection between agents in each stage. Figure 3.1a shows the network topology for the efficient strategy, with only a single supplier for each agent in every stage. A responsive strategy (RS) is flexible to the uncertainty in customer demands. This strategy distributes the demand among all DCs. The SCN topology for responsive strategy is shown in Figure 3.1b, where each retailer is connected to four DCs. A risk-hedging strategy (RH) attempts to hedge the supply risk by having multiple suppliers, as shown in Figure 3.1c. Hence the network topology has four suppliers for each DC. An agile strategy (AS) requires flexibility in all stages. This is shown in Figure 3.1d with each retailer connected to four DCs and each DC is connected to four suppliers.

3.2 Agent-based Model

The SCN model described in this chapter is based on a typical distribution SCN. Each agent in the model represents an SC entity within the SCN. There are in total three different types of agents: (i) supplier, (ii) DC, and (iii) retailer. Two types of event are used in the simulation: *order* and *shipment*. The simulation is executed by time-step, where each time step represents a day of operation in the SCN. At every time step, agents interact with each other by exchanging orders and products. Orders are generated to the upstream agent according to the demand, and the products are delivered by shipment to the downstream agent according to the available inventory.

The *order* is defined with a quantity that is requested by the downstream agent (Order Quantity) and the time when the order is received (Order Time). The amount of product delivered to the downstream agent in a *shipment* is defined as the Shipment Quantity.

Every SC agent has the same operational behaviour, which is shown in Figure 3.2. Each agent is acting both roles of a supplier and consumer. At the start of each time step, the agent will process all the pending orders from its downstream agents in the

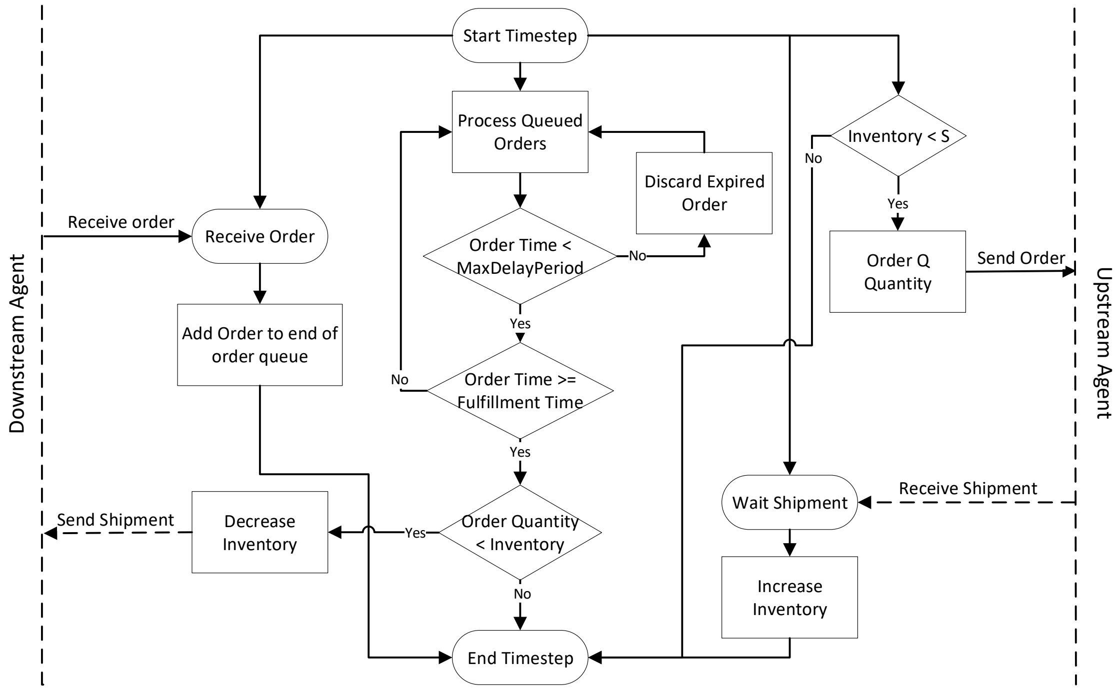


Figure 3.2: Operational behaviour of an SC agent.

order queue. The orders will be fulfilled based on the *fulfilment time*. When the order time is more than the maximum lead time delay period (MaxDelayPeriod), the order is considered as expired and discarded. If the order time has not exceeded the fulfilment time, the order will not be processed and remain in the queue. Otherwise, the agent will attempt to fulfil the order if there is sufficient inventory. After reducing the inventory, the ordered quantity is shipped to the downstream agent. At the same time, when the agent receives the shipment from the upstream agent, the inventory level will be increased according to the shipment quantity received.

The *supplier* agent introduces products into the SCN, which will be delivered to other agents. After receiving orders from its downstream agent, the orders are fulfilled according to the defined production policy. The production policy currently is according to the *supply rate* of the SCN, which fulfils orders according to the available supply. A *retailer* agent represents the customer and consumes the products in the SCN. Orders are generated according to the *demand rate*, which will be fulfilled by its upstream agent. Both the demand and supply rates are defined as parameters to simulate different risk scenarios in the simulation.

The agents make orders to their upstream agent based on their internal policies. The internal policy used in the model is the *SQ inventory policy* [86]. SQ policy is used by all the agents to determine when to replenish their inventory. S refers to the reorder level and Q is the reorder quantity. When the inventory level drops below the reorder level, the agent will place an order of Q quantity to the upstream agent. When the agent receives a new order from the downstream agent, it will be appended to the end of the order queue.

3.3 Simulation Results and Analysis

A simulation is developed based on the ABM described in Section 3.2. A three-stage SCN is constructed with 12 agents, with four agents of each agent type (i.e., supplier, DC, and retailer) in each stage. Different SCN topologies are designed as shown in Figure 3.1. Experiments are conducted using the model to identify the suitable SC strategy for a particular risk scenario. The simulation parameters and scenarios are provided by an SC expert, as shown in Table 3.1. We have also performed preliminary validation of the model with the SC expert.

Table 3.1: Simulation parameters.

Parameter	Value
Back order Cost	0.2 (per unit per day)
Sale Lost Cost	0.1 × Sale Price (per unit)
Inventory Cost	0.1 (per unit per day)
Order Cost	100 (per order)
Operating Cost	100 (per agent per day)
Production Cost	20 (per unit)
Sale Price (Supplier)	40 (per unit)
Sale Price (DC)	50 (per unit)
Sale Price (Retailers)	60 (per unit)
Fulfilment time	1 day
Shipment Lead Time	1 day
Maximum Lead Time Delay	5 days
Initial Inventory	300 units
SQ Policy	$S = 200$ units, $Q = 300$ units

An agent incurs *backorder cost* when the order is not fulfilled within the *fulfilment time*. When an order has expired, a *sale lost cost* is deduced. Each unit of the product also incurs *inventory cost* when the products are stored in the inventory. This represents the overhead cost of the warehouse rental and maintenance of the inventory. The *order cost* is the processing cost of generating a new order. Since each agent represents an SC entity in the SCN, the SC operations also incur an *operating cost* daily. The *production cost* is the cost of producing the products, which is 50% of the selling price at the supplier. Each stage increases the sale price to represent the profit-seeking behaviour at each stage. After processing the order, the product shipment takes *shipment lead time* to reach the customer. The maximum allowed time before the order is expired is the *maximum lead time delay*. Each agent has an initial inventory of 300 units. The agent uses the SQ policy to decide when to replenish the inventory, with the reorder level S and reorder quantity Q.

Four risk scenarios with different demand and supply rates are shown in Table 3.2. Constant rate is used to simulate no uncertainty in demand and supply. To simulate uncertainties, demand and supply are modelled using normal distribution with a specified mean (μ) and standard deviation (σ). The normality assumption for the demand and supply is made based on literature [130].

Table 3.2: Demand and supply rates for different risk scenarios

Risk Scenario	Demand Risk	Supply Risk	Demand Rate (Unit per day)	Supply Rate (Unit per day)
DLSL	Low	Low	100	100
DHSL	High	Low	$N(\mu = 100, \sigma = 50)$	100
DLSH	Low	High	100	$N(\mu = 100, \sigma = 50)$
DHSH	High	High	$N(\mu = 100, \sigma = 50)$	$N(\mu = 100, \sigma = 50)$

The simulation is executed with a step size of 1 day. A total of 500 time steps is executed which is determined empirically, and the warm-up period is estimated to be 100 steps based on the stable trends in the performance. Common random number is also used in all scenarios to reduce the variance in the simulation results. Similar to the existing literature [165], the simulation is replicated for 30 runs due to the small variance in the simulation results. The performance indices of the SCN are averaged across the replications.

3.3.1 Performance Measures

After designing the SCN topologies, the performance of each topology needs to be evaluated to determine the effectiveness of the strategy to mitigate a particular risk. There are extensive researches on SC performance measurement, which can be found in [57]. This section describes two existing performance indices from the literature that can be used to evaluate the performance of the ABM.

The performance measurement of an SCN mainly depends on whether it creates economic value for the stakeholders. Therefore, economic *value-added* (VA) of the supply is often used as the index for measuring SC performance [59, 149].

The VA for an agent i is shown in Equation 3.1, where t is the time step representing a day of operation in the SCN. $R[t]$ is the revenue at the time t, and $C[t]$ is the cost of the firm at the time t. The quantity T is the total number of time steps, or the total operating time period of the SCN in days. The cost of the firm is the summation of the total inventory cost, backorder cost and the operational cost. The revenue of the firm at time t is the product of the quantity sold and the selling price of the product:

$$VA_i = \sum_{t=0}^{T} VA_i[t] = \sum_{t=0}^{T} (R_i[t] - C_i[t]) \tag{3.1}$$

The VA of the SCN can be calculated as the accumulated sum of all the VA_i of each agent i in the SCN, given the number of agents in the SCN is n:

$$VA = \sum_{i=0}^{n} VA_i \tag{3.2}$$

The *customer service level* (CSL) is also considered as an important performance index as it gives the percentage of the goal achieved by the SCN [18]. Low CSL means that customer orders are not satisfied, resulting in loss of sales. Often firms need to pay penalties for the inability to satisfy the order. The net results of low CSL are reduced revenue and increased costs for the whole SCN.

Order fulfilment rate measures the percentage of orders fulfilled. The on-time delivery rate for an order k is the ratio of the number of products delivered on-time, o_k^D, to the quantity ordered o_k. The percentage of the orders fulfilled at agent i is given by the summation of the on-time delivery rate of all the orders at time t:

$$f_i[t] = \frac{1}{K} \sum_{k=1}^{K} \frac{o_k^D[t]}{o_k[t]} \tag{3.3}$$

If there is only 1 order received at agent i and the order is fully fulfilled, ($f_i = 1$). $o_i^R[t]$ is the total orders received at time t by agent i. The CSL for the agent i over the time period T is calculated as:

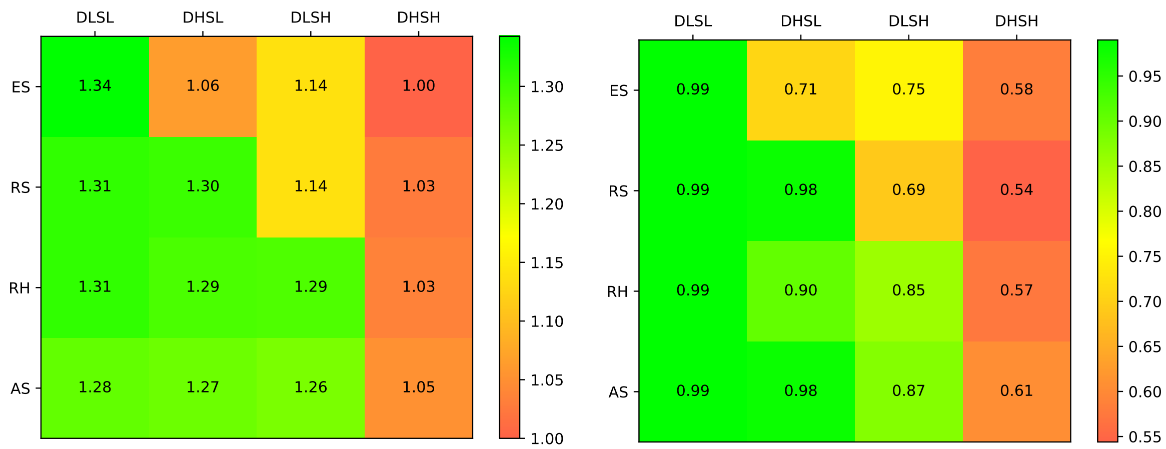
$$CSL_i = \sum_{t=0}^{T} \frac{f_i[t]}{o_i^R[t]} \tag{3.4}$$

The CSL for the whole supply chain is determined by the summation of all the CSL_i for each agent averaged over the total number of agents n:

$$CSL = \frac{1}{n} \sum_{i=1}^{n} CSL_i \tag{3.5}$$

The selection of performance measurement depends on the firm's policy. There is no single performance measurement that can fit all the needs of different firms. Therefore, two different performance indices are used in performance evaluation.

3.3.2 Results



(a) Value-Added (normalized)

(b) Customer Service Level

Figure 3.3: Heat map of performance indices for the SCN under each risk scenarios. Each cell is coloured according to the value of the performance. The intensity varies from red to green: green colour indicates the best performance; while red colour represent the worst performance.

Figure 3.3 shows the performance indices of different strategies under each risk scenario. The topology for each strategy is described in Section 3.1, and risk scenarios are defined in Table 3.2. Figure 3.3a shows the normalised VA of the SCN in each cell, where the column indicates the different risk scenarios, and the rows represent different SCN strategies. VA of each scenario is normalized to the lowest VA (i.e., VA of efficient strategy under DHSH scenario). Each cell is also coloured, varying from red to green: green colour indicates the best performance; while red colour represent the worst performance. Similarly, Figure 3.3b shows the heat map of the CSL of the SCN.

In the **DLSL** scenario, we examine the performance for different SCN strategies by looking at the first column in both Figure 3.3a and Figure 3.3b. The CSL is similar for all the strategies at 0.99. For efficient strategy, it achieves a VA of 1.34. The responsive and risk-hedging strategies have lower VA (1.31). The agile strategy has the lowest VA among the strategies at 1.28.

Next, we look at the second column for the **DHSL** scenario, with uncertain demand. The efficient strategy is unable to handle the demand uncertainties and achieves a relatively lower CSL (0.71) compared to the DLSL scenario when the demand is stable. It also has the lowest VA (1.06) amongst the strategies. Risk-hedging strategy also has better CSL (0.9) compared to the DLSL scenario. Responsive and agile strategies are able to achieve relatively higher CSL (0.98), with the responsive strategy having the highest VA (1.3).

The third column is the **DLSH** scenario, with supply uncertainties. Efficient and responsive strategies are unable to handle the uncertainty in the supply, resulting in lower CSL (0.75 and 0.69). This is also reflected in the lower VA (1.14). Risk-hedging and agile strategies have better CSL and VA than efficient and responsive strategies. The agile strategy has a lower VA than the risk-hedging strategy.

The last column represents the **DHSH** scenario, with uncertainties in both demand and supply. All the strategies are unable to handle the unpredictability in both the demand and supply; only the agile strategy has relatively better performance compared to other strategies.

3.3.3 Discussions

In the **DLSL** scenario, demand and supply are stable. All strategies achieved CSL of 0.99, which indicates that most orders are fulfilled on time by each supplier. However, the topologies have varying VA performance. Except for the efficient strategy, all other strategies have lower VA as there are more orders created based on the number of suppliers for each agent. For example, the responsive strategy splits a single order at the retailer into four orders for each DC. As each order includes a fixed ordering cost, creating more orders incurs an additional cost, thereby reducing the VA. This is more obvious for the agile strategy, with the highest degree of connection at each stage. It generates more orders at every stage. Hence efficient strategy is the most suitable strategy for this particular risk scenario with the highest VA.

In the **DHSL** scenario, the demand is unstable. The efficient strategy is unable to handle the demand uncertainties, which causes the SCN to have more delayed and expired orders. The delayed and expired orders reduce the CSL. In addition, both the delayed and expired orders cause the low VA due to the back order cost and the sale lost cost. Responsive and agile strategies increase the number of connections at the retailers, which distribute the fluctuating demand among all the DCs, as shown in Figure 3.1b and Figure 3.1d. This allows both strategies to fulfil most of the orders, giving the highest CSL. Risk-hedging strategy also improves the CSL by splitting the orders at the suppliers; however it is not as efficient as distributing the demands at the retailers. Agile strategy has a lower VA compared to the responsive and risk-hedging strategies due to the excessive orders created. For this particular risk scenario, we should use the responsive strategy which has the best performance in both VA and CSL.

In the **DLSH** scenario, the supply uncertainty is high. To handle the uncertainty in the supply, risk-hedging and agile strategies increase the number of suppliers for each DC. We can see four connections between the suppliers and DC in Figure 3.1c and Figure 3.1d. Distributing the orders among all the suppliers enables them to fulfil more orders on time. However, in terms of VA, the agile strategy still faces the same problem of the additional cost of generating more orders. Therefore the risk-hedging strategy should be used when the supply risk is high.

In the **DHSH** scenario, both the demand and supply risks are high. This instability causes many orders to be delayed and expired, resulting in lower VA and CSL for all the strategies. Nevertheless, the agile strategy should be used when the demand and supply risk is high, as it has the best performance compared to other strategies.

Based on the results, the selection of strategy according to the demand and supply risk scenarios is summarized in Table 3.3.

Table 3.3: Selection of SCN topology based on demand and supply risk scenarios

		Demand Risk: Low	Demand Risk: High
Supply Risk	Low	Efficient	Responsive
	High	Risk-Hedging	Agile

3.4 Summary

The complexity of global SCs present a challenge to develop effective SCN to mitigate risks in uncertain SC environments. The issue of how to design suitable SCN topology for hierarchical networks to handle demand and supply risk scenarios has not been well investigated. This chapter describes a top-down approach to design SCN topology based on the Uncertainty Framework. Four SCN topologies have been designed to represent different SC strategies: efficient, responsive, risk-hedging, and agile strategies. A bottom-up approach using ABM is proposed to evaluate SCN topologies for mitigating uncertainties. An ABM of SCN is developed to model the operational behaviour of individual entities within the SCN. A hierarchical network is constructed based on a three-stage distribution SCN. Experiments have been conducted to evaluate the performance in terms of the VA and CSL of the SCN under different demand and supply risk scenarios.

From the experimental results, we can see that different risk scenarios can be handled to a certain extent by selecting the effective SCN topologies. In a situation with low demand and supply risk, an *efficient strategy* with a single supplier and retailer is the most suitable. To mitigate the demand risk, we should apply the *responsive strategy*, where the SCN topology has more connections between the DC and retailers. On the other hand, when the supply risk is high, more connections to the suppliers are needed. So a *risk-hedging strategy* should be used in this scenario. When both the demand and supply risks are high, an *agile strategy* should be used, which has flexibility at all stages. Hence, experimental analysis of the SCN shows that the network topology reflects the capabilities of SCN to mitigate the demand and supply uncertainties.

Due to the limited information on the detailed operational processes in the entire SCN, it may be difficult to model the whole SCN using the ABM. Next chapter introduces a hybrid model of SCN that combines models at a different level of details.

Chapter 4

A Hybrid Model for Multi-level Modelling

Due to the accessibility of external data and lacking operation details of other entities in the SCN, it restricts the applicability of the ABM. To address the issue of limited details regarding the operational behaviours of all SC entities in an SCN, this chapter proposes a hybrid model that can represent multiple levels in a manufacturing SCN. The details of a SCN hybrid model are described in Section 4.1. First, an entity-oriented decomposition is used to divide the SCN into individual entities. Then, the high-level macroscopic properties are modelled using SD and low-level microscopic behaviours are modelled using ABM. The ABM introduced in Section 3.2 is extended to support production operations in the entity. To model the entire SCN, SD and ABM are combined using an integration design approach. Each entity within an SCN can be either an SD entity or an agent, depending on the problem scope. The combined model gives a single view of the whole SCN. Section 4.2 describes the case study for a firm to identify cost-effective SCRES strategies to illustrate the applicability of the hybrid model. The simulation results are shown in Section 4.3, and the results are used to analyse the trade-offs between these strategies.

4.1 Hybrid Model of Supply Chain Network

4.1.1 Supply Chain Network Model

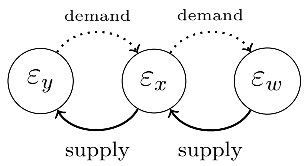


Figure 4.1: An SC consisting of upstream entity (ε_w), current entity (ε_x) and downstream entity (ε_y).

The SCN model studied in this chapter is based on a typical multi-stage manufacturing SCN. First, the entire SCN is modelled as a hierarchical network. Each node in the network represents an SC entity, e.g., manufacturers or suppliers. Assume $\mathcal{E}$ is the set of all entities in an SCN. Figure 4.1 shows an SC with three entities: upstream entity (ε_w), current entity (ε_x) and downstream entity (ε_y). There are two directed edges between each entity: the information flow (*demand flow*) from the downstream entity to the upstream entity, and material flow (*supply flow*) from the upstream entity to the downstream entity.

4.1.2 System Dynamics Model

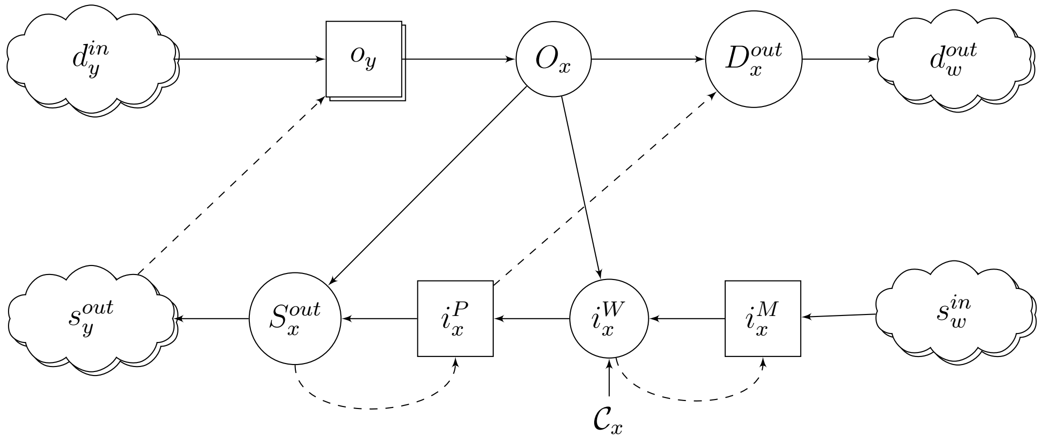


Figure 4.2: Stock-and-flow diagram of a single SC entity. Solid arrows represent positive feedback loop while dotted arrows represent negative feedback loop.

The SD model is created by simplifying the SD supplier model, originally proposed in [109, 182], by considering only the backorders, product inventory and production. It also includes material inventories. Figure 4.2 shows the casual loop diagram of an SC entity ε_x. The definitions of model variables, parameters and generic equations that describe the relationships of the variables are described below.

In Figure 4.2, there are three stocks in the entity (shown in rectangles): orders o_y from each downstream entity ε_y, material inventory i^M and the product inventory i^P. The arrows show the cause and effect relationships between the variables, with the solid arrows indicating positive feedback, and dotted arrows indicating negative feedback. The entity ε_x has a set of downstream entities $\mathcal{E}_x^{in}$ where $\varepsilon_y \in \mathcal{E}_x^{in}$, and a set of upstream entities $\mathcal{E}_x^{out}$ where $\varepsilon_w \in \mathcal{E}_x^{out}$. Entities are connected to each other through the demand and supply flows. Each entity is constrained by the *production capacity*, which is the volume of products or services that can be produced by the entity.

First, the current pending orders $o_y(t)$ from each downstream entity ε_y is the aggregation of the demand flow $d_y^{in}(t)$ from each downstream entity ε_y and the unfulfilled demand from the last period $o_y(t-1)$, minus the out-going supply $s_y^{out}(t-1)$ which is the fulfilled orders (4.1a). The total order quantity $O_x(t)$ is the sum of all pending orders (4.1b). The total outgoing demand $D_x^{out}(t)$ is the total order quantity subtracted by the existing product inventory $i_x^P(t)$ (4.1c). If there are available products in the inventory, it will be used to fulfil the demand directly. Then, the total outgoing demand is distributed according to the available upstream entities (4.1d). The outgoing demand d_w^{out} is connected to the incoming demand d_w^{in} of the upstream entity ε_w.

$$\text{Orders from } \varepsilon_y,\ o_y(t) = o_y(t-1) + d_y^{in}(t) - s_y^{out}(t-1) \tag{4.1a}$$

$$\text{Total Order Quantity, } O_x(t) = \sum_{\varepsilon_y \in \mathcal{E}_x^{in}} o_y(t) \tag{4.1b}$$

$$\text{Total Outgoing Demand, } D_x^{out}(t) = \min(O_x(t) - i_x^P(t), 0) \tag{4.1c}$$

$$\text{Demand Outflow to } \varepsilon_w,\ d_w^{out}(t) = \frac{D_x^{out}(t)}{|\mathcal{E}_x^{out}|} \tag{4.1d}$$

The supply inflow $s_w^{in}(t)$ is aggregated with left-over materials from the last period $i_x^M(t-1)$ (4.2a), subtracted by amount of materials used in production $i_x^W(t-1)$, to form the current material inventory $i_x^M(t)$. Based on the production capacity $\mathcal{C}_x$, current total orders $O_x(t)$ and available materials $i_x^M(t)$, product is manufactured (4.2b). The manufactured product is added to the product inventory $i_x^P(t)$, including the surplus of products from last period $i_x^P(t-1)$ (4.2c), and subtracting the fulfilled supply $S_y^{out}(t-1)$. The total outgoing supply $S_x^{out}(t)$ depends on the current orders $O_x(t)$ and existing products in the inventory (4.2d). Finally, the total outgoing supply is distributed among the downstream entities proportional to the pending demand (4.2e).

$$\text{Material Inventory, } i_x^M(t) = i_x^M(t-1) + \sum_{\varepsilon_w \in \mathcal{E}_x^{out}} s_w^{in}(t) - i_x^W(t-1) \tag{4.2a}$$

$$\text{Production, } i_x^W(t) = \min(O_x(t), \mathcal{C}_x, i_x^M(t)) \tag{4.2b}$$

$$\text{Product Inventory, } i_x^P(t) = i_x^P(t-1) + i_x^W(t) - S_x^{out}(t-1) \tag{4.2c}$$

$$\text{Total Outgoing Supply, } S_x^{out}(t) = \min(O_x(t), i_x^P(t)) \tag{4.2d}$$

$$\text{Supply Flow to } \varepsilon_y\text{, } s_y^{out}(t) = \frac{o_y(t)}{O_x(t)} \times S_x^{out}(t) \tag{4.2e}$$

4.1.3 Agent-Based Model

In ABM, each entity is modelled as agents, which interacts with others by generating discrete events. There are two types of discrete events: *orders* represent the demand, and *shipments* represent the supply. The simulation is executed by time-step, where each time step represents a day of operation in the SC. At every time step, each agent interacts with each other by exchanging orders and shipments. Every agent has the same general behaviour, which is shown in Figure 4.3.

At the start of each time step, the agent will collect all the pending orders from its downstream agent in an order queue. Assuming one unit of material is required to manufacture one unit of product, the agent makes material orders to its upstream agents based on its inventory policy. When the inventory level falls below the safety stock, the agent will generate a replenishment order to the upstream agent that will restore the inventory to the safety stock. The review period is set to every time step. When the upstream agent fulfils the material orders and delivers the material downstream, the agent will collect the material shipments and increase the material inventory according to the shipment quantity received.

