STRATEGIC DECISION MAKING IN SUPPLY CHAINS

UNDER RISK OF DISRUPTIONS

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

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Summary

Strategic level decisions in supply chain are of critical importance to the competitiveness of both individual entities and the supply chain as a whole. The raising concerns of disruption risks have made the strategic decision making in supply chain even more complicated. This thesis aims to provide efficient approaches for strategic decision making in supply chain partner selections with considerations of disruption risks, as well as protection planning against worst case disruptions. The proposed approach for supply chain partner selections complements existing methodologies by considering the combination of trade-off options and supply chain level performance requirements to allow for a wider range of choices and potentially better supply chain structures. The approach developed for supply chain protection planning presents a novel definition of supply chain networks on graphs, which allows for the modeling of disruptions on financial flows and information flows.

This thesis starts from a detailed discussion on the definitions of supply chain performance measurements, followed by an explanation on the trade-off options in supply chain partner selections. The trade-off constraints are integrated into a mixed integer programming model, which allows for multiple supply chain characteristic diversifications in the supply chain designing process. Conditional Value-at-Risk is introduced to model the risk consideration in supply chain design, and a new decomposition scenario management approach is proposed to reduce the number of disruption scenarios to be considered in solving the problem. Numerical analysis and case studies have shown that the proposed approach can provide

valuable information to support strategic decision makings in designing a competitive supply chain.

To consider potential intentional attacks or worst case disruptions in supply chain, this thesis examines possible disruption scenarios due to intentional attacks, and defines each scenario as arc disruptions in a graph. The protection problem is then modeled as a tri-level defender-attacker-user optimization model, which is eventually transformed into an equivalent mixed integer programing model using duality theory and standard linearization techniques. By comparing the solution values of some key variables in numerical analysis, we reconfirm a previous finding that protection decisions based on the solution of traditional bi-level interdiction models may be suboptimal due to its dependency on the attacker's interdiction budget, and find that the solution of our approach is based on the cost efficiency of protecting each arc which is independent of the attacker's budget. A case study of a South African third party logistics company in vaccine industry is presented showing that the proposed approach can be applied to solve realistic problems.

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List of Abbreviations

3PL	Third-party Logistics
AC	Additional Cost
AHP	Analytic Hierarchy Process
CVaR	Conditional Value-at-Risk
DC	Distribution Center
DOH	Department of Health
LNFD	Linearized Network Fortification-Dual (model name)
MAUT	Multi-attribute Utility Theory
MIP	Mixed Integer Program
MOC	Maximize Overall Coverage (model name)
NF	Network Fortification (model name)
NFD	Network Fortification-Dual (model name)
OC	Overall Coverage
SCN	Supply Chain Network
SMA	Scenario Management Approach
TC	Total Cost
VaR	Value-at-Risk
WCDH	Western Cape Department of Health

List of Variables and Symbols

Due to the limitation of useable alphabets, there are some overlapping alphabets used in Chapter 6 that have been used in Chapters 4 and 5. Since Chapter 6 discusses a new problem that is essentially different from the problems discussed in Chapters 4 and 5, the definitions in overlapping alphabets would not cause inconsistency issues. For clarity of presentations, we list the variables and symbols for the two problems in two separate lists.

Chapters 4 and 5

S	Set of suppliers
M	Set of materials
T	Set of distribution centers
R	Set of retailers
i	Supplier, $i \in S = \{1, \ldots, m\}$
j	Material type, $j \in M = \{1, \ldots, n\}$
S_j	Set of suppliers providing material *j*, $S_j \subseteq S$
t	Distribution center (DC), $t \in T = \{1, \ldots, g\}$
r	Retailer, $r \in R = \{1, \ldots, l\}$
f	the total demand for product
f_r	the demand for product from retailer *r*
a_{ij}	capacity of supplier *i* for material *j*, $i \in S_j \subseteq S$
b_{ij}	minimum order quantity of supplier *i* for material *j*, $i \in S_j \subseteq S$
d_j	demand for material *j*
c_{ij}	unit cost of purchasing and shipping material *j* from supplier *i*, $i \in S_j \subseteq S$

K_t	capacity of distribution center (DC) t
u_r	cost of establishing marketing channel with retailer r
v_t	cost of establishing facilities in DC t
q_{ij}	fixed cost of ordering material j from supplier i, $i \in S_j \subseteq S$
e_{tr}	unit cost of shipping product from plant to retailer r via DC t
P_i^S	the probability of disruption in supplier i
P_t^T	the probability of disruption in DC t
P_r^R	the probability of disruption in retailer r
P_m	the probability of disruption in manufacturer
ρ_i^S	the flexibility score for supplier i
ρ_t^T	the flexibility score for DC t
ρ_r^R	the flexibility score for retailer r
ρ_m	the flexibility score for manufacturer
Q_i^S	quality score of supplier i
Q_t^T	quality score of DC t
Q_r^R	quality score of retailer r
I_i^S	innovation score of supplier i
I_t^T	innovation score of DC t
I_r^R	innovation score of retailer r
P_{risk}	the disruption risk threshold index for the supply chain
P_{flex}	the flexibility threshold index for the supply chain
Q	the quality threshold index for the supply chain
I	the innovation threshold index for the supply chain
Mn_j	the minimum number of suppliers for material j
k_{risk}	the weight of material disruptions compared to product disruptions
k_{flex}	the weight of production flexibility compared to service flexibility

k_{fm}	the weight of manufacturing flexibility in the material stage
k_{fr}	the weight of retailing flexibility in the product stage
k_{q1}	the weight of service quality in the material supply stage
k_{q2}	the weight of quality in the product distribution stage
k_{I1}	the weight of innovation in the material supply stage
k_{I2}	the weight of innovation in the product distribution stage
x_{ij}	decision variable, equals to 1 if supplier *i* is selected as the supplier of material *j*, otherwise 0
w_{ij}	decision variable, the fraction of demand for material *j* supplied by supplier *i*, where $\sum_{i \in S_j} w_{ij} = 1, \quad 0 \le w_{ij} \le 1$
y_t	decision variable, equals to 1 if DC *t* is selected, 0 otherwise
z_r	decision variable, equals to 1 if retailer *r* is selected, 0 otherwise
π_{tr}	decision variable, 1 if product for retailer *r* is shipped from DC *t*, 0 otherwise
α	the confidence level
β	disruption scenario, $\beta \in \theta = \{1, \ldots, h\}$
θ	the index set of potential disruption scenarios
P_β	the probability of scenario β
c_j^S	unit cost of handling shortage of material *j*, $j \in M = \{1, \ldots, n\}$
c_t^T	unit cost of handling disruptions in DC *t*
c_r^R	unit cost of handling disruptions in retailer *r*
τ_β	decision variable, tail cost in scenario β
$\delta_{j\beta}^S$	decision variable, shortage of material *j* in scenario β
γ	decision variable, a threshold such that the probability of the total cost exceeding γ is not greater than 1-α

Chapter 6

$\mathbf{N}$	Set of nodes
$\mathbf{N_p}$	Set of purchase contract nodes
$\mathbf{N_d}$	Set of sales contract nodes
$\mathbf{M}$	Set of manufactory nodes
$\mathbf{P}$	Set of product nodes
$\mathbf{N_s}$	Set of supplier nodes
$\mathbf{N_r}$	Set of retailer nodes
$\mathbf{N_{DC}}$	Set of DC nodes
$\mathbf{N_j}$	Set of road junction nodes
$\mathbf{A}$	Set of arcs
$\mathbf{A_p}$	Set of purchase contract arcs
$\mathbf{A_d}$	Set of sales contract arcs
$\mathbf{A_m}$	Set of manufacture arcs
$\mathbf{A_t}$	Set of transportation arcs
$\mathbf{K}$	Set of commodities
f_k	the demand of commodity k, $k \in \mathbf{K}$
s^k	source of commodity flow k
t^k	sink of commodity flow k
o_{ij}	original cost of using arc (i, j)
d_{ij}	additional cost of using arc (i, j)
c_{ij}	cost for interdicting arc (i, j)
e_{ij}	the cost for reinforcing arc (i, j)
B	interdiction budget
H	protection budget
x_{ij}	the decision variable for the network attacker, the percentage of interdiction on arc (i, j), $0 \leq x_{ij} \leq 1, \forall\ (i, j) \in \mathbf{A}$

y_{ij}^k	the decision variable of network user, the flow of commodity k on arc (i, j)
r_{ij}	the decision variable of the defender, which determines the protection decision on arc (i, j)

Chapter 1 Introduction

1.1 Overview

This chapter provides an introduction of the research covered in this study. Firstly, the background and the focus of this research on the strategic decision making in supply chain under disruption risks are explained. The aim and objectives of this study are outlined, followed by a brief introduction of the research approach. Finally, details of the structure of this thesis are presented.

1.2 Research Background

The real competition in contemporary business environment is fought between supply chains and not companies (Mart ńez-Olvera and Shunk, 2006), and therefore achieving strategic alignments of the supply chain is crucial to the competitiveness of each member within the chain. As a matter of fact, each supply chain has one or several core companies and many supporting companies, and the core companies should be responsible in making the right supply chain decisions and achieving strategic alignment of the supply chain. Supply chain decisions can be classified into strategic level decisions, tactical level decisions, and operational level decisions. Strategic level decisions in supply chain include supply chain strategy formulation, supply chain design, product management throughout life cycle, information management, and protection strategies against worst case disruptions. The focus of this study is on the strategic level decision making in supply chain under disruption risks, and the two kinds of strategic level decisions that can be incorporated with risk considerations are supply chain design and protection strategies against worst case disruptions.

As supply chains becoming increasingly complex, designing or renewing a supply chain that supports sustainable value creation becomes a rather difficult but critical task in supply chain management, since the process of designing a supply chain often involves many conflicting criteria such as quality and price, efficiency and responsiveness, etc. When risks in supply chain are concerned, it is suggested in some studies that the degree of integration in supply chain can affect the reliability level of the chain, and thus collaboration within the supply chain could be considered as a risk mitigation strategy (Chang Won, Ik-Whan, and Dennis 2007; Chen, Sohal, and Prajogo 2012). Therefore, in contemporary supply chain management, companies will often keep a long-term partnership with their suppliers and retailers so that performance is in alignment with the supply chain strategy. Thus, it is quite significant that core companies have an effective approach to strategically choose supply chain partners so as to ensure a satisfactory level of performance.

When it comes to managing a supply chain under operation, the strategic level decisions are related to the allocation of protection resources in order to fortify critical components in the supply chain network system. Recent events have demonstrated that a corporation's ability to provide critical services to customers can be affected by a single disruption in supply chain through domino effects (Juttner, Peck and Christopher, 2003). Therefore being able to identify the vulnerable parts of the supply chain where single disruptions can lead to significant degradation in supply chain performance, is of great importance for the decision makers. Risks in supply chain operation stage mainly come from uncertainties and intentional attacks. Dealing with daily uncertainties is more related to tactical and operational level decisions, and these uncertainties are usually modeled by random variables in stochastic optimization or robust optimization models, while disruptions due to intentional attacks require more of strategic level decision makings, since intentional attacks would often bring catastrophic consequences. Efficient methods for identifying critical parts in supply chain to be protected against worst case disruptions are needed in order to help supply chain managers making strategic decisions.

In conclusion, the area of research for this thesis is focused on the field of strategic decision making in supply chain under disruption risks. In particular, supply chain partner selection decisions and decisions on the fortifications of critical parts in supply chain against worst case disruptions will be discussed in this thesis.

1.3 Research Aim and Objectives

The aim of this study is to provide quantitative approaches that support strategic decision making in supply chain subjected to disruption risks. The objective is to perform a detailed review of existing literature on the related subjects, and identify current tools and methods for strategic decision making in supply chain management. Based on the understanding of the state-of-the-art techniques in related research themes, the aim of this study is to improve the understanding on strategic supply chain decisions when aware of disruption risks by investigating practical methods in solving supply chain partner selection problems as well as identifying optimal protection strategies against worst case disruptions. The proposed quantitative approaches will enable companies to make informed decisions on the selection of strategic supply chain partners, which will then enhance the strategic alignment of the supply chain and lead to the increase in competitiveness of the company; supply chain managers would also be able to make informed decisions on the fortification plans of the supply chain based on the solutions of our approach. The specific research objectives in order to achieve the research aims are listed as follows:

1. To develop an efficient approach for strategic decision making in supply chain partner selection, which is incorporated with trade-off options and risk considerations.
2. To develop methods to support strategic decision making in the protection against worst case disruptions in supply chain.
3. To validate the proposed approaches by applying them to case studies in a number of different industries.

The proposed approaches can help to form a conceptual framework for strategic decision making in supply chain under disruption risks, which includes supply chain strategy formulation, supply chain design, supply chain protection strategy, and supply chain monitoring and evaluation. In this study, the research focus is on the partner selections in supply chain design and supply chain protection strategy under disruption risks.

The three case studies discussed are based on three companies in different regions of the world and in different industries (An European company in chemical industry, an Indian company in iron and steel industry, and a South African company in the vaccine industry), and the aim is to examine the applicability of the proposed approach in both developed and developing countries and in different industries.

1.4 Research Approach

This study starts from performing a detailed review of existing literature on the related research fields, which include supply chain strategy formulation, supplier selection, supply chain design, supply chain risk management, and network vulnerability and network interdiction. Then based on the research gaps identified, more practical approaches are developed by using multi-criteria decision making techniques, mathematical programming techniques, and decision analysis theories. Three case studies are applied to validate the proposed approaches. A detailed introduction of research methodology is discussed in Chapter 3.

1.5 Outline of the Thesis

There are seven chapters in this thesis, including this chapter. Table 1.1 briefly explains the structure of this thesis and the content of each chapter.

Chapter 1 introduces the content of the thesis, including the background of this study, the researched questions, the study aim and objectives and briefly outlines contents of each chapter.

Chapter 2 reviews the key concepts and key approaches related to strategic decision making in the context of supply chain, and critically analyses research gaps that need to be filled in future studies. Five interconnected themes are examined in the literature review, including supply chain strategy, supplier selection problem, supply chain network design, supply chain risk management, and network vulnerability and network interdiction.

Chapter 3 presents a conceptual framework for strategic decision making in supply chain, and outlines the related research methodologies applied in this thesis and the justification for the chosen research approach. It explains the theoretical position for researching the strategic decision making approaches in supply chain.

Table 1.1: Structure of the thesis and the focus of each chapter

Chapter	Focus of the chapter
Chapter 1 **Introduction**	Overall introduction to the thesis
Chapter 2 **Literature Review**	Review of theories and methodologies relevant to the topic and outline of key theories and concepts used in this research
Chapter 3 **A Decision Framework for Strategic Planning in Supply Chain and Related Methodologies**	A conceptual framework for strategic decision making in supply chain, and related methodologies used in this research
Chapter 4 **Supply Chain Partner Selection with Trade-off Options**	Supply chain partner selections incorporated with strategic trade-off options and supply chain level performance requirements
Chapter 5 **Supply Chain Partner Selection with Risk Considerations**	Supply chain partner selections incorporated with Conditional Value-at-Risk to account for the risk considerations
Chapter 6 **Supply Chain Fortification Against Worst Case Disruptions**	Identification of optimal protection strategies against intentional attacks or worst case disruptions in supply chains
Chapter 7 **Conclusion**	Conclusions and assessment of the value of this research

Chapter 4 develops a quantitative approach for supply chain partner selections and design, which incorporates the trade-off options and the supply chain level requirements to allow for a greater range of choices and potentially better supply chain structures. Details of the definitions of supply chain performance measurements and trade-off options are explained. The trade-off constraints are integrated into a mixed integer programming model, which allows for multiple supply chain characteristic diversifications in the supply chain design process. Numerical analysis and a case study of a European chemical company are presented in the end of this chapter.

Chapter 5 continues with the discussion of supply chain partner selections and design, and introduces Conditional Value-at-Risk to model the risk consideration in the supply chain designing process. A new decomposition scenario management approach is proposed to reduce the number of disruption scenarios that are needed to be examined in solving the problem. Numerical analysis and a case study of an Indian iron and steel company are presented in the end of this chapter.

Chapter 6 presents a quantitative method for identifying the optimal protection strategies against intentional attacks or worst case disruptions in supply chain. A new way of defining supply chain networks using graph theory is explained. The problem is modeled as a tri-level defender-attacker-user optimization model, which is then transformed into an equivalent MIP model using duality theory and standard linearization techniques. Numerical analysis and a case study of a South African third party logistics company in vaccine industry are presented in the end of this chapter.

Chapter 7 presents the overall research conclusions and final remarks. This chapter reviews the theoretical purpose, implications and the contribution of this research. The key strengths and limitations of the research are discussed in this chapter, followed by recommendations for future research.

1.6 Summary

This chapter provides an overview of the research presented in this thesis. Firstly, this chapter explains the background and the focus of this research on the strategic decision making in supply chain under disruption risks. Then the aim and objectives of this study is outlined, followed by a brief introduction of the research approach. The next chapter reviews the literature, key concepts and theories related to the study.

Chapter 2 Literature Review

2.1 Introduction

The literature review examines key concepts and key approaches related to strategic decision making in the context of supply chain, and critically analyses research gaps that need to be filled in future studies. Five interconnected themes are examined in this literature review, including supply chain strategy, supplier selection problem, supply chain network design, supply chain risk management, and network vulnerability and network interdiction. The review begins with a discussion of the definition of supply chain strategy and how to formulate supply chain strategies. Then the review focuses on supplier selection problems and supply chain network designs. The review examines the evaluation criteria, trade-offs between conflicting criteria as well as decision making approaches in supplier selection problems, and different approaches used for designing a value creating supply chain network. Then the review considers the vulnerability of the supply chain network by examining issues regarding supply chain risk management and network interdiction problems.

2.2 Supply Chain Strategy

2.2.1 Supply chain strategy definition

Supply chain is defined as a ‘networked organization’ based on a group of enterprises collaborating in the value chain to acquire and convert raw materials into the final product and deliver the product (Ivanov, 2010). Supply chain management is the management of flows of goods and services in supply chain, with the objective of reducing cost and boosting efficiency, as well as sustainable value creation. In order to achieve such goals, solid competitive strategy and the corresponding supply chain strategy are needed. Competitive strategy is a holistic, long-term plan for a company to establish a competitive advantage that helps the company outperform others in the industry and guarantees the profitability of the company (Porter, 1985; Porter 1987). The company's supply chain plays an important role in the achievement of the strategic goals specified in the competitive strategy. As discussed in Cetinkaya et al, (2011), supply chain strategy serves as a bridge between competitive strategy and supply chain operations, which determines the goals and configurations of the supply chain in terms of supply chain partners, structures, processes and systems.

2.2.2 Supply chain strategy formulation

The findings of Mckone et al. (2009) revealed that in practice the supply chain strategy is often not linked to the competitive strategy. Even of more concerning are the facts revealed in Saad et al. (2002) showing that companies in certain industries are weak at adapting the supply chain principles. The reason for such phenomenon might lies in the fact that supply chain decisions are commonly based on individual company profitability goals (Leng and Chen, 2012), though there are increasing number of researchers supporting the idea that a supply chain strategy is a single entity system that includes all of the participants in a given supply chain (Mintzberg et al., 1998, Schnetzler et al., 2007, Perez-Franco, 2010). In fact, in a networked supply chain the risks faced by one organization generally cannot be prevented by that company alone. In other words, risk management and reduction in a supply chain also depends on the actions of supply chain partners in the system (Heal and Kunreuther, 2010; Rice and Caniato, 2003). As a matter of fact, business competitions in contemporary society are no longer between individual companies, essentially it has become the competition between supply chains. Therefore, the competitiveness of the group of companies in a supply chain depends on strategic alignment of operations (Sakka et al., 2011), and this fact obviously indicates the importance of a solid supply chain strategy for a company. According to the studies of Yinan, Xiande and Chwen(2011), enhancing the strategic alignment between the supply chain strategy and the competitive strategy has a clear benefit to business performance.

Various methods have been proposed for the supply chain strategy formulation problem. The first stage in supply chain strategy formulation should be understanding the customer, and as Fisher (1997) stated, the most important factors to be considered in formulating supply chain strategy are the demand nature of the product, demand predictability, product life cycle, product variety, market standards and influences such as the percentage of demand filled in from in-stock products. Fisher (1997) also pointed out that the 'efficiency' and 'responsiveness' of a supply chain strategy are fundamental features for the company's success. Alternatively Narasimhan et al. (2008) developed the supply chain strategy based on the assessment of internal and external factors that contribute to or limit a company's potential for competitive success. Qu et al. (2010) optimized the configuration of a supply chain strategy by applying analytical target cascading (ATC) approaches, in which individual companies in the supply chain are represented as separate elements with autonomous and heterogeneous decision systems for optimizing decision variables. Schnetzler et al. (2007) constructed a structured system of goals and means based on applying axiomatic design, the system is known as “supply chain strategy decomposition”, which translates strategic priorities into the supply chain strategic operations to generate value and support the corporate strategy. Ivanov (2010) considers supply chain strategy, supply chain design, tactic decisions and operational decisions as a conceptual system for supply chain planning and adaptation, in which supply chain is considered as a complex multi-structural decentralized system with active independent elements. Some studies made an attempt to apply engineering principles to the supply chain strategy problem. For example, Lertpattarapong (2002) proposed a system dynamics approach, which used the causal loop diagram as a visualization method for the insight of an existing supply chain problem.

In conclusion, supply chain strategy plays an important role in bridging the competitive strategy and supply chain operations, both of which are crucial to a company’s profitability and long-term success. As business competitions nowadays are essentially the competition of supply chains, achieving strategic alignments of the supply chain is crucial to the competitiveness of each member within the chain. The reviewed studies on supply chain strategy formulation have the potential to help supply chain managers to formulate supply chain strategies that work best with the competitive strategy. These studies on supply chain strategy formulation will be considered as one of the theoretical foundations of the decision framework for strategic planning in supply chain proposed in Chapter 3.

2.3 Supplier Selection Problem

Since strategic alignment is crucial to business competitiveness, selecting the right supply chain partners that fit the company's strategies then becomes an important issue. Supplier selection is a complex problem that is closely related to our research interest, and have attracted much research attention over the past fifty years.

2.3.1 Evaluation criterion

Ho, Xu and Dey (2010) reviewed 78 papers on supplier selection problem using multi-criteria decision making approaches that appeared from 2000 to 2008, and found that the most frequently used criteria in literature are: quality, delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment. Figure 2.1 illustrates the most popular evaluation criteria in supplier selection approaches and their percentage of appearance in literatures reviewed in Ho, Xu and Dey (2010). This finding reveals the fact that traditional single criterion approaches based on minimizing cost are no longer robust enough to support decision makings in supplier selection problems. Hence, supplier selection approaches are commonly developed based on Multi-criteria decision making techniques.

Some research efforts are focused on defining and quantifying the characteristics of supply chain partners. As with the various evaluation criteria, supplier characteristics can be classified into intangible characteristics and tangible characteristics. Intangible characteristics such as innovation or service quality are more difficult to define or quantify, and some researchers suggest using the analytic hierarchy process (AHP) approach (Wang, Huang, and Dismukes 2004), while others use a survey-based performance ratings approach (Sarode, Adarsh, and Khodke 2010). The definitions of tangible characteristics are much more straightforward, for example reliability is defined as the rate of on-time delivery in Van Nieuwhnhuyse and Vandeale (2006), and responsiveness is suggested to be defined based on length of lead time and quantity flexibility in Pereira et al (2009). Some studies suggest that strategic trade-offs should be considered in optimization models in order to contribute valuable insights (Huang and Keskar 2007), and a model without specifically quantified criteria incorporated is problematic. The reviewed studies will be used as references in terms of choosing the evaluation criteria in this research.

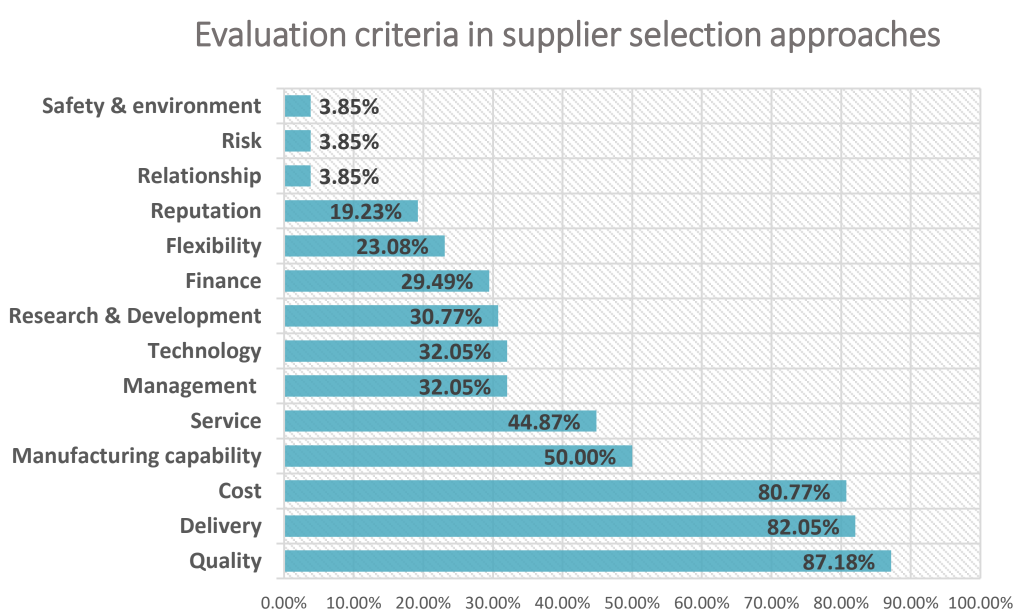


Figure 2.1: Evaluation criteria in supplier selection approaches

2.3.2 Trade-offs between conflicting criteria

As a matter of fact, the many characteristics of potential supply chain partners are often in conflict, and the challenge for a firm is to choose between these conflicting characteristics (Benner and Tushman, 2003; Girotra and Netessine, 2011). These trade-offs between characteristics are often critical to the business performance, as they are the key to achieving strategic alignment. In recent years, some researchers began to consider trade-offs in the modelling of supplier selection problems. Jain, Benyoucef, and Deshmukh (2008) highlighted the value of modelling the trade-offs and the challenge of defining and quantifying the characteristics of suppliers. Later, Chung, Talluri and Narasimhan (2010), and Massow and Canbolat (2014) both used optimization models that has incorporated trade-offs to assist supplier selections. The optimization model discussed in Chung, Talluri, and Narasimhan (2010) selects the best suppliers with a trade-off between flexibility and price taken into consideration, the results of which suggest that considering trade-off options in a decision model could add value to the analysis. Massow and Canbolat (2014) used a mixed integer programming model that allows for diversified supplier strategies based on not only capacity constraints but also risk pooling and minimum performance requirements. For example, sourcing from both a supplier with less risk of disruption and a cheaper supplier from overseas may allow for lower purchasing costs while maintaining the risk at an acceptable level. Massow and Canbolat (2014) also argue that considering risk pooling and minimum performance requirements allows for flexibility in the supply chain decision making process, and may provide a greater range of choices and potentially more cost efficient structures that meet strategic objectives.

In this research, the approach for supply chain partner selection will be developed based on the concepts of trade-offs, risk pooling, and minimum requirements identified from the above reviewed literatures.

2.3.3 Decision making approaches in supplier selection

Various methods have been proposed to solve supplier selection problems in the literature, and can be classified into individual decision making approaches and integrated decision making approaches. Individual approaches include multi-criteria decision making techniques, mathematical programming techniques, and artificial intelligence techniques; while integrated approaches are the combination of several independent approaches, which mainly include integrated AHP (Analytic hierarchy process)/ ANP (Analytic network process) approaches, integrated fuzzy approaches, and integrated DEA (Data envelopment analysis) approaches.

Many different multi-criteria decision making techniques have been applied to solve supplier selection problems. Multi-attribute utility methods, such as analytic hierarchy process (AHP) and analytic network process (ANP), are commonly used in the literature. For example, Levary (2008) uses the analytic hierarchy process to evaluate and rank potential suppliers based on supply risks in order to build a reliable supply chain. Lin et al. (2010) applied the analytic network process technique to cope with an interactive vendor evaluation and selection problem, in which the weightings to each dimension and criterion in the evaluation model are arranged by summarizing the opinions of the expert. Outranking methods are also applied by some researchers to solve supplier selection problems. For example, Sevkli (2010) proposed the fuzzy technique for ELECTRE (ELimination and Choice Expressing REality) to deal with the imprecise or vague nature of linguistic assessment, and applied the proposed method to a manufacturing company in Turkey. In general, the ELECTRE method first constructs the outranking relations to compare each pair of alternatives, and then go through an exploitation procedure that elaborates on the recommendations obtained in the first phase. Chen et al. (2011) presents the fuzzy Preference Ranking Organization Method for Enrichment Evaluation (fuzzy PROMETHEE) to evaluate four potential information system suppliers using seven criteria in an outsourcing context. In general, PROMETHEE method starts by making pairwise comparisons through preference functions, a multi-criteria preference degree is then computed to globally compare every couple of actions, after which the positive and negative preference flows are calculated and aggregated into the net preference flow, which will help to determine the complete ranking. Besides Multi-attribute utility methods and outranking methods, we can also see some application of compromise methods (Yu, 1973) in the supplier selection literature. In such methods, a compromise denotes an agreement on the basis of mutual concessions, and a compromise solution is the closest solution to the ideal one. Chen and Wang (2009) uses the fuzzy VIKOR method to evaluate and assess possible suppliers/vendors in an information system/information technology (IS/IT) outsourcing problem. In general, the VIKOR method determines the best compromise solution from the set of feasible alternatives according to the set of criterion functions, in which each criterion function is assigned a best and a worst value.

Supplier selection problems can also be solved using mathematical programming techniques. Wu and Blackhurst (2009) proposes a supplier evaluation and selection method based on the data envelopment analysis (DEA) approach, in which weight constraints are introduced to reduce the possibility of having inappropriate input and output factor weights. Hsu et al. (2010) applies a well-known method used in fuzzy sets theory called "the resolution identity result", to solve nonlinear programming problems with bounded variables, and then the best suppliers are selected by applying a ranking method of fuzzy preference relations of suppliers. Yu et al. (2012) applies a fuzzy multi-objective program (MOP) to solve a vendor selection problem under lean procurement, which is based on cost minimization, delivery schedule violation minimization, and quality level maximization. Kull and Talluri (2008) proposes an integrated method of analytic hierarchy process and goal programming (GP) for supplier selection problems with disruption risks and product life cycle considerations. Li and Zabinsky (2011) considers a two-stage stochastic programming model and a chance-constrained programming model to determine a minimal set of suppliers and optimal order quantities with consideration of business volume discounts, in which the uncertainty of demand as well as supplier capacity are incorporated into the supplier selection problem.

Methods in artificial intelligence techniques are also applied in supplier selection problems. Guneri et al. (2011) proposes an approach for supplier selection based on Adaptive Neuro-Fuzzy Inference System (ANFIS), in which criteria are first reduced by applying ANFIS input selection method followed by the construction of ANFIS structure using data related to selected criteria and the output of the problem. ANFIS integrates both neural networks and fuzzy logic principles in a single framework, in which the inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Lee and Ouyang (2009) presents an artificial neural network-based predictive model with application for forecasting the supplier's bid prices in supplier selection negotiation process (SSNP). A method of potential support vector machine combined with decision tree is introduced in Guo et al. (2009) to address issues on supplier selection including feature selection.

Examples of Integrated AHP/ANP approaches include integrated AHP and DEA (Saen, 2007), integrated AHP and goal programing (Mendoza et al., 2008), integrated AHP and multi-objective programing (Xia and Wu, 2007), and integrated ANP and multi-objective programing (Demirtas and Üstün, 2008). In terms of the integrated fuzzy approaches, Kahraman et al. (2003) presented an integrated fuzzy AHP approach for supplier selection, in which preferences about the importance of each evaluating criterion could be specified using linguistic variables. Jain et al. (2004) suggested an integrated fuzzy and genetic algorithm (GA) based approach for supplier selection, in which GA was integrated to generate a number of rules inside the rule set according to the nature and type of the priorities associated with the products and their supplier's attributes. Integrated DEA approaches are discussed in Talluri et al. (2008), which utilized a combination of input oriented DEA and multi-objective programming models to determine the negotiation strategies with efficient suppliers. The advantage of integrated approaches is the combined strengths from each individual approach, though sometimes the integrated approaches may be more difficult to implement.

According to the review of Ho, Xu and Dey (2010), the most popular individual approach for supplier selection problem is data envelopment analysis (DEA), while the most popular integrated approach is the AHP-GP approach (Analytic hierarchy process-Goal programming). However, both approaches have limitations. For DEA, there are two major drawbacks. Firstly, the assignment of ratings to qualitative criteria is subjective. The second concern is due to the nature of DEA, in which suppliers generating more outputs while requiring less input are considered as more efficient，but an efficient supplier may not be equivalent to an effective supplier. For AHP-GP, the major concern is that it may be time-consuming in reaching consensus while using the AHP.

In conclusion, supplier selection is a complex multi-criteria decision making problem, which is of crucial importance to the competitiveness of a company. The evaluation criteria for potential suppliers are often in conflict with each other, therefore it is suggested in the literature that trade-offs between conflicting criteria need to be considered in the decision making process. Various decision making approaches in supplier selection are reviewed, including multi-criteria decision making techniques, mathematical programming techniques, artificial intelligence techniques, as well as integrated approaches such as integrated AHP/ANP approaches, integrated fuzzy approaches, and integrated DEA approaches. In some articles, vendor selection was discussed in an outsourcing context, which essentially belongs to a supplier selection problem. Approaches that deal with the selection and evaluation of all types of supply chain partners are rarely seen in the literature.

2.4 Supply Chain Network Design

The design of supply chain networks (SCN) is another closely related topic, which could be categorized into deterministic SCN design, and SCN design under uncertainty. SCN design models can have one or multiple objective functions, and therefore can be further classified into single-objective SCN design models and multi-objective SCN design models. In this section, we will review supply chain network design literatures based on the above two classifications.

2.4.1 Deterministic supply chain network design models

Facility location models (Drezner, 1995; Daskin et al., 2003), which are deterministic models, can be considered as the foundation of SCN design models. Classic facility location problems are developed to cope with the optimal placement of facilities to minimize costs while considering other factors like avoiding placing hazardous materials near certain facilities. Recent research efforts in facility location models have been focused on developing location models incorporated with transportation and inventory management decisions (Shen 2007; Berger et al. 2007; Romeijn et al. 2007), and deterministic multi-period SCN design models (Vila et al 2006; Paquet et al. 2008).

Besides facility location models, other mathematical programing models are also applied to solve SCN design problem. Costi et al. (2004) presents a mixed integer nonlinear programing (MINLP) model for the location of treatment facilities for solid waste management, in which the objective function concerns the economic cost while the environmental issues are modeled as constraints. Georgiadis et al. (2011) proposed a mixed integer linear programing model for the problem of designing supply chain networks operating under time varying demand uncertainty, which was solved to global optimality using standard branch-and-bound techniques. Qiang and Nagurney (2012) developed a linear programing network model for critical needs in the case of disruptions, in which the objective is to minimize the total generalized costs that may include the monetary, risk, time, and social costs. Elia et al. (2011) proposed a mixed-integer linear program to analyze the energy supply chain network for the hybrid coal, biomass, and natural gas to liquids (CBGTL) facilities, and the objective function is to minimize the total cost of facility investment, feedstock purchase and transportation.

The above mentioned works are all based on single-objective optimization models, while some authors consider multiple objectives in deterministic SCN design problems. For example, Chaabane et al. (2012) proposed a multi-period mixed-integer linear programming based framework for sustainable supply chain design, in which two objectives are considered: one is the traditional economic objective while the other is concerned with an environmental objective. Quariguasi Frota Neto et al. (2008) proposed a bi-objective model for the design and evaluation of sustainable logistic networks, in which balancing the profitability and environmental impacts is the objective. Erkut et al. (2008) develop a multi-criteria facility location model with multiple objectives for the municipal solid waste management, which has five objective functions, one is concerned with minimizing total cost of facilities implementation and flows, and the other four are all related to environmental impacts. Yue et al. (2014) developed a multi-objective optimization model for the sustainable design of bioelectricity supply chain networks, which simultaneously considers economic, environmental, and social impacts, in which the multi-objective problem is solved by applying the ε-constraint method. Table 2.1 summarizes the problem formulations discussed in literature with respect to deterministic supply chain network design models.

Table 2.1: Summary of formulation used in deterministic supply chain network design

	Formulation	Literature
Single Objective	Facility location model	Drezner (1995) Daskin et al. (2003) Vila et al (2006) Shen (2007) Berger et al. (2007) Romeijn et al. (2007) Paquet et al. (2008)
	Mixed integer nonlinear programming model *	Costi et al. (2004)
	Mixed integer programming model *	Georgiadis et al. (2011) Elia et al. (2011)
	Linear programming model *	Qiang and Nagurney (2012)
Multiple Objective	Multi-period mixed integer programming model *	Chaabane et al. (2012)
	Multi-objective programming model *	Quariguasi Frota Neto et al. (2008) Yue et al. (2014)
	Multi-criteria facility location model	Erkut et al. (2008)

* stands for models that do not belong to facility location models

2.4.2 Supply chain network design under uncertainty

While deterministic SCN design models provide a solid foundation for SCN design problems, the solutions from deterministic models cannot guarantee future performance, since deterministic models do not take uncertainties into consideration. Uncertainties in supply chain are often modeled by considering uncertain parameters as random variables, and the static program turns into a two-stage stochastic program, in which the design variables must be implemented before the outcome of the random variables. Mak and Shen (2012) proposed stochastic facility location models for supply chain network design with dynamic sourcing under the risk of temporally dependent and temporally independent disruptions of facilities, and argue that allowing small to moderate degrees of dynamic sourcing can improve robustness against both demand uncertainty and disruptions. Baghalian, Rezapour, and Farahani (2013) considers demand-side and supply-side uncertainties simultaneously in designing a supply chain network with multi-product and capacitated facilities, and developed a stochastic mathematical formulation to solve the problem. Verma et al. (2013) proposed a two-stage stochastic programming approach developed based on facility location models, to determine both the location and stockpile of equipment at the emergency response facilities to respond to oil spill events.

Some authors also considered multiple objectives in stochastic SCN design problems. For example, Amin and Zhang (2013) investigate the impact of demand and return uncertainties in a closed-loop supply chain by implementing scenario-based stochastic programming, and both cost minimization and minimizing environmental impacts are considered. Ruiz-Femenia et al. (2013) analyze the effect of demand uncertainty on the economic and environmental performance of a chemical supply chain, in which they developed a stochastic multi-scenario mixed-integer linear program (MILP) with two objectives. Guillén-Gosálbez and Grossmann (2009) considers simultaneously the maximization of the net present value and the minimization of the environmental impact in a bi-criterion stochastic mixed-integer nonlinear program (MINLP) for the design of sustainable chemical supply chains subjected to life cycle inventory uncertainty. The major difficulty in solving stochastic programing models is to cope with the potentially infinite number of scenarios.

The concept of robustness in SCN design has raised many discussions, and robustness is defined as the ability of a SCN to carry its functions under all plausible future scenarios (Dong 2006). A comprehensive literature review on the design of robust supply chain networks can be found in Klibi, Martel and Guitouni (2010). Yu and Li (2000) reformulated a stochastic problem into a robust optimization model, and the method used to solve the robust model is to transform it into a linear program that requires adding n+m variables, which is shown to be highly efficient in solving logistics management problems. Snyder and Daskin (2006) developed a p-robust facility location model that combines the advantages of traditional stochastic and robust optimization approaches, in which the model seeks the minimum-expected-cost solution that is p-robust (whose relative regret in each scenario is no more than p). Compared to stochastic programing approaches, robust optimization models are usually easier to be implemented. However, in practice the problems that robust approaches can be applied to need to be well defined in terms of the uncertainty set, and the solution of robust optimization models can be very conservative in some cases. Table 2.2 summarizes the approaches used in the literature in terms of supply chain network design under uncertainty.

Table 2.2: Summary of formulation used in supply chain network design under uncertainty

	Formulation	Literature
Single Objective	Stochastic facility location model	Mak and Shen (2012)
	Stochastic programming model *	Baghalian, Rezapour, and Farahani (2013) Verma et al. (2013)
	Robust optimization model *	Yu and Li (2000)
	p-robust facility location model	Snyder and Daskin (2006)
Multiple Objective	Stochastic multi-objective programming model *	Amin and Zhang (2013)
	Multi-objective stochastic facility location model	Guillén-Gosálbez and Grossmann (2009) Ruiz-Femenia et al. (2013)

* stands for models that do not belong to facility location models

2.4.3 Other classifications

Besides classifying the SCN design models based on the deterministic and stochastic nature or number of objectives considered, some authors consider other classifications based on the nature of problems that the SCN design models are solving. In Schmidt and Wilhelm (2000), the reviewed literature are classified according to the operational, tactical and strategic decision levels. The strategic level decisions deal with designing the supply chain network, including facility locations and capacity allocations. The tactical level decisions are related to material flow management, including production planning and control, inventory levels, and lot sizes. The operational level decisions cope with scheduling operations to make sure that the final products will be delivered in-time to customers. Lemmens et al. (2016) classifies the existing literature about SCN design based on network characteristics, and the reviewed models are classified as Location-allocation models, Inventory-location models, and Production-distribution models. Location-allocation models (Pappis and Karacapilidis 1994; Shankar et al. 2013) mainly deal with facility locations, demand allocation, and the trade-off between facility costs and transportation costs. Inventory-location models (Erlebacher and Meller 2000; Shen et al., 2003) are developed based on the location-allocation models, which also considered inventory costs. Production-distribution models (Gebennini et al., 2009) includes production decisions besides locating the DCs and allocating demands.

From the review, it can be concluded that existing literatures on SCN design provide support on strategic and tactical decision making in certain parts of the supply chain. The review on supply chain network design approaches can be served as references in the development of our approach for the supply chain partner selection problems. However, most of the models discussed in the literature are NP-hard problems, and thus the already high computational complexity makes it very challenging to consider the entire supply chain in a SCN design model. As it is pointed out in Klibi, Martel and Guitouni (2010), most of the literatures in SCN design models are either trying to get the best outcome with minimum cost or to mitigate the consequences of uncertainties or disruptions. However, this kind of objective is not sufficient to help a company to develop and keep its competitive advantage, the real goal of a company should be sustainable value creation, which indicates that strategy alignment of the supply chain should be an important factor in designing a value added supply chain.

2.5 Supply Chain Risk Management

2.5.1 Definition of supply chain risk

Definitions of supply chain risk in literature have not reached consensus. Some researchers provide definitions that focus on specific parts of supply chain, for example, Ellis, Henry, and Shockley (2010) focus on supply risk and define supply chain risk as 'an individual's perception of the total potential loss associated with the disruption of supply of a particular purchased item from a particular supplier'; the definition given in Jüttner, Peck, and Christopher (2003) says that 'supply chain risk is any risk for the information, material and product flows from original suppliers to the delivery of the final product for the end user'. Some authors define supply chain risks from a general perspective. For example, Bogataj and Bogataj (2007) define supply chain risk as 'the potential variation of outcomes that influence the decrease of value added at any activity cell in a chain'; in Ho et al. (2015), the definition of supply chain risk is given as 'the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities', and they further defined supply chain risk management as 'an inter-organizational collaborative endeavor utilizing quantitative and qualitative risk management methodologies to identify, evaluate, mitigate and monitor unexpected macro and micro level events or conditions, which might adversely impact any part of a supply chain'. Norrman and Jansson (2004) proposed a risk matrix which illustrates that risk in supply chain is determined by both the probability of disruption event and its business impact. Figure 2.2 presents the risk matrix discussed in Norrman and Jansson (2004).

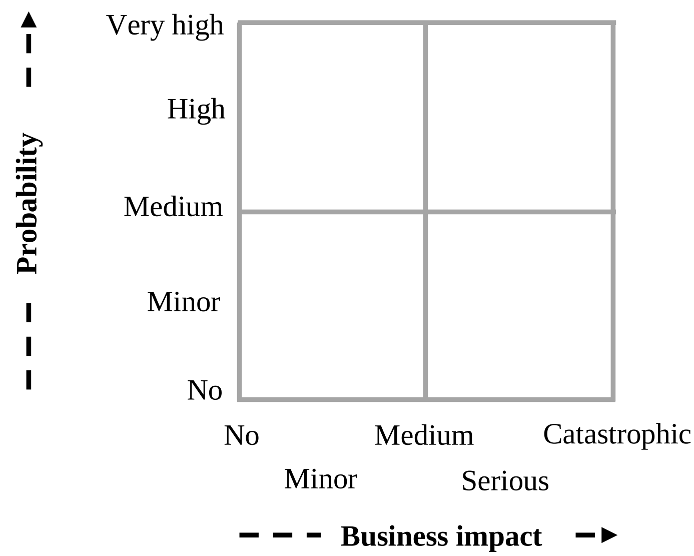


Figure 2.2: Risk matrix (Norrman and Jansson, 2004)

2.5.2 Supply chain risk types

Researchers have classified supply chain risks in different ways in the literature. Tang and Musa (2010) classify supply chain risk according to the flow types, and reviewed major issues discussed in material flow risk, financial flow risk and information flow risk. The common issues regarding material flow risk can be further categorized into sourcing risks, manufacture risks and deliver risks. Sourcing risks include single source risk (Peck et al., 2003), flexible supplier sourcing (Kamrad and Siddique, 2004) and risks regarding supplier selection and outsourcing (Berger et al., 2004). Studies about manufacture risks mainly discuss production capacity risk (Fang and Whinston, 2007) and operational disruption (Tomlin, 2006). Deliver risks are caused by demand volatility, balance of unmet demand and excess inventory, while these issues are often affected by the forecasting difficulties (Tang and Musa, 2010). Financial flow risks include exchange rate risk, price and cost risk and financial handling risk, and relevant studies can be found in Goh et al. (2007), Bovet(2006) and Hartley-Urquhart (2006). Financial strength of supply chain partners is also an important issue in financial flow risk, Hendricks and Singhal (2005) empirically investigates financial flow vulnerability and long-term effect of supply chain disruptions with focus on financial strength of supply chain partners. Information flow risk is another important issue in Supply Chain Risk Management, but the research in this area is still in an early stage, and there is a lack of quantitative models in information flow analysis (Tang and Musa, 2010). It appears that while literatures on managing single risks are well developed, the research effort in analyzing and mitigating the vulnerability of the supply chain with multiple types of risks taken into consideration is hardly seen. Though there is a growing awareness of supply chain risk management in industry, quantitative models for analyzing and mitigating the risks in supply chain is still lacking.

Another type of classification is based on the nature of risks. For example, Olson and Wu (2010) reviews supply chain risk management literature and supply chain risks are categorized into internal risks and external risks. Internal risks come from uncertainties in activities inside the supply chain such as available capacity, internal operations and information systems, while external risks are mainly due to factors outside of the supply chain, like natural disasters, political system, competitors and market uncertainties. Similarly, in Ravindran et al. (2010), supply chain risk is divided into operational risk and disruption risk. Some researchers classified supply chain risk types according to the degree of impact. For example, Ho et al. (2015) argue that supply chain risks can be divided into macro risks and micro risks, where macro risks consist of natural disasters and man-made risks (e.g. war, terrorism and political instability) that have relatively greater negative impacts, and micro risks come from operations within the supply chain and can be further categorized into demand risk, manufacturing risk, supply risk and infrastructural risk.

In conclusion, supply chain risks can be categorized based on different types of flow (material flow, financial flow and information flow), external and internal factors, and degree of negative impact (macro risks and micro risks). Figure 2.3 illustrates the conceptual framework of supply chain risks proposed in Ho et al. (2015). In this research, the risk in supply chain will be examined by different types of flows, specifically, in the partner selection problems (Chapter 4 and 5), since we are focusing more on the supply chain's overall ability of delivering products to customers, the disruption risk will be examined mainly from material flow (which will be divided into raw material flow and product flow), while all three types of flows are considered in Chapter 6.

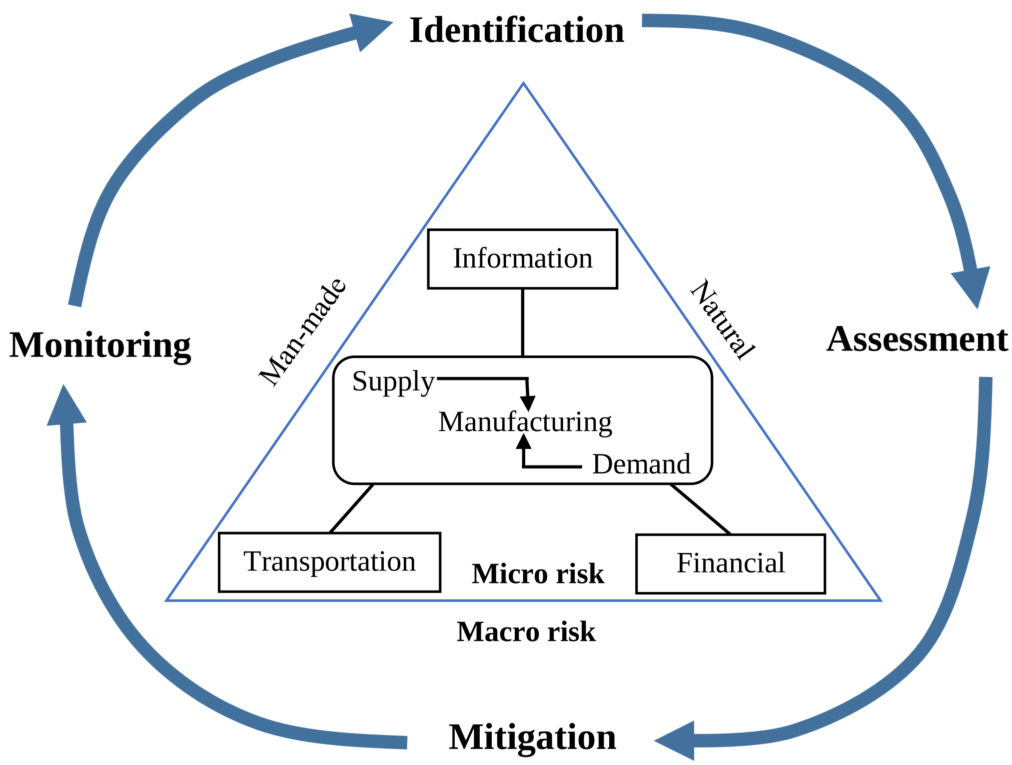


Figure 2.3: Conceptual framework of supply chain risks (Ho et al., 2015)

2.5.3 Supply chain risk mitigation

In terms of supply chain risk mitigation, significant amount of research efforts have been devoted in demand risk mitigation and supply risk mitigation. For demand risk mitigation, one of the natural problems is how to make replenishment plans to best cope with demand uncertainty. Snyder, Daskin, and Teo (2007) proposed a stochastic integer linear programming model with risk pooling to optimize location, inventory, and allocation decisions under demand uncertainty. Schmitt and Singh (2012) developed a simulation model to analyze inventory placement and back-up methodologies in a multi-echelon network under supply disruptions and demand uncertainty. Some researchers focus their effort on the optimal forecasting techniques to mitigate demand risk, for example, a simulation-based decision support framework is presented in Crnkovic, Tayi, and Ballou (2008) to evaluate and select alternative forecasting methods in a supply chain under demand uncertainty. Another risk mitigating method to deal with demand uncertainty is to use risk-sharing contracts to minimize the loss due to uncertain demand. For example in Chen and Yano (2010), a weather-linked rebate is proposed to help improve the manufacturer's expected profit in a manufacturer-retailer supply chain for a seasonal product whose demand is weather sensitive.

For supply risk mitigation, both quantitative and qualitative approaches are applied in literature. Examples of using quantitative methods to determine supplier selection and order allocation include newsvendor model (Giri 2011), data envelopment analysis (Wu and Blackhurst, 2009)), stochastic optimization model (Li and Zabinsky, 2011), and fuzzy multi-objective program (Yu et al., 2012). Some authors discussed the decision of optimal number of suppliers in a supply chain subjected to disruption risks, and there is a consensus that a dual-sourcing strategy outperforms single-sourcing strategy in the presence of supply disruptions (Xanthopoulos, Vlachos, and Iakovou, 2012). There are also some empirical studies showing that supply risk can be mitigated by building strategic relationships with suppliers (Hallikas et al., 2005), as well as through early supplier involvement (Zsidisin and Smith, 2005).

The mitigation methods for other types of supply chain risks are also discussed in literature, though the research attention is limited compared with that of supply and demand risks. Kenné, Dejax, and Gharbi (2012) discussed manufacturing risk mitigation by proposing a manufacturing/remanufacturing policy to deal with the production planning and control problem in a closed-loop reverse logistics network with machines subject to random failures and repairs. Lundin (2012) applied the network flow modelling to mitigate the financial risks in the closed-loop supply chains. Le et al. (2013) proposed an association rule hiding algorithm to remove sensitive knowledge from the released database, and mitigate information risks by minimizing the data distortion. Hale and Moberg (2005) presented a five-stage disaster management framework for macro-risks mitigation, in which the framework consists of planning, mitigation, detection, response and recovery.