Based on the availability of materials, pending orders, and production capacity ($\mathcal{C}_x$), new *production* is generated. The manufacturing process completes the production based on the production time, and adds the produced quantity to the product inventory. Ac-

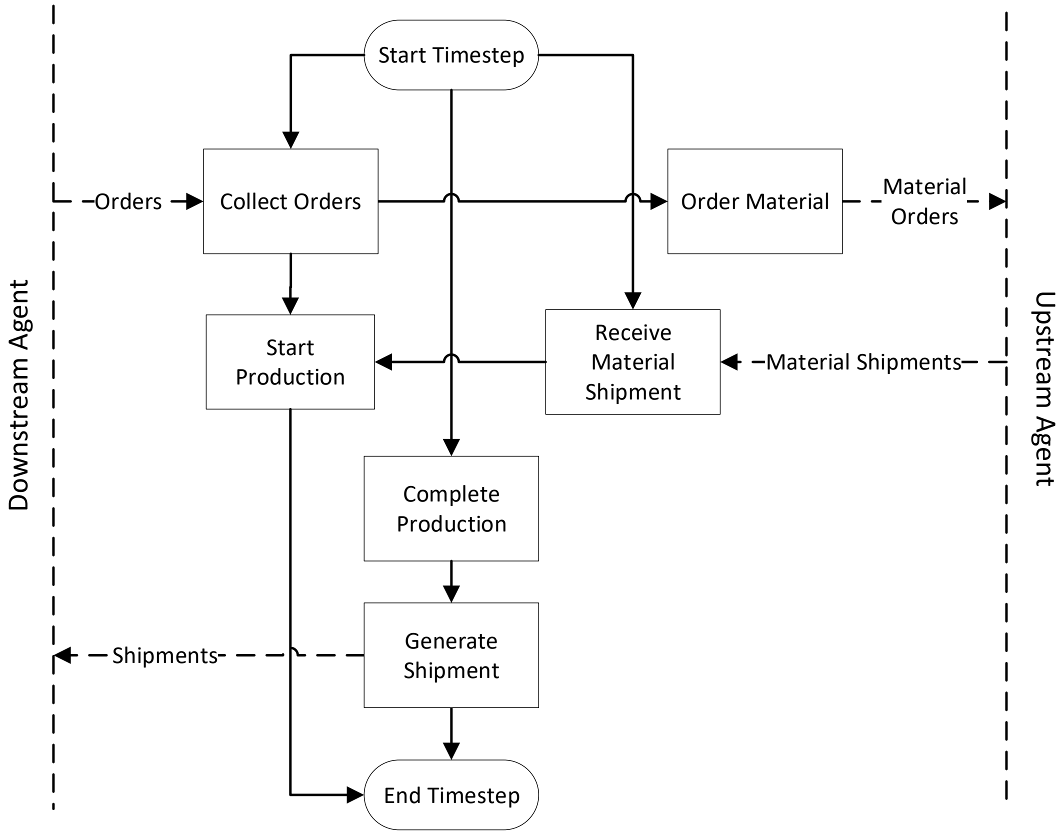


Figure 4.3: Agent model for a single SC entity.

cording to the pending orders and available product in the inventory, shipment will be created and sent to downstream.

4.1.4 Hybrid Model

This hybrid model uses the *integration design* [128], where both ABM and SD model have the same view of the system and execute together. SD uses continuous time and executes in a fixed integration interval, Δt_C whereas ABM advances its time discretely in a fixed time interval, Δt_D. Δt_C is at a finer time resolution compared to Δt_D to synchronize between the two models. The data exchange occurs at the discrete time step Δt_D.

Replacing an SC entity in the SD model with the corresponding agent model will allow the agent model to represent the high level details of the SC entity, while the SD model captures the broad view of the whole SCN. However, adapters need to be created to wrap around an agent to convert between the discrete events and corresponding flows,

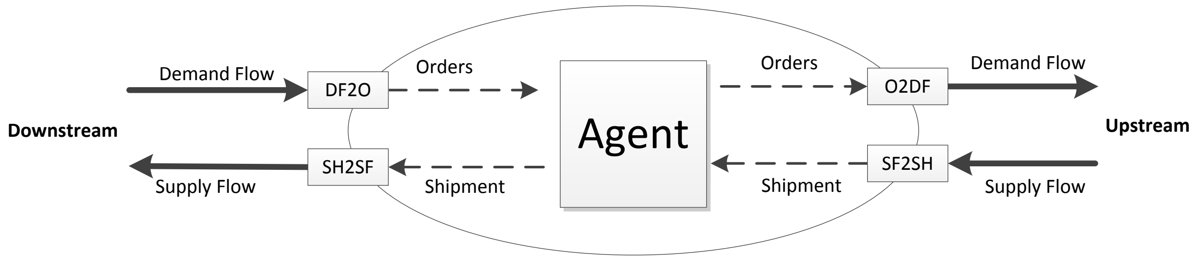


Figure 4.4: Integration of ABM with SD.

as shown in Figure 4.4.

Continuous to discrete adapters contain buffers to accumulate flows during continuous time. Discretization of the flows depends on the *lot size* defined for the order and shipment. The value of lot size depends on the modeller. In the real world SC, the lot size is determined by the two entities when they are performing the transaction. At each discrete time step, the adapter will generate discrete events based on the lot size. Similarly, *discrete to continuous* adapters receive the discrete event and generate the corresponding flow quantity. Given the order lot size $\mathcal{L}^O$, and shipment lot size $\mathcal{L}^S$, conversion procedure for continuous to discrete adapters and discrete to continuous adapters are shown in Table 4.1 and 4.2 respectively.

There are four types of adapters to convert between the flows and the discrete events, as shown in Figure 4.4. Demand flow to Orders (DF2O) converts the demand flow into discrete orders to be sent to the agent. It accumulates the demand flow in a buffer and discretises it into discrete orders based on the order lot size. After processing the orders, the agent may submit orders to suppliers if there are insufficient materials. Orders to Demand Flow (O2DF) receives the material orders and converts them to demand flow upstream. The upstream entity processes the demand flow and generates the corresponding supply flow downstream. Supply Flow to Shipment (SF2SH) accumulates the supply flow in a buffer and discretises it into discrete material shipments based on the shipment lot size. Shipment to Supply Flow (SH2SF) receives the product shipment and converts them to supply flow downstream.

Table 4.1: Continuous to discrete adapters.

Adapter	Continuous	Discrete
Demand Flow to Orders (DF2O)	$\text{Buffer}_d \mathrel{+}= d_y^{in}$	**while** $\text{Buffer}_d > \mathcal{L}^O$ **do** Generate new Order(Quantity = $\mathcal{L}^O$, Time = Δt_D) $\text{Buffer}_d \mathrel{-}= \mathcal{L}^O$
Supply Flow to Shipment (SF2SH)	$\text{Buffer}_s \mathrel{+}= s_w^{in}$	**while** $\text{Buffer}_s > \mathcal{L}^S$ **do** Generate new Shipment(Quantity = $\mathcal{L}^S$) $\text{Buffer}_s \mathrel{-}= \mathcal{L}^S$

Table 4.2: Discrete to continuous adapters.

Adapter	Discrete	Continuous
Orders to Demand Flow (O2DF)	$d_w^{out} \mathrel{+}=$ Order.Quantity	$d_w^{out} \rightarrow$ upstream
Shipment to Supply Flow (SH2SF)	$s_y^{out} \mathrel{+}=$ Shipment.Quantity	downstream $\leftarrow s_y^{out}$

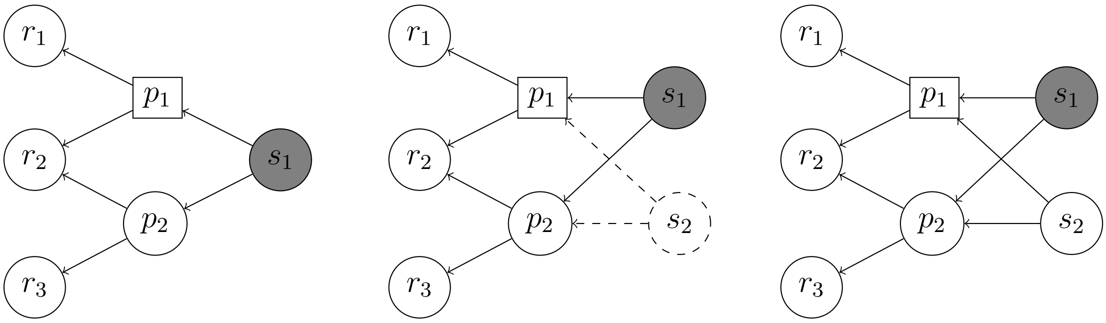
4.2 Case Study

4.2.1 Supply Chain Resilience Strategies

From the reviews of SCRES strategies from Section 2.1.2, there are two general approaches to handle the impact of disruptions: mitigation and contingency strategies. One of the common practices for mitigation strategies is sourcing from more than one supplier. If one of the suppliers is down during the disruption, other suppliers can still fulfil the demand of the firm. However, multi-suppliers can be more costly due to the increase in ordering costs [4]. During a normal scenario, the demand is split between the suppliers, reducing the quantities ordered per supplier. Therefore, it is difficult to negotiate for a lower price of the supplies due to economies of scale.

Contingency strategies are actions that are only taken when the disruption occurs. Hence, the cost of action is incurred only during the activation of the contingency strategy. Contingent re-routing seeks alternative suppliers during disruption, where the demand will be rerouted to the contingent supplier when the primary supplier is not available [185]. However, a contingent supplier often charges a higher cost than regular suppliers [184]. The contingent supplier may need to activate additional manpower in order to fulfil the increase in demand, which translates into higher costs.

4.2.2 Supply Chain Strategy Design



(a) Single Supplier (b) Contingent Supplier (c) Multi-Suppliers

SD Entity Hybrid Entity Disrupted Backup

Figure 4.5: Different SCRES strategies.

Compared to Section 3.1, this section propose a design of SC strategies to reduce the impact of disruption. One of the SCNs (H_1) from the dataset of real-world SCNs has been selected to be used in the case study [201]. This SCN is simplified to consider a single product, where the manufacturer only requires one type of materials to manufacture one type of products. There are three retailers in the network (r_1, r_2 and r_3), two manufacturing plants (p_1 and p_2), and one supplier (s_1), as shown in Figure 4.5a. The arrows in the network represent the supply flow. The firm of interest is p_1, where it is modelled using an agent. Other entities are modelled using SD.

The most common way to model disruption is to assume that the supply process has two states: functioning normally and disrupted [172]. During the disruption, supplier s_1 will be down, and it will be up after the disruption. Disruptions can be infrequent but long, or frequent but short. Figure 4.5 shows three SCRES strategies that are examined in this case study. The original SCN is shown in Figure 4.5a, where there is only a single supplier. The contingent strategy is shown in Figure 4.5b, where contingent supplier s_2 is only utilized during the disruption. s_2 is configured with the same parameters as s_1. The demand will be re-routed to s_2 during the disruption. Figure 4.5c shows the mitigation strategy where multi-suppliers (s_1 and s_2) are used. The demand is split evenly between the two suppliers, where each supplier provides half of the total supply required by p_1. During the disruption, only the remaining supplier will be able to fulfil half of the total demand.

The impact of various costs on the attractiveness of a given strategy is of interest to the firm. By simulating across a spectrum of disruption profiles, we can analyse the cost-effectiveness in terms of two metrics: *backorder cost* and *ordering cost*. Backorder cost is the cost incurred by a firm when it is unable to fill an order and must complete it later. The backorder cost accumulates at a constant rate proportional to both the backorder volume and backlog duration [74]. Purchasing or ordering cost is the cost involved in sourcing the product from the suppliers. It is assumed to be linear to the amount purchased [161].

Trade-offs between these strategies and trade-off between backorder cost and ordering cost are analysed and shown in the next section.

4.3 Simulation Results and Analysis

4.3.1 Experimental Setup

The SD model is calibrated with the demand data from the dataset [201]. Based on the demand data, the supply or production capacity for each entity is assumed to be 10% more than the demand on the entity. This is to allow flexibility in the SCN such that it is possible to clear the backorders when the disruption length is short.

Entity p_1 is modelled as an agent (see Figure 4.5). Other than the demand data, the production lead time and ordering cost from the dataset are also used to calibrate the parameters for the agent. The remaining parameters are based on assumptions. Both ordering lead time and shipment lead time are assumed to be 1 day. The order lot size $\mathcal{L}^O$ and shipment lot size $\mathcal{L}^S$ are both set to 50 units. Assuming that the production lead time for ε_x is $\mathcal{T}_x^P$, ordering lead time is $\mathcal{T}^O$, and shipment lead time is $\mathcal{T}^S$, the safety stock for ε_x is set to $s_x = \mathcal{C}_x \times (\mathcal{T}_x^P + \mathcal{T}^O + \mathcal{T}^S)$.

The simulation is executed for a period of two years, after running for one year as warm up, i.e., the actual simulated time T is 365 days. The agent is executed with a time step of one day, while the system dynamic entities execute at a time step of $\frac{1}{2}$ day. Disruption length and the interval between disruptions are configured according to the experiment in the next subsections. A firm may not respond immediately to disruption at a supplier [4]. For this case study, the contingent supplier is activated only at the middle of the disruption, for a period equal to the disruption length. Assuming that the disruption starts at time t_s for a duration of T_d, the time when the contingent supplier is activated equals $t_s + \frac{T_d}{2}$.

Two metrics are used to measure the performance: backorder cost C_b and ordering cost C_o. The backorder cost is used to measure the additional costs for backordering, while the ordering cost measure the additional costs for having multiple suppliers. To differentiate the additional expense of applying SCRES strategies, multipliers α and β are introduced for the backorder cost and the ordering cost respectively. For example, assuming that the cost of ordering from the regular supplier is 1, if the ordering cost per unit for multi-suppliers or contingent supplier is 20% more than the regular supplier, $\beta = 1.2$. For an agent ε_x, the backorder cost for time step t is defined as:

$$C_{x,b}(t) = O_x(t) \times \alpha \tag{4.3}$$

The average per day backorder cost for the SCN, $\overline{C_b}$, is calculated by:

$$\overline{C_b} = \frac{1}{T} \int_{t=1}^{T} \sum_{\varepsilon_x \in \mathcal{E}} C_{x,b}(t) \delta t \tag{4.4}$$

Similarly, the ordering cost for agent ε_x in time step t is defined as:

$$C_{x,o}(t) = \begin{cases} d_w^{out}(t) \times \beta, & \text{if } w \text{ is contingent or multi-supplier} \\ d_w^{out}(t), & \text{if } w \text{ is regular supplier} \end{cases} \tag{4.5}$$

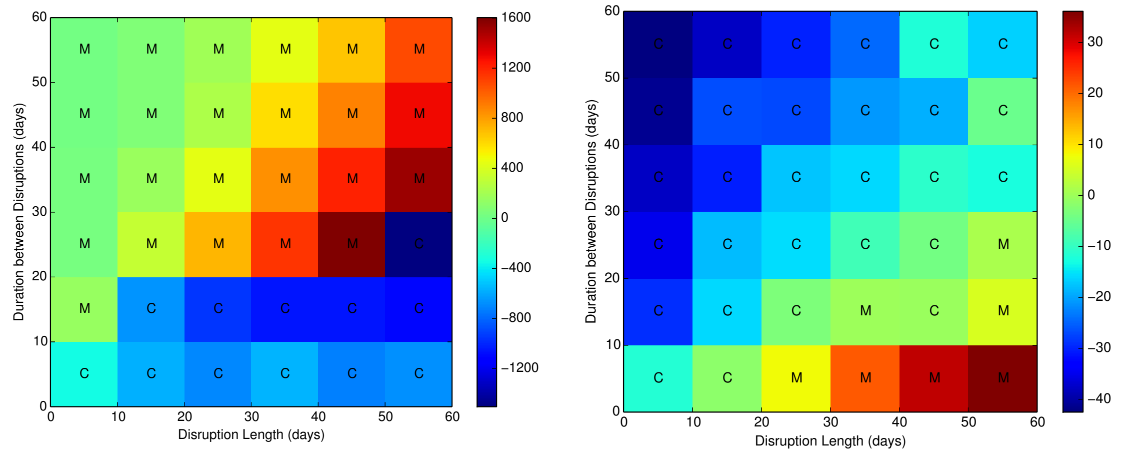
The average per day ordering cost for the SCN, $\overline{C_o}$, is calculated by:

$$\overline{C_o} = \frac{1}{T} \int_{t=1}^{T} \sum_{\varepsilon_x \in \mathcal{E}} C_{x,o}(t) \delta t \tag{4.6}$$

The cost multipliers for each strategy may not be the same, depending on the experiment.

4.3.2 Disruption Scenarios

Figure 4.6 shows the cost-effectiveness of SCRES strategies for different disruption scenarios. The disruption length and the duration between each disruption are varied. Disruptions are frequent but short at the bottom left of the figure, and infrequent but long at the top right. Cost multipliers are set as $\alpha = 1$ and $\beta = 1.2$. The heat map shows the strategy that is more cost-effective for each region. If the multi-supplier strategy has a lower cost compared to the contingent supplier strategy, the heat map will be labelled as M, with reddish colour as the intensity of comparison. Otherwise, if the contingent supplier strategy has a lower cost compared to the multi-supplier strategy, it is labelled as C, with bluish colour as the intensity of comparison.



(a) Backorder cost.

(b) Ordering cost.

Figure 4.6: More cost-effective SCRES strategies (M → Multi-suppliers, C → Contingent Supplier).

Figure 4.6a shows a heat map of the average per day backorder cost for multi-supplier strategy or contingent supplier strategy. Colour intensity represents the average backorder cost, with a darker colour for the higher cost. We can see that when the interval between the disruptions is low (frequent disruptions), contingent supplier strategy will have a lower backorder cost compared to the multi-supplier strategy. Even though the disrupted supplier recovered after disruption, the multi-suppliers do not have sufficient capacity to fulfil the backorders. This will also result in lower order fulfilment for multi-supplier strategy. Since the contingent supplier is continuously engaged even after the disruption ended, it is able to clear the backorders.

When the interval between the disruptions increases (less frequent disruptions), the multi-supplier strategy has a lower backorder cost compared to the contingent supplier strategy. With sufficient time between the disruptions, multi-suppliers are able to clear the backorders. Since the contingent supplier is only activated after a period after the disruption, the firm is unable to manufacture anything during this period, resulting in high backorder cost. Whereas with multi-suppliers, at least the firm is able to continue with production at lower capacity, depending on the remaining supplier. At around 20 to 30 days between disruptions with disruption length of 50 to 60 days, both strategies result in high backorder cost (showing dark red or dark blue). When the length of disruption increases, backorder cost will have the most impact when there is insufficient time to clear the backorders.

Assume the average per day ordering costs for multi-supplier strategy and contingent supplier strategy are $\overline{C_o^m}$ and $\overline{C_o^c}$ respectively. Figure 4.6b shows a heat map of the *difference* between average per day ordering cost for multi-supplier strategy and contingent supplier strategy, i.e., $\overline{C_o^c} - \overline{C_o^m}$. Colour intensity represents the amount of the absolute difference, with darker colour for the higher amount. When the interval between the disruptions is low (frequent disruptions) and disruption length is high, the multi-supplier strategy has a lower ordering cost compared to the contingent supplier strategy. This is due to the fact that multi-suppliers has lower order fulfilment because they are unable to clear the backorders, resulting in lower overall ordering cost. The cost difference is highest at both up-left and bottom-right corners. Multi-suppliers incur higher ordering cost over time if there are few disruptions. The firm is paying for additional costs without any benefits from using multi-suppliers. Overall, the contingent supplier strategy will be more cost-effective in terms of ordering costs if the multi-supplier strategy and contingent supplier strategy have the same cost multiplier.

4.3.3 Ordering Costs Trade-off

Cost multipliers, α and β, represents the real-world cost for the backorders and orders. To compare the trade-offs between multi-supplier strategy and contingent supplier strategy, the cost multipliers for backorder costs and ordering costs for each strategy need to be analysed. It is straightforward to study the backorder cost by comparing the backorder quantity for each strategy, as α is directly proportional to the backorder as shown in Equation 4.3. However, the total ordering cost depends on the type of supplier used, as shown in Equation 4.5. Hence, further analysis of the total ordering cost is needed by comparing the ordering cost multipliers of each strategy.

Figure 4.7 compares the trade-off between the strategies based on different ordering cost multiplier for each strategy. The x-axis shows the ordering cost multiplier for the multi-supplier strategy (β^m), while y-axis shows the cost multiplier for the contingent supplier strategy (β^c). There are four different disruption scenarios, varying between the disruption length (short or long) and the interval between disruptions (frequent with short intervals or infrequent with long intervals). The lines represent the ordering cost where the multi-supplier strategy equals to the contingent supplier strategy, i.e., $\overline{C_o^m} \times \beta^m = \overline{C_o^c} \times \beta^c$.

For most disruption scenarios, contingent supplier strategy is generally more cost effective in terms of ordering cost compared to the multi-supplier strategy, i.e., the gradient

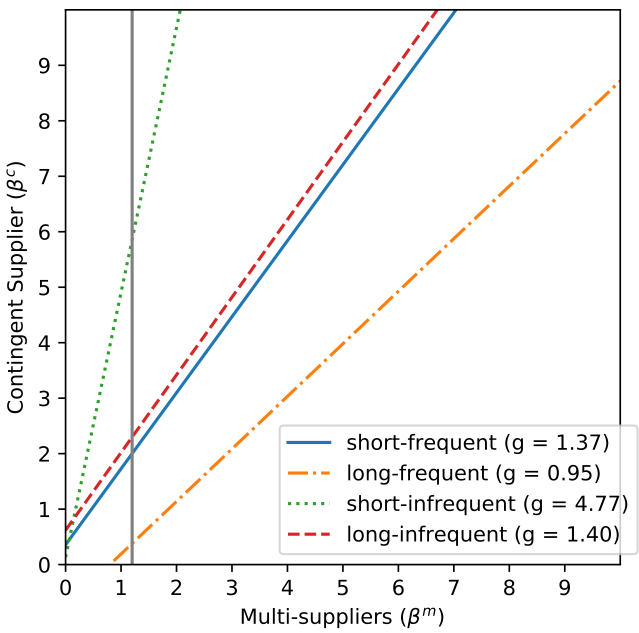


Figure 4.7: Ordering cost trade-off between contingent supplier strategy and multi-supplier strategy. Gradient g of each line is shown in the legends. $\beta^m = 1.2$ is drawn as a grey vertical line.

of the line, g, is greater than 1. This is more prominent when the disruption is short and infrequent (dotted line), where $g = 4.77$. This is because contingent supplier strategy only incurs very little addition cost to engage the contingent supplier only during a few short disruptions. However, the multi-supplier strategy is more cost-effective than the contingent supplier strategy for long and frequent disruption (dot-dash line), where $g = 0.95$. From the previous subsection, the lower ordering cost is due to the low order fulfilment.

To interpret this diagram, we can compare the ordering cost between strategies under different disruption scenarios. In Figure 4.7, for a short and infrequent disruption, point $(1.2, 5.86)$ gives $\overline{C_o^m} \times 1.2 = \overline{C_o^c} \times 5.86$. For example, given that the cost multipliers for two strategies are $\beta^m = 1.2$ and $\beta^c = 1.2$, the point $(1.2, 1.2)$ is below the dotted line, i.e., $\overline{C_o^m} \times 1.2 > \overline{C_o^c} \times 1.2$. This indicates that contingent supplier strategy will be more cost-effective in terms of ordering cost compared to the multi-supplier strategy. For another example, if $\beta^c = 7$, the point $(1.2, 7)$ is above the dotted line, i.e., $\overline{C_o^m} \times 1.2 < \overline{C_o^c} \times 7$. This means that the multi-supplier strategy will be more cost-effective.

4.3.4 Total Relative Cost

Given that the average backorder costs for multi-supplier strategy and contingent supplier strategy are $\overline{C_b^m}$ and $\overline{C_b^c}$ respectively, the normalized backorder costs for the multi-suppliers $\widehat{C_b^m}$ and the contingent supplier $\widehat{C_b^c}$ are shown below:

$$\widehat{C_b^m} = \frac{\overline{C_b^m}}{\max(\overline{C_b^m}, \overline{C_b^c})}$$
$$\widehat{C_b^c} = \frac{\overline{C_b^c}}{\max(\overline{C_b^m}, \overline{C_b^c})}$$

The normalized ordering costs for the multi-suppliers $\widehat{C_o^m}$ and for contingent supplier $\widehat{C_o^c}$ are shown below:

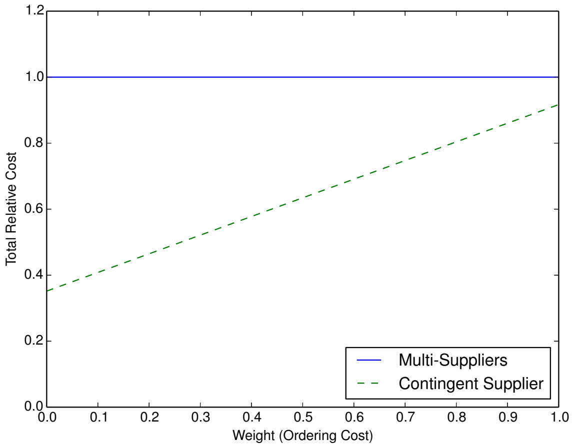
$$\widehat{C_o^m} = \frac{\overline{C_o^m}}{\max(\overline{C_o^m}, \overline{C_o^c})}$$
$$\widehat{C_o^c} = \frac{\overline{C_o^c}}{\max(\overline{C_o^m}, \overline{C_o^c})}$$

After normalizing the costs (backorder cost and ordering cost) between the strategies, the total relative cost is calculated by aggregating the weighted metrics. Assume the weight for the ordering cost is w_1 where $0 \leq w_1 \leq 1$, and the weight for the backorder cost is $1 - w_1$. The total relative costs for multi-suppliers $\mathbf{C}^m$ and contingent supplier $\mathbf{C}^c$ are shown below:

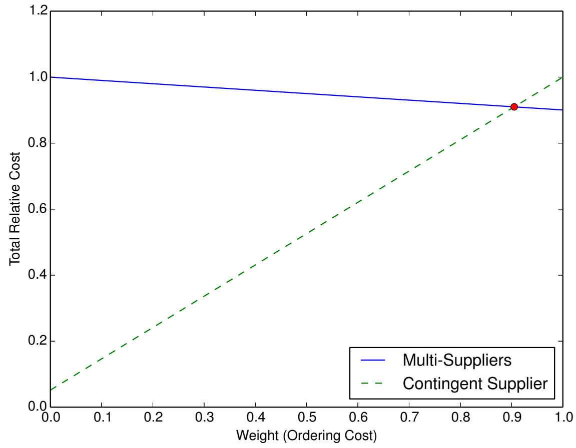
$$\mathbf{C}^m = \widehat{C_b^m} \times w_1 + \widehat{C_o^m} \times (1 - w_1)$$
$$\mathbf{C}^c = \widehat{C_b^c} \times w_1 + \widehat{C_o^c} \times (1 - w_1)$$

Figure 4.8 shows the trade-off between backorder cost and ordering cost based on the two strategies. X-axis represents the weight of the ordering cost w_1. Y-axis is the total relative cost. Strategy with the lower total relative cost is more cost-effective, i.e., the lower line.

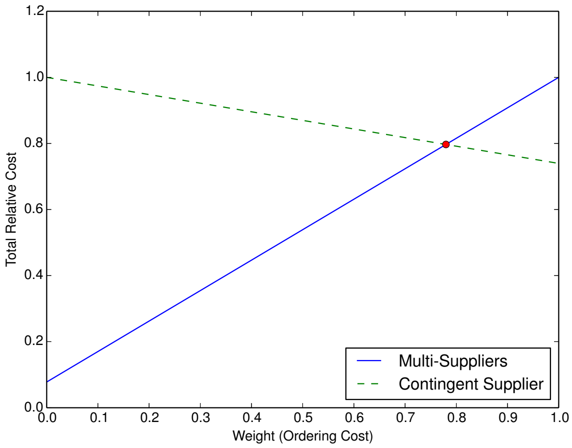
For short and frequent disruption in Figure 4.8a, the contingent supplier strategy has a lower total relative cost than multi-supplier strategy. For the multi-supplier strategy, when one of the suppliers is disrupted, the whole SCN lost 50% of its supply which reduces the overall production by 50%. After the disrupted supplier is restored, there is insufficient spare capacity to clear the backorders before the next disruption occurs. Hence, the multi-supplier strategy is unable to clear the backorders when the disruption is frequent, resulting in higher backorder costs. In addition, these results show that



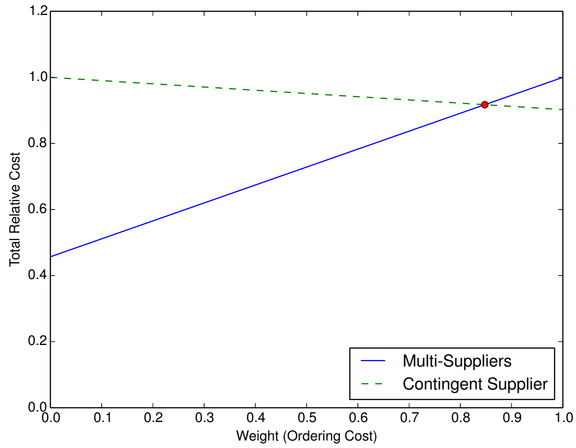
(a) Short and frequent disruption.



(b) Long and frequent disruption.



(c) Short and infrequent disruption.



(d) Long and infrequent disruption.

Figure 4.8: Trade-off between backorder cost and ordering cost.

considering only ordering costs for the trade-off comparison is insufficient for comparison between strategies under short and frequent disruptions. Similarly, for long and frequent disruption in Figure 4.8b, the contingent supplier strategy has a lower total relative cost compared to the multi-supplier strategy when $w_1 < 0.9$. Multi-supplier strategy only becomes more cost-effective when $w_1 > 0.9$. Hence, frequent disruptions have a huge impact on the backorder cost for the multi-supplier strategy and the contingent supplier strategy is generally more cost-effective.

On the other hand in Figure 4.8c, the multi-supplier strategy has a lower total relative cost compared to the contingent supplier strategy when w_1 is low. When the disruption is infrequent, there is more time between the disruptions for the multi-suppliers to clear the backorders. Hence, the multi-supplier strategy has a lower backorder cost compared to the contingent supplier strategy, as shown in Figure 4.6a at the top left. When w_1 increases, the contingent supplier strategy will have a lower total relative cost compared to the multi-supplier strategy due to lower ordering cost. The trend is similar in Figure 4.8d.

In summary, considering a case where the backorder cost carries more weight (lower w_1). For frequent disruptions, the contingency supplier strategy is more cost-effective than multi-supplier strategy, as multi-suppliers is unable to clear backorders. For infrequent disruptions, the multi-supplier strategy is more cost-effective when there is more time to clear the backorders. On the contrast, when the ordering cost is higher (higher w_1), contingency supplier strategy is more cost-effective as more orders are placed in multi-suppliers.

4.4 Summary

In this chapter, a hybrid model is proposed to represent multiple levels of details in an SCN , combining SD and ABM using an integration design approach. Each entity in the SCN can be represented by either an SD entity or an agent, interacting with each other through special adapters that convert between the continuous flow and discrete events. The number of agents in the model depends on the availability of data to calibrate agent model parameters and the level of detail needed for the study. There are several benefits of using the hybrid model. First, it allows the firm to construct a broad view of the whole SCN based on aggregated data through SD. Second, it allows the firm to perform in-depth analysis regarding its own performance by modelling detailed processes using an agent.

A case study on identifying cost-effective SCRES strategies for a three-stage SCN is used to illustrate the applicability of the hybrid model. Two SCRES strategies are studied: mitigation strategy using multi-suppliers and contingency strategy using contingent supplier. Trade-offs between these strategies and trade-offs between backorder cost and ordering cost are analysed and shown in the experimental results. When backorder cost per unit is more expensive, contingency supplier strategy is more cost-effective for frequent disruptions and multi-supplier strategy is more cost-effective for infrequent disruptions. On the contrast, when ordering cost per unit is more expensive, contingency supplier strategy is more cost-effective.

This chapter only provides preliminary analysis of SCRES strategies to showcase the applicability of the hybrid model. A theoretical analysis of the network structure is proposed in Chapter 5, and dynamic analysis on recovery of the SCN after disruptions will be further detailed in in Chapter 6.

Chapter 5

A Graph-based Model to Measure Structural Redundancy

When the supplies of vital materials are concentrated on a single firm, the SCs are inherently susceptible to disruption risks [132]. For example in the Tohoku earthquake, a specific supplier was severely damaged by the disaster. This caused disruptions across multiple part manufacturers, resulting in major automotive manufacturers unable to continue production [119]. When Toyota was forced to rebuild its SC after the earthquake, managers were surprised to discover just how many parts relied on the same few suppliers far upstream [197]. This incident demonstrated that firms must understand material flow in the SC, including not only immediate but also indirect links via the SCs, as well as supply disruption risk of each material. Therefore, they can anticipate whether and how disruptions of specific upstream materials may affect their own production processes.

Based on the research gaps in Section 2.3, current models from literature are unable to analyse the dependencies across multi-stages in an SCN, where vulnerabilities in the upstream stages of the SCN can have a significant impact downstream. In addition, existing research assumed that plants within the SCN or the same stage are equivalent, or the type of material flows between stages are the same. For example, the hierarchical network models used in Chapter 3 and 4 assumed that all entities within the same stage perform the same operations.

Given the above drawbacks, this chapter proposes a graph-based model of a multi-stage SCN to assess SCRES, in terms of the *structural redundancy* at the network level. The graph model of SCN is defined in Section 5.1, where the model considers both materials and plants in the SCN and captures two essential relationships between the materials and plants (that is, *material-to-product relationships* and *inter-plant relationships*). The two relationships form the basic building blocks for constructing a multi-stage SCN. Based on the topological structure of the SCN, all the SCs in the SCN are identified. Correspondingly, an approach to analyse SCRES is proposed to identify the critical plants and measure the number of SCs in the SCN. In Section 5.2, the graph model and the approach for SCRES analysis are illustrated using the real-world SCN from the existing dataset of SCNs [201].

The main theoretical contributions of this chapter are the proposed conceptual model of an SCN that can represent structural redundancy across multiple stages. Based on this model, critical plants in the SCN can be identified and redundancy of SCRES can be assessed. The practical implications of the model and the approach are demonstrated by using mitigation and contingency strategies to build a more resilient SCN. For mitigation strategy, critical plants should be the key priority to reduce the impact of disruption. For contingency strategy, the impact of disruptions on the critical plants determines the level of response toward the disruptions.

5.1 Graph Model of Supply Chain Network

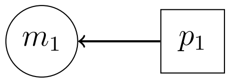
First, the SC model is discussed before introducing the SCN model. We consider a single-product, multi-stage SC, consisting of plants and materials. By extending on Grave's model [56], the dependencies between materials and plants are considered. This allows any general multi-stage production system to be modelled, in which each stage performs a distinct operation and requires its own plants. To represent structural redundancy in the SCN, the model is extended to consider redundant dependencies between the materials and plants. However, there are limitations of the model. The capacity of the plant is not considered in this model. To simplify the analysis, we assume that each plant only produces a single product.

5.1.1 Supply Chain Model

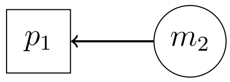
A rooted directed tree G is denoted as $G = (M, P, E, m_o)$, where M and P are disjoint sets of nodes, and E is the set of directed edges between nodes in M and P respectively. The root of the tree is m_o, where $m_o \in M$. Leaves of the tree are nodes in P. G is also a bipartite graph, where the nodes can be divided into two disjoint and independent sets

M and P.

M is the set of materials and P is the set of plants in an SC. m is a material in the SC, such that $m \in M$. p is a plant in the SC, such that $p \in P$. The *end product* of the whole SC is represented by root m_o, which is assumed as the focal product subjected to analysis. There are two basic components in an SC, which represent the dependencies between the material and plant: *output dependency* and *input dependency*.



(a) Material m_1 is produced by plant p_1, such that m_1 has output dependency on p_1.



(b) Material m_2 is processed at plant p_1, such that p_1 has input dependency on m_2.

Figure 5.1: Dependency between plant and material.

Output dependency is the dependency relationship from a plant p to a material m, such that m is produced or supplied by p. A single **stage** in the SC is represented by an output dependency. Hence, an output dependency represents a single production (with input and output materials at p) or supply process (only output material at p). For a production process, the material, such as sub-assembly or intermediate product, is produced from the plant. For a supply process, the material is sourced from the plant. Figure 5.1a shows an example of the material m_1 that is produced from plant p_1. The set of output dependencies in the SC are represented by the set of edges E_O.

Input dependency is the dependency relationship from a material m to a plant p, where the material, e.g., raw material, sub-assembly or intermediate products, is required by the plant for the production process. Input dependencies link stages of the SC together. For example in Figure 5.1b, plant p_1 is dependent on material m_2. The set of input dependencies in the SC is represented by the set of edges E_I. All input dependencies of a plant are necessary to the plant, as they represent the materials directly required by the plant to process the product. Two input dependencies for plant p_1 are shown in Figure 5.2: from m_1 to p_1, and from m_2 to p_1. Since all the input materials are necessary, this can be represented using a logical *AND* relationship ($\wedge$).

Based on the two basic components, two key relationships in the SC can be modelled simultaneously. First, the input dependency and output dependency represent the *material-to-product relationships* in the production process. Whereas the combination of

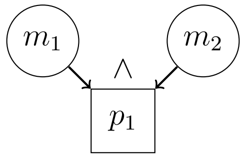


Figure 5.2: Input dependencies of plant p_1 on materials m_1 and m_2.

the output dependency and input dependency forms the *inter-plant relationships* between the plants.

Suppliers provide the raw materials required in the SC. They are not involved in any production processes within the SC. Hence, all the leaves in G represent the suppliers, which are from the set of plants in P.

1. E_O is a set of distinct directed edges, where each directed edge from p to m is represented by an ordered pair of nodes (p, m) or $p \to m$. This relation can be expressed as:
$$E_O \subseteq (P \times M) = \{(p, m) | m \in M, p \in P\} \tag{5.1}$$
where E_O is the subset or equal set of all possible edges from P to M.

2. E_I is a set of distinct directed edges, where each directed edge from m to p is represented by an ordered pair of nodes (m, p) or $m \to p$. This relation can be expressed as:
$$E_I \subseteq (M \times P) = \{(m, p) | m \in M, p \in P\} \tag{5.2}$$
where E_I is the subset or equal set of all possible edges from M to P.

3. Since there are only edges between m and p, there are no edges between nodes from the same set, that is $E = E_O \cup E_I$ and $E_O \cap E_I = \emptyset$.

We denote the set of in-nodes of p as $M^+(p)$, where $\forall m \in M^+(p), (m, p) \in E_I$, and the set of in-nodes of m is denoted as $P^+(m)$, where $\forall p \in P^+(m), (p, m) \in E_O$. For a connected edge-set, e.g., $(p_1, m_1), (m_1, p_2)$, it can also be represented as $p_1 \to m_1 \to p_2$.

Assuming that every plant in an SC produces an unique material:

Proposition 5.1. *For all material $m \in M$, there will be only one plant producing an unique material m in an SC, i.e., $\forall m \in M, |P^+(m)| = 1$.*

Definition 5.1 (Supply Chain)**.** A supply chain is represented by a rooted directed tree $G = (M, P, E, m_o)$, where M is the set of materials and P is the set of plants. The root of the tree, m_o, represents the *end product.* The leaves of the tree from P, represent the *suppliers.* E represents the dependency relationships between materials and plants.

An SC represents the production system to process the material and produce the end product, where all plants play a role in the production process. The minimum number of nodes in G consists of a root m and a single plant p, connected as the output dependency (p, m). This represents a single stage in the SC.

Proposition 5.2. *There is at least one output dependency in a supply chain.*

Since the supply chain is a tree and tree is a connected graph, the following proposition is obvious:

Proposition 5.3 (Supply Chain Connectivity)**.** *An SC is* connected.

Since the SC is connected, all plants and materials must exist in the set of output dependencies, where each stage contains a plant and the corresponding material that is processed. Stages in the SC are linked together through the input dependencies, where the paths represent the material flow from all plants to the end product.

Example 5.1. Figure 5.3 shows an industrial organic chemicals manufacturing SC (H_1) from dataset [201]. It is represented as a two-stage SC G for an end product m_1. Plant p_3, p_4, and p_5 produce material m_2, m_3 and m_4 respectively. Material m_2, m_3 and m_4 are materials required for plant p_1 to produce the end product m_1. Hence, $\{(m_2, p_1), (m_3, p_1), (m_4, p_1)\}$ are the input dependencies for p_1, and $\{(p_1, m_1)\}$ is the output dependency.

5.1.2 Supply Chain Network Model

In order to assess the SC redundancy, we introduce an SCN in which redundant plants can exist. There is more than one plant producing the same material in the SCN, i.e., SCN has **redundant output dependencies**. In the SC, it requires that a material is only produced by one plant (Proposition (5.1)). The SCN model relaxes this constraint, such that there can be multiple plants producing the same material. Hence, an SCN can be defined as a set of SCs [62]. This redundancy represents sourcing policies such as dual or multiple sourcing, as shown in Figure 5.4, where there are two plants p_1 and p_2

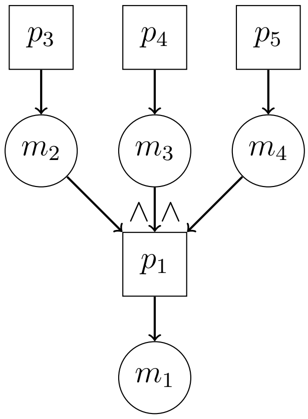


Figure 5.3: A two-stage supply chain.

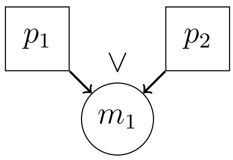


Figure 5.4: Redundant output dependencies of material m_1 on plants p_1 or p_2.

producing the same material m_1. As the output dependencies are redundant, this can be represented using a logical *OR* relationship ($\vee$).

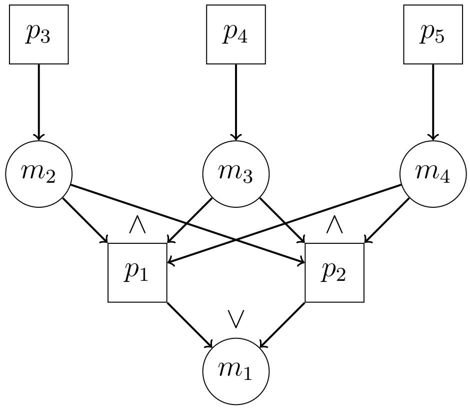
Let $\mathbb{G}$ be the set of trees G with the same root m_o, a rooted directed acyclic graph $H = (M_H, P_H, E_H, m_o)$ is the union of trees $G_x \in \mathbb{G}$, such that:

$$\forall G_x(M_x, P_x, E_x, m_o) \in \mathbb{G},$$

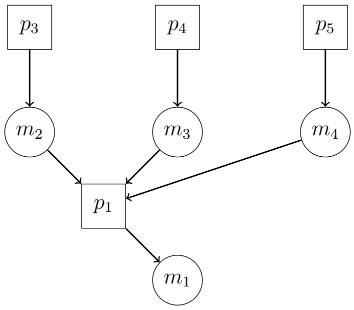
$$\begin{aligned} M_H &= \bigcup_x M_x \\ P_H &= \bigcup_x P_x \\ E_H &= \bigcup_x E_x \\ m_o &\in M_H \end{aligned}$$

Definition 5.2 (Supply Chain Network)**.** Given $\mathbb{G}$ is a set of trees that have the same root m_0, a supply chain network is a rooted directed acyclic graph H, which is a union of trees in $\mathbb{G}$.

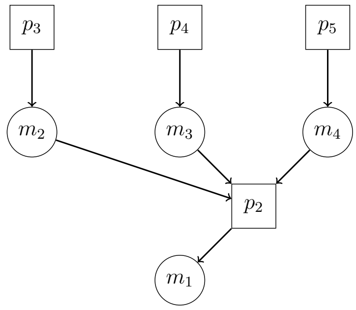
Example 5.2. Figure 5.5a shows a two-stage SCN H for a common end product m_1 based on an existing SCN, H_1, from dataset [201]. It comprises two SCs as shown in Figure 5.5. Since there are two plants producing m_1, there are redundant output dependencies, (p_1, m_1) and (p_2, m_1), for material m_1.



(a) SCN H for end product m_1.



(b) SC G_1 with plant p_1.



(c) SC G_2 with plant p_2.

Figure 5.5: Two-stage supply chain network H contains two SCs G_1 and G_2.

Given the definition of the SCN, the following two propositions are obvious:

Proposition 5.4. *Given an existing SCN, there is at least one SC exists.*

Proposition 5.5 (Supply Chain Network Connectivity)**.** *A supply chain network is connected if there is at least one connected supply chain.*

Since an SCN consists of multiple SCs, as long as one of the SCs is still connected, the end product m_o is still available.

5.1.3 Disruptions in a Supply Chain Network

We consider disruption in an SC as the disruption of plants. If a plant p is disrupted, all dependencies of p will be disrupted. To model the disruption of plant p, all edges connected to p will be removed from the SC. When one or more dependencies is removed from the SC, the SC is disconnected, since removing an edge from a tree will disconnect the tree. Hence, we can define SC disruption in terms of graph connectivity.

Definition 5.3 (Supply Chain Disruption)**.** A supply chain is disrupted if a supply chain is disconnected.

After considering disruptions in the SC, we extend the scope to consider disruptions in the SCN. From Proposition 5.5, if there is no connected SC in an SCN, the SCN is disconnected.

Definition 5.4 (Supply Chain Network Disruption)**.** A supply chain network is disrupted if a supply chain network is disconnected.

Example 5.3. For example in Figure 5.5, there are two SCs G_1 and G_2. When p_1 is disrupted, the SC G_1 is disrupted. When p_2 is disrupted, the SC G_2 is disrupted. If both plants p_1 and p_2 are disrupted, both SCs G_1 and G_2 are disrupted. Hence, the SCN H is disrupted.

5.1.4 Number of Supply Chains in Generic Supply Chain Network

One way of mitigating the impact of disruption is by increasing the number of SCs in an SCN, i.e., increasing redundancy. A higher number of SCs reduces the probability that the SCN will be disconnected when plants are disrupted. To determine the number of SCs in an SCN, we use a *generic SCN*, where the SCN structure of a tree can be constructed based on parameters defined.

Definition 5.5 (Generic Supply Chain Network)**.** A generic supply chain network is a supply chain network where there are α plants producing each material, each plant requires β input materials, and there are L stages.

A generic SCN H is k-ary tree if both $\alpha = k$ and $\beta = k$. The minimum possible generic SCN that is connected is when $\alpha = 1$, $\beta = 1$ and $L = 1$, which is shown in Figure 5.1a. Hence, for a connected generic SCN, it is constrained by $\alpha \geq 1$, $\beta \geq 1$ and $L \geq 1$. Figure 5.6 shows an example of a generic SCN with $L = 2$, $\alpha = 2$ and $\beta = 2$.

Since α represents the number of plants for each material, the number of plants at stage l is α times of the number of materials at stage l. Assuming each stage $l = 0, \ldots, L-1$,

$$\text{Number of materials at stage } l = \alpha^l \times \beta^l \tag{5.3a}$$

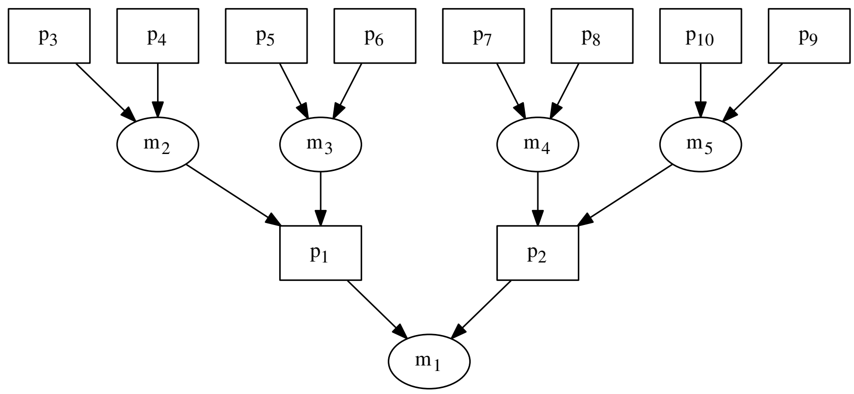


Figure 5.6: A generic supply chain network with parameters $L = 2$, $\alpha = 2$ and $\beta = 2$.

$$\text{Number of plants at stage } l \ = \alpha \times (\alpha^l \times \beta^l) \tag{5.3b}$$

For a general form of a geometric progression, $a, ar, ar^2, ar^3, \ldots, ar^{n-1}$, the summation of the geometric progression is $\frac{a(1-r^n)}{1-r}$. By formulating the Equation 5.3a and 5.3b into the terms a, r and n, the total number of materials and plants can be derived by transforming the sequences to summations:

Assume $\alpha > 1$ and $\beta > 1$, by applying geometric progression to Equation 5.3a and 5.3b where $l = 0, 1, \ldots, L-1$,

$$\begin{aligned} \text{Number of materials, } |M| &= \sum_{l=0}^{L-1} \alpha^l \times \beta^l \\ &= \frac{\alpha^L \beta^L - 1}{\alpha\beta - 1} \end{aligned}$$

$$\begin{aligned} \text{Number of plants, } |P| &= \sum_{l=0}^{L-1} \alpha \times (\alpha^l \times \beta^l) \\ &= \alpha \times \sum_{l=0}^{L-1} (\alpha^l \times \beta^l) \\ &= \alpha \times |M| \end{aligned}$$

The number of plants that produces the same material increases the number of SCs linearly by a factor of α. In Figure 5.6, plant p_1 depends on material m_2 and m_3. Material m_2 depends on plant p_3 and p_4, while m_3 depends on p_5 and p_6. We can form four chains with respect to p_1:

1. $\{p_3 \rightarrow m_2 \rightarrow p_1, p_5 \rightarrow m_3 \rightarrow p_1\}$

2. $\{p_4 \rightarrow m_2 \rightarrow p_1, p_5 \rightarrow m_3 \rightarrow p_1\}$

3. $\{p_3 \rightarrow m_2 \rightarrow p_1, p_6 \rightarrow m_3 \rightarrow p_1\}$

4. $\{p_4 \rightarrow m_2 \rightarrow p_1, p_6 \rightarrow m_3 \rightarrow p_1\}$

As material m_1 depends on either plants p_1 or p_2, the total number of SCs is $4 \times 2 = 8$.

Assuming that the number of SCs for a generic SCN with L stages is n_{L-1},

$$\begin{aligned} n_0 &= \alpha \\ n_l &= \alpha \times (n_{l-1})^{\beta} \end{aligned}$$

By applying $\log_\alpha$ on both sides of the equation:

$$\begin{aligned} \log_\alpha n_0 &= 1 \\ \log_\alpha n_l &= 1 + \beta \log_\alpha (n_{l-1}) \\ \log_\alpha n_1 &= 1 + \beta \log_\alpha n_0 \\ &= 1 + \beta \\ \log_\alpha n_2 &= 1 + \beta \log_\alpha n_1 \\ &= 1 + \beta(1 + \beta) \\ &= 1 + \beta + \beta^2 \end{aligned}$$

By induction,

$$\log_\alpha n_{L-1} = 1 + \beta + \beta^2 + \cdots + \beta^{L-1}$$

So,

$$\log_\alpha n_{L-1} = \frac{1 + \beta^{L-1}}{1 - \beta}$$

and,

$$n_{L-1} = \alpha^{\frac{1+\beta^{L-1}}{1-\beta}} \tag{5.5}$$

5.1.5 Identifying Supply Chains from a Supply Chain Network

However, most of the real-world SCNs cannot be represented using the generic SCN, a more general method is required to determine the number of SCs in an SCN. Given that at least one SC existing in an SCN, an algorithm to find all the SCs in an existing SCN is presented in Algorithm 5.1.

Algorithm 5.1 Find Supply Chains

1: **function** FINDSUPPLYCHAINS(m)
2: $\quad \mathbb{G}_m \leftarrow \emptyset$
3: $\quad$ **for** $p \in P^+(m)$ **do**
4: $\quad\quad \mathbb{G}_p \leftarrow \emptyset$
5: $\quad\quad$ **for** $m_i \in M^+(p)$ **do**
6: $\quad\quad\quad \mathbb{G}_i \leftarrow$FindSupplyChains($m_i$)
7: $\quad\quad\quad \mathbb{G}_{i,p} \leftarrow \{(M \cup \{m, m_i\}, P \cup \{p\}, E \cup \{(m_i, p), (p, m)\}), \forall G(M, P, E, m_i) \in \mathbb{G}_i\}$
8: $\quad\quad\quad$ **if** $\mathbb{G}_p = \emptyset$ **then**
9: $\quad\quad\quad\quad \mathbb{G}_p \leftarrow \mathbb{G}_{i,p}$
10: $\quad\quad\quad$ **else**
11: $\quad\quad\quad\quad \mathbb{G}_p \leftarrow \{G_1 \cup G_2, \forall (G_1, G_2) \in (\mathbb{G}_p \times \mathbb{G}_{i,p})\}$
12: $\quad\quad \mathbb{G}_m \leftarrow \mathbb{G}_m \cup \mathbb{G}_p$
13: $\quad$ **return** $\mathbb{G}_m$

Algorithm 5.1 describes a reverse depth-first traversal algorithm to determine the set of SCs $\mathbb{G}$ from an SCN H. The algorithm recursively traverses H from a material m, to find all the SCs with respect to material m.

The function FindSupplyChains(m) returns $\mathbb{G}_m$, which is the set of trees with the root m. Each plant p producing m is traversed (Line 3) to find the set of trees $\mathbb{G}_p$ with respect to p. For each plant p, m_i denotes the input material required by the plant p (Line 5). For each input material m_i, the set of trees $\mathbb{G}_i$ with respect to m_i is found by calling FindSupplyChains(m_i) (Line 6). Edges from input material m_i to plant p, and from plant p to output product m, are added to each tree in $\mathbb{G}_i$ (Line 7). If the set $\mathbb{G}_p$ is empty, then $\mathbb{G}_p$ equals to $\mathbb{G}_{i,p}$ for the first material in $M^+(p)$. Otherwise, the product $\mathbb{G}_p \times \mathbb{G}_{i,p}$ returns a set of paired trees, where each pair (G_1, G_2) are unioned to form the set of trees $\mathbb{G}_p$ with respect to p (Line 11). This generates the combinations of trees where there are redundant output dependencies for the material m (as described in the previous subsection). Each tree in $\mathbb{G}_p$ is then added to $\mathbb{G}_m$. Hence, all the SCs from an SCN H can be found by calling FindSupplyChains(m_o) to traverse the SCN from the end product m_o.

Example 5.4. In Figure 5.5a, the tree H is traversed starting from the root m_1.

1. There are two plants producing m_1, such that $P^+(m_1) = \{p_1, p_2\}$.

2. For each plant in $P^+(m_1)$, it depends on three materials $\{m_2, m_3, m_4\}$, such that $M^+(p_1) = \{m_2, m_3, m_4\}$ and $M^+(p_2) = \{m_2, m_3, m_4\}$.

3. For each of the materials $\{m_2, m_3, m_4\}$, the trees with respect to each material can be found:

   (a) $\mathbb{G}_2 = \{G(\{m_2\}, \{p_3\}, \{p_3 \to m_2\}, m_2)\}$

   (b) $\mathbb{G}_3 = \{G(\{m_3\}, \{p_4\}, \{p_4 \to m_3\}, m_3)\}$

   (c) $\mathbb{G}_4 = \{G(\{m_4\}, \{p_5\}, \{p_5 \to m_4\}, m_4)\}$

4. For the plant p_1, these trees are added with the edges $\{(m_2, p_1)$, (m_3, p_1), (m_4, p_1), $(p_1, m_1)\}$ to obtain the intermediate set of trees $\mathbb{G}_{2,1}$, $\mathbb{G}_{3,1}$ and $\mathbb{G}_{4,1}$.

   (a) $\mathbb{G}_{2,1} = \{G(\{m_1, m_2\}, \{p_3, p_1\}, \{p_3 \to m_2 \to p_1 \to m_1\})\}$

   (b) $\mathbb{G}_{3,1} = \{G(\{m_1, m_3\}, \{p_4, p_1\}, \{p_4 \to m_3 \to p_1 \to m_1\})\}$

   (c) $\mathbb{G}_{4,1} = \{G(\{m_1, m_4\}, \{p_5, p_1\}, \{p_5 \to m_4 \to p_1 \to m_1\})\}$

5. The union of trees in the sets $\mathbb{G}_{2,1}$, $\mathbb{G}_{3,1}$ and $\mathbb{G}_{4,1}$ form the tree G_1 in Figure 5.5b.

6. Similarly for the plant p_2, these trees are added with the edges $\{(m_2, p_2)$, (m_3, p_2), (m_4, p_2), $(p_2, m_1)\}$ to obtain the intermediate set of trees $\mathbb{G}_{2,2}$, $\mathbb{G}_{3,2}$ and $\mathbb{G}_{4,2}$.