The literatures on supply chain risk mitigation have provided another layer of understanding on supply chain risk management by discussing the detailed methods to mitigate different types of supply chain risks, and can provide guidance in our discussion of supply chain fortification strategies against disruptions in Chapter 6.

2.6 Network Vulnerability and Network Interdiction

2.6.1 Network vulnerability

There is no consensus on the definition of network vulnerability in the literature. Generally, the definition of network vulnerability can be summarized as: a network is considered to be vulnerable if the closure of a set of network elements can cause significant reduction in the network performance. Various methodologies for measuring network vulnerability have been proposed in the literature. For example, importance and exposure measure is proposed in Jenelius et al. (2006) and further developed in Jenelius et al. (2012); Primerano and Taylor (2005) and Taylor et al. (2012) use accessibility measure to study network vulnerability; a measurement developed based on network efficiency is discussed in Holme et al. (2002) and Chen et al. (2012); Kurauchi et al. (2009), and Dinh et al. (2012) discuss network vulnerability from a connectivity point of view; Erath et al. (2010) consider network vulnerability measurement as the direct and indirect consequences of disruptions; in Chen and Miller-Hooks (2012), the measure of resilience is considered as an indicator of network vulnerability. Generally, under each of these measures, a set of network elements is said to be critical if the change in vulnerability measure is most significant when this set of network elements is down. Studies in this area mainly focused on developing the definition of network vulnerability, but little effort was made to improve the computational efficiency. However, the computational burden of this approach can be quite heavy, especially for large networks.

2.6.2 Network interdiction

Network interdiction problem originates from military applications. It involves two players: one is called the attacker, and the other is the defender. The defender uses the network to optimize some objective such as maximizing the amount of flow that can be pushed through the network or minimizing the cost of travelling through the network, while the attacker can operate to impact the functionality of the network under a given budget so as to minimize (or maximize) the defender's objective function. Network interdiction is an instance of a static Stackelberg game (Simaan and Cruz, 1973), and can be applied to different types of network systems such as transportation network, grid network, and water/oil/gas supply network.

For deterministic network interdiction problems, the most basic models are the max flow network interdiction problem (Wood, 1993) and the shortest path network interdiction problem (Fulkerson and Harding, 1977). Shortest path network interdiction problem can be formulated as a mixed-integer-program (MIP), which can be solved readily (Israeli and Wood, 2002). Other variants of shortest path model can be found in Malik, Mittal and Gupta (1989) and Corley and Sha (1982). Lim and Smith (2007) extend the interdiction models to multi-commodity networks. A network interdiction model can be considered as a bi-level optimization problem, where the higher level is a resource allocation problem for the attacker and the lower level is a shortest path or max flow problem for the defender (Shimizu, Ishizuka and Bard, 1997). Although network interdiction models can help to identify the vulnerable parts of the network, protection strategies that are developed based on such information will often lead to suboptimal solutions (Brown et al., 2006). In recent years, tri-level optimization problem has been applied by researchers to develop optimal protection strategies. In tri-level programs, we are dealing with min-max-min or max-min-max problems, i.e., the defender or network user has some knowledge about the interdiction and wants to defend some arcs or nodes under a certain budget so that the loss due to interdiction is minimized. For example, Brown et al. (2006) studied the Defender-Attacker-Defender Model, which is developed based on the max flow network interdiction model, and argue that the final formulation can be solved with Benders decomposition. Cappanera and Scaparra (2010) develop a game theoretic approach to decide the optimal allocation of protection resources in a shortest path network. Jin et al. (2015) developed a tri-level defender–attacker–user game theoretic model for the optimal allocation of protective resources among rail stations in the rail transit network, and the model is solved by applying a nested variable neighborhood search method.

In stochastic variant of network interdiction problems, the interdiction is successful with a known probability and the success of interdiction on each arc is independent, while the objective is to optimize the expected value of shortest path length or the total flow; in other versions of the stochastic network interdiction model, the arc capacities or topology of the network are uncertain, and multiple interdiction attempts may take place (Cormican, Morton and Wood, 1998). A two-stage stochastic mixed-integer program with recourse was proposed in Pan, Charlton, Morton (2003) to identify locations for the installation of nuclear material detectors. Held, Hemmecke, Woodruff (2005) proposed to solve the stochastic network interdiction problem by a decomposition-based method.

The causes of supply chain vulnerability can be categorized into two types: the randomness of nature (natural disasters or accidents) and intentional acts of intelligent attacker (competitors or dissatisfied labor unions). We believe these two different sources of vulnerability should be characterized separately. Specifically, reliability theoretic models are more suitable for analyzing networks subjected to randomness of nature, while game theoretic models are more appropriate for networks that are sensitive to intentional attacks (Golany, Marmur and Rothblum, 2008). Lawrence et al. (2016) classify supply chain disruptions into endogenous disruptions and exogenous disruptions, and point out that endogenous disruptions may be affected by the decision-maker's actions while exogenous disruptions cannot be affected. Therefore, endogenous disruptions can only be modeled using stochastic process, while exogenous disruptions such as natural disasters and accident are often modeled in worst-case disruption models.

Interdiction models can also be applied in facility location problems. Church et al. (2004) presented two interdiction facility location models, the distance-based *r*-interdiction median (RIM) problem and the coverage-based *r*-interdiction covering (RIC) problem, in which *r* out of *p* facilities are to be chosen to interdict in order to cause as much deterioration as possible. Church and Scaparra (2006) present an *r*-interdiction median problem with fortification (RIMF), in which *q* facilities out of *p* existing facilities are chosen to be fortified, in order to minimize the increase in demand-weighted distance caused by a worst case facility interdiction. A capacitated version of the RIMF is proposed in Scaparra and Church (2012). The major differences between network interdiction models and interdiction facility location models are that interdiction can only happen on nodes, and the post-interdiction measure of interest is the distance or travel cost instead of max-flows or shortest path.

To sum up, research efforts in network vulnerability mainly focused on the definition of vulnerability index, while little effort was made to improve the computational efficiency. In fact, the computational burden of this approach is quite heavy, especially for large networks. The most recent research attentions on network interdiction models are related to tri-level network interdiction models and stochastic network interdiction models. Network interdiction models are especially useful in formulating problems that concern with exogenous disruptions or intentional attacks. In Chapter 6, a tri-level network interdiction model is developed to formulate the supply chain fortification problem against worst case disruptions.

2.7 Summary

This review has outlined key areas in the literature that may enhance the understanding of strategic decision making in the supply chain context, which includes supply chain strategy formulation, supplier selection problems, supply chain network design, supply chain risk management, and network vulnerability and network interdiction.

Supply chain strategy plays an important role in bridging the competitive strategy and supply chain operations, both of which are crucial to a company's profitability and long-term success and achieving strategic alignments of the supply chain is crucial to the competitiveness of the entire supply chain. One of the first steps towards strategic alignments is to select an optimal portfolio of suppliers. Supplier selection is a complex multi-criteria decision making problem, in which the evaluation criteria for potential suppliers are often in conflict with each other, and therefore trade-offs between conflicting criteria need to be considered in the decision making process. Though many techniques have been developed in the literature to deal with supplier selections, the research focus is still on optimizing one part of the supply chain partner portfolio. In order to achieve strategic alignments of the entire supply chain, approaches that deal with the evaluation and selection of all types of supply chain partners need to be developed.

Existing literatures on SCN design provide supports on strategic and tactical decision making in certain parts of the supply chain. Most of the models discussed in the literature are NP-hard problems, and thus the already high computational complexity makes it very challenging to consider the entire supply chain in a SCN design model. The traditional objective of minimizing cost or minimizing negative impacts of uncertainties or disruptions is not sufficient to help a company to develop and keep its competitive advantage, where the real goal of a company should be sustainable value creation. Multi-objective SCN design models have been well developed in the area of green supply chain designs. There is a potential for considering multi-objective models for designing a sustainable value creation supply chain.

Risks due to uncertainties or disruptions in supply chain is another crucial area that needs to be considered in the strategic decision making process of supply chain manager. While literatures on managing single risks are well developed, the research effort in analyzing and mitigating the vulnerability of the supply chain with multiple types of risks taken into consideration is hardly seen. Studies that examine the impacts of multiple risk mitigating methods on the supply chain performance or the approaches that can mitigate multiple types of risks are needed in the future.

Studies on network vulnerability and network interdiction can bring insights to the strategic decision making in supply chain as well. Studies in network vulnerability mainly focused on the definition of vulnerability index, but the computational burden of this approach is quite heavy for large networks. Network interdiction models are especially useful in formulating problems concerning exogenous disruptions or intentional attacks. It is revealed in the literature that fortification strategies based on the solution of traditional bi-level network interdiction models may lead to sub-optimal results, and tri-level models based on defender-attacker-user problems are developed to fill the gap. While there are a wide variety of application of network interdiction models in different network systems, applications of network interdiction models in supply chain context is limited in the literature.

In summary, through the literature review we have identified the following research gaps: firstly, there is a lack of approaches dealing with the evaluation and selection of supply chain partners throughout the supply chain in the literature; secondly, there is a need of research effort in analyzing and mitigating the vulnerability of the supply chain with multiple types of risks taken into consideration; thirdly, there is a lack of applications of network interdiction models in supply chain context.

To fulfill these research gaps, this study is intended to provide a holistic framework for strategic decision making in supply chain context, which addresses both partner selection decisions and protection strategies against worst case disruptions. In particular, we introduce a supply chain partner selection approach for achieving the strategic alignment in supply chain, which is also incorporated with risk considerations. The proposed approach for supply chain partner selection addresses the first research gap. A tri-level defender-attacker-user network interdiction model is also developed to identify the optimal protection strategies against worst case disruptions in supply chain, which aims at addressing the second and third research gaps. Case studies are provided to illustrate the strengths of the proposed approaches. The research methodology that guided the research designs in this study is discussed in the next chapter.

Chapter 3 A Decision Framework for Strategic Planning in Supply Chain and Related Methodologies

This chapter starts by presenting a decision framework for strategic planning in the supply chain and specifies the research questions and research focus of this thesis. Then this chapter presents a brief introduction to the related methodologies used in this research.

3.1 A Decision Framework for Strategic Planning in Supply Chain

Based on the concepts and approaches identified in the literature review, we developed a conceptual framework for the strategic decision making in the supply chain, which is presented in Figure 3.1. Essentially, the decision framework starts from the formulation of competitive strategy, followed by the formulation of supply chain strategy. After that comes the supply chain design phase, and then the supply chain implementation phase. Once in the implementation phase, supply chain evaluation is also activated, which provides feedback and enables adjustments for the previous phases (namely, competitive strategy, supply chain strategy, and supply chain design). Product management and information management are factors that can influence the above phases.

More specifically, in the formulation of competitive strategy, the company should specify a long-term plan for establishing a competitive advantage that guarantees the profitability and sustainable growth of the company, as well as developing new products that match this long-term plan. In the next phase, once the competitive strategy is determined, a company should come up with a detailed supply chain strategy that best fits its competitive strategy and business priorities. The third phase comes afterwards, in which the company should build its supply chain based on its supply chain strategy and collectible information about potential partners in supply chain. This process involves supply chain partner selection and supply chain structure design. The strategic decisions in this phase are complicated due to the multiple conflicting criteria in the partner selection problems and supply chain structure designs. The next phase is the supply chain implementation, which includes supply chain risk management and protection planning against worst case disruptions, tactical allocative planning decisions, and operational tasks. Last but not least is the supply chain evaluation. Companies should evaluate the degree to which each level of decisions, namely the competitive strategy, supply chain strategy and supply chain design, is still valid under the ever-changing business environment, and the degree to which each level of decisions is still in alignment with each other.

Product management will influence the formulation of competitive strategy, supply chain strategy, supply chain design, and information management. The product development in product management will also be influenced by the competitive strategy, since the competitive strategy will determine the detailed product characteristics. And product management has an impact on the formulation of competitive strategy because the nature of the product will influence a company's competitive strategy. For example, functional products like gasoline will lead to an efficiency-focused supply chain, while innovative products like the smartphone will often be delivered through a responsive supply chain. Product management also has an influence on the information management system of the company, because the product characteristic will determine the level of involvement of the IT programs and systems in the company's daily operations. Product management can further influence supply chain implementation through information management systems. Information management systems will support the tactical and operational decisions in the implementation phase, by reducing unnecessary procedures and improving efficiency.

In conclusion, the proposed framework is a closed-loop system with a self-adjusting capability, which aims at maintaining competitive advantage and achieving sustainable value creation for the company.

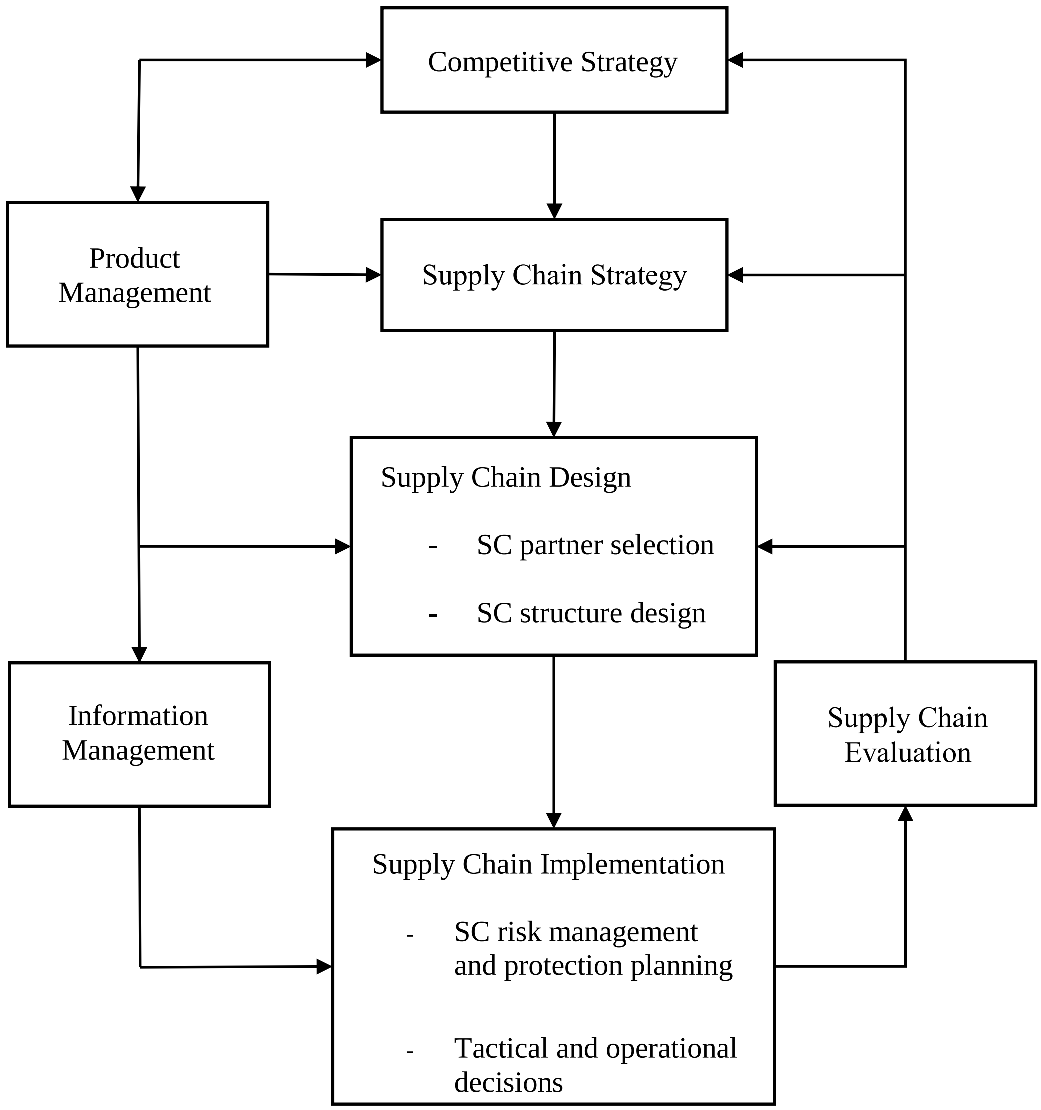


Figure 3.1: A decision framework for strategic planning in supply chain

The main inputs of this framework are the business plan, capital, facilities and manpower, and the outputs are the strategic decisions at each phase and sustainable value creation capability. Supply chain disruptions can be considered as an external factor that can affect the above-mentioned closed-loop and self-adjusting system, and it would be both interesting and important to consider the interactions between disruptions and the strategic decision system, and more importantly, to study how the strategic decision framework can be effectively enhanced to produce more robust strategies, such that the supply chain will be better prepared for or even immune to the future disruption events. Therefore in this thesis, the research focus is on the supply chain partner selection problems under disruption risks, and the optimal protection strategies against worst case disruptions. The research aims are to develop an efficient approach to strategic decision making in supply chain partner selection, which is incorporated with trade-off options and risk considerations; and to develop methods to support strategic decision making in the protection planning against worst case disruptions in supply chain. Based on the ideas, approaches, and methodologies identified in the literature review, Multi-attribute utility theory (MAUT), Analytic Hierarchy Process (AHP) in multi-criteria decision making, and mathematical programming techniques have been chosen as the main research methods in this thesis, which will be briefly introduced in the following sections.

3.2 Multi-Criteria Decision Making

3.2.1 Multi-attribute utility theory

Utility theory is widely accepted in economics and finance, in which utility measures the satisfaction of different individuals towards a service, product, or portfolio, and is often measured based on the price. However, in reality utility does not depend on only one attribute. For example, when an individual is buying a car, there are multiple factors (price, quality, comfortable level, appearance, safety) he/she needs to consider. In such situations, multi-attribute utility theory can be applied, in which the alternatives are first measured using each individual attribute scale and then aggregated by a multi-attribute utility function to arrive at a utility value. More specifically, suppose we have n attributes. Let $(x_1, x_2, \ldots, x_n)$ be the vector of attribute values, then the multi-attribute utility function is denoted by $u(x_1, x_2, \ldots, x_n)$. The multi-attribute utility function $u(x_1, x_2, \ldots, x_n)$ is often calculated by decomposing it into the form of $f(u_1(x_1), u_2(x_2), \ldots, u_n(x_n))$, where each $u_i(x_i)$ is a single-attribute utility function and function f aggregates the individual utilities into a single value. There are three types of multi-attribute utility function, which are additive utility function, multi-linear utility function, and multiplicative utility function. More details of multi-attribute utility theory can be found in Keeney and Raiffa (1976) and Kirkwood (1997). In this research, additive utility function will be applied in the definition of supply chain performance requirements, which will be discussed in detail in Chapter 4.

3.2.2 Analytic hierarchy process

In this research, the performance of supply chain is measured from four aspects: disruption risk, flexibility, quality, and innovation capability. While disruption risk can be quantitatively measured easily by applying the widely accepted definition of probability × consequences, the other three indicators are qualitative concepts that are intangible in nature and are often difficult to be quantified. In such cases, the Analytic Hierarchy Process (AHP) can be applied to measure these qualitative factors. The AHP is a structured technique for organizing and analyzing complex decisions, which is based on three basic functions: structuring complexity using hierarchies, measurements on a ratio scale, and synthesis. As have discussed in

Chapter 2, the AHP is among the popular approaches in supplier selection problems (Ho, Xu and Dey, 2010). More details of the AHP approaches can be found in Appendix A.

In this thesis, the flexibility, quality, and innovation capability of each candidate supply chain partner will be evaluated using the AHP. In particular, the flexibility of a company can be examined from the following five aspects: volume flexibility, delivery flexibility, mix flexibility, new product flexibility, and modification flexibility (Beamon, 1999); quality can be examined from: customer satisfaction, accuracy, fill rate, lead time, response time, and on-time delivery (Chan, 2003; Schonsleben, 2004); the innovation capability of a potential partner can be evaluated from: the ability to launch new products, and the use of new technology (Chan, 2003). More details are discussed in Chapter 4.

3.3 Mathematical Programming

Mathematical programming techniques will be applied to search for the optimal supply chain partner portfolios, as well as the optimal protection strategies against worst case disruptions in supply chain.

As discussed in the literature review in Chapter 2, supplier selection problems can be solved using mathematical programming techniques. In this section, we highlight some key methods that have been applied in the related research topics. Recall that in section 2.3.3, we have reviewed approaches applied in supplier selections, such as data envelopment analysis (DEA) (Wu and Blackhurst, 2009), nonlinear programming (Hsu et al., 2010), multi-objective program (Yu et al., 2012), goal programming (Kull and Talluri, 2008), stochastic programing (Li and Zabinsky, 2011). As discussed in section 2.3.3, multi-criteria decision making techniques can be integrated with mathematical programming techniques to solve partner selection problems, such as, integrated AHP and goal programing (Mendoza et al., 2008), integrated AHP and multi-objective programing (Xia and Wu, 2007), etc.. In this research, after the supply chain performance requirements are properly defined using multi-attribute utility theory and the AHP, a MIP (mixed integer programming) model will be developed to search for the optimal supply chain partner portfolio that supports the company's competitive strategy. Chapters 4 and 5 discuss more details of this approach.

The research approach for the problem of identifying optimal protection strategies against worst case disruptions in supply chain will be developed based on the network interdiction models. As have discussed in Chapter 2, network interdiction is an instance of a static Stackelberg game (Simaan and Cruz, 1973), which involves two players, the attacker and the defender. The basic models in network interdiction problems are the max flow network interdiction model and the shortest path network interdiction model. In shortest path network interdiction problems, we are given a directed graph G(N,A) with arc lengths and an interdiction budget B, and the attacker wants to increase the effective length of some arcs in graph G so that the shortest path is maximized, and the total increase in arc lengths should not exceed the interdiction budget B. As discussed in section 2.6.2, this problem can be formulated as a mixed-integer-program (MIP), which can be solved readily. In this study, the research problem will be analyzed based on the shortest-path/min-cost network interdiction model. More specifically, the formulation of a standard shortest-path/min-cost network interdiction model (Israeli and Wood, 2002) is as follows:

$$\max_{x \in X} \min_{\mathbf{y}} \sum_{(i,j)\in A} (o_{ij} + x_{ij} d_{ij})\, y_{ij}$$

$$s.t. \quad \sum_j y_{ij} - \sum_j y_{ji} = \begin{cases} f\ , & i = s \\ 0, & i \neq s\ ,t \\ -f\ , & i = t \end{cases} \qquad \forall i \in N$$

$$y_{ij} \geq 0 \quad \forall (i, j) \in A$$

where $X = \{x_{ij} \mid x_{ij} \in \{0,1\} \quad \forall (i, j) \in A, \sum_{(i,j)\in A} c_{ij} x_{ij} \leq B\}$

In the above formulation, o_{ij} denotes the length of arc (i, j) or cost of using arc (i, j), d_{ij} is the additional length or cost after the interdiction on arc (i, j), x_{ij} is the decision variable of network attacker determine whether or not to interdict arc (i, j), and y_{ij} is the network flow on arc (i, j), f is the total flow from source s to sink t. c_{ij} is the cost of interdicting arc (i, j), and B is the interdiction budget.

As discussed in Section 2.6.2, protection strategies that are developed based on the solution of the traditional bi-level network interdiction models will often lead to suboptimal solutions, while tri-level optimization problem can be applied to develop optimal protection strategies. Therefore, in this research a tri-level network interdiction model will be developed to identify the optimal protection strategy against worst case disruptions in supply chain, and the details can be found in Chapter 6.

3.4 Summary

In this chapter, the research methodology and methods applied in this thesis and the justification for the chosen research approach are briefly discussed. This chapter starts by presenting a decision framework for strategic planning in supply chain, in which the research question and research focus of this thesis are specified. Then an introduction to the multi-criteria decision making techniques and mathematical programming methods used in this research is presented. Multi-attribute utility theory is applied to quantify the supply chain level performances of each potential partner portfolio, while the AHP approach will be applied to quantify some intangible supply chain characteristics such as flexibility, quality, and innovation capability. Mixed integer program and tri-level network interdiction models will then be applied to solve the two research questions we have specified.

Chapter 4 Supply Chain Partner Selection with Trade-off Options

4.1 Introduction

In contemporary business environment, supply chains are becoming more and more complex, and thus building or renewing a supply chain that supports sustainable value creation becomes a rather difficult but critical task in supply chain management. As discussed in section 2.2.2, when risks in supply chain are concerned, it is shown that in a networked supply chain the risk reduction generally cannot be done by one organization alone, but also depends on the interactions between the organization and other elements of the supply chain system, and such collaborations within the supply chain can be considered as a risk mitigation strategy.

An explicit supply chain strategy is needed when building a value-added supply chain, and there are increasing number of studies in existing literatures supporting the idea that a supply chain strategy is a single entity system and includes all of the participants in a given supply chain (Narasimhan et al., 2008, Perez-Franco, 2010, Ivanov, 2010). Therefore, in contemporary business environment, companies will often keep a long-term partnership with their suppliers and retailers so as to ensure the alignment of supply chain performance and supply chain strategy. Thus, it is quite important for the core companies to be able to effectively and strategically choose supply chain partners. In this chapter, we propose a strategic decision making approach to facilitate the process of selecting supply chain partners and building a value-added chain that incorporates the supply chain level performance requirements and trade-off options between some conflicting criteria.

4.2 Problem Description

Supply chain partners are important participants in the value added chain, and their performance can have significant effects on cost, responsiveness, customer satisfaction and competitiveness of the products, all of which can have a dramatic impact on the profitability of the entire chain. In order to select the optimum supply chain partners, core companies within the supply chain need to first develop a comprehensive supply chain strategy according to the company's competitive strategy, which determines the characteristics of the supply chain. A clear description of these supply chain characteristics can help the company decide the detailed requirements for its partners, and these requirements can be divided into two levels. The first level is the basic requirements, which include specific requirements such as the location of the potential partner, their political and economic environment, accreditation requirements and the minimum or maximum number of suppliers or retailers. The first level requirements serve as a filter for the company to decide which potential partners could be the candidates in the next round of selection. The second level is the supply chain performance requirements, which include performance thresholds that not all partners must meet but on average the supply chain needs to meet (Massow and Canbolat, 2014). Examples of these performance thresholds are overall risk level, flexibility level, overall quality, and innovation capability. Figure 4.1 illustrates the two levels of requirements for potential partners. By considering the performance requirements on the supply chain level, we can enable strategic trade-offs between different characteristics of potential supply chain partners when building the supply chain, so that the strategic fit between the competitive strategy and supply chain strategy is achieved and the strategic alignment of the supply chain is ensured. For example, if innovation is an important factor in a certain supply chain, companies can select partners with greater innovation capability (in parts of the chain that innovation capability is most needed), despite their flexibility level not meeting the common standard, as long as the overall flexibility level of the supply chain is above a threshold value. After the supply chain strategy and different levels of requirements in the supply chain are specified, the decision makers need to decide which partners to select and the allocation of purchase amount or resources to support each partner within the chain.