   (a) $\mathbb{G}_{2,2} = \{G(\{m_1, m_2\}, \{p_3, p_2\}, \{p_3 \to m_2 \to p_2 \to m_1\})\}$

   (b) $\mathbb{G}_{3,2} = \{G(\{m_1, m_3\}, \{p_4, p_2\}, \{p_4 \to m_3 \to p_2 \to m_1\})\}$

   (c) $\mathbb{G}_{4,2} = \{G(\{m_1, m_4\}, \{p_5, p_2\}, \{p_5 \to m_4 \to p_2 \to m_1\})\}$

7. Then the union of trees in the sets $\mathbb{G}_{2,2}$, $\mathbb{G}_{3,2}$ and $\mathbb{G}_{4,2}$ form the tree G_2 in Figure 5.5c.

Hence, two SCs G_1 and G_2 can be obtained from the SCN H.

5.1.6 Assessment Metrics

Based on our SCN model, we proposed a two-level approach to assess the SCRES using structural redundancy. The measures are validated through two case studies on real-world SCN in Section 5.2.

Non-redundant Plants

The first level identifies plants within the SCN without redundancy. When a plant without redundancy is disrupted, it will have a significant impact on the SCN.

Definition 5.6 (Non-redundant Plant)**.** A non-redundant plant is a plant in an SCN for a material m, such that there is only one plant producing the material m.

The set of non-redundant plants can be determined by:

$$P_{nr} = \bigcup_{m \in M_H} \begin{cases} P^+(m) & \text{if } |P^+(m)| = 1 \\ \emptyset & \text{otherwise} \end{cases} \tag{5.6}$$

If there is no *non-redundant plants*, all plants have at least one redundant plant. Hence, the SCN can tolerate at least one plant disruption without disrupting any SCs. If the firm aims to achieve redundancy on all plants, the set of non-redundant plants will be the key areas for building additional redundancy. On the other hand, it is possible for an SCN to have non-redundant plants for materials that are required by redundant plants downstream.

Example 5.5. Given two SCs G_1 and G_2 in an SCN, G_1's set of edges $E_1 = \{p_2 \to m_1 \to p_1 \to m_0\}$, and G_2's set of edges $E_2 = \{p_4 \to m_2 \to p_3 \to m_0\}$. Material m_0 has redundant plants p_1 and p_3. Whereas for m_1 only depends on p_2, and m_2 depends on p_4. Both p_2 and p_4 are non-redundant plants, but m_0 has redundancy with respect to p_2 and p_4.

Definition 5.7 (Critical Plant)**.** A critical plant is a plant that is shared by all the SCs in an SCN.

The set of critical plants P_{crit} is the intersection of the vertex set P of all trees $G \in \mathbb{G}$. If $p \in P_{crit}$ is disrupted, all edges connected to p will be removed from SCN H. Hence, all trees $G \in \mathbb{G}$ will be disconnected.

$$P_{crit} = \bigcap_{G(M,P,E,m_o) \in \mathbb{G}} P \tag{5.7}$$

The set of critical plants is a subset or equal set of the *non-redundant plants*, such that $P_{crit} \subseteq P_{nr}$.

If there is no *critical plant*, there will be no single point of failure that may disrupt the entire SCN. Hence, the critical plants are the key areas to focus on to improve the SCRES.

Redundancy

A large number of critical plants in an SCN indicates large overlapping amongst the SCs (and hence fewer redundancies in the SCN). However, the number of critical plants does not measure the exact amount of redundancies in the SCN, where there may be more than one plant for each material. So, to capture the structural redundancy (i.e., to capture the redundancy at the network level instead of nodes), the second level measures the number of SCs in an SCN. This indicates the SCN's ability to resist disruptions and maintain operations.

Definition 5.8 (Supply chain network redundancy)**.** Supply Chain Network Redundancy is the number of SCs in an SCN H.

$$n_{scn} = |\mathbb{G}| \tag{5.8}$$

A large number of SCs can indicate that there are more alternative production processes for the end product. This redundancy allows the SCN to maintain the production process even when some plants are disrupted, or provide backup plants that can be utilised during disruptions.

The advantage of this measurement approach is the ability to represent structural redundancy in a multi-stage SCN. In addition, upstream disruptions in the SCN may not be felt as quickly as downstream disruptions. But the impact of upstream disruptions can be amplified and outlasting the disruptions themselves [165]. Hence, the redundancies of plants at the lower stages have a larger impact on the SCRES compared to redundancies of plants at higher stages.

One limitation of using the number of SCs in an SCN to measure SCN redundancy is that two SCN designs, one with critical plants and one having redundancies for all plants, may have the same number of SCs. Therefore, this requires a **two-level assessment**: (i) the number of critical plants, and (ii) the number of SCs. It is more important to improve the redundancies for the critical plants, before improving the redundancies of the remaining non-redundant plants in the SCN.

Example 5.6. In Figure 5.5a, there is only one plant producing each material m_2, m_3 and m_4 (i.e., p_3 producing m_2, p_4 producing m_3 and p_5 producing m_4). For the first level analysis, we consider the non-redundant plants in the SCN. The set of non-redundant plants is $P_{nr} = \{p_3, p_4, p_5\}$. The set of critical plants P_{crit} is the same set as P_{nr}. For the second level of analysis, we measure the number of SCs in the SCN. There are two plants p_1 and p_2 producing the same material m_1. Two SCs (Figure 5.5b and Figure 5.5c) can be found from the SCN, i.e, $n_{scn} = 2$.

5.2 Case Studies

To illustrate the applicability of the conceptual model, we conduct analysis using two multi-stage SCNs, H_3 and H_{21}, from an existing set of real-life cases [201]. H_3 is a real-world computer peripheral equipment manufacturing SCN, consisting of nine plants. This SCN is chosen as it is small enough for visual analysis yet contains redundancies within the SCN. H_{21} is another real-world SCN which manufactures perfumes, cosmetics, and other toilet preparations, consisting of 98 plants. This case is used to illustrate the scalability of the model, and to demonstrate the limitation of using visual analysis due to the complexities of the network structure.

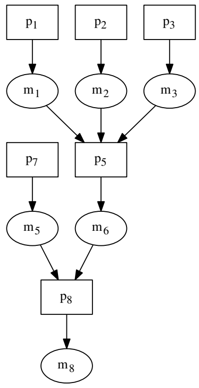
5.2.1 Case I – Contingency Strategy

First, we consider a contingency strategy by performing the contingency actions after an SC disruption has occurred. When a plant disruption has occurred, we first determine whether the disrupted plant is a critical plant. If the disrupted plant is not a critical plant, the SCN can still maintain some functionalities due to the redundancies within the SCN. If a critical plant is disrupted, contingency action such as activating the backup is required.

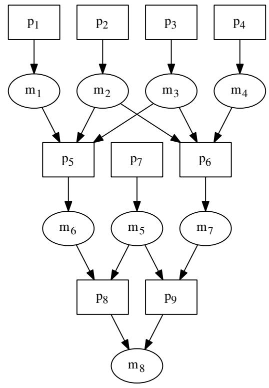
This case study is conducted on H_3, which consists of nine plants, eight materials and a single end product m_8. There are three stages in the SCN, with ten input dependencies and nine output dependencies. There are two SCs in H_3, each containing six plants and six materials.

The first four scenarios are designed based on H_3 to demonstrate the applicability of the model and the contingency strategy to improve the resilience of the SCN against disruptions. The SCNs in these four scenarios are evaluated using the metrics introduced in Section 5.1.6, and the results are tabulated in Table 5.1. To determine the potential risk within the SCN, the set of non-redundant plants P_{nr} and the set of critical plants P_{crit} are identified.

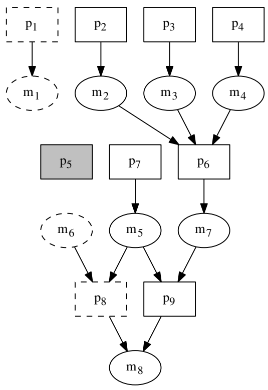
Scenario 1 is an SC of H_3, as shown in Figure 5.7a. It represents an SCN without



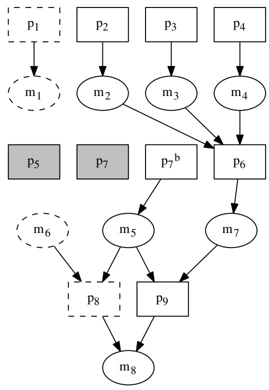
(a) *Scenario 1* – a single SC in H_3



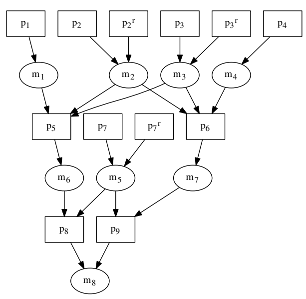
(b) *Scenario 2* – original SCN H_3



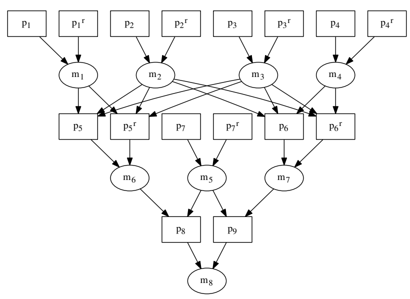
(c) *Scenario 3* – p_5 disrupted



(d) *Scenario 4* – p_5 and p_7 disrupted



(e) *Scenario 5* – redundant critical plants



(f) *Scenario 6* – all redundant plants

Figure 5.7: Six scenarios based on H_3 from dataset [201], where the disrupted plant is shaded and the dotted nodes represent plants that are affected by the disruption.

Table 5.1: Assessment for H_3.

Scenario	$\lvert P \rvert$	P_{nr}	P_{crit}	n_{scn}
1	6	$\{p_1, p_2, p_3, p_5, p_7, p_8\}$	$\{p_1, p_2, p_3, p_5, p_7, p_8\}$	1
2	9	$\{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}$	$\{p_2, p_3, p_7\}$	2
3	7	$\{p_1, p_2, p_3, p_4, p_6, p_7, p_9\}$	$\{p_2, p_3, p_7\}$	1
4	7	$\{p_1, p_2, p_3, p_4, p_6, p_7^b, p_9\}$	$\{p_2, p_3, p_7\}$	1
5	12	$\{p_1, p_4, p_5, p_6\}$	$\emptyset$	16
6	16	$\emptyset$	$\emptyset$	64

any redundancy, i.e., there is only one SC in this scenario. Hence, all the plants have no redundancies. The lack of redundancies causes the SCN to not able able to tolerate any disruptions.

Scenario 2 is the original SCN in H_3 as shown in Figure 5.7b. It contains redundancies in the SCN, such that there are two SCs in H_3. As such, the SCN has a smaller number of critical plants in the SCN compared to *Scenario 1*.

Considering a scenario where there is a plant disruption in the SCN, whether or not the disrupted plant is a critical plant needs to be determined. *Scenario 3* is the remaining SCN of H_3 after a plant p_5 is disrupted. In Figure 5.7c, it shows the shaded plant p_5 is disrupted and the dependencies $\{(m_1, p_5), (m_2, p_5), (m_3, p_5), (p_5, m_6)\}$) are removed from the SCN. As a result, nodes $\{p_1, p_8, m_1, m_6\}$ are affected by the disruption (as drawn in dotted lines). We can see that one of the SCs is disconnected when p_5 is disrupted. Since p_5 is not a critical plant, the SCN is still connected after disruption due to the redundancies within the SCN. As the SCN is still connected, the firm can still afford to wait passively for the disruption to end, and for the plant p_5 to recover.

Scenario 4 represents another scenario where a critical plant p_7 is disrupted in the *Scenario 3*. Since p_7 is a critical plant, it disrupts all the SCs in the SCN, resulting in disruption of the whole SCN. Hence, *contingency policies* need to be taken to recover the SCN from disruption. One possible policy is to use contingent re-routing, to seek alternative plants after disruption, where the demand will be rerouted to the backup plant [185]. To recover the production capabilities of the SCN, the firm needs to re-route the demand to the backup plant p_7^b to maintain the flow of the material m_5.

5.2.2 Case II – Mitigation Strategy

For mitigation strategy, we prioritise risk mitigation in the SCN by improving redundancy of non-redundant plants in the SCN. One possible strategy to redesign the SCN is to improve the SCRES against disruption by having multiple sourcing options for its products [134]. Multiple plants diversify risks by decreasing the likelihood that a disruption to a single plant significantly impacts the SCN. If we assume that each plant has the same fixed setup cost, the number of plants in the SCN is proxy for setup costs for the plants. More complex operational costs of dual sourcing, such as variable ordering costs, are part of the future works.

For the mitigation strategy, there are two additional scenarios. To improve the SCRES of *Scenario 2*, dual sourcing is implemented for all critical plants, where one additional plant is added for the critical plants $P_{crit} = \{p_2, p_3, p_7\}$ identified in Table 5.1. *Scenario 5* is a redesigned SCN after adding the redundant plants for all the critical plants in *Scenario 2*, where it has 12 plants and 8 materials, as shown in Figure 5.7e. There are in total 10 input dependencies and 12 output dependencies. The additional plants do not affect the total number of materials in the SCN. Another approach to mitigating risks is to improve the redundancy for all non-redundant plants. *Scenario 6* implements dual sourcing for all the non-redundant plants of *Scenario 5*, i.e., $P_{nr} = \{p_1, p_4, p_5, p_6\}$, as shown in Figure 5.7f. It has 16 plants and eight materials, with 16 input dependencies and 16 output dependencies. Hence, it has redundancy in the all plants, where there are at least two plants producing each material. This means that all the materials can tolerate at least one plant that produces the material to be disrupted.

To analyse the resilience of SCN against random disruptions, we simulate disruptions of the plants using Monte-Carlo simulation and evaluate the probability that the SCN remains connected. For the simulation, we randomly generate a set of plants to be disrupted, varying from 0% to 100%. Based on the percentage of the plants that are disrupted, the number of SCs in the remaining SCN is calculated. This process is sampled $10,000$ times to obtain the average number of SCs for each percentage of plants that are disrupted. The results are shown in Figure 5.8, which plots the percentage of plants disrupted against the number of remaining SCs in logarithmic scale ($log(n_{scn} + 1)$). The number of remaining SCs reduces as more plants are disrupted. At around 65% of plants disrupted, the SCNs in all scenarios are disrupted.

Scenario 5 has a better resilience during disruption compared to *Scenario 2*, where it

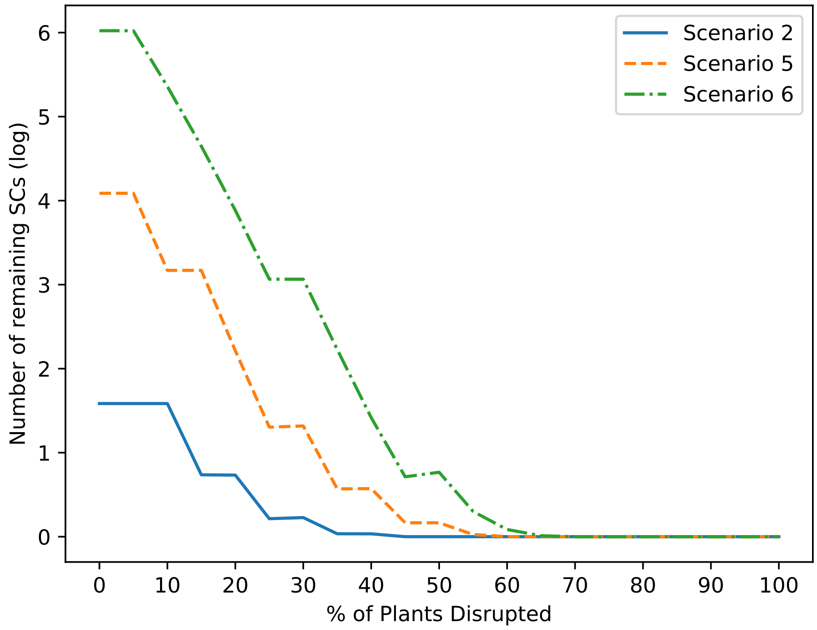


Figure 5.8: Percentage of plants disrupted against number of remaining SCs in H_3.

requires 55% of the plants to be disrupted in order to disrupt the whole SCN, compared to 45% in *Scenario 2*. Hence, the SCN is more resilient against disruptions if redundant plants are added for the three critical plants (33% additional redundant plants). *Scenario 6* demonstrates the best resilience compared to *Scenario 2* and *Scenario 5*, as shown in Figure 5.8, where it can remain connected up to 65% of the plants disrupted. However, this requires around 77% more plants to achieve the level of the SCRES, which is a significant investment to consider.

5.2.3 Case III – Evaluation of a Large Supply Chain Network

This case applies the same mitigation strategy as the previous case II, but on a larger SCN. H_{21} consists of 98 plants, 89 materials and a single end product m_1. There are six stages in the production process, with 187 input dependencies and 98 output dependencies. Figure 5.9 shows the non-redundant plants and critical plants in H_{21}.

Three scenarios are designed based on H_{21}: *Scenario 7* is the original SCN H_{21} that is implemented by the industry, such that there are 10 SCs. To determine the potential risks within H_{21}, the set of 88 non-redundancy plants and four critical plants are identified. To improve the resilience of *Scenario 7*, four additional plants are added for the critical plants identified in *Scenario 7*. In *Scenario 8*, the new SCN has 102 plants and 89 materials.

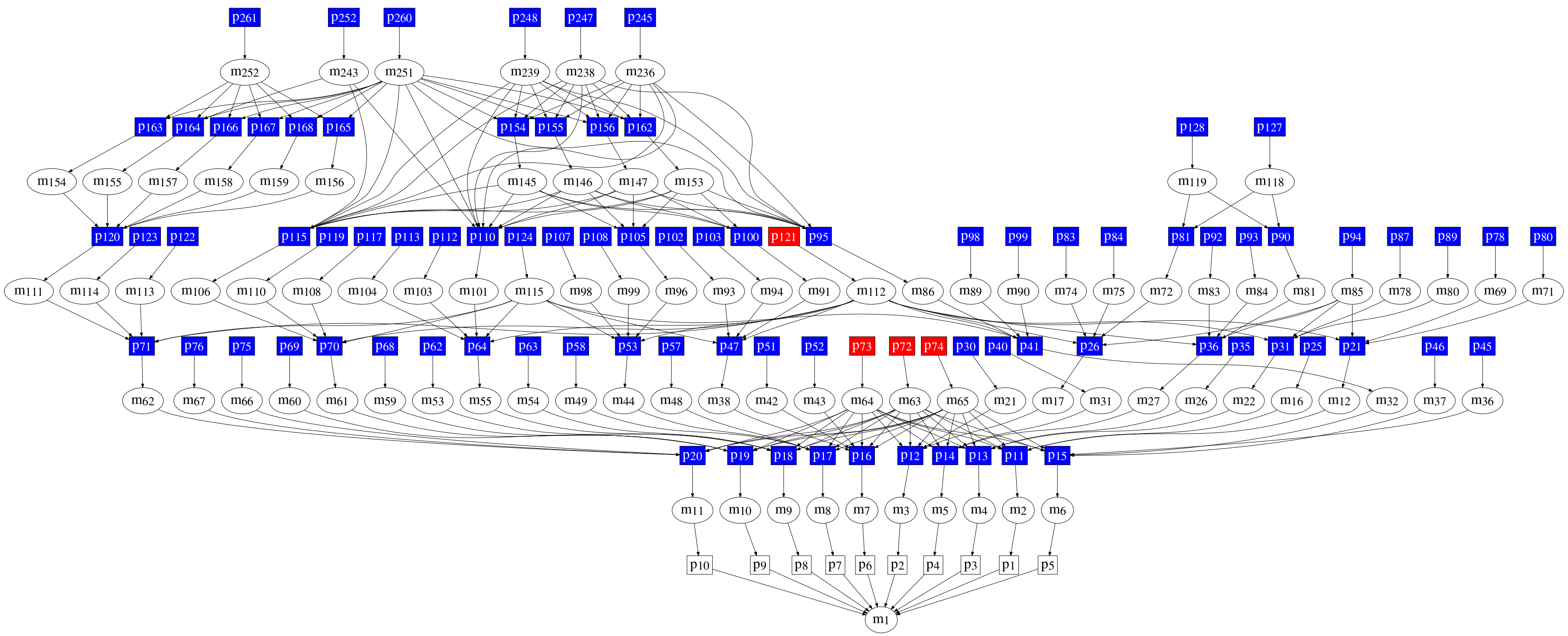


Figure 5.9: SCN H_{21} from dataset [201], where non-redundant plants are identified: critical plants in red, and remaining non-redundant plants in blue.

There are in total 187 input dependencies and 102 output dependencies. The additional plants do not affect the total number of materials in *Scenario 8*. Another possible strategy to improve the SCRES is implementing dual sourcing for all the non-redundant plants by adding 88 new plants in *Scenario 9*. It has 186 plants and 89 materials, with 364 input dependencies and 186 output dependencies.

Table 5.2: Assessment for H_{21}.

Scenario	$\|P\|$	$\|P_{nr}\|$	P_{crit}	n_{scn}
7	98	88	$\{p_{72}, p_{73}, p_{74}, p_{121}\}$	10
8	102	84	$\emptyset$	160
9	186	0	$\emptyset$	354,334,820,352

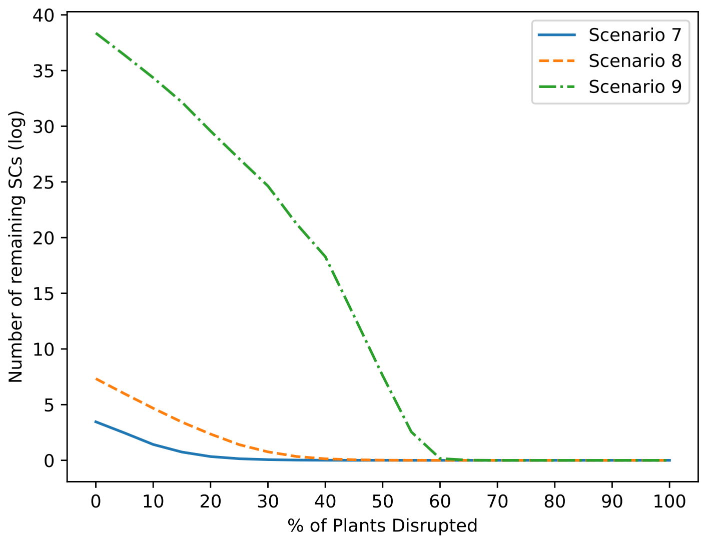


Figure 5.10: Percentage of plants disrupted against the number of remaining SCs in H_{21}.

Based on these scenarios, the SCNs are evaluated and tabulated in Table 5.2. Similarly, a Monte-Carlo simulation is conducted to simulate random disruptions in H_{21}. The results are shown in Figure 5.10, which plots the percentage of plants disrupted against the number of remaining SCs in logarithmic scale ($log(n_{scn} + 1)$).

From Figure 5.10, when 30% of the plants in *Scenario 7* are disrupted, the whole SCN will be disrupted. Hence, these non-redundancy plants should be the priority to redesign the SCN to improve redundancy. For *Scenario 8*, it requires around 40% of the

SCN to be disrupted, in order to disrupt the whole SCN. Therefore, *Scenario 8* is more resilient against disruptions if dual sourcing is used for the four critical plants. This is just by building additional 4% of redundant plants in *Scenario 7* to achieve this level of resilience.

Whereas for *Scenario 9*, the whole SCN is disrupted only after 60% of the plants are disrupted. *Scenario 9* demonstrates the best resilience against disruption as shown in Figure 5.10. However, to achieve redundancy for all the plants, this requires additional 90% of the redundant plants in the SCN, compared to *Scenario 8*. This can be considered a huge investment to implement redundancy for all the plants. A more practical and cost-effective strategy is to just implement redundancy for the critical plants.

5.3 Summary

This chapter presents a conceptual model of an SCN based on graph theory. The model considers both the materials and plants in an SC and captures two essential dependency relationships between the materials and plants (that is, input dependency and output dependency). The two dependency relationships form the basic building blocks for constructing a multi-stage SCN. The chapter also proposes an approach to assess SCRES in terms of structural redundancy using critical plants and number of SCs in an SCN. The applicability of the model is demonstrated by case studies using real-world SCNs from dataset.

Two SCNs (i.e., H_3 and H_{21}) from the existing dataset are used to illustrate the applicability of the approach for assessing the SCRES. H_3 is used to demonstrate the model and approach for designing both mitigation and contingency strategies. The similar mitigation strategy is also applied to a larger SCN (i.e., H_{21}). To evaluate the mitigation strategy, random disruptions are simulated in the SCN, and it shows that the SCRES can be improved by adding redundant plants. However, adding redundancy to all the non-redundant plants requires significant investments.

5.3.1 Theoretical Contributions

The theoretical contribution of this chapter to the SCRES literature is the graph-based model of an SCN capable of representing the structural redundancy. Previous literature mainly considered redundancy between two stages, and are unable to analyse redundancy or the corresponding vulnerability in the upstream stages of the SCN. In our model, structural redundancy in multi-stage SCNs is represented by the dependencies between the materials and plants.

In this chapter, we proposed an approach to assess the SCRES. The number of SCs in the SCN measures the structural redundancy in the SCN. We also highlighted the importance of assessing vulnerability in the SCN by identifying critical plants at the upstream stages of the SCN. Disruptions in the production of vital upstream material can propagate and affect the production processes downstream.

The graph model also enables a quick analysis of the remaining connectivity in the SCN after disruptions. This is used to assess the resistance phase in the SCRES during the disruptions. The resistance of the SCN against the disruptions is measured using the number of remaining SCs after the disruption.

5.3.2 Practical Implications

The presented model provides a top-down approach for decision-makers to build a more resilient SCN, where detailed visibility of all SC operations may not be available. The practical applicability of mitigation and contingency strategies to mitigate the disruptions has already been illustrated in the case studies and are further discussed in this subsection.

For proactive mitigation strategy, the decision-makers can build a more resilient SCN by reinforcing the critical plants through building flexibility and redundancy in the SCN. Redundancy can be created through the SCN, such as building additional redundant plants. The SCN can be designed with multiple plants for each of the materials. These plants diversify risks by decreasing the likelihood that a disruption to a single plant will disrupt the entire SCN. However, this needs to be balanced by the additional costs involved by having additional plants. The additional costs include the construction costs of the plant and reduction of the economics of scale by having lower production quantity at each plant. To achieve redundancies for all the plants, at least two plants are needed to produce each material. A flexible SCN with production flexibility at the critical plants allows the SCN to recover quickly after a disruption. The production flexibility enables the critical plants to ramp up the production capacity in order to clear the back-orders.

For contingency strategy, the decision-makers need to monitor the SCN to determine an appropriate response to the disruption. Response to the disruption depends on whether a critical plant is affected by the disruption. If the non-critical plant is disrupted, the firm can delay the response or passively accept the disruption and wait for recovery. However, when a critical plant is disrupted, an immediate response, such as activation of contingency actions, is required.

5.3.3 Limitations

The current graph model does not consider any flow quantity in the SCN. Chapter 6 proposed an extension to this graph model to consider the inventory system and material flows, such that the dynamic response of an SCN during disruptions can be analysed. This enables the evaluation of the disruption-recover behaviours of SC strategies to build SCRES. To balance the trade-off between resilience and cost, more complex cost measures, such as operational costs including production, inventory and delivery costs, are also considered.

Chapter 6

A Structural-aware Simulation-based Analysis

Chapter 5 analyses the structural characteristics of SCNs to reveal the SC dependencies and vulnerabilities. Structural analysis of SCNs can help decision-makers identify what nodes in the network create the greatest risk exposure. However, structural analysis alone cannot capture the dynamics of recovery following disruption [27]. Analytical models have been used to design SCRES strategies considering recovery, but they are analytically intractable for complex multi-stage SCN [172].

Unlike analytical closed-form analysis, simulation is capable of handling complex problem settings with situational behavioural changes in the system over time [73, 84]. Several studies have performed simulation-based analyses of SCRES (summarised in Section 2.2.3). These studies typically built a simulation model of an SCN and then evaluated the effectiveness of different SCRES strategies at handling the impact of disruptions. However, there is very few existing research using simulation that considers the structural properties of SCN for building resilience in the SCN.

Given this limitation of previous approaches, this chapter proposes a simulation-based analysis of SCRES that considers network structural properties in order to promote recovery of an SCN after disruption. In Section 6.1, a simulation model is developed by extending the graph model from Chapter 5 with operational behaviours from Chapter 4, such as information and material flows, considering the inventory-production system with backorders. Based on structural analysis, mitigation strategies are designed to build redundancy . Contingency strategies are analysed to prioritise recovery of the affected SCN. New SCRES indexes are proposed by assessing SC performance (i.e., Time-to-

Recover (TTR) and total cost) during disruption for each plant and aggregating the measures according to the criticality of the plants in the SCN. These indexes avoid the need for predictions about rare disruptions and can evaluate the response to any disruption that might occur within the SCN.

In Section 6.2, the applicability of this simulation-based analysis is then demonstrated using a complex multi-stage SCN from an existing sample of real-world SCNs [201]. This simulation-based analysis enables evaluation of performance impact of disruption and SC performance improvement after executing the SCRES strategies, thereby allowing comparison and contrast among different SCRES strategies. In addition, the practical implications are demonstrated by the cost analysis to determine different trade-offs for decision-making. The recovery time analysis also enables decision-makers to understand the long-term recovery required to fulfil the backorders.

6.1 Structural-aware Simulation Model

A structural-aware simulation analysis is proposed for SCRES. First, the network structure of an SCN is modelled as a graph (see Section 5.1). Next, ABM is built on the graph model to consider the inventory-production system with backordering (see Section 4.1.3). SCRES strategies are designed based on the SCN structure. New SCRES indexes are proposed to assess these strategies quantitatively.

6.1.1 Agent-based Model

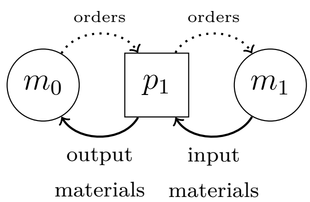


Figure 6.1: Two flows in an SCN: information flows (orders) from material m_0 to plant p_1 and p_1 to m_1; material flows from m_1 to p_1 and p_1 to m_0.

To analyse the dynamic response of SCN during disruption, an ABM is developed to consider the inventory system, and information and material flows in the SCN. The simulation time t is advanced by day ($\Delta t = 1$).

An SCN is modelled as a flow network of agents, where the agents map directly to the nodes in the graph. The *material agent* m represents the inventory system. There can be more than one plant sharing a warehouse or distribution centre that maintains the common inventory. *Plant agent* p represents the production plant that processes the input materials to produce the output material. Figure 6.1 shows an example of a flow network where the agents are connected with two types of directed edges, representing the information and material flows. The dotted line represents the orders flow upstream, while the dashed line represents the material flows downstream. The plant p_1 receives orders to manufacture the product (output material) from m_0, it then orders the part (input material) from the inventory upstream (m_1). The *end product* node in the graph is modelled as a specialized type of material agent, which represents the customer-facing inventory, e.g., the brick-and-mortar store supplies directly to the customers. This special agent generates a demand which will consume the product in the inventory.

Material Agent

A material agent models the inventory system for material m. The cycle stock is maintained separately for each upstream plant, as each plant may have a different production lead time and delivery lead time. Assume $P^+(m)$ is the set of upstream plants that produces material m, also known as the *producing plants*, while $P^-(m)$ is the set of downstream plants that orders from material m.

Material m fulfils the orders from each downstream plant $p \in P^-(m)$ according to the available inventory. First, the demand d_m is accumulated based on the orders $o_{p,m}$ received from the downstream plants:

$$d_m[t] = d_m[t-1] + \sum_{p \in P^-(m)} o_{p,m}[t]$$

Instead of receiving orders from downstream plants, for the end product agent m_o to model customer demand, a constant order quantity $\mathcal{O}_{m_o}$ is generated for every Δt:

$$d_{m_o}[t] = d_{m_o}[t-1] + \mathcal{O}_{m_o}$$

Order fulfilment f_m of material m depends on the current available inventory i_m:

$$f_m[t] = \min(d_m[t], i_m[t])$$

After fulfilment, the inventory i_m and demand d_m are reduced accordingly:

$$i_m[t+1] = i_m[t] - f_m[t]$$
$$d_m[t+1] = d_m[t] - f_m[t]$$

If there is insufficient inventory, the orders will accumulate in d_m as backorders.

To determine the quantity of material m that each upstream plant $p \in P^+(m)$ needs to produce, the cycle stock to maintain for plant p, $S_{m,p}$, is determined by the average demand scaled by the lead time of producing plants. The average demand over a time window of $\mathcal{T}^W$ days is thus calculated by:

$$\overline{d_m}[t] = \frac{1}{\mathcal{T}^W} \sum_{\tau=t-\mathcal{T}^W}^{t} d_m[\tau]$$

A simple ordering policy is used where there is no preference for selecting the producing plant. This can be extended to a more complex ordering policy based on the case. The average demand, $\overline{d_m}$, is evenly divided among the producing plants $P^+(m)$. The lead time includes the production lead time of plant p, $\mathcal{T}_p^P$ days, and the delivery lead time from p to m, $\mathcal{T}_{p,m}^D$ days. The inventory is assumed to be reviewed only every Δt, and the orders submitted are only processed the next time step. Hence, the total lead time is $\mathcal{T}_p^P + \mathcal{T}_{p,m}^D + \Delta t$. The cycle stock for p is determined by:

$$\forall p \in P^+(m), S_{m,p}[t] = \frac{\overline{d_m}[t]}{|P^+(m)|} \times (\mathcal{T}_p^P + \mathcal{T}_{p,m}^D + \Delta t)$$

To determine the orders for upstream plants, the current inventory i_m is divided by the number of producing plants and the reorder quantity is then calculated based on the individual cycle stock for each producing plant $S_{m,p}$.

$$\forall p \in P^+(m), o_{m,p}[t] = S_{m,p}[t] - \frac{i_m[t]}{|P^+(m)|}$$

Individual orders are submitted to each producing plant $p \in P^+(m)$.

Plant Agent

The plant agent models the production process of plant p, where the input materials are processed at the plant to produce the output material. Assuming $M^+(p)$ is the set of input materials for plant p, Figure 6.2 shows the information and material flows in plant agent p, with output material agent m^- downstream and a set of input material agents $m^+ \in M^+(p)$ upstream.

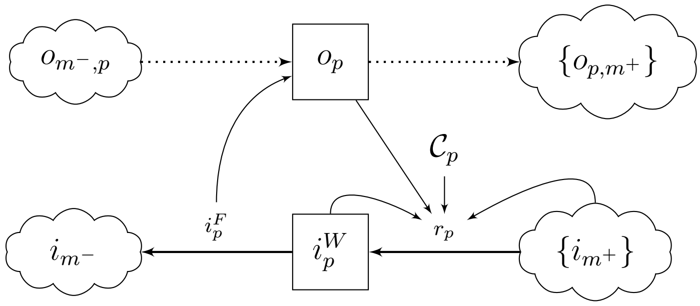


Figure 6.2: Information and material flows in plant agent p, with output material agent m^- downstream and a set of input material agents $\{m^+\}$ upstream.

First, plant p receives order $o_{m^-,p}$ from the output material m^- agent downstream. Orders $o_{m^-,p}$ accumulate as production orders o_p.

$$o_p[t] = o_p[t-1] + o_{m^-,p}[t]$$

The production order is propagated upstream as o_{p,m^+} to the set of input material agents $\{m^+\}$.

$$\forall m^+ \in M^+(p), o_{p,m^+}[t] = o_p[t]$$

Based on the production orders, the plant will process the input materials to produce the output material within the production lead time. The production rate r_p is determined by (i) the quantity of input materials i_p^+, (ii) the current production orders o_p, (iii) the production capacity $\mathcal{C}_p$ and (iv) the current work-in-progress inventory i_p^W. The *production capacity* is the volume of product that can be processed at the plant per unit time, considering the equipment and manpower available at the plant. The work-in-progress inventory keeps track of the quantity of material under production.

For simplicity, it is assumed that each unit of output material requires 1 unit of each input materials. The Leontief Input-Output model can be used for a more complex input-output relationship [106]. The material agent is assumed to serve the downstream plants fairly by evenly distributing the inventory. The quantity of input materials available depends on the number of downstream plants that each input material is serving:

$$i_p^+[t] = \min_{m^+ \in M^+(p)} \frac{i_{m^+}[t]}{|P^-(m^+)|}$$

The production rate is calculated by:

$$r_p[t] = \min(i_p^+[t], \mathcal{C}_p - i_p^W[t], o_p[t])$$

According to the production rate, new production is issued every Δt. The production is accumulated in the work-in-progress inventory as:

$$i_p^W[t] = i_p^W[t-1] + r_p[t]$$

This production is completed after $\mathcal{T}_p^P$ days of processing and i_p^F finished product is produced:

$$i_p^F[t + \mathcal{T}_p^P] = r_p[t]$$

This will reduce the work-in-progress inventory i_p^W and production orders o_p due to the order fulfilment:

$$\begin{aligned} i_p^W[t + \mathcal{T}_p^P] &= i_p^W[t + \mathcal{T}_p^P - 1] - i_p^F[t + \mathcal{T}_p^P] \\ o_p[t + \mathcal{T}_p^P] &= o_p[t + \mathcal{T}_p^P - 1] - i_p^F[t + \mathcal{T}_p^P] \end{aligned}$$

The finished product i_p^F will be delivered to output material agent m^- after $\mathcal{T}_{p,m^-}^D$ days.

$$i_{m^-}[t + \mathcal{T}_p^P + \mathcal{T}_{p,m^-}^D] = i_{m^-}[t + \mathcal{T}_p^P + \mathcal{T}_{p,m^-}^D - 1] + i_p^F[t + \mathcal{T}_p^P]$$

Supply Chain Disruption

SC disruption is modelled as an interruption in the production process of a plant for a fixed duration [26]. When plant p is disrupted, the plant agent will interrupt all of its operations, i.e., it no longer accepts orders from downstream material agents, no production orders will be generated and processing of the work-in-progress inventory is suspended. During the disruption, the output material agent will start to accumulate backorders as the plant is no longer processing any materials. After the period of the disruption, the plant will recover and resume all operations.

6.1.2 Design of SCRES Strategies

Based on structural analysis of SCNs, more effective SCRES strategies can be designed to better withstand the impact of disruption and recover from disruption in a timely manner. The SCRES strategies are designed to target the critical plants that are identified through the structural analysis. Two proactive mitigation strategies are designed to build redundancy in the SCN: *redundant structure* and *redundant capacity*. For reactive contingency strategies, *backup plant* and *backup SC* are designed to prioritise recovery on the affected parts of the SCN.

Redundant Structure: To build redundancy in SCNs, an SCN redesign is proposed in Section 5.2.2 for prioritising risk mitigation in the SCN by improving the redundancy of critical plants in the SCN. As a mitigation strategy, the SCN is redesigned with redundant plants. Based on the graph model of SCN H, the set of critical plants in the SCN can be identified by Equation 5.7. After identifying the set of critical plants, the redundant plants are duplicated for each critical plant in P_{crit} with the same production capacity. This enables the SCN to maintain production if any plants in P_{crit} are disrupted.

Redundant Capacity: Redundant capacity provides additional production capacity to fulfil incoming demands and to simultaneously assist with the fulfilment of the accumulated backorders. As a mitigation strategy, the SCN is built with redundant production capacity. The redundant capacity is modelled as additional production capacity for all plants in an SCN. If a plant is disrupted, this additional production capacity for the disrupted plant will also be unavailable. However, if there is more than one SC in the SCN, the remaining SCs with additional capacities can fulfil the demand of the disrupted SC. The production capacity $\mathcal{C}_p$ for all plants in the SCN is scaled by the redundancy factor $\mathcal{F}_p^r$. The final production capacity is $\mathcal{C}_p^r = \mathcal{C}_p \times (1 + \mathcal{F}_p^r)$.

Backup Plant: Having back-up procedures in place and able to be quickly implemented can significantly reduce the impact of a disruption [163]. A backup plant provides an alternative capacity for the critical plant to allow downstream nodes to continue working during a disruption [29, 36, 185]. During a plant disruption, the backup plant is selectively activated depending on the criticality of the disrupted plant. If a non-critical plant is disrupted, the SCN will not activate the backup plant as the redundant plants can still handle production. When a critical plant in the SCN is disrupted, this disrupts all SCs in the SCN and the SCN can no longer fulfil any customers' demand. Hence, the backup plant is necessary to fulfil the customers' demand during the disruption.

If a disruption occurs in plant p in the set of critical plants P_{crit}, the corresponding backup plant is activated with a capacity factor of $\mathcal{F}_p^b$, which gives a final production capacity $\mathcal{C}_p^b = \mathcal{C}_p \times \mathcal{F}_p^b$. During the disruption, the backup plant can partially fulfil the incoming orders and reduce the accumulation of backorders. After the disruption, the backup plant continues to help fulfil backorders. After the SCN recovers from the disruption, the backup plant is deactivated. Hence, the backup plant can reduce the recovery time by decreasing the backorders and increasing backorder fulfilment.

Backup Supply Chain: However, backup plant cannot significantly improve recovery as the production rate of the end product is constrained by the production capacity in the remaining SCN. A disrupted plant may disrupt one or more SCs in an SCN due to dependencies (see Section 5.1.3). To improve the recovery of the SCN, backup plants for all plants in the disrupted SC are activated after disruption. This increases the overall production capacity of the disrupted SC, thereby increasing the speed of backorder fulfilment.

When plant p_d is disrupted, the set of disrupted SCs ($\mathbb{G}_d$), i.e., all SCs containing p, is identified.

$$\mathbb{G}_d(p_d) = \bigcup_{G(M,P,E,m_o)\in\mathbb{G}} \begin{cases} G & \text{if } p_d \in P \\ \emptyset & \text{otherwise} \end{cases} \tag{6.1}$$

After the disruption, all plants in $\mathbb{G}_d$ will activate their corresponding backup plants with a production capacity of $\mathcal{C}_p^b$. The plants in the backup SC will be deactivated after the SCN clear the backorders. Because more backup plants are utilised in the backup SC strategy, this is a more expensive strategy than the backup plant strategy.

6.1.3 SCRES Assessment

The most important step to determine the SCRES measure for an SCN is to find its key performance indexes (KPIs) [111]. By monitoring the change in order fulfilment during the disruption, the two SC performance measures are used as the KPIs: *TTR* and *Total Cost*. TTR can represent both the mitigation and recovery capabilities of the SCN, while the total cost measures the financial impact of the disruption. New SCRES indexes are proposed to aggregate the SC performance measures obtained with each plant disruption in the SCN. The aggregated indexes would allow the decision makers to compare different alternative strategies in terms of the mean of outcome in probability sense.

Time-to-Recover

To determine the effectiveness of a particular strategy for SCN recovery, TTR measures the time taken for the SCN to recover its operations after a disruption. For long-term recovery from disruptions, Chen [27] described that SC performance should undergo similar behaviour as shown in Figure 6.3. Tomlin and Wang [186] reported that one of the primary drivers of recovery time is the additional capacity after a disruption. Hence, a more resilient SCN will incur less performance loss due to the impact of disruption. To fully recover from the performance loss, this requires the SCN to have the capacity to absorb and bounce back after a disruption. During the disruption as the SCN is unable to fulfil the orders, these orders will be retained as backorders. To recover after disruption, the SCN needs to have the additional capacity to fulfil the backorders. This assumes that the SCN does not lose sales by rejecting any orders during the disruption.

Assume t_1 is the start of the disruption, t_2 is the time of the largest impact, t_3 is the end of the disruption and the start of the recovery, t_4 is the time of recovery to the original level, and t_5 is the time of restoration to the original level after fulfilling backorders.

When a plant is disrupted, the order fulfilment can be used to illustrate the drop in performance during the disruption and quantify the recovery required to restore the SCN back to the original level. Order fulfilment f_{m_o} of the end product m_o is used to measure the operational performance of an SCN, where $\overline{f_{m_o}}$ is the average order fulfilment in a normal state. Figure 6.3 shows the order fulfilment of an SCN during disruption and recovery. When the disruption first occurs at t_1, the performance should decrease significantly until it reaches the largest impact at t_2. After the disruption ends or contingency actions are put in place at t_3, the performance gradually recovers and reaches the original level at t_4. During the period between t_1 and t_4, the orders accumulate as backorders. Next, production begins to ramp up to fulfil the backorders (between t_4 and t_5). Finally, when the backorders are fulfilled, the performance of the SCN is restored to its original level.

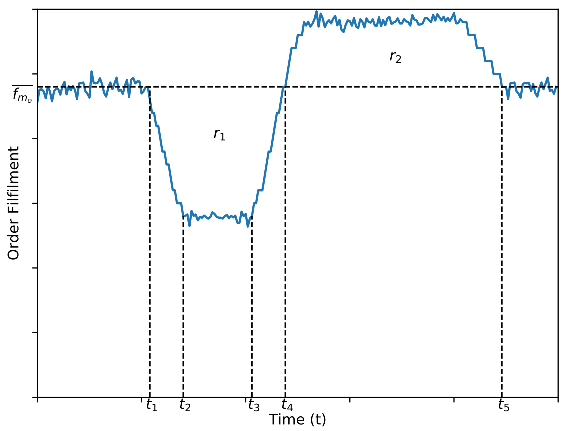


Figure 6.3: Disruption and recovery in an SCN.

The severity of disruption can be measured as the *performance loss* (r_1), which is the area between the original performance $\overline{f_{m_o}}$ and current performance $f_{m_o}[t]$ from the time of initial performance drop t_1 to the end of disruption at t_4 [129]. The corresponding area of recovery to performance loss is termed the *performance recovery* (r_2), which is the area between the original performance and current performance from the end of disruption (t_4) until the end of recovery (t_5). Performance loss from disruption accumulate as backorders during this period of time. After the disruption ends, additional capacity is required to recover the backorders. To determine the end of recovery, the performance recovery r_2 should be equal to the performance loss r_1 (i.e., $r_2 = r_1$). Hence, TTR (t_r) is measured from the start of disruption (t_1) until the end of recovery (t_5):

$$t_r = t_5 - t_1 \tag{6.2}$$

Total Cost

The economic consequences of disruption can be influenced by the mitigation and contingency strategies taken by the firm. The impact of various cost affects the attractiveness of a given strategy. Generally, variable costs are more relevant to the decision makers than fixed costs. Hence, this simulation model only considers the operational costs in the SCN.

At the material agent, the inventory-holding cost c_m is considered. This means that holding excessive inventory to mitigate the impact of disruption is not desirable. The total inventory cost is calculated by:

$$C_m[t] = \sum_{m \in M_H} i_m[t] \times c_m$$

At the plant agent, there is a production cost c_p per unit to process input materials to produce output material. The total production cost is:

$$C_p[t] = \sum_{p \in P_H} r_p[t] \times c_p$$

There is a cost c_r for backup plants to reserve capacity. A firm usually pays a higher marginal price for reserved capacity than it does for committed capacity [185]. Reserved capacity is typically *take-or-pay*, i.e., the firm must pay for the reserved capacity even if it is not fully utilised [64]. The total production cost for the backup plants is determined by:

$$C_r[t] = \sum_{p \in P_H} r_p[t] \times c_r$$

Multi-supplier strategies can be more costly in the presence of economies of scale due to the increase in ordering costs [4]. Hence, there is a plant-dependent ordering cost c_o for each order that is placed on a plant [13]. This ordering cost encompasses both the transactional costs and transportation costs between the plants and warehouses. Each order $o_{m,p}$ from material m to plant p will incur the ordering cost. The total ordering cost is thus:

$$C_o[t] = \sum_{m \in M_H} \sum_{p \in P_H} o_{m,p}[t] \times c_o$$

Backorder costs include the cost incurred by a business when it is unable to fulfil an order and must complete it later. For each unit time when the material agent is unable to fulfil an order, it will incur an additional cost c_b per unit. This is the main cost of disruptions: orders cannot be fulfilled due to disruption of the plants. The total backorder cost depends on the current unfulfilled demand d_m for each material m:

$$C_b[t] = \sum_{m \in M_H} d_m[t] \times c_b$$

The total operational cost of SCN $C[t]$ at time t is the summation of all above mentioned costs:

$$C[t] = C_m[t] + C_p[t] + C_r[t] + C_o[t] + C_b[t] \tag{6.3}$$

The operational total cost $\mathbf{C}$ is the summation of $C[t]$ across the whole simulation time period.

SCRES Indexes

Typically, an overall SCRES index can be aggregated as a weighted average of SC performance in which the weights are the probability of disruptive events and/or the priorities in which the decision-makers assigned to them [133]. However, the weights are still dependent on prior knowledge of the decision makers, which is typically lacking for disruptions that are infrequent yet high impact. To avoid the need for predictions about rare disruptions, new SCRES indexes are proposed by measuring SC performance for disruption of each plant in the SCN. For example, the SCN will be measured with a different plant disrupted each time. This measures the response to any disruption that might occur within the SCN, regardless of the cause. The SC performance measures are then aggregated with weights based on the criticality of the plants in the SCN. The disruptive impact of critical plants is given a higher weight due to its criticality in the SCN. With this approach, the decision makers would be able to determine the overall resilience of the network and the weights of different types of events without any prior knowledge.

The SC performance measures are scaled according to the criticality of the plant in the SCN. Assuming the number of SCs in an SCN is n_{scn}, where $n_{scn} = |\mathbb{G}|$, $n_{scn}(p)$ is defined as the number of SCs that contains plant p. The criticality of the plant p, $\phi(p)$, is determined by:

$$\epsilon(P, p) = \begin{cases} 1 & \text{if } p \in P \\ 0 & \text{otherwise} \end{cases}$$

$$\forall G(M, P, E, m_o) \in \mathbb{G},\ n_{scn}(p) = |\epsilon(P, p)|$$

$$\phi(p) = \frac{n_{scn}(p)}{n_{scn}}$$

For a critical plant that exists in all SCs, the SC performance is scaled by $\phi = 1$. Non-critical plants have a $\phi < 1$.

Two SC performance measures, namely TTR and Total Cost, are formulated as SCRES indexes. Assuming $t_r(p)$ is the TTR of the SCN when plant p is disrupted, the SCRES index for recovery time, $\mathcal{R}_t$, is calculated by:

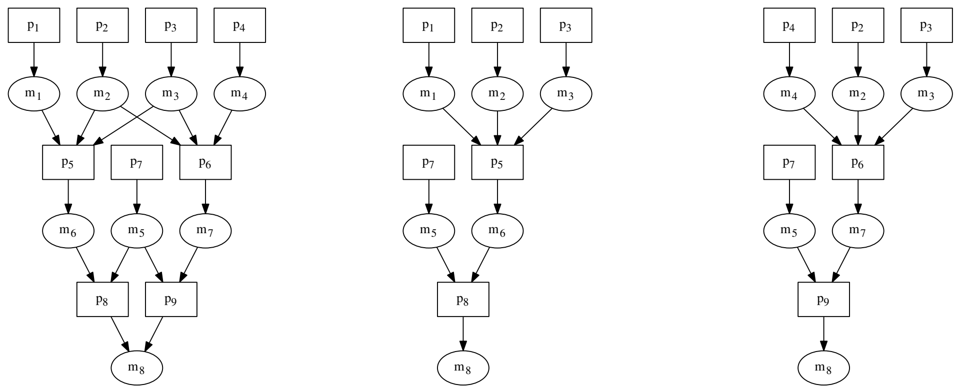
$$\mathcal{R}_t = \frac{1}{|P_H|} \sum_{p \in P_H} \phi(p) \times t_r(p) \tag{6.4}$$

To determine the financial impact of disruption, a function $\mathbf{C}(p)$ is defined to return the total cost of the SCN over the simulated time when a plant p is disrupted. The SCRES index for the total cost, $\mathcal{R}_c$, is calculated similarly:

$$\mathcal{R}_c = \frac{1}{|P_H|} \sum_{p \in P_H} \phi(p) \times \mathbf{C}(p) \tag{6.5}$$

Cost-Effectiveness of a Proposed Strategy

The cost-effectiveness of a proposed SCRES strategy can be determined from simulation results by considering the investment cost. A strategy is cost-effective in terms of both



(a) SCN H_3 (b) SC G_1 in H_3. (c) SC G_2 in H_3.

Figure 6.4: Case study of a real-world SCN, H_3.

investment and operational cost if its cost saving is greater than the investment cost. Assuming that *default* strategy D is the baseline configuration for an SCN, a proposed strategy s in terms of the operational cost, $\mathcal{R}_c(s)$, can be compared to the operational cost of the default strategy, $\mathcal{R}_c(D)$. The cost-saving can be determined by $\mathcal{R}_c(D)-\mathcal{R}_c(s)$. Assuming $\mathbf{C}_I(s)$ is the investment cost to implement strategy s, s is cost-effective if and only if:

$$\mathcal{R}_c(D) - \mathcal{R}_c(s) \geq \mathbf{C}_I(s) \tag{6.6}$$

6.2 Simulation Results and Analysis

6.2.1 Experimental Setup

For analysis of SCRES, simulation studies are conducted using a three-stage SCN, H_3, obtained from an existing set of samples [201]. H_3 is a computer peripheral equipment manufacturing SCN, consisting of nine plants, eight materials and one end product m_8, as shown in Figure 6.4a. There is structural redundancy within H_3, such that there are two SCs, namely G_1 in Figure 6.4b and G_2 is Figure 6.4c. For H_3, the critical plants are $\{p_2, p_3, p_7\}$, since they exist in both G_1 and G_2. The production capacity $\mathcal{C}_p$ and production lead time $\mathcal{T}_p^l$ are based on the data set.

Additional parameters in the simulation are derived from the dataset. Each material maintains an inventory buffer of the production lead time $\mathcal{T}_p^l$. The order quantity $\mathcal{O}_{m_8}$

for the end product m_8 is 24 units per day. This provides the total production capacity of the SCN since it assumes that the demand equals the production capacity. The time window length $\mathcal{T}^W$ is 20 days.

As a baseline for comparison, passive acceptance is often used as the default strategy even when it is not appropriate [185]. For the default strategy, it is assumed that the SCN has an additional production capacity of 10% to enable recovery after disruption. Without this additional capacity, the default strategy will never be able to fulfil the backorders as the SCN only has sufficient capacity to fulfil the current orders. For a fair comparison, all SCRES strategies are designed based on the default strategy. Since the simulation model is deterministic, each scenario is only executed once. The simulation is executed for a total of 1095 days (3 years).

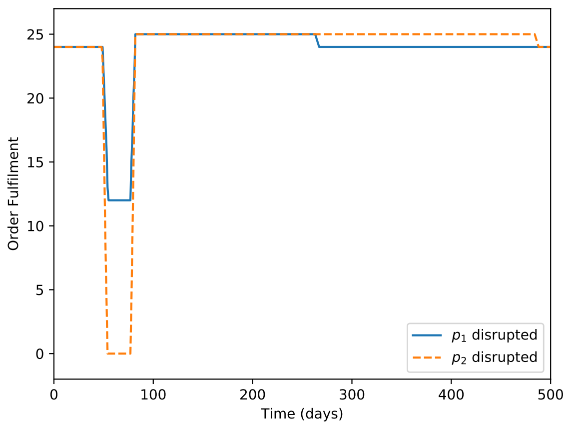
The cost parameters are not included in the dataset. To define the case, the following costs were chosen: holding cost c_m of 0.1/unit, production cost c_p of 1/unit, backup capacity cost c_r of 2.5/unit, ordering cost c_o of 20/plant, and backorder cost c_b of 1/unit. These values are based largely on another published simulation study [166]. Since the backup plant must set aside certain capacity to use during disruption, there will be a higher unit production cost compared to the redundant capacity [72].

6.2.2 Validation

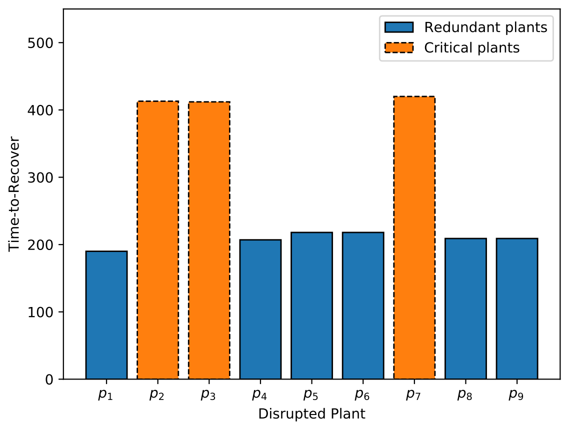
Similar to existing works [80, 83, 164], validation was performed on the baseline model based on the original example without any disruption. In this baseline scenario, order fulfilment is stable and there are no accumulated backorders. This means that the production of the SCN is able to meet demands without the need to keep excess inventories.

Next, face validation was performed against the existing disruption-recovery models [27, 186]. The aggregated SC performance of the model demonstrated similar behaviour to the curve shown in Figure 6.3, where there is a drop in performance and a subsequent increase in performance for recovery. According to the graph model in Section 5.1, an SCN with a redundant structure is more resilient to disruptions as redundant plants are less impacted by disruption.