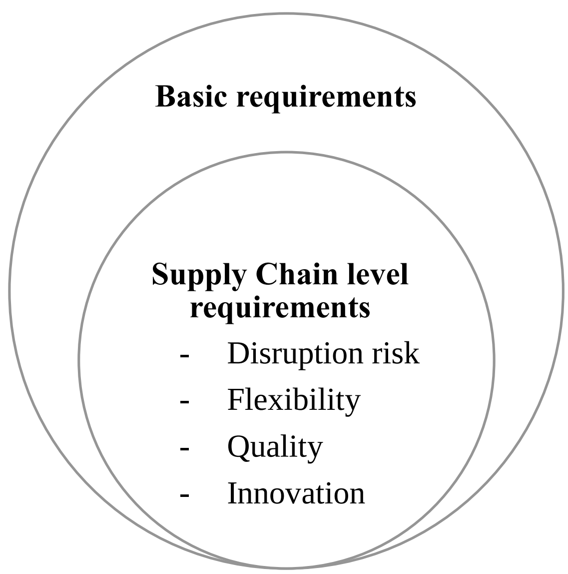


Figure 4.1: Two levels of requirements for identifying potential supply chain partners

In this study, we consider a four-echelon supply chain with a single product produced in a single manufacturing plant but with various types of raw materials, multiple suppliers, distribution centers and retailers, and we assume that all kinds of demand are deterministic and can be estimated by historical data. Popular research factors such as uncertainties, and lead times in different stages of the supply chain are represented by different supply chain performance indices. In this study, we look at the supply chain performance requirements from four aspects, namely the disruption risks, flexibility, quality of service, and innovation capability. Firstly, disruptions could happen on suppliers, DCs, retailers as well as production sites, and disruptions that happen in transportation process are considered as site disruptions in this study. For example, all the inbound and outbound transportation disruptions associated with DCs are considered as DC disruptions. Then, in order to measure the overall flexibility level, quality of service, and innovation capability of the supply chain, we define the flexibility score, quality score, and innovation score for each type of partners, and all these scores can be evaluated using AHP (Analytic Hierarchy Process) approaches. Then, by using the multi-attribute utility theory, we define the supply chain level performance indices for disruption risks, flexibility, quality, and innovation capability. In the supply chain partner selection process, it is required that the supply chain level performance indices of the chosen partner portfolio must be above the corresponding threshold for each type of performance measure.

In this study, the strategic decisions include the selection of suppliers, retailers, as well as the selection of DCs. Let x_{ij} be the decision variable for the selection of supplier, i.e. x_{ij} is 1 if supplier i is selected as the supplier of material j, otherwise x_{ij} is 0. Also, w_{ij} denotes the fraction of demand for material j supplied by supplier i, where $\sum_{i\in S_j} w_{ij} = 1, \quad 0 \le w_{ij} \le 1$. Similarly, we define y_t as the binary decision variable for the selection of DCs. Let z_r be the binary decision variable for the selection of retailers, and π_{tr} is 1 if product for retailer r is shipped from DC t, otherwise π_{tr} is 0. The details of the above definitions and notations are listed below:

Sets

S	Set of suppliers
M	Set of materials
T	Set of distribution centers
R	Set of retailers

Indices

i	Supplier, $i \in S = \{1,...,m\}$
j	Material type, $j \in M = \{1,...,n\}$
t	Distribution center (DC), $t \in T = \{1,...,g\}$
r	Retailer, $r \in R = \{1,...,l\}$

Decision variables

x_{ij}	1 if supplier i is selected as the supplier of material j, otherwise 0
w_{ij}	the fraction of demand for material j supplied by supplier i, where $\sum_{i\in S_i} w_{ij} = 1,\ 0 \le w_{ij} \le 1$
y_t	1 if DC t is selected, 0 otherwise
z_r	1 if retailer r is selected, 0 otherwise
π_{tr}	1 if product for retailer r is shipped from DC t, 0 otherwise

Parameters

f	the total demand for product
f_r	the demand for product from retailer r
a_{ij}	capacity of supplier i for material j, $i \in S_j \subseteq S$, S_j is the set of suppliers providing material j
b_{ij}	minimum order quantity of supplier i for material j, $i \in S_j \subseteq S$
d_j	demand for material j
c_{ij}	unit cost of purchasing and shipping material j from supplier i
K_t	capacity of distribution center (DC) t
u_r	cost of establishing marketing channel with retailer r
v_t	cost of establishing facilities in DC t
q_{ij}	fixed cost of ordering material j from supplier i, $i \in S_j \subseteq S$
e_{tr}	unit cost of shipping product from plant to retailer r via DC t
P_i^S	the probability of disruption in supplier i
P_t^T	the probability of disruption in DC t
P_r^R	the probability of disruption in retailer r
P_m	the probability of disruption in manufacturer
ρ_i^S	the flexibility score for supplier i
ρ_t^T	the flexibility score for DC t
ρ_r^R	the flexibility score for retailer r
ρ_m	the flexibility score for manufacturer
Q_i^S	quality score of supplier i
Q_t^T	quality score of DC t
Q_r^R	quality score of retailer r
I_i^S	Innovation score of supplier i
I_t^T	innovation score of DC t
I_r^R	innovation score of retailer r
P_{risk}	the disruption risk threshold index for the supply chain
P_{flex}	the flexibility threshold index for the supply chain
Q	the quality threshold index for the supply chain

I	the innovation threshold index for the supply chain
Mn_j	the minimum number of suppliers for material j
k_{risk}	the weight of material disruptions compared to product disruptions
k_{flex}	the weight of production flexibility compared to service flexibility
k_{fm}	the weight of manufacturing flexibility in the material stage
k_{fr}	the weight of retailing flexibility in the product stage
k_{q1}	the weight of service quality in the material supply stage
k_{q2}	the weight of quality in the product distribution stage
k_{I1}	the weight of innovation in the material supply stage
k_{I2}	the weight of innovation in the product distribution stage

4.3 Definition of Supply Chain Performance Indices

As have discussed in Chapter 3, Multiple Attribute Utility Theory can be applied in our definition of supply chain performance indices. The performance index of each echelon in supply chain, can be defined as single attribute utility function, and then aggregated by a multi-attribute utility function to arrive at a utility value for the supply chain level performance. In this research, out of three types of multi-attribute utility function (additive utility function, multi-linear utility function, and multiplicative utility function), additive utility function is chosen in the definition of the supply chain performance indices.

Additive utility function is valid when the n attributes are mutually additive independent. Two attributes X and Y are additive independent if the paired preference comparison of any two alternatives, defined by two joint probability distributions on $X \times Y$, depends only on their marginal distributions. In other words, the preference comparison can be established by comparing the values one attribute at a time. In this research, the supply chain level performances are measured from the bottom up, i.e. supply chain level performance index is a function of individual performance indices for every part of the supply chain. If we consider each individual performance index as a single utility function, then the supply chain level performance index is the multi-attribute utility function. In this study, we assume that performance indices for each part of the supply chain are mutually additive independent, and then the supply chain level performance can be represented by the weighted sum of each individual performance index. The additive utility function in Multiple Attribute Utility Theory is defined as follows:

$$u(x_1, x_2, \cdots, x_n) = \sum_{i=1}^{n} k_i u_i(x_i), \tag{4.1}$$

where each $u_i(x_i)$ is a single attribute utility function, $u(x_1, x_2, \ldots, x_n)$ and each $u_i(x_i)$ are normalized with the worst case utility being 0, best case utility being 1; each k_i is the positive scaling constants, and $\sum_{i=1}^{n} k_i = 1$. In practice, the k's are determined by the domain experts using AHP method.

4.3.1 Disruption index

There are two major types of commodities in the supply chain system, namely materials and products, and we argue that the disruption index for materials and products should be considered separately. In this study, disruption in material supply and manufacturing stage is defined as any event that interrupts material supply and production process, such as supply uncertainties, transportation disruptions, and facility breakdowns etc. Disruption in product distribution and retailing stage refers to any event that affects the sales of product, such as demand uncertainties, transportation disruptions, and service failures. Though materials and products are physically linked, the risks of processing them in the supply chain are essentially different. A disruption in processing materials may indeed affect the operations of delivering final products to the customers, but that should be considered as the consequences of the disruption of materials since the risk of processing the products remains unchanged. In typical risk management studies, risk is often defined as the product of the probability and the severity of consequence. The consequence of material and manufacturing disruptions are more severe since disruptions in this stage will have a wider impact to the supply chain, and so it is reasonable to assign a larger weight to the material disruption index. Therefore, in this study, the disruption in material supply and manufacturing stage and disruption in product distribution and retailing stage can be considered as two additive independent attributes.

The disruption index for material supply and manufacturing stage is defined as:

$$RIndex_1(\boldsymbol{w}) = \sum_{j \in M} \frac{1}{n} \sum_{i \in S_j} (1 - P_i^S)(1 - P_m) w_{ij}, \tag{4.2}$$

where n is the number of material types, and P_i^S, and P_m are the probabilities of disruptions in suppliers and manufacturing plant. We assume that the shortage consequence of any type of material is the same, because any kind of shortage will lead to not being able to produce enough product to fulfill the market demand, and therefore we can actually use the decision variable w_{ij} (the fraction of demand for material j supplied by supplier i) to represent the consequences of supply shortage. $(1\text{-}P_i^S)(1\text{-}P_m)$ is the probability that the material can be processed without disruption.

We use this probability instead of the probability that there is some disruption (which would be 1-(1-P_i^s)(1-P_m)) because the terms would be simpler while either definition is equivalent to each other.

Similarly, the disruption index for the product distribution and retailing stage is defined as:

$$RIndex_2(\boldsymbol{\pi}) = \sum_{t \in T} \sum_{r \in R} (1 - P_t^T)(1 - P_r^R)\, \pi_{tr} f_r / f \ , \tag{4.3}$$

where P_t^T, and P_r^R are the probabilities of disruptions in DCs and retailers, and $\pi_{tr} f_r / f$ represents the fraction of demand for products from retailer *r* that is distributed by DC *t*. For simplicity, we assume that the outcome of any disruption event will be the worst case, i.e. all demand from that affected retailer is disrupted.

Then, the overall disruption index for the supply chain is defined as:

$$ORIndex = k_{risk} RIndex_1(\boldsymbol{w}) + (1 - k_{risk}) RIndex_2(\boldsymbol{\pi}) \, , \tag{4.4}$$

where k_{risk} is the weight of material disruptions compared to product disruptions. As what we have discussed at the beginning of this section, k_{risk} should be larger than 0.5 so that the consideration that material disruptions will often have a wider range of impact to the supply chain is included in our definition.

4.3.2 Flexibility index

There are various definitions of flexibility in the literature. Generally, flexibility is a company's ability to respond to changes. Some studies in the literature have proposed quantitative measurements for flexibility (Beamon, 1999; Chan, 2003;

Schonsleben, 2004). In this study, we apply a measurement that is developed based on the one discussed in Beamon (1999). More specifically, the flexibility of a company is examined from the following five aspects: volume flexibility, delivery flexibility, mix flexibility, new product flexibility, and modification flexibility. Volume flexibility refers to the ability to change the output level of products produced; delivery flexibility is the ability to change planned delivery dates; mix flexibility refers to the ability to change the variety of products produced; new product flexibility refers to the ability to introduce new products; modification flexibility is the ability to accomplish product modification without incurring high transition penalties. After these five sub-indices are specified, the multi-attribute decision making method AHP can be applied to measure the flexibility of each potential supply chain partner. The advantage of the AHP approach is its adaptability, which makes it easier to be applied in different situations for various industries, since the weight of sub-indices can be changed according to different requirements of each industry.

Similar to the definition of disruption index, we consider the overall flexibility index separately. More specifically, the overall flexibility index is divided into two sub-indices: production flexibility index and service flexibility index. The production flexibility index is for the material supply and manufacturing stage, and is defined as:

$$FlexIndex_1(\boldsymbol{w}) = (1-k_{fm})\sum_{j\in M}\frac{1}{n}\sum_{i\in S_j}\rho_i^S w_{ij} + k_{fm}\rho_m, \tag{4.5}$$

where n is the number of material types, ρ_i^S is the flexibility score for supplier i, and ρ_m is the flexibility score for manufacturer, w_{ij} is the fraction of demand for material j supplied by supplier i, and k_{fm} is the weight of manufacturing flexibility compared to material supply flexibility in this stage.

The service flexibility index of the product distribution and retailing stage is defined as:

$$FlexIndex_2(\boldsymbol{\pi}, \mathbf{z}) = (1-k_{fr})\sum_{t\in T}\rho_t^T \sum_{r\in R}\pi_{tr} f_r / f + k_{fr}\sum_{r\in R}\rho_r^R z_r f_r / f \ , \tag{4.6}$$

where ρ_t^T, ρ_r^R, are the flexibility score for DCs and retailers, and k_{fr} is the weight of retailing flexibility compared to distribution flexibility in this stage. $z_r \ f_r / f$ is the fraction of total demand that is assigned to retailer r.

The overall flexibility index of the supply chain is then defined as the multiple attribute utility function:

$$OFlexIndex = k_{flex} FlexIndex_1(\boldsymbol{w}) + (1-k_{flex}) FlexIndex_2(\boldsymbol{\pi}, \mathbf{z}) \ , \tag{4.7}$$

where k_{flex} is the weight of production flexibility compared to service flexibility.

4.3.3 Quality index and Innovation index

The measurement of quality as a supply chain performance indicator has been discussed in many published works (Chan, 2003; Schonsleben, 2004). Generally, quality is related to the satisfactory level provided by products and services that a company has to offer. In this study, we examine the quality of potential supply chain partners from the following aspects: customer satisfaction, accuracy, fill rate, lead time, response time, and on-time delivery. More specifically, customer satisfaction is the percentage of satisfied customers; accuracy refers to the percentage of accurate goods delivered to customers; fill rate is the proportion of immediately filled orders; lead time is the time it takes from manufacturing the product to it being fully processed; response time refers to the time between an order and the corresponding delivery; on-time delivery is the percentage of deliveries that are on-time.

The innovation score of each partner could be examined from the ability to launch new products and the use of new technology (Chan, 2003). More specifically, the ability to launch new products is measured by the number of new products launched by a company compared to the average number of new products in the industry within the same period; the use of new technology refers to the percentage decrease in time necessary for producing the same product. The quality scores and innovation scores of each potential partners are then generated through an AHP approach, in which we can assign different weight to each sub-criterion according to industrial difference.

The definitions of Quality index and Innovation index are different from the previous definitions, since quality and innovation are measured based on the partners instead of commodity types. Therefore we defined three single quality/innovation indices for suppliers, DCs and retailers respectively. The quality/innovation score of manufacturer is not considered in our definitions, because we only consider one manufacturer and the quality/innovation score for the manufacturer is a constant which can be merged with the threshold value. The quality index for suppliers is defined as:

$$QIndex_1(\boldsymbol{w}) = \sum_{j\in M} \frac{1}{n} \sum_{i\in S_j} Q_i^S w_{ij}\,, \tag{4.8}$$

where Q_i^S is the quality score of supplier *i*. The quality score is weighted by the fraction of demand of material that is supplied by this supplier, which is then summed for all suppliers and material types, and then the quality index can be derived by dividing the sum by *n*, which is the number of material types, since we assume that all types of materials are equally important.

The quality index of DCs is defined as:

$$QIndex_2(\boldsymbol{\pi}) = \sum_{t\in T} Q_t^T \sum_{r\in R} \pi_{tr}\, f_r / f\,, \tag{4.9}$$

where Q_t^T, is the quality score for DCs, and $\sum_{r\in R} \pi_{tr}\, f_r / f$ is the fraction of product demand that is distributed by DC *t*, which can be considered as the weight of DC *t*.

The quality index of retailers is defined as:

$$QIndex_3(\mathbf{z}) = \sum_{r\in R} Q_r^R z_r\ f_r / f\,, \tag{4.10}$$

where Q_r^R is the quality score for retailers, and $z_r\ f_r / f$ is the fraction of total demand that is assigned to retailer *r*.

The overall quality index of the supply chain is then defined as:

$$OQIndex = k_{q1} QIndex_1(\mathbf{w}) + k_{q2} QIndex_2(\boldsymbol{\pi}) + (1 - k_{q1} - k_{q2}) QIndex_3(\mathbf{z})\,, \tag{4.11}$$

where k_{q1}, k_{q2} are the weights for supplier quality index and DC quality index, respectively. $0 < k_{q1}, k_{q2} < 1$, and $0 < k_{q1} + k_{q2} < 1$.

The innovation indices are defined similarly. The innovation index for suppliers is defined as:

$$IIndex_1(\boldsymbol{w}) = \sum_{j \in M} \frac{1}{n} \sum_{i \in S_j} I_i^S w_{ij}\,, \tag{4.12}$$

where I_i^S is the innovation score of supplier i, and n is the number of material types.

The innovation index of DCs is defined as:

$$IIndex_2(\boldsymbol{\pi}) = \sum_{t \in T} I_t^T \sum_{r \in R} \pi_{tr} f_r / f\,, \tag{4.13}$$

where I_t^T, is the innovation score for DCs, and $\sum_{r \in R} \pi_{tr} f_r / f$ is the fraction of product demand that is distributed by DC t, which can be considered as the weight of DC t.

The innovation index of retailers is defined as:

$$IIndex_3(\mathbf{z}) = \sum_{r \in R} I_r^R z_r\ f_r / f\,, \tag{4.14}$$

where I_r^R is the innovation score for retailers, and $z_r\ f_r / f$ is the fraction of total demand that is assigned to retailer r.

The overall innovation index of the supply chain is:

$$OIIndex = k_{I1} IIndex_1(\boldsymbol{w}) + k_{I2} IIndex_2(\boldsymbol{\pi}) + (1 - k_{I1} - k_{I2}) IIndex_3(\mathbf{z})\,, \tag{4.15}$$

where k_{I1}, k_{I2} are the weights for supplier innovation index and DC innovation index, respectively. $0 < k_{I1}$, $k_{I2} < 1$, and $0 < k_{I1} + k_{I2} < 1$.See Table 4.1 for the details of all the definitions of the indices.

Table 4.1: Definitions of supply chain performance indices

Index name	Definition
Material disruption index	$RIndex_1(\boldsymbol{w}) = \sum_{j\in M}\frac{1}{n}\sum_{i\in S_i}(1-P_i^S)(1-P_m)w_{ij}$
Product disruption index	$RIndex_2(\boldsymbol{\pi}) = \sum_{t\in T}\sum_{r\in R}(1-P_t^T)(1-P_r^R)\pi_{tr}f_r/f$
Overall disruption index	$k_{risk}RIndex_1(\boldsymbol{w})+(1-k_{risk})RIndex_2(\boldsymbol{\pi})$
Production flexibility index	$FlexIndex_1(\boldsymbol{w}) = (1-k_{fm})\sum_{j\in M}\frac{1}{n}\sum_{i\in S_i}\rho_i^S w_{ij} + k_{fm}\rho_m$
Service flexibility index	$FlexIndex_2(\boldsymbol{\pi},\mathbf{z}) = (1-k_{fr})\sum_{t\in T}\rho_t^T\sum_{r\in R}\pi_{tr}f_r/f + k_{fr}\sum_{r\in R}\rho_r^R z_r f_r/f$
Overall flexibility index	$k_{flex}FlexIndex_1(\boldsymbol{w})+(1-k_{flex})FlexIndex_2(\boldsymbol{\pi},\mathbf{z})$
Supplier quality index	$QIndex_1(\boldsymbol{w}) = \sum_{j\in M}\frac{1}{n}\sum_{i\in S_j}Q_i^S w_{ij}$
DC quality index	$QIndex_2(\boldsymbol{\pi}) = \sum_{t\in T}Q_t^T\sum_{r\in R}\pi_{tr}f_r/f$
Retailer quality index	$QIndex_3(\mathbf{z}) = \sum_{r\in R}Q_r^R z_r\ f_r/f$
Overall quality index	$k_{q1}QIndex_1(\boldsymbol{w})+k_{q2}QIndex_2(\boldsymbol{\pi})+(1-k_{q1}-k_{q2})QIndex_3(\mathbf{z})$
Supplier innovation index	$IIndex_1(\boldsymbol{w}) = \sum_{j\in M}\frac{1}{n}\sum_{i\in S_j}I_i^S w_{ij}$
DC innovation index	$IIndex_2(\boldsymbol{\pi}) = \sum_{t\in T}I_t^T\sum_{r\in R}\pi_{tr}f_r/f$
Retailer innovation index	$IIndex_3(\mathbf{z}) = \sum_{r\in R}I_r^R z_r\ f_r/f$
Overall innovation index	$k_{I1}IIndex_1(\boldsymbol{w})+k_{I2}IIndex_2(\boldsymbol{\pi})+(1-k_{I1}-k_{I2})IIndex_3(\mathbf{z})$

4.4 Supply Chain Partner Selection Models

4.4.1 The basic model

In this section we present the **Basic Model** for the selection of supply chain partners with supply chain level performance requirements:

$$\text{Min} \quad TC = \sum_{j\in M}\sum_{i\in S_j} q_{ij}x_{ij} + \sum_{j\in M}\sum_{i\in S_j} c_{ij}w_{ij}d_j + \sum_{t\in T} v_t y_t + \sum_{t\in T}\sum_{r\in R} f_r \pi_{tr} e_{tr} + \sum_{r\in R} u_r z_r \qquad (4.16)$$

s.t

$$w_{ij} \le x_{ij} \qquad \forall j \in M, \quad i \in S_j \qquad (4.17)$$

$$w_{ij} d_j \le a_{ij} \qquad \forall j \in M, \quad i \in S_j \qquad (4.18)$$

$$w_{ij} d_j \ge b_{ij} x_{ij} \qquad \forall j \in M, \quad i \in S_j \qquad (4.19)$$

$$\sum_{i\in S_j} w_{ij} = 1 \qquad \forall j \in M \qquad (4.20)$$

$$\sum_{r\in R} f_r z_r = f \qquad (4.21)$$

$$\sum_{r} \pi_{tr} f_r \le K_t \qquad \forall t \in T \qquad (4.22)$$

$$\pi_{tr} \le y_t \qquad \forall t \in T, \quad r \in R \qquad (4.23)$$

$$\sum_{t} \pi_{tr} = z_r \qquad \forall r \in R \qquad (4.24)$$

$$k_{risk} RIndex_1(\boldsymbol{w}) + (1 - k_{risk}) RIndex_2(\boldsymbol{\pi}) \ge P_{risk} \qquad (4.25)$$

$$k_{flex} FlexIndex_1(\boldsymbol{w}) + (1 - k_{flex}) FlexIndex_2(\boldsymbol{\pi}, \mathbf{z}) \geq P_{flex} \tag{4.26}$$

$$k_{q1} QIndex_1(\boldsymbol{w}) + k_{q2} QIndex_2(\boldsymbol{\pi}) + (1 - k_{q1} - k_{q2}) QIndex_3(\mathbf{z}) \geq Q \tag{4.27}$$

$$k_{I1} IIndex_1(\boldsymbol{w}) + k_{I2} IIndex_2(\boldsymbol{\pi}) + (1 - k_{I1} - k_{I2}) IIndex_3(\mathbf{z}) \geq I \tag{4.28}$$

$$\sum_{i \in S_j} x_{ij} \geq Mn_j \qquad \forall j \in M \tag{4.29}$$

$$0 \leq w_{ij} \leq 1 \qquad \forall j \in M, \quad i \in S_j \tag{4.30}$$

$$x_{ij} \in \{0,1\} \qquad \forall j \in M, \quad i \in S_j \tag{4.31}$$

$$y_t \in \{0,1\} \qquad \forall t \in T \tag{4.32}$$

$$z_r \in \{0,1\} \qquad \forall r \in R \tag{4.33}$$

$$\pi_{tr} \in \{0,1\} \qquad \forall t \in T, \quad r \in R \tag{4.34}$$

The objective function (4.16) is the total cost (TC) of the supply chain, which consists of the ordering cost, purchasing costs, cost in DC, product shipping cost, and retailing cost. Constraints (4.17) ensure that if supplier *i* is not chosen then no demand will be allocated to it. Constraints (4.18) and (4.19) require the amount of material demand for each supplier not to exceed the capacity of the supplier, and to at least meet the minimum order quantity. Constraints (4.20) ensure that for each material type *j*, the demand allocation fraction adds up to 1, i.e. material supply must be equal to the demand. Constraint (4.21) requires the sum of demands from the chosen retailers be equal to the total demand for the product. Constraints (4.22) ensure the total amount of product in DC t does not exceed its capacity. In constraints (4.23), we ensure that no products will be shipped between a DC and a retailer if this DC is not chosen, while constraints (4.24) require that a DC will be assigned to deliver products to a retailer if this retailer is chosen. Constraints (4.25) - (4.28) are supply chain requirements constraints. Constraint (4.25) requires the overall disruption risks of the supply chain formed by the chosen partners not to exceed a certain threshold. Constraint (4.26) ensures the overall flexibility level of the supply chain is at least equal to a threshold value. Similarly, constraints (4.27) and (4.28) require the overall quality level and the overall innovation level of the supply chain to at least meet a minimum satisfactory value, respectively. Constraint (4.29) ensures the number of suppliers for material j is no less than the minimum requirement value. Constraints (4.30)-(4.34) are the non-negativity and integrality constraints.

4.4.2 Strategic trade-off model

In the Basic Model, the supply chain performance requirements included can enable various strategic trade-offs, which could be critical to business performance. In other words, after ensuring the supply chain performances are within some satisfactory level, the core company may also seek to achieve certain level of performance in specific parts of the supply chain, and all these kinds of special requirements could be achieved by imposing the trade-off options into the decision making process, which can help to fulfill the supply chain strategy. In this circumstance, we can add in some additional constraints to the Basic Model to represent these special requirements, and the resulting new model shall be called Strategic trade-off Model.

The **Strategic trade-off Model** is the Basic Model plus some of the following sets of constraints:

$$RIndex_1(\mathbf{w}) \geq P_{risk1} \text{ or } RIndex_2(\boldsymbol{\pi}) \geq P_{risk2} \tag{4.35}$$

$$FlexIndex_1(\mathbf{w}) \geq P_{flex1} \text{ or } FlexIndex_2(\boldsymbol{\pi}, \mathbf{z}) \geq P_{flex2} \tag{4.36}$$

$$QIndex_1(\mathbf{w}) \geq Q_1 \text{ or } QIndex_2(\boldsymbol{\pi}) \geq Q_2 \text{ or } QIndex_3(\mathbf{z}) \geq Q_3 \tag{4.37}$$

$$IIndex_1(\mathbf{w}) \geq I_1 \text{ or } IIndex_2(\boldsymbol{\pi}) \geq I_2 \text{ or } IIndex_3(\mathbf{z}) \geq I_3 \tag{4.38}$$

where the right hand side parameters are the special requirements each single performance index must meet, with details in Table 4.2.

Table 4.2: New parameters in Strategic trade-off Model

Parameters	
P_{risk1}	the disruption risk threshold index for the material stage
P_{risk2}	the disruption risk threshold index for the product stage
P_{flex1}	the flexibility threshold index for the material stage
P_{flex2}	the flexibility threshold index for the product stage
Q_1	the quality threshold index for suppliers
Q_2	the quality threshold index for DCs
Q_3	the quality threshold index for retailers
I_1	the innovation threshold index for suppliers
I_2	the innovation threshold index for DCs
I_3	the innovation threshold index for retailers

Constraint (4.35) requires the disruption risk of the material stage or the product stage be within a certain level. It is important to note that there can be at most one constraint chosen from each set of constraints in one supply chain strategy, because there will be no trade-off if we require all parts of the chain to perform at highest standards. For example, once the disruption risk threshold index for the supply chain P_{risk} and the disruption risk threshold for material stage P_{risk1} are determined, P_{risk2} will automatically be determined by $k_{risk}*P_{risk1}+(1-k_{risk})*P_{risk2}= P_{risk}$. Similarly, constraint (4.36) requires the flexibility level of the material stage or the product stage be no less than a certain threshold. Constraint (4.37) ensures that the quality of the suppliers or DCs or retailers be no less than a certain level. Constraint (4.38) requires the innovation level of suppliers or DCs or retailers be no less than a certain threshold.

4.5 Numerical Analysis

In this section computational examples are applied to test the proposed mixed integer programming model for the basic cases, and the Strategic Trade-off Model. The computational experiments were performed on a Dell OPTIPLEX 990, Intel Core i5-2500, 3.30GHz, RAM 8GB/CPLEX 12.5. The data of the base case computational example is illustrated in Appendix G.

Table 4.3 summarizes the optimal base case results, when P_{risk} = Q = 0.85, P_{flex} =0.75, and I = 0.65. The computational example applied consists of 16 potential suppliers, 3 material types, 6 potential DCs, and 12 potential retailers. By changing the inputs of threshold indices, we may get different solutions, while each solution represents the optimal supply chain partner portfolio under that particular performance level. For instance, one possible combination of threshold indices for this computational example is when $P_{risk} = Q = 0.9$, $P_{flex} = 0.8$, and $I = 0.7$, and the total cost in this case would be 21654. Figures 4.2, 4.3, 4.4 and 4.5 illustrate the changes of total cost when we increase each of the single performance threshold value. The four resulting curves are all increasing with an increasing rate. From these preliminary results, we can see that the Basic Model behaves as expected, essentially better performances require higher costs.

Table 4.3: Results of the Base Case

	Results of Base Case ($P_{risk} = Q = 0.85$, $P_{flex} = 0.75$, $I = 0.65$)		
Total cost	19624		
Suppliers selected(w_{ij})	Material 1	Material 2	Material 3
	S1(0.4), S2(0.6)	S9(0.3), S10(0.4), S11(0.3)	S12(0.78), S15(0.22)
DC selected	DC2(distributes R5 and R12), DC3(distributes R2, R3, R4 and R9)		
Retailer selected	R2, R3, R4, R5, R9, R12		

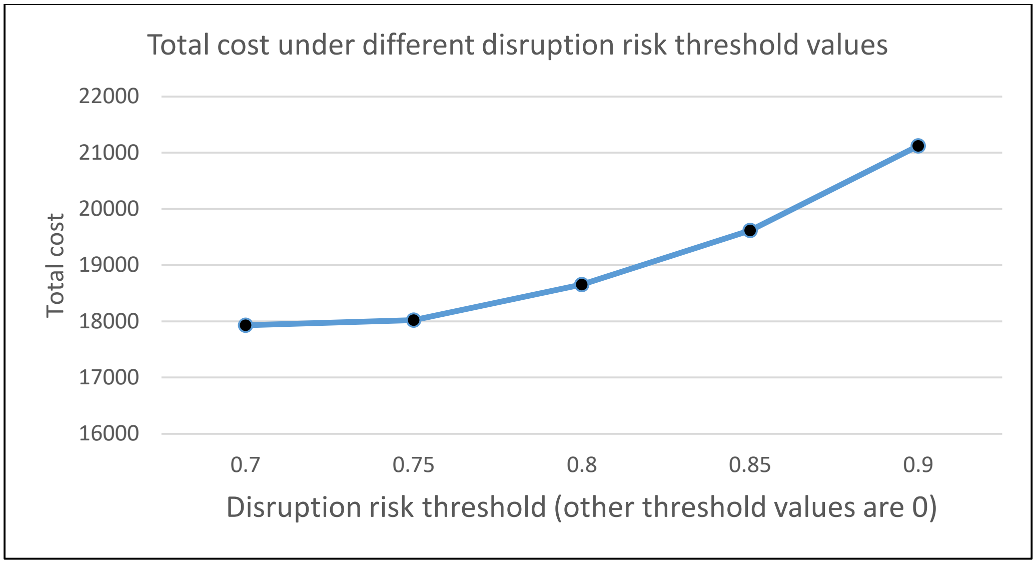


Figure 4.2: The changes of total cost when disruption risk threshold value increases

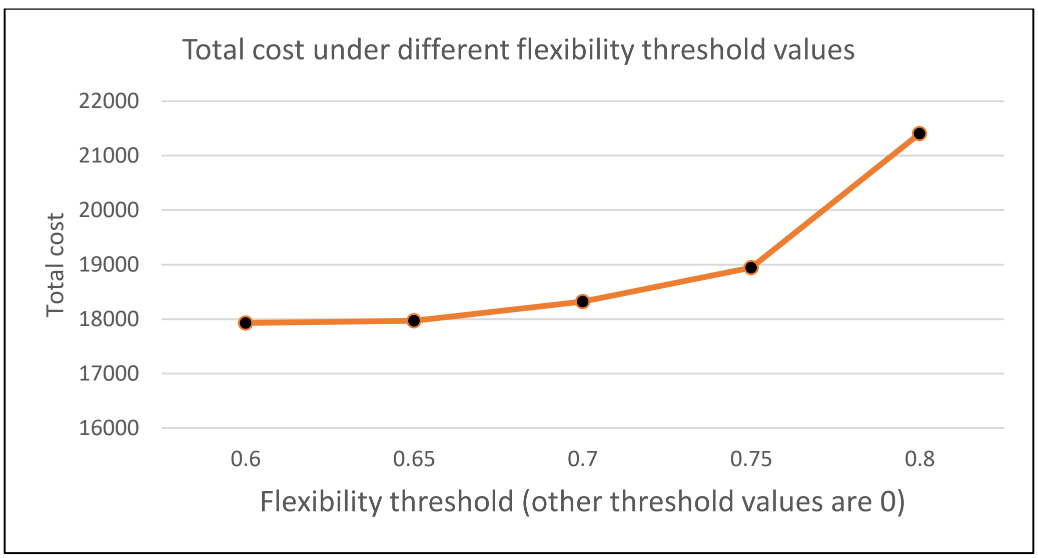


Figure 4.3: The changes of total cost when flexibility threshold value increases

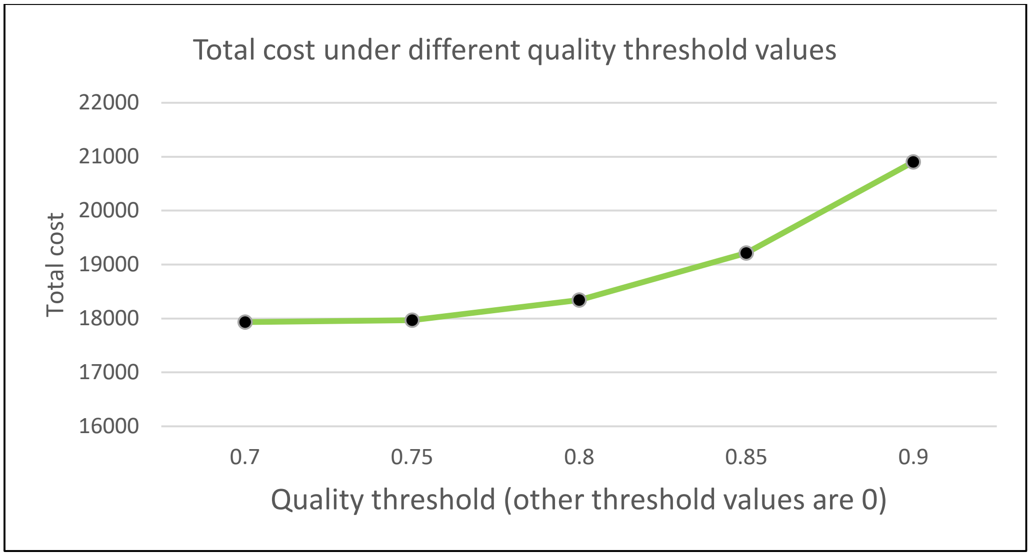


Figure 4.4: The changes of total cost when quality threshold value increases

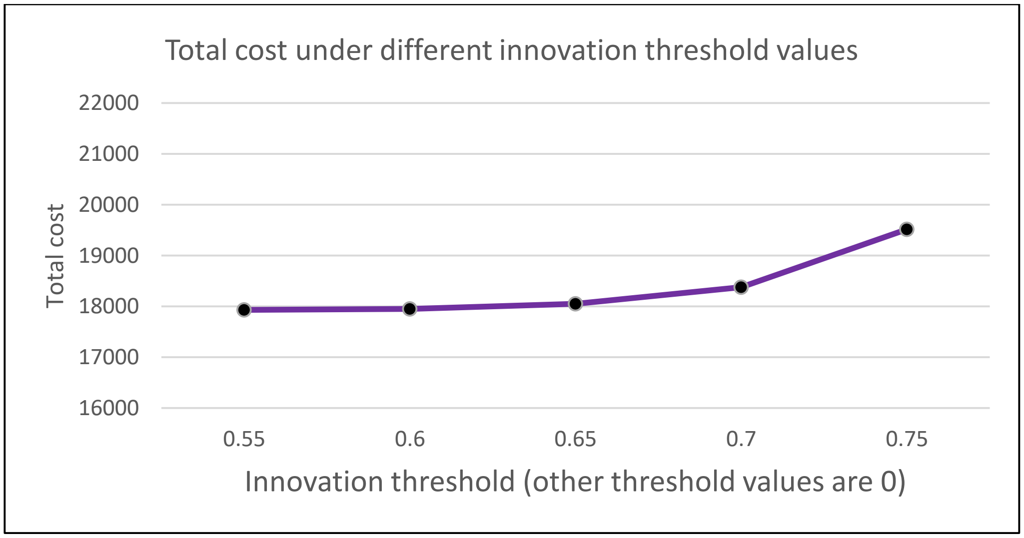


Figure 4.5: The changes of total cost when innovation threshold value increases

In order to test the Strategic trade-off Model, we designed two different strategies to see how the optimal solution would differ under these different strategies. Specifically, strategy A requires low risk in the upper stream of the supply chain and high flexibility level in the lower stream of the chain, and also requires high quality of service and innovation level in the retailers to boost customer satisfaction and increase the chance of revisit. Therefore, we set P_{risk1}=0.9, P_{flex2}=0.9, Q_3=0.9, I_3=0.7 for strategy A. For strategy B, low risk and high flexibility in the upper stream of the chain are required, as well as high quality materials and high innovation capability from suppliers, so we set P_{risk1}=0.9, P_{flex1}=0.9, Q_1=0.9, I_1=0.8 for strategy B. In general, strategy A would often be adopted by fashion industries, while strategy B would be more suitable for famous companies in high-technology industries.

The results we got after applying the two strategies to the Strategic trade-off Model are illustrated in Table 4.4. The results indicate that under different supply chain strategies, we should choose different portfolios of supply chain partners, which is consistent with what we have expected. More specifically, in strategy A, suppliers 12 and 14 are selected for material type 3, while in strategy B, the suppliers for material type 3 are suppliers 13 and 14, and this result is consistent with the requirements of the two strategies, because compared to supplier 12, supplier 13 has a higher flexibility level as well as lower risk of disruption. Similarly, DCs 2 and 5 are selected for strategy A, while for strategy B, DCs 2 and 3 are chosen, and for the selection of retailers, four out of six chosen retailers are different between the two strategies, because such combination of DCs and retailers in strategy A would provide higher flexibility level in the lower stream than that of strategy B. In conclusion, the comparison of results between these two strategies indicates that the Strategic trade-off Model is capable of providing optimal suggestions to help achieve the strategic fit of the supply chain.

Table 4.4: Comparison of results between strategy A and strategy B

		Results ($P_{risk} = P_{flex} = Q = 0.85$, $I = 0.65$)		
Total cost	Strategy A	20734		
	Strategy B	20385		
Supplier selected		Material 1	Material 2	Material 3
	Strategy A	S2, S3	S6, S7, S9	S12, S14
	Strategy B	S2, S3	S6, S7, S9	S13, S14
DC selected	Strategy A	DC2, DC5		
	Strategy B	DC2, DC3		
Retailer selected	Strategy A	R1, R2, R3, R4, R6, R12		
	Strategy B	R3, R4, R5, R8, R10, R11		

4.6 Case Study

Based on the Basic Model and Strategic trade-off Model presented above, we developed a customized model to optimize the supply chain network for a European chemical company. Similar to the numerical analysis section, the optimization problems in this section are formulated using OPL in CPLEX Optimization Studio 12.5, and the mathematical models are solved using a Dell OPTIPLEX 990, Intel Core i5-2500, 3.30GHz, RAM 8GB.

This case is about a network design project for a leading chemical company in Europe, which was first discussed in Francas and Simon (2011). The company's supply chain network originally has 4 manufacturing plants, 2 central DCs, and 12 local warehouses. The 4 manufacturing plants are located in Netherlands, southern France, Germany, and Poland; the 2 central DCs are in Germany and southern France; while the 12 local warehouses locate in the United Kingdom, northern France, Netherlands, Spain, Portugal, Italy, Austria, Czech Republic, Hungary, Poland, and Sweden. Figure 4.6 shows the supply chain before re-design. As can be seen, the company has local facilities in most of the major countries in Western Europe. With such highly localized distribution network, the transportation process cannot have economies of scale, which leads to high transportation cost. Inventory level in local warehouses is high due to demand uncertainties, which leads to high inventory cost. Therefore, the company is looking for a supply chain network re-design solution to reduce its high transportation and inventory costs and to meet the following business requirements:

- Requires the re-designed network to support the company's service coverage in Western Europe, as well as the expansion plan in the Middle East markets;
- Requires the overall disruption risk, service quality, and flexibility of the new network to be at acceptable levels.
- Focuses on reducing the complexity of the distribution network.

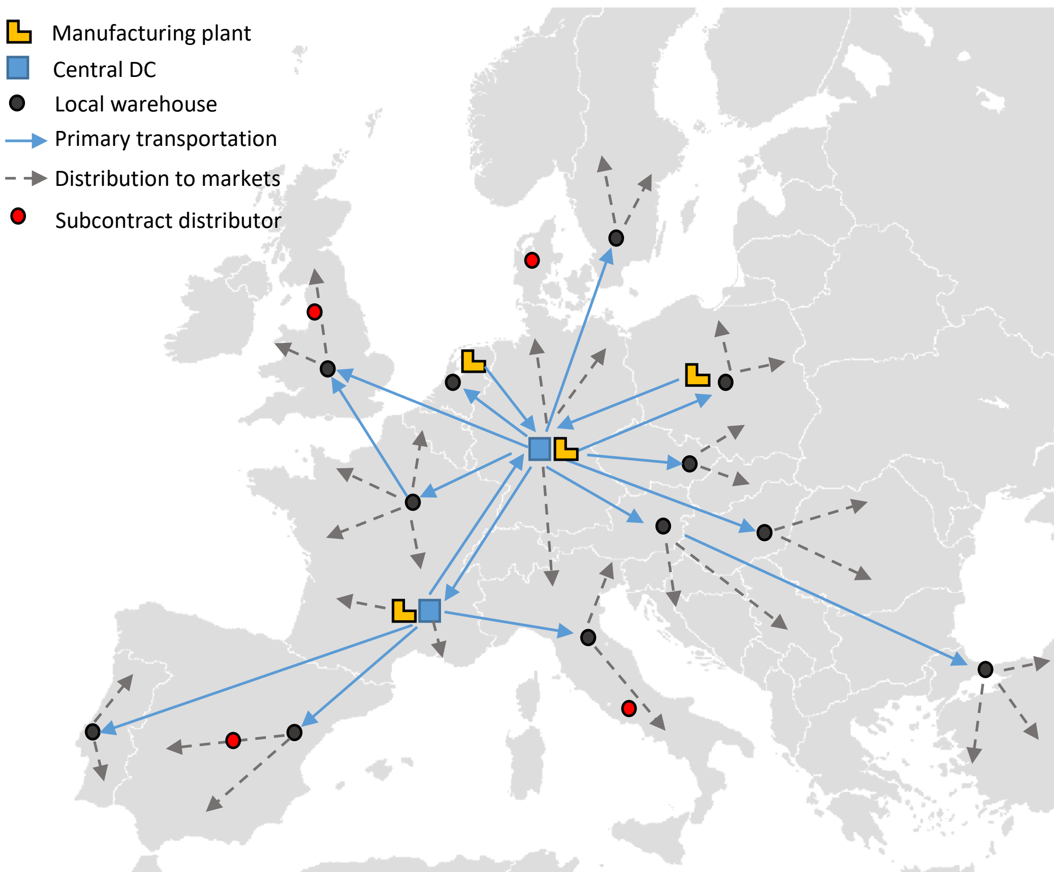


Figure 4.6: European supply chain before re-design

After a preliminary research on the existing network, the company decides to keep the central DC located in Germany, while the central DC in southern France is downgraded to a local warehouse. This is because by aggregating the product inventory in a single central DC, the demand uncertainties from each local markets will be balanced out, and the transportation process would have scale economy achieved. Then, in order to further reduce the complexity of the distribution network, the company need to decide which local facilities to keep and upgrade, by choosing from the existing 12 local warehouses plus the southern France warehouse degraded from the original DC. The company also considers 4 subcontract distributors (SD) located in United Kingdom, Spain, Italy, and Denmark, see Figure 4.6. Table 4.5 summarizes the cost of establishing the capability for each facility and the demand each local facility can handle, as well as the distribution cost of each facility once it is chosen. The cost of establishing the capability for each subcontract distributor is calculated by subtracting the price of its service by the monetary return for selling the nearest company-owned local facility. For example, if the subcontract distributor in Denmark is chosen, then the company would sell the local facility in Sweden. Since the company would have only one local facility in each regional market, the distribution cost of each facility is determined by assuming all demand of the nearby markets is provided by that facility. The demand capability data for the central DC in Germany is for the direct distribution to nearby local markets only, i.e. it does not include those product demands distributed to other local warehouses.

Table 4.5: Establishing cost, distribution cost, and capability level in each facility

Facility	Establishing cost (100 $)	Demand can handle per month (ton)	Distribution cost (100 $)
United Kingdom	5,000	6,000	40
Sweden	5,000	8,000	70
Netherlands	5,000	3,000	30
northern France	5,000	6,000	45
Poland	8,000	5,000	68
Czech Republic	8,000	6,000	50
Austria	8,000	6,000	55
Hungary	8,000	6,000	65
Italy	6,000	6,000	43
Spain	6,000	5,000	45
Portugal	6,000	3,000	60
Turkey	8,000	5,000	55
southern France	0	10,000	48
Germany	0	10,000	75
United Kingdom (SD)	5,750	6,000	35
Spain (SD)	6,500	5,000	40
Italy (SD)	6,400	6,000	35
Denmark (SD)	6,800	8,000	80

The remaining challenge is to optimally choose local warehouses so that the requirements are satisfied with minimum costs. Note that in this project, the material supply stage is not considered, since the project is focusing on the re-design of the distribution network. Therefore, only the product disruption risk index, service flexibility index, and DC quality index are included in the optimization model of this project. By applying the AHP method, the company determines the flexibility score and service quality score for each facility. The flexibility score is examined from these three aspects: delivery flexibility, mix flexibility, and volume flexibility. The service quality score is examined from the following aspects: customer satisfaction, response time, on-time delivery, accuracy, and fill rate. Table 4.6 summarizes the probability of disruption, flexibility score, and service quality score for each facility. Details of the problem data and notations can be found in Appendix B. Note that some parameters are estimated or collected from the available information on the internet.

The optimization model for this project is as follows:

Min $$TC = \sum_{t \in T} (v_t y_t + e_t f_t y_t + \chi_t y_t) \tag{4.39}$$

s.t

$$\sum_{t \in T} f_t y_t = f \tag{4.40}$$

$$\sum_{t \in T_{NW}} f_t y_t \geq f_{NW} \tag{4.41}$$

$$\sum_{t \in T_{EA}} f_t y_t \geq f_{EA} \tag{4.42}$$

$$\sum_{t \in T_{NE}} f_t y_t \geq f_{NE} \tag{4.43}$$

$$\sum_{t \in T_{SU}} f_t y_t \geq f_{SU} \tag{4.44}$$

$$\sum_{t \in T_{IB}} f_t y_t \geq f_{IB} \tag{4.45}$$

$$\sum_{t \in T_{FR}} f_t y_t \geq f_{FR} \tag{4.46}$$

$$\sum_{t \in T_{ME}} f_t y_t \geq f_{ME} \tag{4.47}$$

$$\sum_{t \in T_{CE}} f_t y_t \geq f_{CE} \tag{4.48}$$

$$(1 - P_{cDC}) \sum_{t \in T} (1 - P_t^T)\, f_t y_t / f \geq P_{risk} \tag{4.49}$$

$$\rho_{cDC} \sum_{t \in T} \rho_t^T \ f_t y_t / f \geq P_{flex} \tag{4.50}$$

$$Q_{cDC} \sum_{t \in T} Q_t^T \ f_t y_t / f \geq Q \tag{4.51}$$

$$y_t \in \{0,1\} \qquad \forall t \in T \tag{4.52}$$

In the above formulation, χ_t is the cost of distributing products to markets for each facility t, $t = 1 \ldots 18$, and the index of t stands for local facility in different areas. For example, y_1 stands for the selection option for the local warehouse in the United Kingdom, while the index from 2 to 11 stands for the local warehouse in Sweden, Netherlands, northern France, Poland, Czech Republic, Austria, Hungary, Italy, Spain, and Portugal. y_{12} stands for the selection option for the local warehouse in Turkey, and therefore according to the requirements of the company, this local warehouse has to be chosen for the expansion plan in the Middle East markets. y_{13} represents the option of whether to choose the local warehouse in southern France. y_{14} stands for the central DC in Germany. y_{15}, y_{16}, y_{17}, y_{18} represent the subcontract distributors in the United Kingdom, Spain, Italy, and Denmark, respectively. To ensure the demands from all regional markets are covered by the distribution network, constraints (4.41) to (4.48) are included in the formulation. For instance, constraint (4.45) indicates that enough local facilities in Spain and Portugal will be selected to make sure that the Iberian Peninsula markets are covered. Figure 4.7 illustrates the new distribution network according to the optimal solution.

Table 4.6: Disruption probability, flexibility and service quality scores for each facility

Facility	Disruption probability	Flexibility score	Service quality score
United Kingdom	0.01	0.85	0.85
Sweden	0.03	0.9	0.85
Netherlands	0.05	0.75	0.9
northern France	0.05	0.8	0.7
Poland	0.05	0.7	0.6
Czech Republic	0.01	0.95	0.85
Austria	0.03	0.75	0.65
Hungary	0.05	0.8	0.95
Italy	0.01	0.85	0.85
Spain	0.01	0.7	0.9
Portugal	0.04	0.8	0.6
Turkey	0.02	0.95	0.9
southern France	0.01	0.95	0.9
Germany	0.01	0.95	0.97
United Kingdom (SD)	0.05	0.95	0.95
Spain (SD)	0.05	0.9	0.9
Italy (SD)	0.05	0.95	0.95
Denmark (SD)	0.01	0.95	0.95

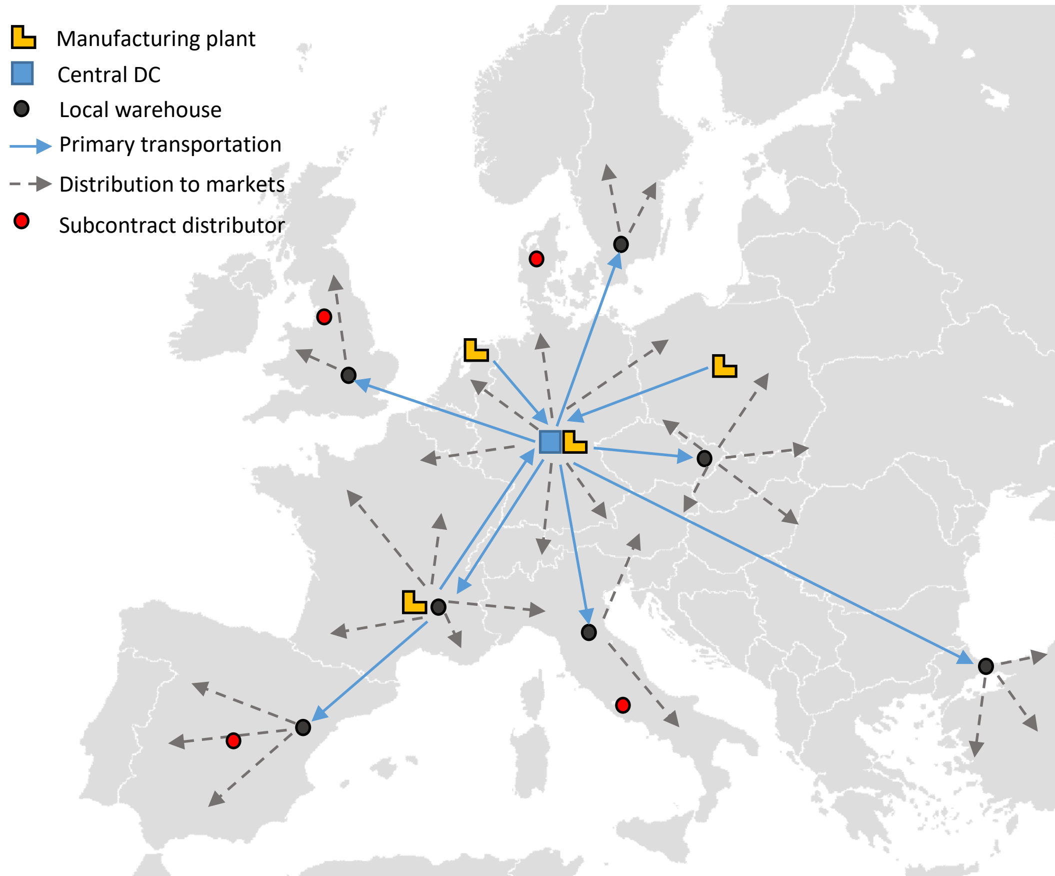


Figure 4.7: European supply chain after re-design

After applying the optimization model, the number of local warehouses is reduced to 7, which are located in the UK, southern France, Spain, Italy, Sweden, Czech Republic, and Turkey. The new distribution network is much less complicated, while the overall risk, flexibility and service quality are maintained at a satisfactory level. Specifically, the disruption risk threshold is 0.9, the flexibility threshold is 0.8, and service quality threshold is 0.8.