Since disruption risks have a low probability but a huge impact, it is difficult to collect real-world data detailing the impact of disruption on an SCN. Disruption scenarios are usually defined based on historical data and expert opinions; SCRES strategies have thus not been implemented in real life to deal with such disruption. Real-world data do not exist to validate the disruption model. Hence, face validation is one of the viable approach.



(a) Disruptive impact of critical plant (p_2) and redundant plant (p_1).



(b) TTR for each plant disrupted.

Figure 6.5: Evaluating 30 days disruption on SCN H_3 using passive acceptance strategy.

The criticality of an SCN was also validated through the following scenario. The passive acceptance strategy was applied to a real-world SCN H_3, where each plant in the SCN was evaluated with a disruption duration of 30 days to measure the direct impact on the SCN. During disruption, the plant's production capacity is reduced to 0. Figure 6.5a measures order fulfilment of H_3 over time when redundant plant p_1 is disrupted comparing to critical plant p_2 being disrupted. In Figure 6.5b, each bar represents a scenario where one of the plants is disrupted (labelled on the x-axis) and the corresponding TTR due to disruption.

Figure 6.5a shows the drop in order fulfilment when the plant is disrupted, and the subsequent recovery before stabilising at the end of simulation. The simulation results also illustrate the impact of disruption of redundant plants and critical plants on the SCN. The disruption of redundant plant p_1 has less impact (order fulfilment drops to 12), and thus the recovery time is shorter ($\mathcal{R}_t$ = 190 days). When p_1 is disrupted, the remaining SC G_2 is still connected. Hence, the SCN is still able to fulfil partial demand during disruption. Compared to disruption of critical plant p_2, this disruption has a larger impact (order fulfilment reaches 0 at t = 55) and the recovery time is longer ($\mathcal{R}_t$ = 413 days).

Two distinct clusters of TTR can be identified in Figure 6.5b. The average TTR for redundant plants is 208 days compared to 415 days for critical plants. Hence, disruption of critical plants has a larger impact and a longer TTR compared to disruption of redundant plants.

6.2.3 SCRES Strategies Evaluation

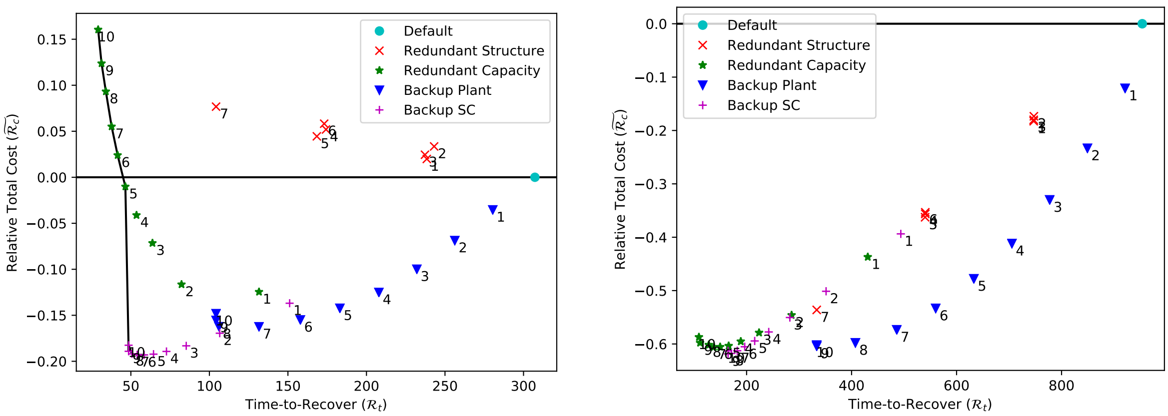
To evaluate the effectiveness of the SCRES strategies, various disruption scenarios are simulated using H_3. For each disruption scenario with an expected disruption duration, the disruptions of each plant in the SCN is examined. To analyse the short-term and long-term impacts of disruption on the SCN, deterministic disruption durations are used to model two disruption scenarios: *short-term disruption* (30 days) and *long-term disruption* (90 days) [27, 40]. Long-term disruptions have been analysed in the literature, with a planning horizon over a period of three years [78, 79]. The long-term disruption scenario represents a situation where it is costly for the customer to cancel the order and search for a replacement due to a large initial payment or long production lead time. Hence, the customer will tolerate such a long recovery time and wait for backorder fulfilment. Each SCRES strategy is parametrised and evaluated with the disruption scenarios.

Table 6.1: SCN designs to increase structural redundancy.

SCN	Additional Plants	Number of SCs	Number of Plants
R_1^s	p_2'	4	10
R_2^s	p_3'	4	10
R_3^s	p_7'	4	10
R_4^s	p_2', p_3'	8	11
R_5^s	p_2', p_7'	8	11
R_6^s	p_3', p_7'	8	11
R_7^s	p_2', p_3', p_7'	16	12
			Total Simulations: 75

For the *redundant structure* strategy, Table 6.1 shows seven SCN designs (R_1^s to R_7^s) to increase structural redundancy. The SCNs are designed by adding plants to the critical plants $\{p_2, p_3, p_7\}$. For example, in R_1^s, an additional plant p_2' is added such that two plants produce material m_2. The number of SCs and plants for each SCN design is shown in Table 6.1. A total of 75 simulations were executed for evaluating this strategy.

There are 10 different parameters for each of the remaining strategies. For the *redundant capacity* strategy, the redundant capacity factor $\mathcal{F}_p^r$ varies from 10% to 100% (R_1^c to R_{10}^c). The redundant capacity is applied to the default strategy to all plants in the SCN. For the *backup plant* strategy, a backup plant is activated when a critical plant in the SCN is disrupted. This backup plant has a production capacity varying from 10% to 100% of the original plant (B_1^p to B_{10}^p). In the *backup SC* strategy, backup plants for the disrupted SC are activated after disruption. The production capacity of the backup plants varies from 10% to 100% (B_1^{sc} to B_{10}^{sc}). Hence, for each disruption scenario, each strategy executes 90 (9 plant disruptions × 10 parameters) simulations. For each disruption scenario, a total of 345 (75 + 90 + 90 + 90) simulations are executed to evaluate all strategies.



(a) Short-term disruption of 30 days.

(b) Long-term disruption of 90 days.

Figure 6.6: Comparisons of SCRES strategies using SCRES indexes.

Each point in Figure 6.6 shows a different configuration of the strategies and the corresponding SCRES indexes based on the disruption scenario. The x-axis shows the TTR ($\mathcal{R}_t$) while the y-axis shows the relative total cost ($\widetilde{\mathcal{R}_c}$) compared to the default strategy. Assuming $\mathcal{R}_c(s)$ is the SCRES index for total cost of strategy s, the relative total cost of strategy s is:

$$\widetilde{\mathcal{R}_c}(s) = \frac{\mathcal{R}_c(s) - \mathcal{R}_c(D)}{\mathcal{R}_c(D)} \tag{6.7}$$

If $\widetilde{\mathcal{R}_c}(s) < 0$, it means that strategy s is more cost-effective than the default strategy.

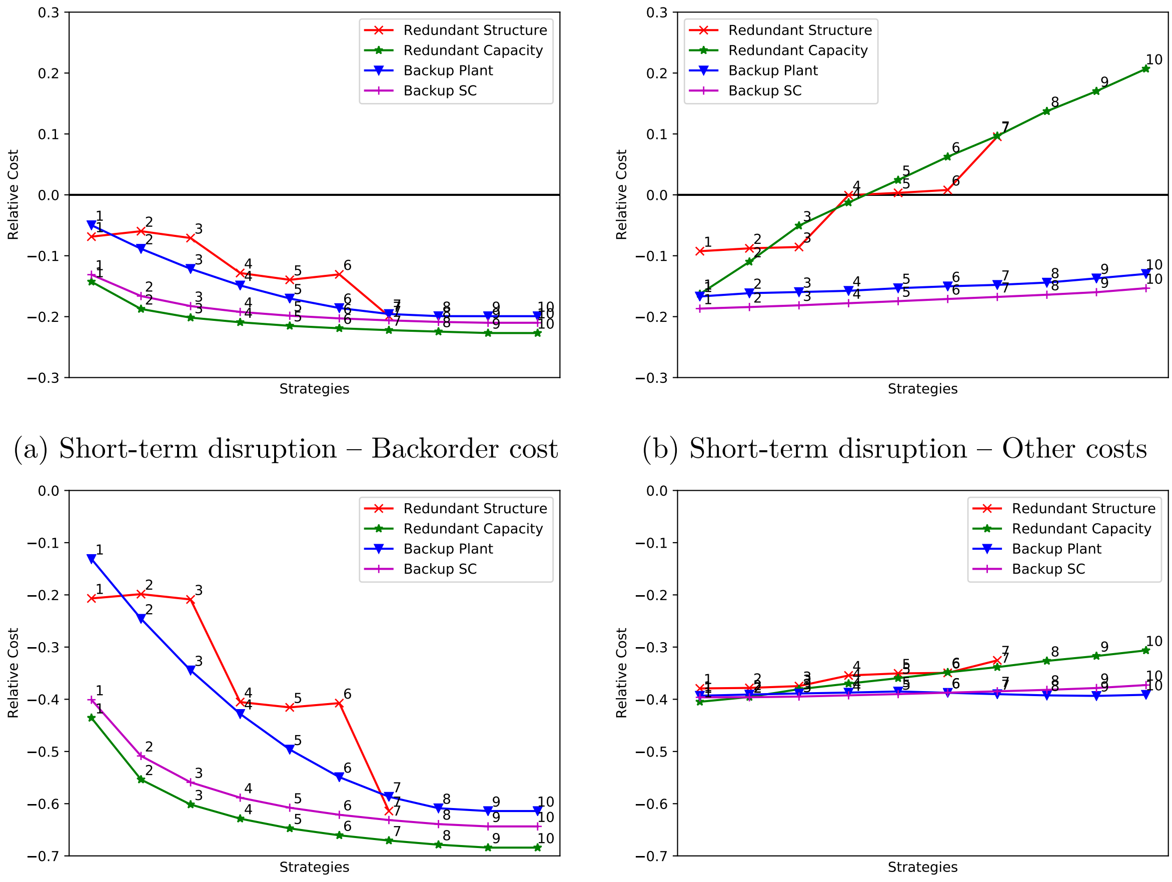
The label number on the point indicates the parameter design for the strategy. The black line highlights the optimal strategies based on the SCRES indexes.

Figure 6.7 shows the relative cost of each strategy compared to the default strategy. Since the backorder cost is the main contributing factor to the total cost, the total cost is broken down into the *backorder cost* and *other costs* excluding the backup cost. Similar to Figure 6.6, each point in Figure 6.7 represents a different strategy. Increasing the number of redundant plants or production capacities in the strategy results in a decrease in the backorder costs and an increase in the other costs. However, the redundant structure strategy and redundant capacity strategy show a larger increase in other costs compared to the backup plant strategy and backup SC strategy. Therefore as shown in Figure 6.6a, this leads to an increase in the total costs across the redundant structure strategy and redundant capacity strategy, but a decrease in the total costs for the backup plant strategy and backup SC strategy.

Short-Term Disruption

Figure 6.6a shows the results of short-term disruption. The *default* strategy requires 307 days, the longest time, for the SCN to recover. Figure 6.7a and Figure 6.7b show the trend of backorder cost and the other costs across different strategies. More detailed views of the impact of disruption on the redundant plant p_1 and critical plant p_2 when applying selected strategies are shown in Figure 6.8.

For the *redundant structure* strategy, as the number of SCs increases in the SCN, the overall $\mathcal{R}_t$ decreases. R_7^s has the lowest $\mathcal{R}_t$ of 104 days and a $\widetilde{\mathcal{R}_c}$ of 0.07, while R_1^s has a $\mathcal{R}_t$ of 238 days and the lowest $\widetilde{\mathcal{R}_c}$ of 0.02. Due to the additional plants added for all critical plants in the SCN, R_7^s improves TTR by enabling the SCN to continue to fulfil demands during disruption. Since there are redundant plants for all critical plants in the SCN for R_7^s, the $\mathcal{R}_t$ is the lowest amongst all SCN designs. This is shown in Figure 6.8a where R_7^s is used. When critical plant p_2 is disrupted, the orders are sent to the redundant plant p_2'; hence, the order fulfilment is not affected. However, the additional plants incur higher ordering costs as the orders are distributed among more plants. For example in R_1^s, orders from m_2 are sent to plants p_2 and p_2', resulting in higher ordering costs from m_2 compared to the SCN shown in Figure 6.4a. When additional plants are added to the SCN, the increase in other costs (Figure 6.7b) is higher than the decrease in backorder cost (Figure 6.7a). Hence, it is more expensive to use the redundant structure strategy.



(a) Short-term disruption – Backorder cost

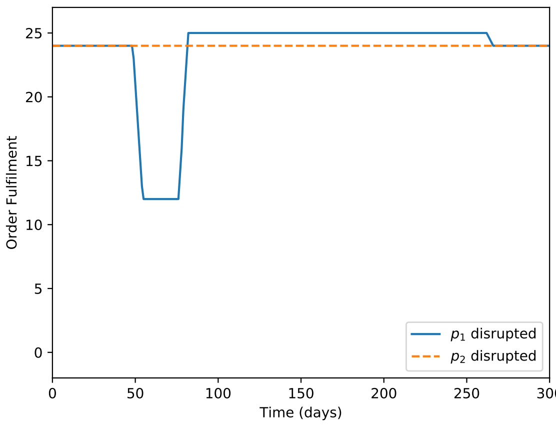
(b) Short-term disruption – Other costs

(c) Long-term disruption – Backorder cost

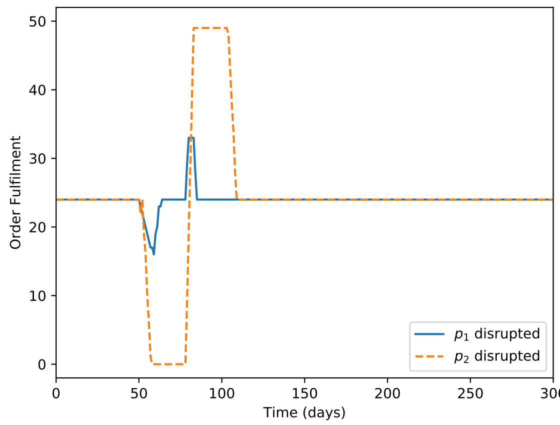
(d) Long-term disruption – Other costs

Figure 6.7: Relative costs of each strategy compared to the default strategy.

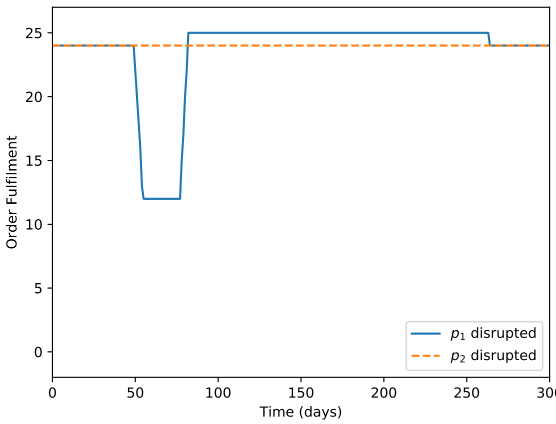
The *redundant capacity* strategy greatly reduces TTR as the redundant capacity increases. R^c_{10} has a minimal $\mathcal{R}_t$ of 48 days but with a $\widetilde{\mathcal{R}}_c$ of 0.16, whereas R^c_1 has a $\mathcal{R}_t$ of 131 days and a minimal $\widetilde{\mathcal{R}}_c$ of -0.12. R^c_{10} gives the overall lowest $\mathcal{R}_t$ amongst all strategies. During disruption, the remaining SCs with higher capacity can partially fulfil the incoming orders. Figure 6.8b shows that the disruptive impact of p_1 has a smaller performance loss. When p_1 is disrupted, another SC (i.e., G_2) remains in the SCN to partially fulfil the orders. This increase in production capacity enables the SCN to fulfil the backorders faster. Figure 6.8b also shows that both disruptions of p_1 and p_2 have a shorter recovery time compared to the redundant structure and backup plant strategies due to the higher production capacity. However, there is a trade-off between redundant capacity and total cost. As the production capacity increases, $\mathcal{R}_t$ decreases with a steep increment in total cost, as shown in Figure 6.6a. When the redundant production capacities are increased, the reduction in backorder costs (Figure 6.7a) is comparatively smaller than the relative



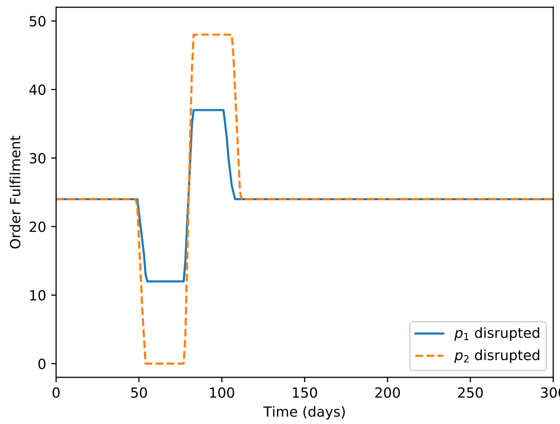
(a) Redundant Structure (R_7^s)



(b) Redundant Capacity (R_{10}^c)



(c) Backup Plant (B_{10}^p)



(d) Backup SC (B_{10}^{sc})

Figure 6.8: Impact of short-term disruption on critical plant (p_2) and redundant plant (p_1) for selected SCRES strategies.

increase in other costs (Figure 6.7b). The SCN bears the penalty cost of unused capacity, especially when the disruption is short. When the redundant capacity exceeds 50% (R_5^c), it is more expensive to implement this strategy than the default strategy.

The *backup plant* strategy is only activated when a critical plant is disrupted. B_{10}^p has the lowest $\mathcal{R}_t$ of 104 days and a $\widetilde{\mathcal{R}_c}$ of -0.14, whereas B_7^p has a $\mathcal{R}_t$ of 131 days at the lowest $\widetilde{\mathcal{R}_c}$ of -0.16. The backup plants improve TTR by providing the capacity to partially fulfil current orders during disruption. Figure 6.8c shows that B_{10}^p which has a backup plant at 100% production capacity of p_2, can avoid performance loss when p_2 is disrupted by fulfilling the incoming orders. Hence, full backup in terms of production capacity of the disrupted plant can prevent performance loss. In case of a backup plant that only provides partial production capacity of the disrupted plant, the backup plant can also assist with recovery after disruption by providing additional capacity until backorders are fulfilled. Since backup plants are only activated for critical plants, the total cost is low, as shown by the slight increase in other costs in Figure 6.7b. However, backup plants will not improve recovery in scenarios where non-critical plants are disrupted. Overall, the backup plant strategy is more effective in terms of both TTR and total cost compared to the default strategy, although TTR is higher compared to the redundant capacity strategy.

Compared to the backup plant strategy, the *backup SC* strategy is activated after disruption. The corresponding disrupted SCs activate their backup plants. For example, if plant p_1 is disrupted, the disrupted SC G_1 will activate its backup plants for $\{p_1, p_2, p_3, p_5, p_7, p_8\}$. B^{sc}_{10} has the lowest $\mathcal{R}_t$ of 48 days at a $\widetilde{\mathcal{R}_c}$ of -0.18, while B^{sc}_6 has a $\mathcal{R}_t$ of 58 days and the lowest $\widetilde{\mathcal{R}_c}$ of -0.19. Figure 6.6a shows that increasing the production capacity of the backup SCs reduces the TTR. Figure 6.8d shows that the TTR for both critical and non-critical plants is similar, hence reducing overall TTR. Increasing the production capacity of the backup SC enables additional capacity upstream and downstream, thereby increasing the overall material flows in the backup SC. In the backup SC strategy, both the backorder cost (Figure 6.7a) and other costs (Figure 6.7b) are low. Hence, this strategy has the lowest cost amongst all strategies.

Pareto set is the set of solutions that are all Pareto optimal. In this study, a strategy s is Pareto optimal if there does not exist another strategy that dominates s. Assuming s is a strategy and $\mathbb{S}$ is the set of all strategies, the pareto set of $\mathbb{S}$ is $\{s \in \mathbb{S} : \{s' \in \mathbb{S} : s' \prec s, s' \neq s\} = \emptyset\}$, where $s' \prec s$ means that strategy s' dominates s in both TTR and total cost. The strategies in the Pareto set are $\{R^c_{10}, R^c_9, R^c_8, R^c_7, R^c_6, R^c_5, B^{sc}_{10}, B^{sc}_9, B^{sc}_8, B^{sc}_7, B^{sc}_6\}$. At two extreme ends of the Pareto set are B^{sc}_6 (minimum cost) and R^c_{10} (minimum TTR). By identifying the Pareto set, the decision maker can make trade-offs within this set, rather than considering all strategies.

In summary for short-term disruption, mitigation strategies have the issue of maintaining unused capacity, although the redundant capacity strategy enables the SCN to have lower TTR. The backup SC strategy has the lowest cost amongst all strategies. Generally, the contingency strategies are more cost-effective compared to the mitigation strategies and are therefore more suitable for short-term disruption.

Long-Term Disruption

Figure 6.6b shows the simulation results of long-term disruption. The default strategy is the worst amongst all strategies, taking around 953 days to recover from disruption. As the disruption duration is long, the backorder cost becomes a major component of the total cost. The relative costs compared to the default strategy are shown in Figure 6.7c (backorder cost) and Figure 6.7d (other costs). However, when the number of redundant plants and production capacities increase, the increase in other costs is lower significantly compared to the decrease in the backorder costs. This leads to the overall decrease in total costs across all strategies as shown in Figure 6.6b. Hence, it is more important to utilise SCRES strategies for long-term disruption.

The *redundant structure* strategy is more effective at reducing both the TTR and total cost compared to the short-term disruption. The best SCN design is R^s_7, where $\mathcal{R}_t$ is reduced to 333 days with a $\widetilde{\mathcal{R}_c}$ of -0.54. When the number of redundant plants increases, the relative increase in other costs (Figure 6.7d) is lower compared to the short-term disruption scenario (Figure 6.7b). The *redundant capacity* strategy, R^c_{10}, has the shortest $\mathcal{R}_t$ of 109 days with a $\widetilde{\mathcal{R}_c}$ of -0.59; while R^c_7 has a $\mathcal{R}_t$ of 137 days and a minimal $\widetilde{\mathcal{R}_c}$ of -0.61. Similarly, when the redundant production capacity increases, the increase in other costs (Figure 6.7d) is relatively lower compared to the short-term disruption scenario (Figure 6.7b), resulting in overall lower total costs. Hence, the redundant structure strategy and redundant capacity strategy are more cost-effective for the long-term disruption scenario.

The *backup plant* strategy shows a decrease in the TTR when the production capacity are increased. B^p_{10} has both the lowest $\mathcal{R}_t$ of 333 days and $\widetilde{\mathcal{R}_c}$ of -0.60. The *backup SC* strategy shows a similar trend for the short-term disruption scenario: the overall TTR and total costs are greatly reduced as the larger production capacity is utilised by the backup plants. B^{sc}_{10} has the lowest $\mathcal{R}_t$ of 164 days and a $\widetilde{\mathcal{R}_c}$ of -0.61.

In summary, for the long-term disruption, all strategies are shown to be more effective than the default strategy in terms of both TTR and total cost. When the disruption is long, the ability to quickly fulfil backorders becomes a key consideration. The Pareto set is $\{R^c_{10}, R^c_9, R^c_8, R^c_7, B^{sc}_{10}, B^{sc}_9\}$, where R^c_{10} has the shortest TTR and B^{sc}_9 has the lowest cost. Hence, the redundant capacity strategy is more effective at reducing the TTR while the backup SC strategy is the most cost-effective.

6.3 Summary

The presented model provides a simulation-based analysis for decision-makers to determine the strategies and parameters best suited for building resilience in their SCN. An ABM is built based on a graph model of an SCN, which enables an analysis of the SCN structure while capturing the dynamics of disruption and recovery. The model represents the materials and plants as separate agents. Agents are connected to form an SCN, considering the dependencies between the agents. The model also considers the inventory-production system with backordering.

Through structural analysis of the SCN, mitigation strategies are designed to build redundancy and contingency strategies are developed to prioritise recovery on the affected SCN. New SCN indexes are proposed to provide an overview of the SCRES by evaluating disruptions for each plant in the SCN and aggregating the results based on the criticality of the plants.

A case study based on a real-world SCN is used to compare and contrast different SCRES strategies against the default strategy of passive acceptance. Simulation results show that these strategies can be used to build resilience by enabling the SCN to recover faster after disruptions. Further, the results demonstrate that mitigation strategies are more suitable for long-term disruptions while contingency strategies are more effective for short-term disruptions. The redundant capacity strategy enables an SCN to have lower TTR, whereas the backup SC strategy has the lowest cost amongst all strategies.

6.3.1 Theoretical Insights

The key theoretical insight obtained from the simulation-based study is the improvement of recovery process through the use of effective SCRES strategies. These improvements come from two key areas: (i) reducing accumulated backorders, and (ii) increasing the rate of backorders fulfilment. In Figure 6.3, the performance loss r_1 represents the accumulated backorders. By reducing the area of r_1, this also reduces the performance recovery r_2. Therefore, the overall recovery time is shortened. In addition, increasing the backorders fulfilment rate will reduce the width of r_2, also shortening the overall recovery time too. Effective SCRES strategies can be designed by focusing on these two areas.

First, reduction in accumulated backorders can be seen in the redundant structure and backup plant strategies. The redundant structure strategy reduces backorders at the critical plant by providing additional plants that can continue to fulfil the demand when the critical plant is disrupted. Similarly, the backup plant reduces backorders by partially fulfilling incoming orders during disruption. Even if these strategies cannot provide the full capacity, they enable partial fulfilment of customers' demand and serve to shorten the disruption interval experienced by customers.

Second, improvement in recovery can be observed in the redundant capacity and backup SC strategies. Redundant capacity can fulfil backorders at a faster rate through larger production capacity. Since the backup plants only serve the disrupted plants, the overall production rate cannot be increased if the upstream plants are unable to supply additional materials to increase the production downstream. To effectively fulfil the backorders at the disrupted plant, material flows across the affected SCs must be increased. Hence, the backup SC provides additional capacity for the affected parts of the SCN.

6.3.2 Practical Implications

This simulation-based analysis can be used in cost analysis to determine the different trade-offs when implementing SCRES strategies, such as the TTR vs total costs. Investment costs are also included in the cost analysis to help decision-makers justify the investment costs to implement these strategies.

As shown in Figure 6.7, two main factors contribute to the overall operational costs: (i) accumulation of backorders during disruption, and (ii) the additional cost of operating SCRES strategies. To determine the overall cost of a proposed strategy, there needs to be a balance between these two cost factors. Based on the total cost from the simulation results, the cost-effectiveness of a proposed SCRES strategy can be determined by evaluating Equation 6.6.

Simulation-based analysis can also improve decision-making by enabling decision-makers to evaluate SCRES without the need to make predictions about disruption events. There is rarely historical data regarding disruptions in an SCN. This results in difficulty evaluating the impact of disruptions and the effectiveness of SCRES strategies. To avoid assumptions regarding the disruptive event or probability, a new approach is required for designing and implementing resilient SCNs that can operate efficiently regardless of environmental changes [82]. By simulating the disruption for each plant in an SCN, the proposed approach aggregates SC performance to give an overall SCRES index.

Chapter 7

Conclusions and Future Works

This chapter concludes the thesis and discusses several directions for future work.

7.1 Contributions of the Current Work

In this thesis, models are proposed to analyse SCRES by using complex system approaches. Efficient and cost-effective SCRES strategies are also proposed to build a more resilient SCN.

Firstly, Chapter 3 describes a top-down approach to design SCN topology based on the Uncertainty Framework. Four SCN topologies have been designed to represent different SC strategies – efficient, responsive, risk-hedging, and agile strategies. An ABM is developed to model the operational behaviour of individual entities within an SCN and to evaluate the operational performance of the corresponding SCN. A case study is carried out on a three-stage hierarchical network modelled based on a typical SC distribution network. Experiments have been conducted to evaluate the performance in terms of the VA and CSL of the SCN under different demand and supply risk scenarios. The experimental analysis shows that the network topology reflects the capabilities of the SCN to mitigate the demand and supply uncertainties.