Now suppose the company is considering improving its supply chain performance, and has proposed two plans: plan A is to reduce the disruption rate to 2%, while the flexibility level and service quality level remain the same as before; plan B is to increase the flexibility level and service quality level to 0.9, while the disruption rate is kept within 5%. After applying the optimization model, the optimal solution suggests to choose the local facilities located in the United Kingdom, Czech Republic, Italy, Spain, Turkey, southern France, and a subcontract distributor in Denmark for plan A; while for plan B, it is suggested to choose the local facilities located in Czech Republic, Turkey, southern France, and four subcontract distributors in the United Kingdom, Spain, Italy, and Denmark. Table 4.7 compares the total cost, the number of local warehouses chosen, and the number of subcontract distributors chosen in the solution for plan A, plan B, and the base case. From the comparison in Table 4.7, we can see that the difference between the solutions of plan A and the base case is: the local warehouse in Sweden is replaced by the subcontract distributor in Denmark. This change has brought a small increase of 210 units in total cost. However, the total cost for plan B increases by 21,442 units compared with that of the base case, and the local warehouses in the United Kingdom, Spain, Italy, and Sweden are replaced by subcontract distributors in the United Kingdom, Spain, Italy, and Denmark.

Table 4.7: Comparison of base case solution and plan A, plan B solutions

	Base case	A	B
Total cost (100$)	415226	415436	436668
Number of local warehouses	7	6	3
Number of subcontract distributors	0	1	4
Overall disruption index	0.958	0.981	0.969
Overall flexibility index	0.881	0.869	0.907
Overall quality index	0.868	0.881	0.902
United Kingdom	√	√	-
Sweden	√	-	-
Netherlands	-	-	-
northern France	-	-	-
Poland	-	-	-
Czech Republic	√	√	√
Austria	-	-	-
Hungary	-	-	-
Italy	√	√	-
Spain	√	√	-
Portugal	-	-	-
Turkey	√	√	√
southern France	√	√	√
Germany	Central DC	Central DC	Central DC
United Kingdom (SD)	-	-	√
Spain (SD)	-	-	√
Italy (SD)	-	-	√
Denmark (SD)	-	√	√

For the base case optimal solution, the overall disruption index is 0.958, the overall flexibility index is 0.881, and the overall quality index is 0.868. We can see that all three indices exceed the corresponding performance requirement threshold, indicating that the re-designed distribution network performs better than expected. For the optimal solution of plan A, the overall disruption index (0.981) just meets the required performance threshold, while the overall flexibility index (0.869) is lower than that of the base case, but the overall quality index (0.881) is higher. This result suggests that by changing the Sweden local facility to a subcontract distributor in Denmark, the company can reduce the disruption rate to less than 2%, while keeping the flexibility and quality level of the distribution network at a similar level as in the base case. For the optimal solution of plan B, the overall disruption index (0.969) is slightly lower than that of plan A, but the overall flexibility index (0.907) and the overall quality index (0.902) are both higher than in plan A. However, in order to achieve higher flexibility and quality level, the company need to pay much more money to hire all four subcontract distributors. This result suggests that by subcontracting the non-core services to the third-party service providers, the company can run the distribution network on a higher level of overall performance.

In summary, this case study has shown that customized optimization models can be developed based on the proposed supply chain partner selection approach to solving a real world problem.

4.7 Summary

In this chapter, we have proposed a strategic decision approach for supply chain partner selections and design that considers the strategic trade-offs between different performance requirements. The proposed approach provides a perspective of considering the performance requirements on a supply chain level, and also integrates risk considerations into the decision making process by considering a threshold of supply chain level risk . A mixed integer programming model called Strategic trade-off Model is presented to test the proposed approach. Numerical results and case study suggest that the proposed strategic decision approach can effectively support strategic decision makings on supply chain partner selections. The work in this chapter addresses the first research gap identified in Chapter 2, which is the lack of approaches dealing with the evaluation and selection of supply chain partners throughout the supply chain in the literature.

Chapter 5 Supply Chain Partner Selection with Risk Considerations

5.1 Introduction

In contemporary supply chains, material flows are vulnerable to unexpected disruption events which are of low probability but high consequences. For example, a supply shortage of DRAM chips led to Apple losing many customer orders (Sheffi, 2005). The disruptions in the electronics industry due to the catastrophic Thailand flooding in 2011 have led to huge losses of many Japanese companies (Fuller, 2012). All these disruption events suggest that disruption risk should be considered when building a value-added supply chain. Chapter 4 has covered situations when the decision maker wishes to control the overall risk level in supply chain, and when controlling the risk level in specific parts in supply chain is desired. In this chapter, a situation that occurs more often needs to be discussed, i.e. decision makers want to minimize the potential losses in worst cases in supply chain when they are selecting partners.

Here, we use the Conditional Value-at-risk (CVaR) to measure the loss in worst cases in supply chain. Specifically, we assume that the decision maker is looking for partner portfolios for which the probability of total cost (including additional costs due to disruptions) greater than VaR (a threshold value known as Value-at-risk) is no greater than 1-α, where α is the confidence level. As what Acerbi and Tasche (2002) have shown, CVaR belongs to the class of coherent risk measures having the following properties: monotonicity, sub-additivity, positive homogeneity and translation invariance, which can imply many real world observations in financial risk management. For example, sub-additivity implies diversification is beneficial, positive homogeneity implies that the risk of a portfolio is proportional to its size, and translation invariance implies that the addition of a sure amount of capital reduces the risk by the same amount. With these properties, CVaR could serve as an appropriate risk measure in the Min-risk Model.

5.2 Partner Selection with Risk Consideration

In the previous models, additional costs due to disruptions are not considered because in the definition of the disruption index, the consequences of any disruptions are modeled by the proportion of the affected amount in the total amount of materials or products. However, when the decision maker wants to minimize the worst case losses, considering the disruption index alone is no longer appropriate, and the additional costs resulting from disruptions have to be taken into consideration. In the Min-risk model, the definition of disruption index and the corresponding disruption index constraint need not to be modified, since the supply chain requirement constraints represent the strategic considerations of the supply chain, while the additional costs due to disruptions are for the considerations of consequences from potential disruptions which would be an essential part in minimizing risk, and these two different types of requirements should be presented and examined separately in the new model. Hence, we define disruption scenarios $\beta \in \theta = \{1, \ldots, h\}$, cost of handling disruptions and shortage of materials as shown in Table 5.1. Note that the cost of handling shortage of materials could be from repurchasing materials from other suppliers at a higher cost and additional costs due to production delays etc. The cost of handling disruptions in DC could be from cost of fixing the disruption, additional cost of transportation, and potential loss of sales etc. The cost of handling disruptions in retailers could include loss of sales and additional marketing cost. Denote P_β as the probability that disruption scenario β happens. Suppose the disruption events are independent, then P_β should be:

$$P_\beta = \prod_{i \in S_\beta} P_i^S \prod_{i \notin S_\beta} (1 - P_i^S) \prod_{t \in T_\beta} P_t^T \prod_{t \notin T_\beta} (1 - P_t^T) \prod_{r \in R_\beta} P_r^R \prod_{r \notin R_\beta} (1 - P_r^R), \tag{5.1}$$

where S_β, T_β, R_β are the subset of suppliers, DCs and retailers with disruptions in scenario β, respectively.

Table 5.1: New parameters and variables in the Min-risk Model

Parameters	
α	the confidence level
β	disruption scenario, $\beta \in \theta = \{1, \ldots, h\}$
θ	the index set of potential disruption scenarios
P_β	the probability of scenario β
$\boldsymbol{c_j^S}$	unit cost of handling shortage of material j, $j \in M = \{1, \ldots, n\}$
$\boldsymbol{c_t^T}$	unit cost of handling disruptions in DC t
$\boldsymbol{c_r^R}$	unit cost of handling disruptions in retailer r
Decision Variables	
$\boldsymbol{\tau_\beta}$	tail cost in scenario β
$\boldsymbol{\delta_{j\beta}^S}$	shortage of material j in scenario β
$\boldsymbol{\gamma}$	a threshold such that the probability of the total cost exceeding γ is not greater than 1-α

In Sawik (2013), an auxiliary function introduced by Rockafellar and Uryasev (2000) is applied to simulate the risk-averse behavior of a decision maker in a supplier selection problem. Define τ_β as the tail cost in scenario β, where tail cost is the amount by which the total cost in scenario β exceeds VaR. Denote γ as the threshold such that the probability of the total cost exceeding it is not greater than 1- α. Then the Conditional Value-at-Risk could be represented by the auxiliary function below:

$$CVaR = \gamma + (1-\alpha)^{-1} \sum_{\beta \in \theta} P_\beta \tau_\beta \tag{5.2}$$

According to Rockafellar and Uryasev (2000), minimizing CVaR is equivalent to minimizing the right hand side of equation (5.2) subjected to some common constraints in portfolio optimization problems plus the following two constraints, $\tau_\beta \geq 0$ for all $\beta \in \theta$ and the sum of γ and τ_β must be no smaller than the total cost. In the Min-risk case, the total cost should include the additional cost (AC) due to disruptions, which should be represented by:

$$AC = \sum_{j \in M} c_j^S \delta_{j\beta}^S + \sum_{t \in T_\beta} c_t^T \sum_{r \in R} \pi_{tr} f_r + \sum_{r \in R_\beta} c_r^R z_r f_r \ , \tag{5.3}$$

where $\delta_{j\beta}^S = \sum_{i \in S_\beta} w_{ij} d_j$ is the shortage of material j in scenario β. Then, the total cost under disruption scenario β in the Min-risk model should be:

$$TC = \sum_{j \in M} \sum_{i \in S_j} q_{ij} x_{ij} + \sum_{j \in M} \sum_{i \in S_j} c_{ij} w_{ij} d_j + \sum_{t \in T} v_t y_t + \sum_{t \in T} \sum_{r \in R} f_r \pi_{tr} e_{tr} + \sum_{r \in R} u_r z_r$$
$$+ \sum_{j \in M} c_j^S \delta_{j\beta}^S + \sum_{t \in T_\beta} c_t^T \sum_{r \in R} \pi_{tr} f_r + \sum_{r \in R_\beta} c_r^R z_r f_r \tag{5.4}$$

Hence, the **Min-risk Model** could be represented by:

$$\text{Min} \qquad CVaR = \gamma + (1-\alpha)^{-1} \sum_{\beta \in \theta} P_\beta \tau_\beta \tag{5.5}$$

s.t

Constraints (4.17) - (4.34) of the **Basic Model** in Chapter 4

Constraints (4.35) – (4.38) of the **Strategic trade-off Model** in Chapter 4

$$\gamma + \tau_\beta \geq \sum_{j \in M} \sum_{i \in S_j} q_{ij} x_{ij} + \sum_{j \in M} \sum_{i \in S_j} c_{ij} w_{ij} d_j + \sum_{t \in T} v_t y_t + \sum_{t \in T} \sum_{r \in R} f_r \pi_{tr} e_{tr}$$

$$+ \sum_{r \in R} u_r z_r + \sum_{j \in M} c_j^S \delta_{j\beta}^S + \sum_{t \in T_\beta} c_t^T \sum_{r \in R} \pi_{tr} f_r + \sum_{r \in R_\beta} c_r^R z_r f_r \qquad \forall \beta \in \theta \tag{5.6}$$

$$\tau_\beta \geq 0 \qquad \forall \beta \in \theta \tag{5.7}$$

$$\delta_{j\beta}^S = \sum_{i \in S_\beta} w_{ij} d_j \qquad \forall \beta \in \theta, \quad j \in M \tag{5.8}$$

The number of variables and constraints in the Min-risk Model grows exponentially with the number of potential supply chain partners, since the number of disruption scenarios is $h=2^{m+g+l}$, where m, g, l are the number of potential suppliers, DCs and retailers respectively. In some cases, the number of potential supply chain partners would be tens or even hundreds. For example, assuming we have 20 potential supply chain partners, then the number of potential disruption scenarios is 1048576. The resulting large size problem can be very computationally heavy as the number of potential partners grows, and therefore methods to reduce the number of disruption scenarios to be examined need to be discussed.

5.3 Scenario Management

In fact, scenario reduction techniques have been well developed in the fields of stochastic programming, in which the uncertain parameters of the second stage could lead to a large number of scenarios. The basic idea of scenario reduction is to select a subset of scenarios from the original scenario set such that the objective value approximated from the subset is as close as possible to the original objective value. Various approaches have been developed in the literature, such as the forward selection (FS) and backward reduction (BR) heuristics (Dupacova et al., 2003), clustering algorithms (Latorre et al., 2007), and importance sampling approach (Papavasiliou and Oren, 2013). However, none of these approaches can be applied to effectively reduce the size of the Min-risk Model, since these techniques were developed based on scenario trees for multistage models. A scenario management approach for environmental disaster planning introduced by Jenkins (2000) could be applied to reduce the number of scenarios for our problem, which is developed based on maximizing similarity between selected scenarios and original set of scenarios. Based on the ideas in these scenario reduction techniques, a detailed scenario management approach is discussed in this section.

Similar to the scenario reduction algorithms developed in Growe-Kuska et al. (2003), two criteria are used to determine the scenario subset and assign new probabilities to the selected scenarios in the subset.

Criterion 1: the selected scenarios should represent the original scenarios as closely as possible in terms of the overall risks

Criterion 2: the new probability of a selected scenario is the sum of its former probability and all the probabilities of deleted scenarios that are represented by it.

There are two important concepts in this scenario management approach, namely similarity and coverage. In Jenkins (2000), similarity is defined as the extent to which the disruption scenario does the same damage as another disruption scenario. In our case, damage of a disruption refers to the maximum percentage of materials and products that are affected, and thus the similarity could be given as $\varphi_{jk} = 1 - \sum_{i=1}^{3} \omega_i |\varepsilon_{ij} - \varepsilon_{ik}|$, where *i* is the index for material supply disruptions, DC disruptions and retailer disruptions, and *j*, *k* are indices for different disruption scenarios. ε_{ij} is the damage of type *i* disruption in scenario *j*, which is scaled between 0 and 1, and ω_i is the weight for disruption type *i*. Coverage refers to the similarity of a candidate disruption scenario to all possible scenarios including itself, and thus can be defined as $\sum_{j=1}^{h} \varphi_{jk}$. Let Ψ be the maximum number of candidate scenarios to be selected, η_k is the binary variable deciding whether candidate scenario *k* is selected, ξ_{jk} is 1 only if scenario *k* is selected, and for each *j* ξ_{jk} should have value 1 for the scenario *k* that scenario *j* resembles most. The definitions of parameters and variables are listed as follows:

ω_i	the weight for disruption type *i*, $\sum \omega_i$=1.
ε_{ij}	the damage level of type *i* disruption in scenario *j*, which is scaled between 0 and 1.
φ_{jk}	similarity between disruption scenario *j* and *k*, the extent to which scenario *j*. does the same damage as scenario *k*; $\varphi_{jk} = 1 - \sum_{i=1}^{3} \omega_i |\varepsilon_{ij} - \varepsilon_{ik}|$.
Ψ	the maximum number of candidate scenarios to be selected.

η_k the binary variable deciding whether candidate scenario *k* is selected.

ξ_{jk} a variable that equals to 1 only if scenario *k* is selected.

Then we can use the integer program introduced in Jenkins (2000) to maximize the overall coverage weighted by the probability, which gives the formulation **MOC** (Maximize Overall Coverage) as follows:

$$\text{Max} \qquad OC = \sum_k \sum_j P_j \varphi_{jk} \xi_{jk} \tag{5.9}$$

Subject to

$$\sum_k \eta_k \le \Psi \tag{5.10}$$

$$\sum_k \xi_{jk} \le 1, \quad j = 1, \ldots, h \tag{5.11}$$

$$\xi_{jk} \le \eta_k, \quad j = 1, \ldots, h \quad k = 1, \ldots, q \tag{5.12}$$

$$0 \le \xi_{jk} \le 1, \quad j = 1, \ldots, h \quad k = 1, \ldots, q \tag{5.13}$$

$$\eta_k \in \{0, 1\}, \quad k = 1, \ldots, q \tag{5.14}$$

Note that in the above integer program, *k* represents the index of candidate disruption scenarios, and *q* is the total number of candidate disruption scenarios. Constraint (5.10) ensures that no more than Ψ candidate scenarios could be selected; constraints (5.11) requires that for each scenario *j*, ξ_{jk} should have value 1 for the scenario *k* that scenario *j* resembles most; constraints (5.12) ensure that ξ_{jk} is 1 only if scenario *k* is selected. Due to the number of disruption scenarios *h* being large, the number of ξ_{jk} variables would be even larger, and hence the resulting integer program would also be a large size problem. In order to cope with the large size problems, we introduce a **Decomposition Scenario Management** approach in this section. The idea of this new approach is inspired by the clustering algorithms discussed in Latorre et al. (2007). The decomposition approach is described as follows:

Step 1: Divide the disruption scenarios into several subsets (e.g 50 subsets) with each subset containing similar disruption events, which can be done by applying the Clustering techniques in Data Mining.

Step 2: For each subset, compute and rank the risk (which is the product of probability and damage) for all scenarios, and choose the top q scenarios with highest risk as the candidate set; then compute the similarity φ_{jk} between each candidate scenario k and each scenario j in the subset.

Step 3: For each subset of scenarios, run **MOC** model and select some scenarios from the candidate set, assign new probabilities to the selected scenarios and put them into the final candidate set. The number of candidates drawn from each subset is determined according to the sum of scenario probabilities in that subset, i.e. subsets with a higher total probability would have more candidates selected into the final candidate set. More specifically, let n_1 be the number of candidates drawn from subset 1, p_1 be the sum of probabilities in subset 1, and λ be the total number of candidates to be drawn; then $n_1 = \lfloor p_1 \lambda \rfloor$. If $n_1=0$, then set n_1 to be 1. Repeat the process until all the subsets are scanned, after which the new set of candidate scenarios becomes available.

Step 4: Compute the similarity φ_{jk} between each scenario in the final candidate set, and do another **MOC** run with q = h = the number of scenarios in the final candidate set, and choose Ψ scenarios as the final set of representatives for the disruption scenarios, assign new probabilities to the final set of representatives.

Note that according to Criterion 2, after each **MOC** run, the probability of each selected candidate scenario would be changed to the sum of probabilities of those scenarios it represents including itself, so that the probabilities of the final set of representatives would still add up to one. The major effort in the above approach is to determine every similarity value ξ_{jk} as the input data. In this study, the clustering stage is carried out by applying the clustering package in R, while the **MOC** runs are conducted in CPLEX Optimization Studio. Figure 5.1 illustrates the basic procedures of this decomposition approach.

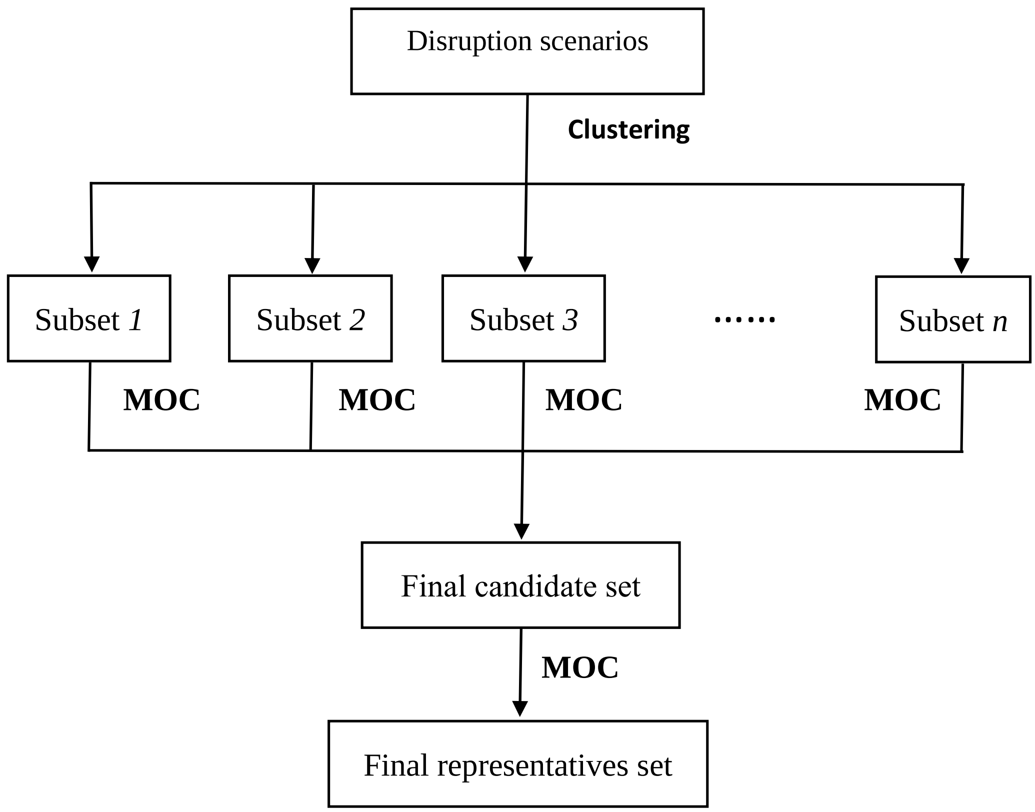


Figure 5.1: The basic procedures of the decomposition scenario management approach

5.4 Numerical Analysis

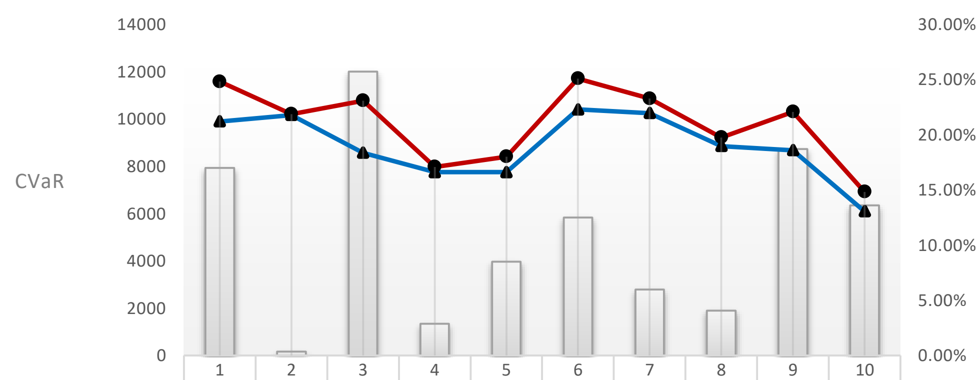
In this section, computational examples are applied to test the proposed mixed integer programming model for the Min-risk Model. A comparison between the traditional scenario management approach and the proposed decomposition scenario management approach has also been conducted. The computational experiments were performed on a Dell OPTIPLEX 990, Intel Core i5-2500, 3.30GHz, RAM 8GB/CPLEX 12.5.

The proposed decomposition scenario management approach is tested and compared with the results of the traditional scenario management approach. In order to see how accurate the two approaches are in predicting the real impact of all potential scenarios, we use a set of randomly generated data with relatively smaller size, i.e. with 4 potential suppliers, 3 potential DCs and 3 potential retailers, which makes $h=2^{10}$, so that calculating the result of real impact of potential disruptions with all possible scenarios taken into consideration is made possible. Table 5.2 compares the results of the two approaches and the original results with all disruption scenarios considered. For simplicity, the original results with all scenarios considered would be called 'Original' in the table, while the traditional scenario management approach is called 'Traditional SMA' and the decomposition approach is called 'Decomposition SMA'. The 'Solution Gap' indicates the differences between the CVaR solutions of the scenario management approaches and that of the original solutions, in which the CVaRs of the two scenario management approaches are calculated by using the values of the decision variables along with the data for the original problem. This is because the CVaRs we directly obtained from the solutions for the two approaches are based on the reduced version of the disruption scenario set, and so they cannot represent the real CVaRs under the corresponding solutions when all potential disruption scenarios are considered. Therefore the real CVaRs for all the Traditional SMA solutions and the Decomposition SMA solutions need to be calculated, so that we can clearly see and compare the quality of the solutions. Figure 5.2 and Figure 5.3 demonstrate and compare the CVaRs of the original problem and the real CVaRs of the traditional and decomposition SMA, as well as the solution gaps between the two.

Table 5.2: Comparison between the Traditional SMA and the Decomposition SMA

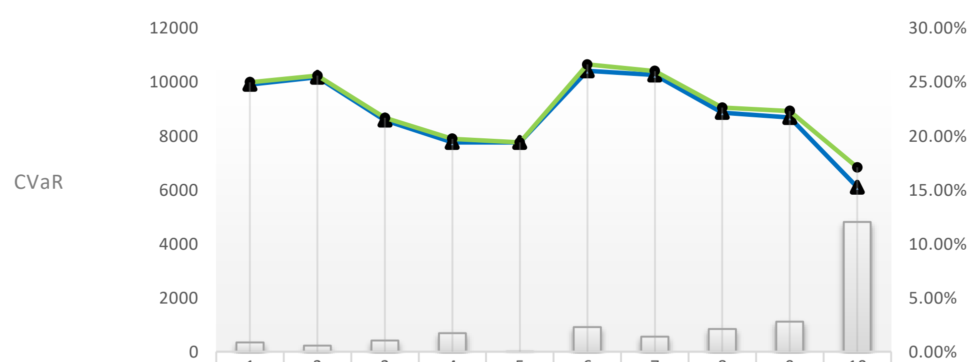
α =0.95	Original	Traditional SMA		Decomposition SMA	
	CVaR	CVaR	Solution Gap	CVaR	Solution Gap
Data 1	9901.5	11583.7	16.99%	9985.8	0.85%
Data 2	10170.4	10208.4	0.37%	10228.5	0.57%
Data 3	8574.7	10782	25.74%	8665.2	1.06%
Data 4	7757.3	7979.9	2.87%	7890.3	1.71%
Data 5	7753.5	8412.7	8.50%	7755	0.02%
Data 6	10409.6	11711.1	12.50%	10646.5	2.28%
Data 7	10254.7	10868.9	5.99%	10398.1	1.40%
Data 8	8859.5	9219.9	4.07%	9046.2	2.11%
Data 9	8679.9	10304.6	18.72%	8921.7	2.79%
Data 10	6095.8	6926.2	13.62%	6829.2	12.03%

From comparison of results in the table and graphs, we can see that the Decomposition SMA has outperformed the Traditional SMA in terms of the CVaR solution gap. The reason for this result lies in the fact that Decomposition SMA has reserved some positions for the low probability scenarios in the final representatives set, while the traditional SMA generally would only choose scenarios with highest probabilities. Given that the decomposition approach is more capable of dealing with huge data sets, we have clearly shown that it can be applied to solve the Min-risk Model. Thus, it can be concluded that the proposed Decomposition Scenario Management Approach could be applied for the selection of supply chain partners with risk considerations in a supply chain subjected to disruption risks.



	1	2	3	4	5	6	7	8	9	10
Solution Gap	16.99%	0.37%	25.74%	2.87%	8.50%	12.50%	5.99%	4.07%	18.72%	13.62%
Original	9901.5	10170.4	8574.7	7757.3	7753.5	10409.6	10254.7	8859.5	8679.9	6095.8
Traditional SMA	11583.7	10208.4	10782	7979.9	8412.7	11711.1	10868.9	9219.9	10304.6	6926.2

Figure 5.2: Real CVaRs between Original problem and Traditional SMA



	1	2	3	4	5	6	7	8	9	10
Solution Gap	0.85%	0.57%	1.06%	1.71%	0.02%	2.28%	1.40%	2.11%	2.79%	12.03%
Original	9901.5	10170.4	8574.7	7757.3	7753.5	10409.6	10254.7	8859.5	8679.9	6095.8
Decomposition SMA	9985.8	10228.5	8665.2	7890.3	7755	10646.5	10398.1	9046.2	8921.7	6829.2

Figure 5.3: Real CVaRs between Original problem and Decomposition SMA

The computation complexity for both approaches is O(hq), where h is the number of potential disruption scenarios, and q is the number of candidate scenarios. In the worst case, when q=h, the computation complexity becomes O(h^2). The comparison of CPU time of the two approaches is illustrated in Table 5.3. Note that the total CPU time of Decomposition SMA consists of the CPU time of clustering, the CPU time of second stage MOCs, and the CPU time of final stage MOC. We compare the running time using three data sets of different sizes, in which the size is determined by the number of potential disruption scenarios. For each data set, the number of candidate scenarios selected is the same for both approaches. From the comparison, we can see that Decomposition SMA generally requires less CPU time to process. Moreover, as the problem size grows larger, the CPU time of traditional SMA grows rapidly, and when dealing with 2^{20} scenario data set, the traditional SMA becomes inaccessible, while Decomposition SMA could still be processed. It is clear that Decomposition SMA is more capable of solving problems with large data set. In fact, the bottleneck for the Decomposition SMA lies in the clustering stage, because the clustering stage is the only stage that deals with large data set, after which the data is divided into multiple subsets that can be processed efficiently. Since the clustering is executed in R, the real bottleneck becomes the RAM of the computer. As long as there is enough RAM for R to work with the data, there is no concern over problem size. However, since the Decomposition SMA has O(h^2) computation complexity, the running time would be quite long when working with extremely large data. In practice, the number of potential disruption scenarios can be reduced by eliminating the ones that are unlikely to happen. Alternatively, certain rules could be added to the decomposition approach to make it more efficient. For example, when processing the first stage MOC runs, clusters that with individual probabilities lower than a certain number (e.g. 10^{-8}) can be skipped and be replaced with one scenario randomly chosen from this cluster with a probability that equals to the sum of probabilities in this cluster.

Table 5.3: Comparison of CPU time (sec.) between Traditional and Decomposition SMA

	Traditional SMA	Decomposition SMA
2^{10} data set	0.59	0.32
2^{15} data set	296.92	19.43
2^{20} data set	NA	592.38

Table 5.4 presents the results of Min-risk Model (confidence level α=0.9) compared with the results of Basic Model. The observations from Table 5.4 indicate that when the decision maker is aiming at lowering the risk, more suppliers would be selected and partners with lower risk of disruptions would be favored regardless of the higher cost. More specifically, all the suppliers are selected in the Min-risk Model results in order to mitigate the high cost of material shortage, and the combination of D_1 and R_2, R_3 would indeed produce less risk while keeping the total cost as low as possible. Refer to Appendix H for the detailed data.

Table 5.4: Results of Min-risk Model compared with Basic Model

	Min-risk Model	Basic Model
Cost	4268	3725
CVaR	8574.7	——
Supplier selected	S1,S2,S3,S4	S1,S2,S4
w_{ij}	w_{11}=0.25, w_{21}=0.75, w_{32}=0.5, w_{42}=0.5	w_{11}=0.25, w_{21}=0.75, w_{42}=1
DC selected	D_1	D_1, D_2
Retailer selected	R_2, R_3	R_1, R_2
π_{tr}	π_{12}=1, π_{13}=1	π_{11}=1, π_{22}=1

5.5 Case Study

Base on the proposed supply chain partner selection approach, we developed a customized model in this section to optimize the supply chain network for an India company in the iron and steel industry. The optimization problems are also formulated using OPL in CPLEX Optimization Studio 12.5, and the mathematical models are solved using a Dell OPTIPLEX 990, Intel Core i5-2500, 3.30GHz, RAM 8GB.

Taken from Parida and Andhare (2014), this case is about a thermo mechanically treated (TMT) bar manufacturing company in Maharashtra, India. The major products of this company are L channels and iron bars, which are supplied to distributors located in western part of India. The distributors basically cover areas like Maharashtra, Gujarat, Karnataka, Andhra Pradesh, and Madhya Pradesh. Raw materials (mild steel) are supplied by foreign suppliers and shipped by vehicles from Mumbai to Maharashtra, and transportation cost in this stage is borne by the company. The final products are manufactured through different processes such as heat treatment and rolling mill, and the cost incurred in the manufacturing stage includes labor cost and manufacturing overhead. The supply chain network includes only suppliers and distributors without retailers. More specifically there are two foreign suppliers (one from Japan, the other from China), one manufacturing plant, and four distributors situated at Vadodara (Gujarat), Amaravati (Maharashtra), Baramati (Maharashtra) and Ahwa (Gujarat). Figure 5.4 illustrates the existing supply chain network of the company.

Now suppose that the company's supply chain is suffering from high frequency of service failures in some of its distributors and is therefore in desperate need for a supply chain re-design. After a thorough survey, it is reported that there are two major problems with the existing distributors: one being the low service quality which leads to customer complaints and loss of future sales, and the other problem is the high occurrence of disruptions in transporting the products. The company is also looking for new suppliers that provide decent quality raw materials with negotiable prices to be potential long-term partners. After a market research, the company has identified two potential suppliers and six potential distributors. Now the company is considering the newly identified two potential suppliers along with the two existing suppliers as the candidates for long-term partners, and six newly identified distributors along with two of the existing distributors that have relatively decent performance are considered as the candidate long-term partners. The two existing distributors with decent performance are located in southern Gujarat (Vadodara) and central Maharashtra (Amaravati). The six newly identified distributors are located in central Gujarat, Madhya Pradesh, eastern Maharashtra, southern Maharashtra, Karnataka, and Andhra Pradesh, see Figure 5.4. The company has carefully evaluated each candidate in terms of their quality of products or services and their disruption risks. The quality score is examined from the following aspects: customer satisfaction, response time, on-time delivery, accuracy, and fill rate. Table 5.5 summarizes the supply capacity of each supplier, the cost of purchasing and shipping material from each supplier, ordering cost from each supplier, disruption probability of each supplier, and quality score for each supplier. Table 5.6 presents the cost of establishing the partnership with each distributor, the demand each distributor can handle, the cost of shipping product from plant to each distributor, probability of disruption for each distributor, and the quality score for each distributor.

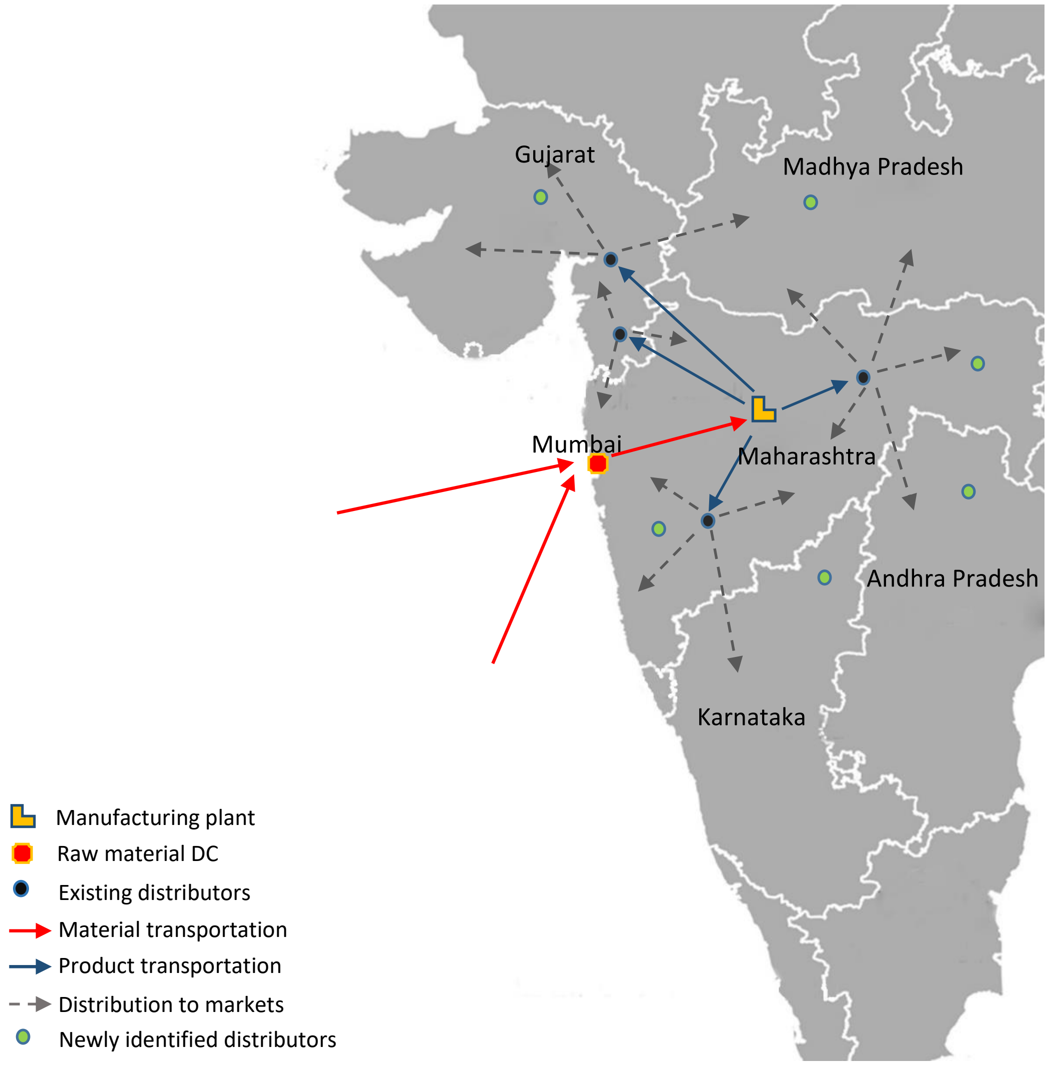


Figure 5.4: The supply chain network of the company before re-design

Table 5.5: Summary of input parameters for potential suppliers

Supplier	Supply capacity per month (ton)	purchasing and shipping cost ($/ton)	Ordering cost ($)	Disruption probability	Quality Score
Supplier A	18,000	440	6,000	0.02	0.9
Supplier B	24,000	440	5,000	0.01	0.8
Supplier C	30,000	420	4,500	0.05	0.98
Supplier D	15,000	450	5,000	0.02	0.95

Table 5.6: Summary of input parameters for potential distributors

Distributor Location	Establishing cost (100 $)	Demand can handle per month (ton)	Shipping cost ($/ton)	Disruption probability	Quality Score
central Maharashtra	1,500	3,600	15.5	0.05	0.75
southern Gujarat	2,000	3,600	19	0.02	0.85
Madhya Pradesh	5,000	3,600	17	0.03	0.98
southern Maharashtra	5,000	3,600	17.5	0.01	0.9
Karnataka	5,000	3,600	19	0.05	0.95
eastern Maharashtra	6,500	3,600	19	0.01	0.9
central Gujarat	6,000	3,600	23	0.01	0.9
Andhra Pradesh	5,600	3,600	19	0.01	0.9

Details of these data and problem notations can be found in Appendix C. Note that some data are estimated or collected from the available information on the internet. Besides the overall supply chain performance requirements, the company also wants to control the distribution disruption risk level, and the quality level for the product distribution. The Strategic trade-off Model is applied to solve the company's problem, and the mathematical formulation is as follows:

Min $$TC = \sum_{i \in S} q_i x_i + \sum_{i \in S} c_i w_i d + \sum_{t \in T} (v_t y_t + e_t f_t y_t) \quad (5.15)$$

Subject to

$$w_i \le x_i \qquad \forall i \in S \quad (5.16)$$

$$w_i d \le a_i \qquad \forall i \in S \quad (5.17)$$

$$w_i d \geq b_i x_i \qquad \forall i \in S \tag{5.18}$$

$$\sum_{i \in S} w_i = 1 \tag{5.19}$$

$$\sum_{t \in T} f_t y_t = f \tag{5.20}$$

$$k_{risk} \sum_{i \in S} (1 - P_i^S)(1 - P_m) w_i + (1 - k_{risk}) \sum_{t \in T} (1 - P_t^T)\ f_t y_t / f \geq P_{risk} \tag{5.21}$$

$$k_q \sum_{i \in S} Q_i^S w_i + (1 - k_q) \sum_{t \in T} Q_t^T\ f_t y_t / f \geq Q \tag{5.22}$$

$$\sum_{t \in T} (1 - P_t^T)\ f_t y_t / f \geq P_{riskT} \tag{5.23}$$

$$\sum_{t \in T} Q_t^T\ f_t y_t / f \geq Q_T \tag{5.24}$$

$$\sum_{i \in S} x_i \geq 2 \tag{5.25}$$

$$0 \leq w_i \leq 1 \qquad \forall i \in S \tag{5.26}$$

$$x_i, y_t \in \{0,1\} \qquad \forall i \in S, t \in T \tag{5.27}$$

The optimal solution suggests the company to keep one of the old suppliers from Japan as the secondary supplier, while the majority of raw material (85.7%) will be supplied by a new supplier from China. In terms of the distributors, one of the old distributors located in southern Gujarat (Vadodara) and three new distributors located at Madhya Pradesh, southern Maharashtra, and Karnataka are chosen as the new distributors. Figure 5.5 illustrates the new supply chain network after re-design.

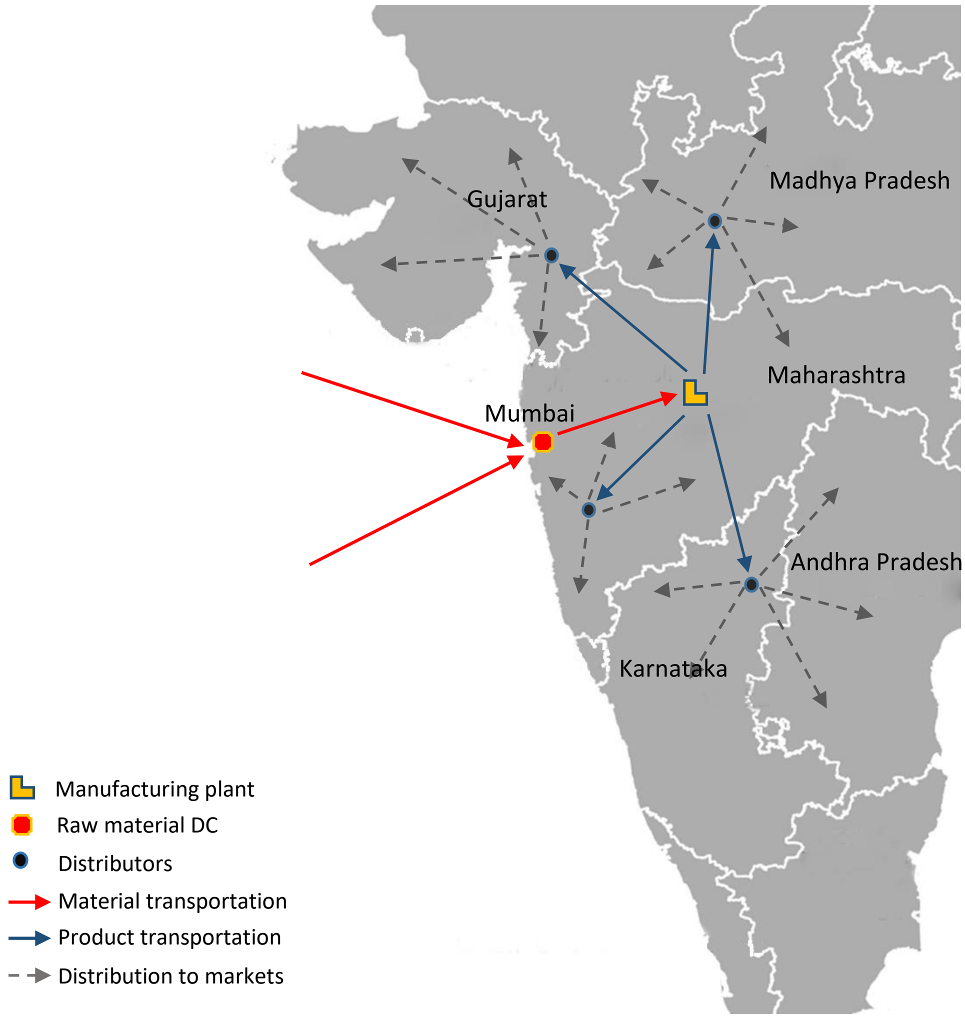


Figure 5.5: The supply chain network of the company after re-design

The company also has concerns about the worst case cost of the new supply chain network design. Therefore the Min-risk Model is also applied to examine whether the newly designed network is also optimal under the min-risk requirements. The additional costs of handling disruptions are carefully estimated by the company. The details of the Min-risk formulation are presented in Appendix D. The confidence level α is 0.95, define c^S as the unit cost of handling supply disruptions, while c_t^T refers to the unit cost of handling product disruptions in distributor t, where specifically in this case study, the product disruptions refer to disruptions in transporting the final product to distributors. In this case, c^S is 820\$/ton, and the value of c_t^T is 15\$ /ton, 20\$/ton, 18\$/ton, 16\$/ton, 18.5\$/ton, 15.5\$/ton, 15\$/ton, and 16\$/ton for t=1…8, respectively. In particular, the index t from 1 to 8 refers to the distributor located in central Maharashtra, southern Gujarat, Madhya Pradesh, southern Maharashtra, Karnataka, eastern Maharashtra, central Gujarat, and Andhra Pradesh. The Min-risk formulation is shown as follows:

$$\text{Min} \qquad CVaR = \gamma + (1-\alpha)^{-1} \sum_{\beta \in \theta} P_\beta \tau_\beta \tag{5.28}$$

Subject to

Constraints (5.16) – (5.27)

$$\gamma + \tau_\beta \geq \sum_{i \in S} q_i x_i + \sum_{i \in S} c_i w_i d + \sum_{t \in T} (v_t y_t + e_t f_t y_t) + \mathrm{c}^S \sum_{i \in S_\beta} w_i d + \sum_{t \in T_\beta} c_t^T f_t$$

$$\forall \beta \in \theta \tag{5.29}$$

$$\tau_\beta \geq 0 \qquad\qquad \forall \beta \in \theta \tag{5.30}$$

The result we obtained after applying the Min-risk Model suggests choosing the distributors located in central Gujarat, eastern Maharashtra, southern Maharashtra, and Andhra Pradesh, while all four suppliers are chosen in Min-risk Model compared to two suppliers chosen in strategic trade-off model. The percentages of material supply for the four chosen suppliers are 28.2%, 28.6%, 27.8%, and 15.4%. Figure 5.6 illustrates the supply chain network design suggested by the Min-risk Model. Table 5.7 compares the differences between the strategic trade-off results and the min-risk results.

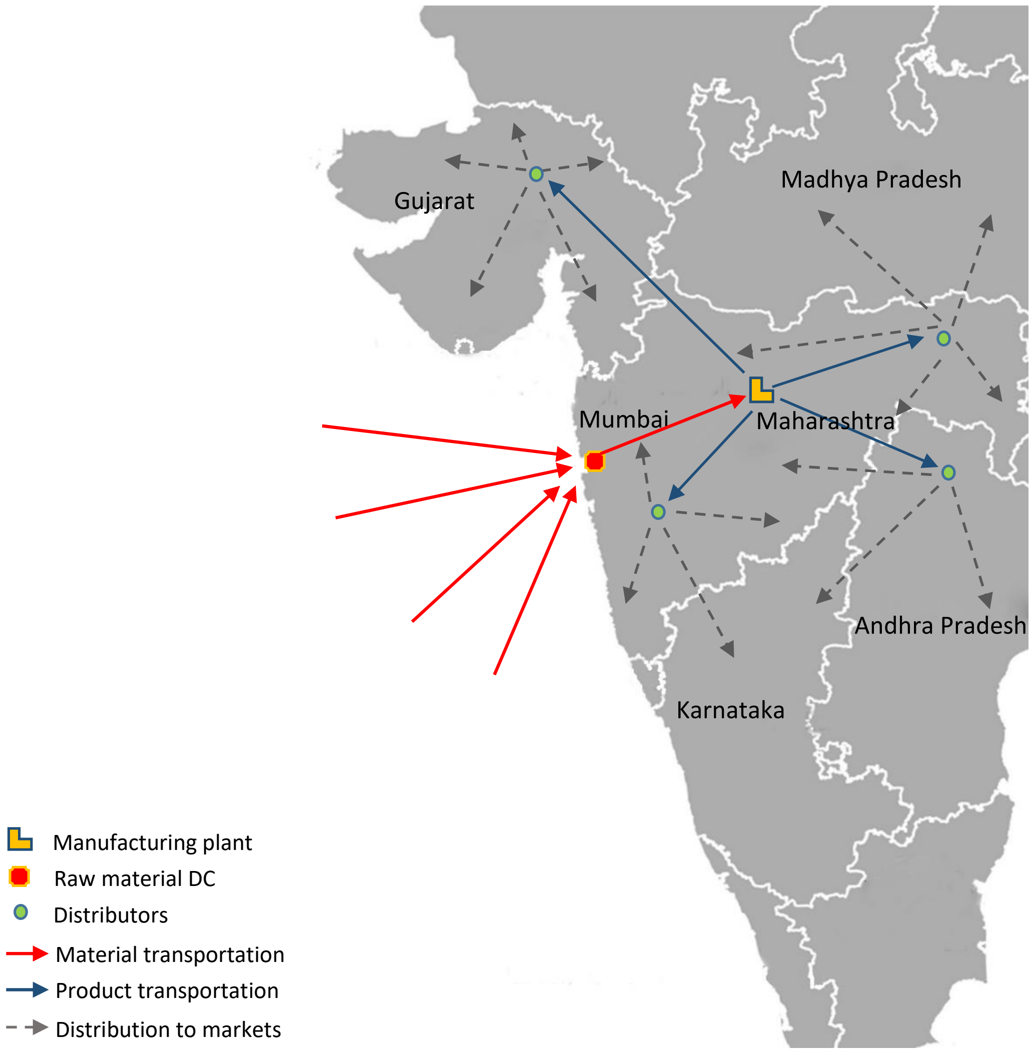


Figure 5.6: The supply chain network design suggested by the Min-risk Model

Compared to the strategic trade-off results, the min-risk results produce a higher total cost, and the overall disruption index is higher than that of strategic trade-off results, indicating a less disruption risk. The overall quality index is lower than that of the strategic trade-off results, but still above the performance requirement threshold value. The disruption index and quality index for distributors for the min-risk results share the same trend as the overall indices. Compared to the strategic trade-off results, all four suppliers are chosen in the min-risk results, which indicates that having multiple suppliers can effectively reduce the supply risks. The min-risk results suggest to choose distributors that have lower disruption risks but with higher establishing cost and shipping cost, indicating that when minimizing the disruption risk becomes the objective, the supply chain partner portfolio will change to include those partners with lower risk, as long as the performance requirements can be satisfied.

Table 5.7: Comparison of base case solution and min-risk solutions

	Strategic Trade-off	Min-risk
Total cost (1000$)	9,168.5	9,481.78
Overall disruption index	0.956	0.975
Overall quality index	0.939	0.901
Distributor disruption index	0.973	0.990
Distributor quality index	0.920	0.90
Supplier A	√	√
Supplier B	-	√
Supplier C	√	√
Supplier D	-	√
central Maharashtra	-	-
southern Gujarat	√	-
Madhya Pradesh	√	-
southern Maharashtra	√	√
Karnataka	√	-
eastern Maharashtra	-	√
central Gujarat	-	√
Andhra Pradesh	-	√

5.6 Summary

In this chapter, we proposed a Min-risk Model that incorporated the basic supply chain partner selection approach with conditional value-at-risk measurements, and developed a Decomposition Scenario Management approach to deal with the resulting large size problems of the Min-risk Model. Numerical results have shown that the proposed Decomposition Scenario Management approach outperformed the traditional Scenario Management approach in terms of CVaR solution gaps and can be applied to search for the near optimal solution for the selection of supply chain partners in the context when minimizing risk is the objective. By comparing the results of Min-risk Model under different confidence levels and the results of Basic Model for supplier selection, we have shown that the solutions of Min-risk Model are in line with real world observations, indicating that the proposed Min-risk Model is capable of supporting the decision making in supply chain partner selection problems when minimizing the risk is the first priority. In conclusion, the proposed strategic decision making approach in supply chain partner selections meets the needs identified in the literature review, and can help practitioners to better achieve strategic alignment and create value in supply chain.

The proposed strategic decision approach for supply chain partner selections is also extendable. For example, nowadays global climate change is a big issue and the need for greener supply chain is pressing. In such a circumstance, we can add in the carbon footprint as one of our supply chain level requirements as well as trade-off options in our model. Another extension would be considering the outsourcing of manufacture. In this case, manufacturers would also be considered as supply chain partners, and besides cost new factors such as economic stability, political stability etc. should be considered. In conclusion, the proposed approach can be applied to help with making strategic supply chain decisions under different business environments.