Secondly, due to the limited information on the detailed operational processes in an SCN, it may be difficult to model the whole SCN using ABM. Chapter 4 proposes a hybrid model of SCN, combining SD and ABM using an integration design approach. The ABM is developed by extending the model from Chapter 3 to consider production operations. The whole SCN is divided into individual SC entities, where each entity can be represented by either an SD entity or an agent. The entities interact with each other through special adapters that convert between continuous flow and discrete events. The number of agents in the model depends on the availability of data to calibrate agent model parameters and the level of detail needed for the study. There are several benefits of using the hybrid model. First, this allows the firm to construct a broad view of the whole SCN based on aggregated data through SD. Next, it allows the firm to perform in-depth analysis regarding its own performance by modelling detailed processes using an agent. A case study to identify optimal SCRES strategies for a two-stage real-world SCN is used to illustrate the applicability of the hybrid model. Two SCRES strategies are studied: mitigation strategy using multi-suppliers and contingency strategy using contingent supplier. Trade-offs between these strategies and between backorder and ordering costs are analysed and shown in the experimental results. When backorder cost per unit is high, the contingency supplier strategy is more cost-effective for frequent disruptions and multi-supplier strategy is more cost-effective for infrequent disruptions. When ordering cost per unit is high, the contingency supplier strategy is more cost-effective.

Thirdly, the models based on the hierarchical network have limited applicability to the complex multi-stage SCNs. Chapter 5 proposes a conceptual model of an SCN based on graph theory. The proposed model is capable of representing structural redundancy. This model considers both the materials and plants in an SC and captures two essential dependency relationships between the materials and plants (that is, input dependency and output dependency). The two dependency relationships form the basic building blocks for constructing a multi-stage SCN. An approach to assess SCRES is proposed to measure the structural redundancy using the number of SCs in an SCN. The importance of assessing vulnerability in an SCN is highlighted by identifying critical plants at the upstream stages of the SCN. Disruptions in the production of vital upstream material can propagate and affect the production processes downstream. The applicability of the graph model is demonstrated by case studies on two real-world manufacturing SCNs. To evaluate the mitigation strategy, random disruptions are simulated in the SCNs. It shows that SCN can become more resilient against the impact of disruptions by adding redundant plants. However, adding redundancy to all the non-redundant plants requires significant investments. Case studies also demonstrate a contingency strategy with the reactive response to disruption using the graph model.

Finally, structural analysis alone cannot capture the dynamics of disruption and recovery. Chapter 6 proposes a simulation-based analysis for decision-makers to determine the strategies and parameters best suited for building resilience in their SCN. An ABM is built using agent behaviours and graph model from Chapters 4 and 5 respectively, which enables an analysis of the SCN structure while capturing the dynamics of disruption and recovery. The model represents the materials and plants as separate agents, and agents are connected via dependencies to form an SCN. The model also considers the inventory-production system with backordering. Through structural analysis of SCN, mitigation strategies are designed to build redundancy and contingency strategies are also developed to prioritise recovery on the affected SCN. New SCN indexes are proposed to provide an overview of the SCRES by evaluating disruptions of each plant in an SCN

Table 7.1: Summary of research gaps addressed by each chapter.

Research Gaps	Chapter 3	4	5	6
Building a Resilient SCN				
1) Resistance against disruption	✓	✓	✓	✓
2) Recovery from disruption		✓	✓	✓
3) SCRES Assessment	✓	✓	✓	✓
Modelling using Complex System Approaches				
4) Heterogeneity	✓	✓	✓	✓
5) Structural Redundancy			✓	✓
6) Dynamic Response		✓		✓
7) Hybrid Modelling		✓		

Table 7.2: SCRES strategies developed in each chapter.

	SCRES Strategies	
Chapter	Mitigation	Contingency
3	SCN topologies	-
4	Multi-supplier	Contingent supplier
5	Redundant Structure	Backup plant
6	Redundant Structure & Redundant capacity	Backup plant & Backup SCs

Table 7.3: SCRES analysis in each chapter.

Chapter	SCRES Analysis
3	Performance analysis under different demand and supply risk scenarios.
4	Cost analysis between multi-suppliers and contingent suppliers.
5	Structural analysis of a SCN graph model to assess redundancy.
6	Simulation-based analysis to evaluate aggregated SC performance during disruption and recovery.

and aggregating the results based on the criticality of plants in the SCN. A case study based on a real-world three-stage manufacturing SCN is used to compare and contrast different SCRES strategies against the default strategy of passive acceptance. Simulation results show that these strategies can be used to build resilience by enabling the SCN to recover faster after disruptions. In addition, mitigation strategies are suitable for long-term disruptions while contingency strategies are more cost-effective for short-term disruptions.

In summary, the contributions of each chapter are tabulated in Table 7.1. The models/approaches proposed in the thesis are used to design SCRES strategies in Table 7.2. In addition, these models are also used for analysis of SCRES in Table 7.3.

7.2 Future Works

The key directions for future work are the design and evaluation of more realistic SCNs by considering additional real-world issues.

7.2.1 Lost Sales

Complete backordering is not always a reasonable assumption. For example, in a restaurant when the food is readily available, the consumers can just order and receive the food. Some consumers are willing to wait for the food to be prepared but will leave if the preparation time is too long. Hence, the restaurant is only able to backorder the food demand for a short period of time. Therefore, lost sales need to be considered to model more realistic consumer behaviour. Unfulfilled demand causes customers to become unsatisfied and will incur penalty cost. To this regard, the model proposed by Montreuil et al. [127] for client satisfaction versus order delivery time can be used to determine the rejection time. By considering the rejection time, this will significantly affect the quantity of backorders in a disrupted SCN in Chapter 6, and in return the TTR. In addition, suitable lost sale cost needs to be determined to consider the trade-offs between backorder costs and lost sale costs.

7.2.2 Multi-product Supply Chain Networks

One of the assumptions made in this research is that the manufacturer in an SC only produces a single type of product. In today's global market, it is difficult for an enterprise to compete only with a single product; multi-product SC needs to be considered during the decision-making processes. Hence, the SCN model needs to be extended to support multi-products, where each plant can have more than one output material. This requires the Bill-of-Materials (BOM) to be defined, which contains the list of input materials and the quantities of each needed to manufacture each output product. BOM indicates the exact dependency between the materials in the in-edges of a plant node and the output products in the out-edges. It will give the exact material dependency required at the plant and provide a more realistic description of real-world SCNs. Based on the BOM, the graph model in Chapter 5 needs to be redesigned as the Proposition 5.1 is no longer valid. A possible solution to this issue is to have a separate tree for each of the output products. However, this will lead to numerous trees for a large-scale SCN.

7.2.3 Realistic Disruption Models

Currently, all operations in the plant are interrupted when the plant is disrupted and are recovered when the disruption ends. This is a simplified model of disruption in an SCN. To model a more realistic disruption model, the following should be considered:(i) partial capacity disruption, (ii) gradual recovery, and (iii) permanent disruption. Some real-world disruptions, like worker strikes, may only reduce the production capacity of the plant partially instead of a total shutdown of the plant. So, instead of a total shutdown of a plant when disrupted, the plant can be modelled to operate at partial capacity during the disruption. In addition, the recovery of the SC operations is not straightforward – faulty equipment may take a significant amount of time to be repaired or replaced.

A gradual recovery of the SC operations can be modelled, where there is a ramp-up time before the plant fully recovers. Partial disruptions and gradual recovery increase complexity in the design of contingency strategies to account for the uncertainties in capacity planning. Moreover, there can be also situations where the disrupted plant is permanently shutdown. This requires a reconfiguration of the SCN to seek a permanent solution for the disruption. An adaptive approach for SCN reconfiguration can improve the resilience of SC to resilience against future disruptions.

By completing these future works, these enable us to model more complex real-world SCNs and improves the simulation results to more accurately reflect the real world scenarios. Hence, our SCRES analysis can be used to improve the resilience of these SCNS.

Bibliography

[1] B. Adenso-Díaz, C. Mena, S. García-Carbajal, and M. Liechty, “The impact of supply network characteristics on reliability,” *Supply Chain Management: An International Journal*, vol. 17, no. 3, pp. 263–276, Apr. 2012.

[2] B. Adenso-Díaz, J. Mar-Ortiz, and S. Lozano, “Assessing supply chain robustness to links failure,” *International Journal of Production Research*, vol. 56, no. 15, pp. 5104–5117, 2018.

[3] L. An, D. Brown, W. Rand, and S. Page, “Can statistical methods on land-use change patterns calibrate agent-based models?” in *Ann Arbor*, 2005.

[4] Y. Arda and J.-C. Hennet, “Inventory control in a multi-supplier system,” *International Journal of Production Economics*, vol. 104, no. 2, pp. 249–259, 2006.

[5] A. Arreola-Risa and G. A. DeCroix, “Inventory management under random supply disruptions and partial backorders,” *Naval Research Logistics*, vol. 45, p. 17, 1998.

[6] N. Azad and E. Hassini, “Recovery strategies from major supply disruptions in single and multiple sourcing networks,” *European Journal of Operational Research*, vol. 275, no. 2, pp. 481–501, Jun. 2019.

[7] A. Azadeh, N. Atrchin, V. Salehi, and H. Shojaei, “Modelling and improvement of supply chain with imprecise transportation delays and resilience factors,” *International Journal of Logistics Research and Applications*, vol. 17, no. 4, pp. 269–282, Nov. 2013.

[8] S. G. Azevedo, K. Govindan, H. Carvalho, and V. Cruz-Machado, “Ecosilient Index to assess the greenness and resilience of the upstream automotive supply chain,” *Sustainability management beyond corporate boundaries*, vol. 56, pp. 131–146, Oct. 2013.

[9] N. Bakshi and P. Kleindorfer, "Co-opetition and investment for supply-chain resilience," *Production and Operations Management*, vol. 18, no. 6, pp. 583–603, 2009.

[10] A.-L. Barabási and R. Albert, "Emergence of Scaling in Random Networks," *Science*, vol. 286, no. 5439, pp. 509–512, Oct. 1999.

[11] A. P. Barroso, V. H. Machado, A. R. Barros, and V. C. Machado, "Toward a resilient supply chain with supply disturbances," in *2010 IEEE International Conference on Industrial Engineering and Engineering Management*, Dec. 2010, pp. 245–249.

[12] A. Barroso, V. Machado, H. Carvalho, and V. Cruz Machado, "Quantifying the supply chain resilience," in *Applications of Contemporary Management Approaches in Supply Chains*, H. Tozan and A. Ertürk, Eds. Croatia: InTech, Apr. 2015.

[13] C. Basnet and J. M. Y. Leung, "Inventory lot-sizing with supplier selection," *Computers & Operations Research*, vol. 32, no. 1, pp. 1–14, Jan. 2005.

[14] R. C. Basole and M. A. Bellamy, "Supply network structure, visibility, and risk diffusion: A computational approach," *Decision Sciences*, vol. 45, no. 4, pp. 753–789, 2014.

[15] B. Behdani, "Evaluation of paradigms for modeling supply chains as complex socio-technical systems," in *Proceedings of the 2012 Winter Simulation Conference*. Berlin, Germany: Winter Simulation Conference, 2012, pp. 413:1–413:15.

[16] B. Bertok, K. Kalauz, Z. Sule, and F. Friedler, "Combinatorial algorithm for synthesizing redundant structures to increase reliability of supply chains: Application to biodiesel supply," *Industrial & Engineering Chemistry Research*, vol. 52, no. 1, pp. 181–186, 2013.

[17] J. Blackhurst, K. S. Dunn, and C. W. Craighead, "An empirically derived framework of global supply resiliency," *Journal of Business Logistics*, vol. 32, no. 4, pp. 374–391, 2011.

[18] D. J. Bowersox, D. J. Closs, and M. B. Cooper, *Supply chain logistics management*. New York: McGraw-Hill, 2002, vol. 2.

[19] S. C. Brailsford, T. Eldabi, M. Kunc, N. Mustafee, and A. F. Osorio, “Hybrid simulation modelling in operational research: A state-of-the-art review,” *European Journal of Operational Research*, Oct. 2018.

[20] E. Brandon-Jones, B. Squire, C. W. Autry, and K. J. Petersen, “A contingent resource-based perspective of supply chain resilience and robustness,” *Journal of Supply Chain Management*, vol. 50, no. 3, pp. 55–73, 2014.

[21] A. Brintrup, A. Ledwoch, and J. Barros, “Topological robustness of the global automotive industry,” *Logistics Research*, vol. 9, no. 1, pp. 1–17, 2015.

[22] M. Bruneau, S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O’Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. von Winterfeldt, “A framework to quantitatively assess and enhance the seismic resilience of communities,” *Earthquake spectra*, vol. 19, no. 4, pp. 733–752, 2003.

[23] L. P. Bucklin, “Postponement, speculation and the structure of distribution channels,” *Journal of Marketing Research*, vol. 2, no. 1, pp. 26–31, 1965.

[24] L. Bukowski, J. Feliks, and K. Majewska, “Modelling and simulation of disruption risk in the complex logistic networks — a multimethod approach,” in *Modelling and Simulation of Disruption Risk in the Complex Logistic Networks — a Multimethod Approach*. CRC Press, Sep. 2015, pp. 3911–3918.

[25] H. Carvalho, A. P. Barroso, V. H. Machado, S. G. Azevedo, and V. C. Machado, “Supply chain resilience: A simulation study,” *Annals of DAAAM & Proceedings*, pp. 1611–1612, Jan. 2011.

[26] H. Carvalho, A. P. Barroso, V. H. Machado, S. Azevedo, and V. Cruz-Machado, “Supply chain redesign for resilience using simulation,” *Computers & Industrial Engineering*, vol. 62, no. 1, pp. 329–341, Feb. 2012.

[27] Y. Chen, “Enhancing the resilience of a semiconductor supply network via modeling and simulation of business continuity strategies for alternative sites: A case study of building a resilient supply network at infineon,” Ph.D. dissertation, TU Delft, 2017.

[28] T. Y. Choi, K. J. Dooley, and M. Rungtusanatham, “Supply networks and complex adaptive systems: Control versus emergence,” *Journal of Operations Management*, vol. 19, no. 3, pp. 351–366, 2001.

[29] S. Chopra and P. Meindl, *Supply Chain Management: Strategy, Planning & Operation*, 7th ed. Boston: Pearson, Jan. 2018.

[30] M. M. H. Chowdhury and M. Quaddus, “Supply chain resilience: Conceptualization and scale development using dynamic capability theory,” *International Journal of Production Economics*, vol. 188, pp. 185–204, Jun. 2017.

[31] M. Christopher, “The agile supply chain: Competing in volatile markets,” *Industrial marketing management*, vol. 29, no. 1, pp. 37–44, 2000.

[32] ——, *Logistics & Supply Chain Management*. Pearson Higher Ed, 2016.

[33] M. Christopher and H. Peck, “Building the resilient supply chain,” *International Journal of Logistics Management, The*, vol. 15, no. 2, pp. 1–14, 2004.

[34] C. Colicchia, F. Dallari, and M. Melacini, “A simulation-based framework to evaluate strategies for managing global inbound supply risk,” *International Journal of Logistics Research and Applications*, vol. 14, no. 6, pp. 371–384, Dec. 2011.

[35] C. W. Craighead, J. Blackhurst, M. J. Rungtusanatham, and R. B. Handfield, “The severity of supply chain disruptions: Design characteristics and mitigation capabilities,” *Decision Sciences*, vol. 38, no. 1, pp. 131–156, 2007.

[36] M. Dada, N. C. Petruzzi, and L. B. Schwarz, “A newsvendor’s procurement problem when suppliers are unreliable,” *Manufacturing & Service Operations Management*, vol. 9, no. 1, pp. 9–32, Jan. 2007.

[37] J. M. Day, “Fostering emergent resilience: The complex adaptive supply network of disaster relief,” *International Journal of Production Research*, vol. 52, no. 7, pp. 1970–1988, 2014.

[38] L. A. Deleris and F. Erhun, “Quantitative risk assessment in supply chains: A case study based on engineering risk analysis concepts,” in *Planning Production and Inventories in the Extended Enterprise*, ser. International Series in Operations

Research & Management Science, K. G. Kempf, P. Keskinocak, and R. Uzsoy, Eds. Springer New York, 2011, no. 152, pp. 105–131.

[39] A. Dolgui and C. Prodhon, "Supply planning under uncertainties in MRP environments: A state of the art," *Annual Reviews in Control*, vol. 31, no. 2, pp. 269–279, 2007.

[40] A. Dolgui, D. Ivanov, and B. Sokolov, "Ripple effect in the supply chain: An analysis and recent literature," *International Journal of Production Research*, vol. 56, no. 1-2, pp. 414–430, 2018.

[41] D. D. Eisenstein, "Recovering cyclic schedules using dynamic produce-up-to policies," *Operations Research*, vol. 53, no. 4, pp. 675–688, Aug. 2005.

[42] S. M. Elzarka, "Supply chain risk management: The lessons learned from the Egyptian revolution 2011," *International Journal of Logistics Research and Applications*, vol. 16, no. 6, pp. 482–492, Dec. 2013.

[43] P. Erds and A. Rényi, "On the evolution of random graphs," *Publication of the Mathematical Institute of the Hungarian Academy of Science*, vol. 5, pp. 17–61, 1960.

[44] B. Fahimnia, C. S. Tang, H. Davarzani, and J. Sarkis, "Quantitative models for managing supply chain risks: A review," *European Journal of Operational Research*, vol. 247, no. 1, pp. 1–15, Nov. 2015.

[45] M. Falasca, C. W. Zobel, and D. Cook, "A decision support framework to assess supply chain resilience," in *Proceedings of the 5th International ISCRAM Conference*, 2008, pp. 596–605.

[46] H. Fang, D. Jiang, T. Yang, L. Fang, J. Yang, W. Li, and J. Zhao, "Network evolution model for supply chain with manufactures as the core," *PLOS ONE*, vol. 13, no. 1, p. e0191180, Jan. 2018.

[47] J. Fiksel, "Sustainability and resilience: Toward a systems approach," *Engineering Management Review, IEEE*, vol. 35, no. 3, pp. 5–5, 2007.

[48] J. Finnigan, "The science of complex systems," *Australasian science*, vol. 26, no. 5, pp. 32–34, 2005.

[49] M. L. Fisher, "What is the right supply chain for your product?" *Harvard Business Review*, vol. 75, pp. 105–117, 1997.

[50] J. W. Forrester, "Industrial dynamics," *Journal of the Operational Research Society*, vol. 48, no. 10, pp. 1037–1041, 1997.

[51] J. W. Forrester and J. W. Forrester, *Urban dynamics.* MIT Press Cambridge, 1969, vol. 114.

[52] G. Gallego, "When is a base stock policy optimal in recovering disrupted cyclic schedules?" *Naval Research Logistics*, vol. 41, no. 3, pp. 317–333, Apr. 1994.

[53] R. S. Gaonkar and N. Viswanadham, "Analytical framework for the management of risk in supply chains," *IEEE Transactions on Automation Science and Engineering*, vol. 4, no. 2, pp. 265–273, Apr. 2007.

[54] N. Gilbert and S. Bankes, "Platforms and methods for agent-based modeling," *Proceedings of the National Academy of Sciences*, vol. 99, no. suppl 3, pp. 7197–7198, 2002.

[55] K. Govindan, S. G. Azevedo, H. Carvalho, and V. Cruz-Machado, "Impact of supply chain management practices on sustainability," *Special Volume: Making Progress Towards More Sustainable Societies through Lean and Green Initiatives*, vol. 85, pp. 212–225, Dec. 2014.

[56] S. C. Graves and B. T. Tomlin, "Process flexibility in supply chains," *Management Science*, vol. 49, no. 7, pp. 907–919, 2003.

[57] A. Gunasekaran and B. Kobu, "Performance measures and metrics in logistics and supply chain management: A review of recent literature (1995–2004) for research and applications," *International Journal of Production Research*, vol. 45, no. 12, pp. 2819–2840, 2007.

[58] C. Guoping and Z. Xinqiu, "Research on supply chain resilience evaluation," in *Proceedings of the 7th International Conference on Innovation & Management*, 2010, pp. 1558–1562.

[59] G. J. Hahn and H. Kuhn, "Value-based performance and risk management in supply chains: A robust optimization approach," *International Journal of Production Economics*, vol. 139, no. 1, pp. 135–144, 2012.

[60] G. Hamel and L. Valikangas, "The quest for resilience," *Harvard Business Review*, vol. 81, no. 9, pp. 52–65, 2003.

[61] J. Han and K. Shin, "Evaluation mechanism for structural robustness of supply chain considering disruption propagation," *International Journal of Production Research*, vol. 54, no. 1, pp. 135–151, Jan. 2016.

[62] C. M. Harland, "Supply chain management: Relationships, chains and networks," *British Journal of Management*, vol. 7, pp. S63–S80, Dec. 1996.

[63] C. M. Harland, R. C. Lamming, J. Zheng, and T. E. Johnsen, "A taxonomy of supply networks," *Journal of Supply Chain Management*, vol. 37, no. 3, pp. 21–27, Sep. 2001.

[64] J. Hazra, B. Mahadevan, and S. Seshadri, "Modeling capacity reservation contract," in *6th National Conference of the Society of Operations Management*, Kozhikode, India, 2002, p. 23.

[65] E. J. Hearnshaw and M. M. Wilson, "A complex network approach to supply chain network theory," *International Journal of Operations & Production Management*, vol. 33, no. 4, pp. 442–469, Mar. 2013.

[66] M. Helal, L. Rabelo, J. Sepúlveda, and A. Jones, "A methodology for integrating and synchronizing the system dynamics and discrete event simulation paradigms," in *Proceedings of the 25th International Conference of the System Dynamics Society*, vol. 3, 2007, pp. 1–24.

[67] H. Hishamuddin, R. A. Sarker, and D. Essam, "A disruption recovery model for a single stage production-inventory system," *European Journal of Operational Research*, vol. 222, no. 3, pp. 464–473, Nov. 2012.

[68] W. Ho, T. Zheng, H. Yildiz, and S. Talluri, "Supply chain risk management: A literature review," *International Journal of Production Research*, vol. 53, no. 16, pp. 5031–5069, Aug. 2015.

[69] J. H. Holland, "Complex adaptive systems and spontaneous emergence," in *Complexity and Industrial Clusters*, ser. Contributions to Economics, P. A. Q. Curzio and P. M. Fortis, Eds. Physica-Verlag HD, 2002, pp. 25–34.

[70] ——, *Emergence: From Chaos to Order.* OUP Oxford, 2000.

[71] ——, *Hidden Order: How Adaptation Builds Complexity.* Addison-Wesley, 1995.

[72] W. J. Hopp, S. M. R. Iravani, and Z. Liu, "Mitigating the impact of disruptions in supply chains," in *Supply Chain Disruptions: Theory and Practice of Managing Risk*, H. Gurnani, A. Mehrotra, and S. Ray, Eds. London: Springer London, 2012, pp. 21–49.

[73] S. Hosseini, D. Ivanov, and A. Dolgui, "Review of quantitative methods for supply chain resilience analysis," *Transportation Research Part E: Logistics and Transportation Review*, vol. 125, pp. 285–307, May 2019.

[74] W.-t. Hu, S.-L. Kim, and A. Banerjee, "An inventory model with partial backordering and unit backorder cost linearly increasing with the waiting time," *European Journal of Operational Research*, vol. 197, no. 2, pp. 581–587, Sep. 2009.

[75] P. Huang and J. Zhang, "Facts related to August 12, 2015 explosion accident in Tianjin, China," *Process Safety Progress*, pp. 313–314, 2015.

[76] R. Hübner, *Strategic Supply Chain Management in Process Industries: An Application to Specialty Chemicals Production Network Design.* Springer Science & Business Media, 2007, vol. 594.

[77] R. Ishfaq, "Resilience through flexibility in transportation operations," *International Journal of Logistics Research and Applications*, vol. 15, no. 4, pp. 215–229, Aug. 2012.

[78] D. Ivanov, "'A blessing in disguise' or 'as if it wasn't hard enough already': Reciprocal and aggravate vulnerabilities in the supply chain," *International Journal of Production Research*, pp. 1–11, Jun. 2019.

[79] ——, "Disruption tails and revival policies: A simulation analysis of supply chain design and production-ordering systems in the recovery and post-disruption periods," *Computers & Industrial Engineering*, vol. 127, pp. 558–570, Jan. 2019.

[80] ——, "Simulation-based ripple effect modelling in the supply chain," *International Journal of Production Research*, vol. 55, no. 7, pp. 2083–2101, Apr. 2017.

[81] ——, *Structural Dynamics and Resilience in Supply Chain Risk Management*, ser. International Series in Operations Research & Management Science. Cham: Springer International Publishing, 2018, vol. 265.

[82] D. Ivanov and A. Dolgui, "Low-Certainty-Need (LCN) supply chains: A new perspective in managing disruption risks and resilience," *International Journal of Production Research*, vol. 57, no. 15-16, pp. 5119–5136, Aug. 2019.

[83] D. Ivanov and M. Rozhkov, "Coordination of production and ordering policies under capacity disruption and product write-off risk: An analytical study with real-data based simulations of a fast moving consumer goods company," *Annals of Operations Research*, pp. 1–21, Sep. 2017.

[84] D. Ivanov, A. Dolgui, B. Sokolov, and M. Ivanova, "Literature review on disruption recovery in the supply chain," *International Journal of Production Research*, vol. 55, no. 20, pp. 6158–6174, Oct. 2017.

[85] A. Jafarnejad Chaghooshi, M. Momeni, B. Abdollahi, H. Safari, and I. Nakhai Kamalabadi, "Planning for disruptions in supply chain networks," *Uncertain Supply Chain Management*, pp. 135–148, 2018.

[86] P. A. Jensen and J. F. Bard, *Inventory Theory: S5 The (s, Q) inventory policy.* New Jersey: Wiley Hoboken, 2001.

[87] G. Ji and C. Zhu, "Study on supply chain disruption risk management strategies and model," in *Service Systems and Service Management, 2008 International Conference On*. IEEE, 2008, pp. 1–6.

[88] B. Jovanoski, R. N. Minovski, G. Lichtenegger, and S. Voessner, "Managing strategy and production through hybrid simulation," *Industrial Management & Data Systems*, vol. 113, no. 8, pp. 1110–1132, Aug. 2013.

[89] U. Jüttner and S. Maklan, "Supply chain resilience in the global financial crisis: An empirical study," *Supply Chain Management: An International Journal*, vol. 16, no. 4, pp. 246–259, Jun. 2011.

[90] M. Kamalahmadi and M. M. Parast, “An assessment of supply chain disruption mitigation strategies,” *International Journal of Production Economics*, vol. 184, pp. 210–230, Feb. 2017.

[91] ——, “A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research,” *International Journal of Production Economics*, vol. 171, Part 1, pp. 116–133, Jan. 2016.

[92] S. A. Kauffman, *The Origins of Order: Self Organization and Selection in Evolution*. Oxford University Press, USA, 1993.

[93] O. Khan, M. Christopher, and A. Creazza, “Aligning product design with the supply chain: A case study,” *Supply Chain Management: An International Journal*, vol. 17, no. 3, pp. 323–336, Apr. 2012.

[94] Y. Kim, T. Y. Choi, T. Yan, and K. Dooley, “Structural investigation of supply networks: A social network analysis approach,” *Journal of Operations Management*, vol. 29, no. 3, pp. 194–211, Mar. 2011.

[95] Y. Kim, Y.-S. Chen, and K. Linderman, “Supply network disruption and resilience: A network structural perspective,” *Journal of Operations Management*, vol. 33, pp. 43–59, 2015.

[96] T. Kito, A. Brintrup, S. New, and F. Reed-Tsochas, “The structure of the toyota supply network: An empirical analysis,” *SSRN Electronic Journal*, 2014.

[97] W. Klibi and A. Martel, “Modeling approaches for the design of resilient supply networks under disruptions,” *Green Manufacturing and Distribution in the Fashion and Apparel Industries*, vol. 135, no. 2, pp. 882–898, Feb. 2012.

[98] W. Klibi, A. Martel, and A. Guitouni, “The design of robust value-creating supply chain networks: A critical review,” *European Journal of Operational Research*, vol. 203, no. 2, pp. 283–293, Jun. 2010.

[99] A. G. Kök, M. L. Fisher, and R. Vaidyanathan, “Assortment planning: Review of literature and industry practice,” in *Retail Supply Chain Management*, ser. International Series in Operations Research & Management Science, N. Agrawal and S. A. Smith, Eds. Springer US, 2008, no. 122, pp. 99–153.

[100] S. Kumar and M. Sosnoski, "Decision framework for the analysis and selection of appropriate transfer pricing for a resilient global SME manufacturing operation – a business case," *International Journal of Production Research*, vol. 49, no. 18, pp. 5431–5448, Apr. 2011.

[101] L. Lättilä, P. Hilletofth, and B. Lin, "Hybrid simulation models – When, Why, How?" *Expert Systems with Applications*, vol. 37, no. 12, pp. 7969–7975, 2010.

[102] P. Leat and C. Revoredo-Giha, "Risk and resilience in agri-food supply chains: The case of the ASDA PorkLink supply chain in Scotland," *Supply Chain Management: An International Journal*, vol. 18, no. 2, pp. 219–231, Mar. 2013.

[103] A. Ledwoch, H. Yasarcan, and A. Brintrup, "The moderating impact of supply network topology on the effectiveness of risk management," *International Journal of Production Economics*, vol. 197, pp. 13–26, Mar. 2018.

[104] H. L. Lee, "Aligning supply chain strategies with product uncertainties," *California management review*, vol. 44, no. 3, pp. 105–119, 2002.

[105] ——, "The triple - A supply chain," *Harvard Business Review*, vol. 82, no. 10, pp. 102–113, 2004.

[106] W. W. Leontief, "The structure of american economy, 1919-1939: An empirical application of equilibrium analysis." Tech. Rep., 1951.

[107] C. Lertpattarapong, "Applying system dynamics approach to the supply chain management problem," M.Sc. Thesis, Massachusetts Institute of Technology, 2002.

[108] C. Li, J. Ren, and H. Wang, "A system dynamics simulation model of chemical supply chain transportation risk management systems," *Computers & Chemical Engineering*, vol. 89, pp. 71–83, Jun. 2016.

[109] H. Li, L. H. Lee, E. P. Chew, and Y. Long, "A three-echelon system dynamics model on supply chain risk mitigation through information sharing," in *Proceedings of the 2015 Winter Simulation Conference*. Winter Simulation Conference, Dec. 2015, pp. 2045–2056.

[110] H.-H. J. Li, K. H. Tan, and A. Hida, “Sustaining growth in electronic manufacturing sector: Lessons from Japanese mid-size EMS providers,” *International Journal of Production Research*, vol. 49, no. 18, pp. 5415–5430, Apr. 2011.

[111] R. Li, Q. Dong, C. Jin, and R. Kang, “A new resilience measure for supply chain networks,” *Sustainability*, vol. 9, no. 1, p. 144, Jan. 2017.

[112] Y. Li, G. Jia, Y. Cheng, and Y. Hu, “Additive manufacturing technology in spare parts supply chain: A comparative study,” *International Journal of Production Research*, vol. 55, no. 5, pp. 1498–1515, Mar. 2017.

[113] F. Longo and T. Ören, “Supply chain vulnerability and resilience: A state of the art overview,” in *Proceedings of European Modeling & Simulation Symposium*, 2008.

[114] B. C. Lynn, *End of the Line: The Rise and Coming Fall of the Global Corporation.* Crown Business, 2006.

[115] Y.-f. Ma, L.-w. Chen, S.-d. Meng, and C.-q. Yi, “A study on the risk control of supply chain under the background of globalization,” *Journal of Industrial and Production Engineering*, vol. 31, no. 4, pp. 221–228, May 2014.

[116] B. D. MacArthur and R. J. Sánchez-García, “Spectral characteristics of network redundancy,” *Physical Review E*, vol. 80, no. 2, p. 026117, Aug. 2009.

[117] I. Manuj and J. T. Mentzer, “Global supply chain risk management strategies,” *International Journal of Physical Distribution & Logistics Management*, vol. 38, no. 3, pp. 192–223, Apr. 2008.

[118] S. I. Mari, Y. H. Lee, M. S. Memon, Y. S. Park, and M. Kim, “Adaptivity of complex network topologies for designing resilient supply chain networks,” *International Journal of Industrial Engineering*, vol. 22, no. 1, pp. 102–116, 2015.

[119] H. Matsuo, “Implications of the Tohoku earthquake for Toyota’s coordination mechanism: Supply chain disruption of automotive semiconductors,” *International Journal of Production Economics*, vol. 161, pp. 217–227, Mar. 2015.

[120] L.-G. Mattsson and E. Jenelius, “Vulnerability and resilience of transport systems – A discussion of recent research,” *Transportation Research Part A: Policy and Practice*, vol. 81, pp. 16–34, Nov. 2015.

[121] S. A. Melnyk, "Understanding supply chain resilience," *Supply Chain Management Review*, vol. 18, no. 1, pp. 34–41, 2014.

[122] S. A. Melnyk, E. W. Davis, R. E. Spekman, and J. Sandor, "Outcome-driven supply chains," *MIT Sloan Management Review*, vol. 51, no. 2, p. 33, 2010.

[123] P. Mensah and Y. Merkuryev, "Developing a resilient supply chain," *Procedia - Social and Behavioral Sciences*, vol. 110, pp. 309–319, Jan. 2014.

[124] J. T. Mentzer, W. DeWitt, J. S. Keebler, S. Min, N. W. Nix, C. D. Smith, and Z. G. Zacharia, "Defining supply chain management," *Journal of Business Logistics*, vol. 22, no. 2, pp. 1–25, 2001.

[125] M. Mitchell, "Complex systems: Network thinking," *Artificial Intelligence*, vol. 170, no. 18, pp. 1194–1212, 2006.

[126] K. J. Mizgier, M. P. Jüttner, and S. M. Wagner, "Bottleneck identification in supply chain networks," *International Journal of Production Research*, vol. 51, no. 5, pp. 1477–1490, Mar. 2013.

[127] B. Montreuil, O. Labarthe, and C. Cloutier, "Modeling client profiles for order promising and delivery," *Simulation Modelling Practice and Theory*, vol. 35, pp. 1–25, Jun. 2013.

[128] J. S. Morgan, S. Howick, and V. Belton, "A toolkit of designs for mixing Discrete Event Simulation and System Dynamics," *European Journal of Operational Research*, vol. 257, no. 3, pp. 907–918, 2017.

[129] A. Munoz and M. Dunbar, "On the quantification of operational supply chain resilience," *International Journal of Production Research*, vol. 53, no. 22, pp. 6736–6751, Nov. 2015.

[130] S. Nahmias and T. L. Olsen, *Production and Operations Analysis.* Waveland Press, 2015.

[131] A. Nair and J. M. Vidal, "Supply network topology and robustness against disruptions–an investigation using multi-agent model," *International Journal of Production Research*, vol. 49, no. 5, pp. 1391–1404, 2011.

[132] J. Nakatani, K. Tahara, K. Nakajima, I. Daigo, H. Kurishima, Y. Kudoh, K. Matsubae, Y. Fukushima, T. Ihara, Y. Kikuchi, A. Nishijima, and Y. Moriguchi, "A graph theory-based methodology for vulnerability assessment of supply chains using the life cycle inventory database," *Omega*, Mar. 2017.

[133] H. Q. Nguyen, "Optimizing the recovery of disrupted supply networks," Doctoral Dissertation, Rensselaer Polytechnic Institute, 2018.

[134] N. Ni, B. J. Howell, and T. C. Sharkey, "Modeling the impact of unmet demand in supply chain resiliency planning," *Omega*, Sep. 2017.

[135] J. Pastrana, M. Helal, M. Marin, and C. Mendizabal, "Enterprise scheduling: Hybrid and hierarchical issues," in *Proceedings of the 2010 Winter Simulation Conference*. Baltimore, Maryland: Winter Simulation Conference, 2010, pp. 3350–3362.

[136] S. K. Paul, R. Sarker, and D. Essam, "A quantitative model for disruption mitigation in a supply chain," *European Journal of Operational Research*, vol. 257, no. 3, pp. 881–895, Mar. 2017.

[137] S. K. Paul, S. Asian, M. Goh, and S. A. Torabi, "Managing sudden transportation disruptions in supply chains under delivery delay and quantity loss," *Annals of Operations Research*, vol. 273, no. 1, pp. 783–814, Feb. 2019.

[138] H. Peck, "Drivers of supply chain vulnerability: An integrated framework," *International Journal of Physical Distribution & Logistics Management*, vol. 35, no. 4, pp. 210–232, Apr. 2005.

[139] C. R. Pereira, M. Christopher, and A. L. D. Silva, "Achieving supply chain resilience: The role of procurement," *Supply Chain Management: An International Journal*, vol. 19, no. 5/6, pp. 626–642, Sep. 2014.

[140] T. J. Pettit, J. Fiksel, and K. L. Croxton, "Ensuring supply chain resilience: Development of a conceptual framework," *Journal of Business Logistics*, vol. 31, no. 1, pp. 1–21, 2010.

[141] T. J. Pettit, K. L. Croxton, and J. Fiksel, "Ensuring supply chain resilience: Development and implementation of an assessment tool," *Journal of Business Logistics*, vol. 34, no. 1, pp. 46–76, Mar. 2013.

[142] J. Pires Ribeiro and A. Barbosa-Povoa, "Supply chain resilience: Definitions and quantitative modelling approaches – A literature review," *Computers & Industrial Engineering*, vol. 115, pp. 109–122, Jan. 2018.

[143] S. T. Ponis and E. Koronis, "Supply chain resilience: Definition of concept and its formative elements," *Journal of Applied Business Research*, vol. 28, no. 5, p. 921, 2012.

[144] S. Y. Ponomarov and M. C. Holcomb, "Understanding the concept of supply chain resilience," *International Journal of Logistics Management, The*, vol. 20, no. 1, pp. 124–143, 2009.

[145] P. Priya Datta, M. Christopher, and P. Allen, "Agent-based modelling of complex production/distribution systems to improve resilience," *International Journal of Logistics: Research and Applications*, vol. 10, no. 3, pp. 187–203, 2007.

[146] X. Qi, J. F. Bard, and G. Yu, "Supply chain coordination with demand disruptions," *Omega*, vol. 32, no. 4, pp. 301–312, Aug. 2004.

[147] L. Rabelo, M. Helal, A. Jones, and H.-S. Min, "Enterprise simulation: A hybrid system approach," *International Journal of Computer Integrated Manufacturing*, vol. 18, no. 6, pp. 498–508, 2005.

[148] R. Rajesh, V. Ravi, and R. Venkata Rao, "Selection of risk mitigation strategy in electronic supply chains using grey theory and digraph-matrix approaches," *International Journal of Production Research*, vol. 53, no. 1, pp. 238–257, Sep. 2014.

[149] A. Rappaport, *Creating shareholder value: A guide for managers and investors.* New York: Simon and Schuster, 1999.

[150] ——, *Creating Shareholder Value: A Guide for Managers and Investors.* Simon and Schuster, 1999.

[151] G. Reiner, "Customer-oriented improvement and evaluation of supply chain processes supported by simulation models," *International Journal of Production Economics*, vol. 96, no. 3, pp. 381–395, 2005.

[152] R. Reyes Levalle and S. Y. Nof, "Resilience by teaming in supply network formation and re-configuration," *International Journal of Production Economics*, vol. 160, pp. 80–93, Feb. 2015.

[153] J. B. Rice and F. Caniato, "Building a secure and resilient supply network," *Supply Chain Management Review*, vol. 7, no. 5, pp. 22–30, 2003.

[154] R. Ruiz-Benítez, C. López, and J. C. Real, "The lean and resilient management of the supply chain and its impact on performance," *International Journal of Production Economics*, vol. 203, pp. 190–202, Sep. 2018.

[155] E. H. Sabri and B. M. Beamon, "A multi-objective approach to simultaneous strategic and operational planning in supply chain design," *Omega*, vol. 28, no. 5, pp. 581–598, 2000.

[156] S. Saghafian and M. P. Van Oyen, "The value of flexible backup suppliers and disruption risk information: Newsvendor analysis with recourse," *IIE Transactions*, vol. 44, no. 10, pp. 834–867, Jan. 2012.

[157] N. Salehi Sadghiani, S. Torabi, and N. Sahebjamnia, "Retail supply chain network design under operational and disruption risks," *Transportation Research Part E: Logistics and Transportation Review*, vol. 75, pp. 95–114, Mar. 2015.

[158] R. Sarathy, "Security and the global supply chain," *Transportation Journal*, vol. 45, no. 4, pp. 28–51, 2006.

[159] T. Sawik, "Disruption mitigation and recovery in supply chains using portfolio approach," *Omega*, vol. 84, pp. 232–248, Apr. 2019.

[160] ——, "Selection of resilient supply portfolio under disruption risks," *Omega*, vol. 41, no. 2, pp. 259–269, 2013.

[161] H. Scarf, "The optimality of (s, s) policies in the dynamic inventory problem," in *Optimal pricing, inflation, and the cost of price adjustment*, 1959, ch. 3, pp. 49–56.

[162] K. P. Scheibe and J. Blackhurst, "Supply chain disruption propagation: A systemic risk and normal accident theory perspective," *International Journal of Production Research*, vol. 56, no. 1-2, pp. 43–59, 2018.

[163] A. J. Schmitt, "Strategies for customer service level protection under multi-echelon supply chain disruption risk," *Transportation Research Part B: Methodological*, vol. 45, no. 8, pp. 1266–1283, Sep. 2011.

[164] A. J. Schmitt and M. Singh, "Quantifying supply chain disruption risk using monte carlo and discrete-event simulation," in *Proceedings of the 2009 Winter Simulation Conference*. Austin, Texas: Winter Simulation Conference, 2009, pp. 1237–1248.

[165] ——, "A quantitative analysis of disruption risk in a multi-echelon supply chain," *Supply Chain Risk Management*, vol. 139, no. 1, pp. 22–32, Sep. 2012.

[166] T. G. Schmitt, S. Kumar, K. E. Stecke, F. W. Glover, and M. A. Ehlen, "Mitigating disruptions in a multi-echelon supply chain using adaptive ordering," *Omega*, vol. 68, no. Supplement C, pp. 185–198, Apr. 2017.

[167] J. G. Shanthikumar and R. G. Sargent, "A unifying view of hybrid simulation/analytic models and modeling," *Operations Research*, vol. 31, no. 6, pp. 1030–1052, Dec. 1983.

[168] Y. Sheffi, "Building a culture of flexibility: Longer supply chains means more risk. what's needed is a nimble organization," *World Trade*, vol. 18, no. 12, p. 26, 2005.

[169] Y. Sheffi and J. B. Rice Jr, "A supply chain view of the resilient enterprise," *MIT Sloan management review*, vol. 47, no. 1, 2005.

[170] Y. Shuai, X. Wang, and L. Zhao, "Research on measuring method of supply chain resilience based on biological cell elasticity theory," *2011 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pp. 264–268, 2011.

[171] L. V. Snyder and Z.-J. M. Shen, "Supply and demand uncertainty in multi-echelon supply chains," *Submitted for publication, Lehigh University*, vol. 15, 2006.

[172] L. V. Snyder, Z. Atan, P. Peng, Y. Rong, A. J. Schmitt, and B. Sinsoysal, "OR/MS models for supply chain disruptions: A review," *IIE Transactions*, vol. 48, no. 2, pp. 89–109, 2016.

[173] U. Soni, V. Jain, and S. Kumar, "Measuring supply chain resilience using a deterministic modeling approach," *Computers & Industrial Engineering*, 2014.

[174] V. L. Spiegler, M. M. Naim, and J. Wikner, "A control engineering approach to the assessment of supply chain resilience," *International Journal of Production Research*, vol. 50, no. 21, pp. 6162–6187, 2012.

[175] A. St. George, M. Y. Yoshino, and C.-I. Knoop, *Li, and Fung: Beyond 'Filling in the Mosaic'*. Boston, Massachusetts: Harvard Business School, 1998.

[176] M. Stevenson and M. Spring, "Flexibility from a supply chain perspective: Definition and review," *International Journal of Operations & Production Management*, vol. 27, no. 7, pp. 685–713, 2007.

[177] G. L. Stewart, K. A. Manges, and M. M. Ward, "Empowering sustained patient safety: The benefits of combining top-down and bottom-up approaches," *Journal of nursing care quality*, vol. 30, no. 3, pp. 240–246, 2015.

[178] S.-Y. Sun, M.-H. Hsu, and W.-J. Hwang, "The impact of alignment between supply chain strategy and environmental uncertainty on scm performance," *Supply Chain Management: An International Journal*, vol. 14, no. 3, pp. 201–212, 2009.

[179] A. A. Tako and S. Robinson, "The application of discrete event simulation and system dynamics in the logistics and supply chain context," *Decision Support Systems*, vol. 52, no. 4, pp. 802–815, 2012.

[180] C. Tang and B. Tomlin, "The power of flexibility for mitigating supply chain risks," *International Journal of Production Economics*, vol. 116, no. 1, pp. 12–27, 2008.

[181] C. S. Tang, "Robust strategies for mitigating supply chain disruptions," *International Journal of Logistics Research and Applications*, vol. 9, no. 1, pp. 33–45, Mar. 2006.

[182] Y. Tao, L. H. Lee, and E. P. Chew, "Quantifying the effect of sharing information in a supply chain facing supply disruptions," *Asia-Pacific Journal of Operational Research*, vol. 33, no. 04, p. 1650029, 2016.

[183] H. Thadakamaila, U. N. Raghavan, S. Kumara, and R. Albert, "Survivability of multiagent-based supply networks: A topological perspect," *Intelligent Systems, IEEE*, vol. 19, no. 5, pp. 24–31, 2004.

[184] B. Tomlin, "Disruption management strategies for short life-cycle products," *Naval Research Logistics*, vol. 56, no. 4, pp. 318–347, 2009.

[185] ——, "On the value of mitigation and contingency strategies for managing supply chain disruption risks," *Management Science*, vol. 52, no. 5, pp. 639–657, 2006.

[186] B. Tomlin and Y. Wang, "Operational strategies for managing supply chain disruption risk," in *The Handbook of Integrated Risk Management in Global Supply Chains*, P. Kouvelis, L. Dong, O. Boyabatli, and R. Li, Eds. John Wiley & Sons, Inc., 2011, pp. 79–101.

[187] S. Torabi, M. Baghersad, and S. Mansouri, "Resilient supplier selection and order allocation under operational and disruption risks," *Transportation Research Part E: Logistics and Transportation Review*, vol. 79, pp. 22–48, Jul. 2015.

[188] B. R. Tukamuhabwa, M. Stevenson, J. Busby, and M. Zorzini, "Supply chain resilience: Definition, review and theoretical foundations for further study," *International Journal of Production Research*, vol. 53, no. 18, pp. 5592–5623, Apr. 2015.

[189] L. Urciuoli, S. Mohanty, J. Hintsa, and E. G. Boekesteijn, "The resilience of energy supply chains: A multiple case study approach on oil and gas supply chains to Europe," *Supply Chain Management: An International Journal*, vol. 19, no. 1, pp. 46–63, Jan. 2014.

[190] J. Vargas and D. González, "Model to assess supply chain resilience," *International Journal of Safety and Security Engineering*, vol. 6, no. 2, pp. 282–292, Jun. 2016.

[191] S. P. Venkatesan and M. Goh, "Strategic sourcing under supply disruption risk," in *Supply Chain Risk Management*. Springer, Singapore, 2018, pp. 179–200.

[192] S. M. Wagner and N. Neshat, "Assessing the vulnerability of supply chains using graph theory," *International Journal of Production Economics*, vol. 126, no. 1, pp. 121–129, 2010.

[193] D. Wang and W. Ip, "Evaluation and analysis of logistic network resilience with application to aircraft servicing," *Systems Journal, IEEE*, vol. 3, no. 2, pp. 166–173, 2009.

[194] W. Wang, W. Fu, H. Zhang, and Y. Wang, "Hybrid modeling and simulation of automotive supply chain network," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 6, no. 9, pp. 1598–1605, 2013.

[195] W. Wang, W. N. Street, and R. E. deMatta, "Topological resilience analysis of supply networks under random disruptions and targeted attacks," in *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015.* New York, NY, USA: ACM, 2015, pp. 250–257.

[196] Y. Wang and R. Xiao, "An ant colony based resilience approach to cascading failures in cluster supply network," *Physica A: Statistical Mechanics and its Applications*, vol. 462, pp. 150–166, Nov. 2016.

[197] J. Ward, "Insight on Risk & Resilience," DHL, Tech. Rep., 2016.

[198] P. Wicher and R. Lenort, "Comparison of AHP and ANP methods for resilience measurement in supply chains," in *23rd International Conference on Metallurgy and Materials.* Metal, 2014.

[199] P. Wicher, R. Lenort, and E. Krausová, "Possible applications of resilience concept in metallurgical supply chains," in *Proceedings of METAL Conference*, 2012, pp. 23–25.

[200] A. Wieland and C. M. Wallenburg, "The influence of relational competencies on supply chain resilience: A relational view," *International Journal of Physical Distribution & Logistics Management*, vol. 43, no. 4, pp. 300–320, May 2013.

[201] S. P. Willems, "Data set — Real-world multiechelon supply chains used for inventory optimization," *Manufacturing & Service Operations Management*, vol. 10, no. 1, pp. 19–23, 2007.

[202] World Economic Forum, "Global Risks 2015," World Economic Forum, Tech. Rep., 2015.

[203] T. Wu, Simin Huang, J. Blackhurst, Xiaoling Zhang, and Shanshan Wang, "Supply chain risk management: An agent-based simulation to study the impact of retail stockouts," *Engineering Management, IEEE Transactions on*, vol. 60, no. 4, pp. 676–686, Nov. 2013.

[204] C. Wycisk, B. McKelvey, and M. Hülsmann, ““Smart parts” supply networks as complex adaptive systems: Analysis and implications,” *International Journal of Physical Distribution & Logistics Management*, vol. 38, no. 2, pp. 108–125, 2008.

[205] Y. Xia, M.-H. Yang, B. Golany, S. M. Gilbert, and G. Yu, “Real-time disruption management in a two-stage production and inventory system,” *IIE Transactions*, vol. 36, no. 2, pp. 111–125, Feb. 2004.

[206] R. Xiao, T. Yu, and X. Gong, “Modeling and simulation of ant colony's labor division with constraints for task allocation of resilient supply chains,” *International Journal on Artificial Intelligence Tools*, vol. 21, no. 3, p. 1240014, Jun. 2012.

[207] M. Xu, X. Wang, and L. Zhao, “Predicted supply chain resilience based on structural evolution against random supply disruptions,” *International Journal of Systems Science: Operations & Logistics*, vol. 1, no. 2, pp. 105–117, Apr. 2014.

[208] J. Yang, X. Qi, and G. Yu, “Disruption management in production planning,” *Naval Research Logistics*, vol. 52, no. 5, pp. 420–442, Aug. 2005.

[209] Y. Yao and B. Meurier, “Understanding the supply chain resilience: A dynamic capabilities approach,” in *Proceedings of 9th International Meetings of Research in Logistics 2012*, 2012, p. 18.

[210] K. Zhao, A. Kumar, and J. Yen, “Achieving high robustness in supply distribution networks by rewiring,” *IEEE Transactions on Engineering Management*, vol. 58, no. 2, pp. 347–362, May 2011.

[211] K. Zhao, A. Kumar, T. P. Harrison, and J. Yen, “Analyzing the resilience of complex supply network topologies against random and targeted disruptions,” *Systems Journal, IEEE*, vol. 5, no. 1, pp. 28–39, 2011.

[212] G. A. Zsidisin and S. M. Wagner, “Do perceptions become reality? The moderating role of supply chain resiliency on disruption occurrence,” *Journal of Business Logistics*, vol. 31, no. 2, pp. 1–20, 2010.

List of Publications

[1] Wen Jun Tan, Zhengping Li, and Wentong Cai. Design of supply chain topology to mitigate demand and supply risks. In *Proceedings of the 2015 Winter Simulation Conference*, pages 230–241, 2015. doi: 10.1109/WSC.2015.7408167.

[2] Wen Jun Tan, Wentong Cai, and Zhengping Li. Adaptive resilient strategies for supply chain networks. In *2016 IEEE International Conference on Big Data (Big Data)*, pages 3779–3784, December 2016. doi: 10.1109/BigData.2016.7841048.

[3] Wen Jun Tan, Wentong Cai, and Allan NengSheng Zhang. Integration design of supply chain hybrid simulation. In *Proceedings of the 2017 Winter Simulation Conference*, pages 493–504, December 2017. doi: 10.1109/WSC.2017.8247810.

[4] Wen Jun Tan, Allan NengSheng Zhang, and Wentong Cai. A graph-based model to measure structural redundancy for supply chain resilience. *International Journal of Production Research*, 57(20):6385–6404, 2019. ISSN 0020-7543. doi: 10.1080/00207543.2019.1566666.

[5] Wen Jun Tan, Wentong Cai, and Allan NengSheng Zhang. Structural-aware supply chain network simulation approach for building supply chain resilience. *International Journal of Production Research*, pages 1–28, 2020. doi: 10.1080/00207543.2019.1705421.

Appendix A

List of SCRES Definitions

Authors	Definitions
Barroso et al. [11]	"The SC's ability to react to the negative effects caused by disturbances that occur at a given moment in order to maintain the SC's objectives."
Blackhurst et al. [17]	"The ability to absorb disruptions or enables the supply network to return to stable conditions faster and thus has a positive impact on performance."
Brandon-Jones et al. [20]	"The ability of a system to return to its original state, within an acceptable period of time, after being disturbed."
Carvalho et al. [25]	"The ability of the SC to cope with unexpected disturbances."
Christopher and Peck [33], Peck [138]	"The ability of a system to return to its original state or move to a new, more desirable state after being disturbed."
Falasca et al. [45]	"The ability of an SC to reduce the probabilities of disruptions, to reduce the consequences of those disruptions, and to reduce the time to recover normal performance."
Fiksel [47]	"The capacity to survive, adapt, and grow in the face of turbulent change."
Gaonkar and Viswanadham [53]	"The ability of an SC to maintain, resume, and restore operations after a disruption."
Guoping and Xinqiu [58]	"The ability of the SC to return to its original or ideal status under emergency risk environment."
Hearnshaw and Wilson [65]	"The ability of the system as a whole to continue to provide flows despite disturbances."
Jüttner and Maklan [89]	"The ability to recover from inevitable risk events more effectively."

Kamalahmadi and Parast [91]	"The adaptive capability to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the SC to a robust state of operations."
Kim et al. [95]	"A network-level attribute to withstand disruptions that may be triggered at the node or arc level."
Klibi et al. [98]	"The capability to avoid disruptions or quickly recover from failures. The capacity of a system to survive, adapt, and grow in the face of unforeseen changes, even catastrophic incidents."
Kumar and Sosnoski [100]	"The ability to maintain, resume and restore operations after any disruption."
Longo and Ören [113]	"Allows the SC to react to internal/external risks and vulnerabilities, quickly recovering an equilibrium state capable of guaranteeing high performance and efficiency levels."
Melnyk [121]	"The ability of an SC to both resist disruptions and recover operational capability after disruptions occur."
Pereira et al. [139]	"The capability to respond quickly to unexpected events so as to restore operations to the previous performance level or even to a new and better one."
Pettit et al. [141]	"The ability to survive, adapt and grow in the face of turbulent change."
Ponis and Koronis [143]	"The ability to proactively plan and design an SCN for anticipating unexpected disruptive (negative) events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a post event robust state of operations, if possible, more favourable than the one prior to the event, thus gaining competitive advantage."
Ponomarov and Holcomb [144]	"The adaptive capability of the SC to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function."
Priya Datta et al. [145]	"Not only the ability to maintain control over performance variability in the face of disturbance, but also a property of being adaptive and capable of sustained response to sudden and significant shifts in the environment in the form of uncertain demands."
Rice and Caniato [153]	"The ability to react to unexpected disruptions and restore normal operations."
Sarathy [158]	"To bounce back quickly from a disruption."

Sawik [160]	“The capacity to survive, adapt, and grow in the face of change and uncertainty.”
Schmitt and Singh [165]	“The ability to sustain operation and recovery quickly in the face of a disruption.”
Sheffi and Rice Jr [169]	“The ability of the company to bounce back from a large disruption including the speed with which it returns to a normal level of performance.”
Shuai et al. [170]	“The rapid recovery ability to equilibrium after the SC is attacked by a disturbance.”
Xiao et al. [206]	“The SC’s ability to return to the original or ideal status after external disruption and includes both the abilities of adaptability to the environment and recovery from the disruption.”
Yao and Meurier [209]	“The ability to bounce back from disruptions and to permanently deal with and respond to the changing environment.”
Zsidisin and Wagner [212]	“The ability to return to normal performance levels following an SC disruption.”