Chapter 6 Supply Chain Fortification against Worst Case Disruptions

6.1 Introduction

When a supply chain is fully built through the strategic planning and careful selections of supply chain partners that we have discussed in the previous chapters, the next challenge is to make sure the supply chain will function smoothly in the operation stage. Risks in supply chain operation stage mainly come from various types of uncertainties (demand uncertainty, supply uncertainty, natural disasters, or accidents), and intentional attacks (from business competitors, enemies, terrorist attacks, or dissatisfied labors). Supply chain disruptions due to uncertainties are more related to tactical and operational level decisions, and are usually modeled by applying stochastic optimization or robust optimization approaches, while disruptions due to intentional attacks require more of strategic level decision makings, since intentional attacks would often bring catastrophic consequences. Essentially, the strategy against intentional attacks is to identify and protect the most vulnerable parts in the network system, so that the potential damage is minimized. Recent events have demonstrated that a single disruption in supply chain can have domino effects, which will directly affect a corporation's ability to provide critical services to customers. For example, in the year 2000, a fire accident in Ericsson's chips supplier immediately disrupted the material supply, which led to a loss of about USD 400 million (Norrman and Jansson, 2004). A simple accident on a weak spot in supply chain can already bring such a huge loss, and there would be worse consequences if the disruptions are deliberately caused by intelligent attackers. Therefore being able to identify the vulnerable parts of the supply chain, where a single disruption can lead to significant degradation in supply chain performance, is of great importance for the decision makers. Essentially, given the supply chain network and typical operational information, one should be able to identify the areas of weakness in the network, and based on such information, improvements and protections can be made.

Consider a company in a highly competitive market or a company dealing with strategic products that are crucial to the economic development or land security of a country. Business competitors or terrorists/enemies/dissatisfied labors will intentionally cause disruptions in order to maximize the damage taken up by the company, which could be profit loss, market share loss, or reputation loss etc. In such situations, given a limited protection budget, the company wants to know how to allocate the resources to protect the supply chain against these intentional attacks such that the damage taken is minimized. In this chapter, we will explore the optimal protection strategies against intentional attacks in supply chain. By studying the protection strategies against intentional attacks, we can have a better understanding of the supply chain network in terms of its vulnerable parts, and therefore can be better prepared to deal with future worst case disruption events.

As have discussed in the literature review, network interdiction models can be applied to model intentional attacks in supply chain. In particular, we use a tri-level defender-attacker-user network interdiction model to simulate the problem in this study, since protection decisions based on the solution of traditional two-level network interdiction model may be suboptimal. In tri-level programs, we are dealing with min-max-min or max-min-max problems, i.e., the defender or network user has some knowledge about the interdiction and wants to defend some arcs or nodes under a certain budget so that the loss due to interdiction is minimized. The major challenge of modeling risk from intentional attacks in supply chain is the definition of attacks in the network, and in this study we provide a detailed definition of different types of intentional attacks in supply chain that can be readily applied in the tri-level network interdiction model.

6.2 Problem Description

6.2.1 Define the supply chain network

Consider the supply chain as a directed graph G(**N,A**), where **N** is the set of nodes, and **A** is the set of arcs. Nodes can represent factories, DCs, warehouses or retailers, while arcs can be roads, production processing lines or procedures. We assume that disruptions only happen on arcs. In fact, disruptions happening in nodes can be transformed into arc disruptions if we define the network properly (see Bertsimas and Tsitsiklis, 1997). In particular, disruptions in a node can be replaced by two nodes connected by an arc, so that only arc disruptions need to be considered. The flows in the supply chain network include material flow, money flow and information flow, and material flow can be defined as commodities that flow from a source node to a sink node in the network. Since money flow and information flow could also be the target of intentional attacks in this information age, it is important to define these two types of flows in the network. Therefore, we define special nodes and arcs to help represent money and information flows in a supply chain network. The nodes in supply chain network can be categorized into supplier nodes, retailer nodes, contract nodes, manufactory nodes, product nodes, DC nodes and road junction nodes. Contract nodes and product nodes are special nodes defined to help represent the money flow and information flow. In particular, as shown in in Table 6.1, we define the following node sets for different types of nodes.

Table 6.1: Definition of node sets

Definition of node sets	
Purchase contract nodes	$\mathbf{N_p}$
Sales contract nodes	$\mathbf{N_d}$
Manufactory nodes	$\mathbf{M}$
Product nodes	$\mathbf{P}$
Supplier nodes	$\mathbf{N_s}$
Retailer nodes	$\mathbf{N_r}$
DC nodes	$\mathbf{N_{DC}}$
Road junction nodes	$\mathbf{N_j}$

Similarly, arcs in supply chain are classified into purchase contract arcs, sales contract arcs, manufacture arcs and transportation arcs, with specific definitions are shown in Table 6.2

Table 6.2: Definition of arc sets

Definition of arc sets		
purchase contract arcs	$\mathbf{A_p}$	The set of arcs linking $\mathbf{N_p}$ to $\mathbf{M}$
sales contract arcs	$\mathbf{A_d}$	The set of arcs linking $\mathbf{N_d}$ to $\mathbf{P}$
manufacture arcs	$\mathbf{A_m}$	The set of arcs linking $\mathbf{M}$ to $\mathbf{P}$
transportation arcs	$\mathbf{A_t}$	All other arcs($\mathbf{A}\backslash(\mathbf{A_p}\cup\mathbf{A_d}\cup\mathbf{A_m})$)

Purchase contract arcs start from the purchase contract nodes and end with manufactory nodes, and sales contract arcs start from the sales contract nodes and end with product nodes. The flows on these arcs are special commodities representing the purchase or sales contracts. Figure 6.1 shows an example of a supply chain consisting of two suppliers, two retailers, one factory and two products. Nodes A and B are suppliers, X and Y are retailers, A' and B' are purchase contract nodes, and X_1, Y_2 are sales contract nodes. The nodes without any label are road junction nodes. The blue arcs ($\mathbf{A_t}$) are transportation arcs, purple arcs ($\mathbf{A_m}$) are manufacture arcs, black arcs ($\mathbf{A_p}$) are purchase contract arcs, red arcs ($\mathbf{A_d}$) are sales contract arcs. Essentially, the material flows will travel through the transportation and manufacture arcs, while the financial and information flows will travel through the purchase and sales contract arcs.

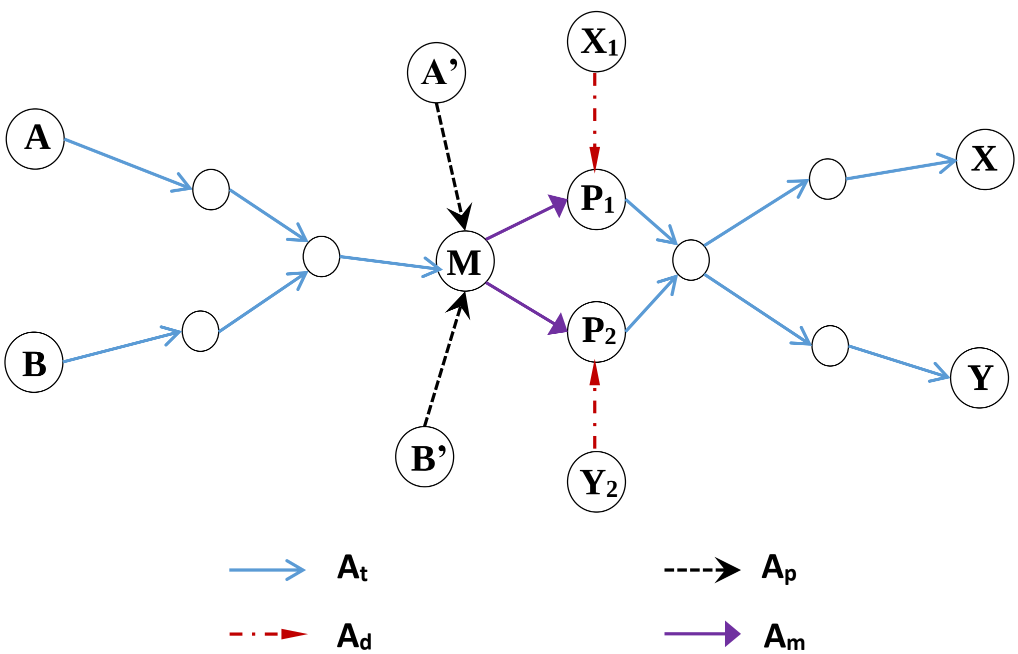


Figure 6.1: An example of supply chain network

6.2.2 Define disruptions due to intentional attacks

Intentional attacks from business competitors would mainly focus on the contract arcs, whose disruptions will affect all three types of flows in the supply chain system. For example, competitors can make it more difficult for the company to get sales contracts by promoting sales campaigns or introducing new competitive products; competitors can also increase the sourcing cost for the company by forming strategic partnerships with its key suppliers. Note that information flow is affected because competitions from other entities will cause suppliers and distributors or retailers to hide certain information from the company, and lead to distrust issues and information distortions. All these acts from competitors and the corresponding impacts will eventually lead to supply disruptions or demand disruptions. Supply disruptions could be the price increase of raw materials or the decrease in amount of supply, which is assumed to happen only on the purchase contract arcs ($\mathbf{A_p}$). When supply disruption happens, the company will look for other suppliers or negotiate with the existing supplier to make sure enough raw materials are supplied, which leads to the increase in sourcing cost. If the company fails to get enough raw materials, there will be backlogs or even loss of sale, which leads to the increase of selling costs and marketing cost or revenue loss (equivalent to increase in cost). Therefore we assume that the increase in arc cost includes all the additional costs caused by supply disruption. Similarly, demand disruptions will only happen on sales contract arcs ($\mathbf{A_d}$), and will lead to promotion or loss of sale, and the increase in arc cost includes all the additional costs (revenue loss) caused by decrease in demand.

Intentional attacks from terrorists/enemies/dissatisfied labors would mainly be targeted on material flows, and will lead to manufacture disruptions and transportation disruptions. Manufacture disruptions can be strikes or breaking down of facility due to intentional damage, which happen only on manufacture arcs ($\mathbf{A_m}$), and will lead to strike handling costs, overtime costs etc. The consequence of transportation disruptions would be delays of delivery and the increase in various costs, and we assume that transportation disruptions happen only on transportation arcs ($\mathbf{A_t}$). The increase in arc cost includes all the additional costs caused by manufacture disruptions and transportation disruptions.

Protective activities are measures that can be taken by the company to reduce the loss caused by disruptions, which include signing strategic contracts and developing strategic partnerships with suppliers and retailers, reserving redundant facility/capacity, having emergency inventories, improving the welfare of workers and buying insurance. Signing strategic contracts can reinforce the contract arcs ($\mathbf{A_p} \cup \mathbf{A_d}$), while reserving redundant facility/capacity, having emergency inventories and improving the welfare of workers can reinforce the manufacture arcs and transportation arcs ($\mathbf{A} \backslash (\mathbf{A_p} \cup \mathbf{A_d})$). Theoretically, buying insurance can reinforce any arcs in the network, but in reality insurance can only mitigate the monetary loss while leaving the impact of disruptions undisposed. Therefore, buying insurance will not be considered as a protective strategy against intentional attacks and worst case disruptions in this study. The cost for protecting each arc is the estimation of monetary cost the company has to pay for completely securing this arc from potential harms by using one or more of the above mentioned protective measures.

As mentioned previously, the consequences of all the disruptions are measured by the increase in monetary cost. Therefore, the objective is to minimize the total cost after interdiction, which means the network interdiction model we are about to discuss is based on the minimum-cost network flow problem.

6.2.3 Problem formulation

In this study, we are dealing with a multi-commodity flow network, in which each commodity $k \in \mathbf{K}$ has a commodity flow from source s^k to sink t^k, where $\mathbf{K}$ is the set of commodities. f_k is the demand for commodity k. o_{ij} is the original cost of using arc (i, j), d_{ij} is the additional cost of using arc (i, j) if it is interdicted, c_{ij} is the cost for interdiction on arc (i, j) and B is the interdiction budget. x_{ij} is the decision variable for the network attacker, which determines the percentage of arc (i, j) destroyed by the attacker, and the additional cost of using arc (i, j) is increased by x_{ij} ×100 %. y_{ij}^k is the decision variable for network user, which represents the flow of commodity k on arc (i, j). In terms of the company's defensive options, let r_{ij} be the decision variable of the defender, which determines the protection decision on arc (i, j), such that the disruption x_{ij} on this link must satisfy $x_{ij} \leq 1-r_{ij}$. Define e_{ij} as the cost for reinforcing arc (i, j), and H as the company's budget for such defensive options. We specify the list of notations as follows:

$\mathbf{N}$	set of nodes
$\mathbf{A}$	set of arcs
$\mathbf{K}$	set of commodities
f_k	the demand of commodity k, $k \in$ K
s^k	source of commodity flow k
t^k	sink of commodity flow k
o_{ij}	original cost of using arc (i, j)
d_{ij}	additional cost of using arc (i, j)
c_{ij}	cost for interdicting arc (i, j)
e_{ij}	the cost for reinforcing arc (i, j)
B	interdiction budget

H protection budget

x_{ij} the decision variable for the network attacker, the percentage of interdiction on arc (i, j), $0 \le x_{ij} \le 1, \forall\, (i,j) \in \mathbf{A}$.

y_{ij}^k the decision variable of network user, determines the flow of commodity k on arc (i, j).

r_{ij} the decision variable of the defender, which determines the protection decision on arc (i, j)

The Network Fortification (**NF**) formulation for the tri-level defender-attacker-user problem is as follows:

$$[\mathbf{NF}] \quad \min_{\mathbf{r}\in\mathbf{R}} \max_{\mathbf{x}\in\mathbf{X}} \min_{\mathbf{y}} \quad \mathrm{TC}=\sum_{k\in\mathbf{K}} \sum_{(i,j)\in\mathbf{A}} (o_{ij} + x_{ij} d_{ij})\, y_{ij}^k \tag{6.1}$$

$$s.t \quad \sum_j y_{ij}^k - \sum_j y_{ji}^k = \begin{cases} f_k, & i = s^k \\ 0, & i \ne s^k, t^k \\ -f_k, & i = t^k \end{cases} \quad \forall k \in \mathbf{K} \quad \forall i \in \mathbf{N} \tag{6.2}$$

$$y_{ij}^k \ge 0 \quad \forall (i,j) \in \mathbf{A} \quad \forall k \in \mathbf{K} \tag{6.3}$$

$$x_{ij} \le 1 - r_{ij} \quad \forall (i,j) \in \mathbf{A} \tag{6.4}$$

$$\text{where } X = \{x_{ij} \mid 0 \le x_{ij} \le 1 \quad \forall (i,j) \in \mathbf{A}, \sum_{(i,j)\in A} c_{ij} x_{ij} \le \mathrm{B}\}$$

$$R = \{r_{ij} \mid r_{ij} \in \{0,1\} \quad \forall (i,j) \in \mathbf{A}, \sum_{(i,j)\in A} e_{ij} r_{ij} \le \mathrm{H}\}$$

X is the domain of the attacker's decision variable, requiring the total cost of interdiction not to exceed the interdiction budget B. R is the domain of the defender's decision variable, bounded by the protection budget constraint. Note that arc capacity is not considered in this study, because the consequences of intentional attacks or worst case disruptions are represented by cost increase. Moreover, since we are focused on the strategic level decisions, we can assume that the capacities of transportation arcs are unlimited in most cases. In terms of manufacturing capacity, it can also be ignored in this study because consequences of manufacturing disruptions are modeled as cost increase, and the flows between manufacturing nodes to product nodes are independent flows and are predefined in the problem data.

6.3 Optimal Protection against Worst Case Disruptions

In this section, we discuss how to solve the tri-level optimization problem presented in the previous section, so that optimal protection strategies against intentional attacks in supply chain are identified.

Consider Model **NF**. If we fix **x** and **r**, and take the dual of the inner minimization, then release **x**, the formulation becomes:

$$
\begin{aligned}
&\min_{\mathbf{r}\in\mathbf{R}} \max_{\mathbf{x},\mathbf{p}} \sum_{k\in\mathbf{K}} f_k (p_s^k - p_t^k) \\
&s.t. \quad p_i^k - p_j^k - d_{ij} x_{ij} \le o_{ij} \quad \forall (i,j)\in\mathbf{A} \quad \forall k\in\mathbf{K} \\
&\qquad \sum_{(i,j)\in\mathbf{A}} c_{ij} x_{ij} \le \mathrm{B} \\
&\qquad 0 \le x_{ij} \le 1 - r_{ij} \quad \forall (i,j)\in\mathbf{A}
\end{aligned}
$$

where $R = \{ r_{ij} \mid r_{ij} \in \{0,1\} \quad \forall (i,j)\in\mathbf{A}, \sum_{(i,j)\in A} e_{ij} r_{ij} \le \mathrm{H} \}$

This formulation is a bi-level mixed integer optimization problem. Similarly, if we fix **r**, and take the dual of inner maximization, then release **r**, we have:

$$[\mathbf{NF D}] \qquad \min_{\mathbf{r},\boldsymbol{\pi},\boldsymbol{\alpha},\beta} TC = \sum_{k\in\mathbf{K}} \sum_{(i,j)\in\mathbf{A}} o_{ij} \alpha_{ij}^k + \mathrm{B}\beta + \sum_{(i,j)\in\mathbf{A}} \pi_{ij} (1 - r_{ij}) \tag{6.5}$$

$$s.t \quad \sum_j \alpha_{ij}^k - \sum_j \alpha_{ji}^k = \begin{cases} f_k, & i = s^k \\ 0, & i \ne s^k, t^k \\ -f_k, & i = t^k \end{cases} \qquad \forall k\in\mathbf{K} \quad \forall i\in\mathbf{N} \tag{6.6}$$

$$c_{ij}\beta - \sum_{k\in\mathbf{K}} d_{ij} \alpha_{ij}^k + \pi_{ij} \ge 0 \quad \forall (i,j)\in\mathbf{A} \tag{6.7}$$

$$\sum_{(i,j)\in\mathbf{A}} e_{ij} r_{ij} \le \mathrm{H} \tag{6.8}$$

$$r_{ij} \in \{0,1\} \quad \forall (i,j)\in\mathbf{A} \tag{6.9}$$

$$\boldsymbol{\alpha} \geq 0, \beta \geq 0, \boldsymbol{\pi} \geq 0 \tag{6.10}$$

The objective function of model **NFD** (Network Fortification-Dual) is bilinear, because π_{ij} and r_{ij} are both decision variables. **NFD** can be solved via standard linearization techniques discussed in Lim and Smith (2007). For each bilinear term $\pi_{ij}r_{ij}$, we substitute it with a single variable λ_{ij}. In addition we add the following constraints:

$$\lambda_{ij} - \pi_{ij} \leq 0, \tag{6.11}$$

$$\lambda_{ij} - \overline{\pi_{ij}} r_{ij} \leq 0, \tag{6.12}$$

where $\overline{\pi_{ij}}$ is the upper bound of π_{ij}. If r_{ij}=1, λ_{ij} cannot be greater than the upper bound $\overline{\pi_{ij}}$, while if r_{ij}=0, λ_{ij} cannot be positive. The upper bound of π_{ij} can be found by analyzing constraints (6.7): $\pi_{ij} \geq \sum_{k \in \mathbf{K}} d_{ij}\alpha_{ij}^k - c_{ij}\beta$, $\forall (i,j) \in \mathbf{A}$. According to duality theory, the economic meaning of π_{ij} is the attacker's gain if one unit of interdiction variable x_{ij} is allowed. Therefore, as c_{ij} becomes very large, π_{ij} should become 0. Since the objective function is to be minimized, we then have

$$\pi_{ij} = \begin{cases} \sum_{k \in \mathbf{K}} d_{ij}\alpha_{ij}^k - c_{ij}\beta \leq \sum_{k \in \mathbf{K}} f_k d_{ij}, & if \sum_{k \in \mathbf{K}} d_{ij}\alpha_{ij}^k - c_{ij}\beta \geq 0 \\ 0 \leq \sum_{k \in \mathbf{K}} f_k d_{ij}, & if \sum_{k \in \mathbf{K}} d_{ij}\alpha_{ij}^k - c_{ij}\beta < 0 \end{cases} \quad \forall (i,j) \in \mathbf{A} \tag{6.13}$$

Hence, $\overline{\pi_{ij}} = \sum_{k \in \mathbf{K}} f_k d_{ij}$ is an upper bound of π_{ij}. After applying the standard linearization techniques, the formulation becomes:

$$[\mathbf{LNFD}] \quad \min_{\mathbf{r},\boldsymbol{\pi},\boldsymbol{\alpha},\beta} TC = \sum_{k\in\mathbf{K}} \sum_{(i,j)\in\mathbf{A}} o_{ij}\alpha_{ij}^{k} + \mathrm{B}\beta + \sum_{(i,j)\in\mathbf{A}} \pi_{ij} - \sum_{(i,j)\in\mathbf{A}} \lambda_{ij} \tag{6.14}$$

$$s.t \quad \sum_{j} \alpha_{ij}^{k} - \sum_{j} \alpha_{ji}^{k} = \begin{cases} f_k, & i = s^k \\ 0, & i \neq s^k, t^k \\ -f_k, & i = t^k \end{cases} \quad \forall k \in \mathbf{K} \quad \forall i \in \mathbf{N} \tag{6.15}$$

$$c_{ij}\beta - \sum_{k\in\mathbf{K}} d_{ij}\alpha_{ij}^{k} + \pi_{ij} \geq 0 \quad \forall (i,j) \in \mathbf{A} \tag{6.16}$$

$$\sum_{(i,j)\in\mathbf{A}} e_{ij} r_{ij} \leq \mathrm{H} \tag{6.17}$$

$$\lambda_{ij} - \pi_{ij} \leq 0 \quad \forall (i,j) \in \mathbf{A} \tag{6.18}$$

$$\lambda_{ij} - r_{ij} \sum_{k\in\mathbf{K}} f_k d_{ij} \leq 0 \quad \forall (i,j) \in \mathbf{A} \tag{6.19}$$

$$r_{ij} \in \{0,1\} \quad \forall (i,j) \in \mathbf{A} \tag{6.20}$$

$$\boldsymbol{\alpha} \geq 0, \beta \geq 0, \boldsymbol{\pi} \geq 0, \boldsymbol{\lambda} \geq 0 \tag{6.21}$$

Model **LNFD** (Linearized Network Fortification-Dual) is a mixed integer program and can be extended to model multiple attackers. For example, if we have two types of attackers, namely business competitors and terrorists/enemies/dissatisfied labors, the objective function would become:

$$\min_{\mathbf{r},\boldsymbol{\pi},\boldsymbol{\alpha},\boldsymbol{\beta}} TC = \sum_{k\in\mathbf{K}} \sum_{(i,j)\in\mathbf{A}} o_{ij}\alpha_{ij}^{k} + \mathrm{B}_c\beta_c + \mathrm{B}_u\beta_u + \sum_{(i,j)\in\mathbf{A}} \pi_{ij} - \sum_{(i,j)\in\mathbf{A}} \lambda_{ij} \tag{6.22}$$

and constraints (6.16) become:

$$c_{ij}\beta_c - \sum_{k\in\mathbf{K}} d_{ij}\alpha_{ij}^{k} + \pi_{ij} \geq 0 \quad \forall (i,j) \in \mathbf{A}_p \bigcup \mathbf{A}_d \tag{6.23}$$

$$c_{ij}\beta_u - \sum_{k\in\mathbf{K}} d_{ij}\alpha_{ij}^{k} + \pi_{ij} \geq 0 \quad \forall (i,j) \in \mathbf{A} \setminus (\mathbf{A}_p \bigcup \mathbf{A}_d) \tag{6.24}$$

Note that B_c and B_u are the interdiction budgets for competitor and terrorists/enemies/dissatisfied labors respectively. The formulation remains a MIP.

Next, we develop a Lemma and a Theorem to show that model **LNFD** can be used to solve the problem represented by Model **NF**.

LEMMA 1. If an optimal solution $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \boldsymbol{\lambda}^*, \mathbf{r}^*)$ solves **LNFD** and if $\lambda_{ij}^* = \pi_{ij}^* r_{ij}^* \quad \forall (i,j) \in \mathbf{A}$, then $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \mathbf{r}^*)$ is an optimal solution to **NFD**.

Proof.

If $\lambda_{ij} = \pi_{ij} r_{ij} \quad \forall (i,j) \in \mathbf{A}$ holds, the value of objective function in **LNFD** equals to that in **NFD**, and $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \mathbf{r}^*)$ in $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \boldsymbol{\lambda}^*, \mathbf{r}^*)$ satisfies all the constraints in **NFD**, in addition, constraints (6.18) and (6.19) only help to guarantee $\lambda_{ij} = \pi_{ij} r_{ij} \quad \forall (i,j) \in \mathbf{A}$, so the feasible set of $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \mathbf{r}^*)$ is the same for both models. Hence, if $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \boldsymbol{\lambda}^*, \mathbf{r}^*)$ is an optimal solution to **LNFD**, $(\boldsymbol{\alpha}^*, \beta^*, \boldsymbol{\pi}^*, \mathbf{r}^*)$ is an optimal solution to **NFD**. □

Next, we prove that the optimal solution **r** in **LNFD** is also optimal to **NF**.

THEOREM 1. The optimal solution **r** in **LNFD** is also optimal to **NF**.

Proof.

First we prove that the optimal solution **r** in **NFD** is also optimal to **NF**. According to the property of duality, the optimal objective value of **NFD** equals to that of **NF**, and because **r** is the decision variable in outer level minimization problem, it remains unchanged during the two dual transformations. Therefore, the optimal **r** in **NFD** is also optimal in **NF**.

Next, we show that the optimal **r** in **LNFD** is also optimal to **NFD**. Since each r_{ij} is binary, if r_{ij}=1, λ_{ij} cannot be greater than the upper bound $\overline{\pi_{ij}}$ and therefore it is bounded to π_{ij}, and since the objective function is to be minimized, we must have λ_{ij}=π_{ij}; while if r_{ij}=0, λ_{ij} is 0. Thus, $\lambda_{ij} = \pi_{ij} r_{ij} \quad \forall (i, j) \in \mathbf{A}$ is ensured. According to LEMMA 1, we know that the optimal **r** in **LNFD** is also optimal to **NFD**, and therefore optimal to **NF**.

Hence, THEOREM 1 is proved. □

6.4 Numerical Analysis

6.4.1 Preliminary results

We first test model **LNFD** using a simple network consisting of 20 nodes and 22 arcs with 2 suppliers, 2 retailers and 2 products. Extreme cases were used in order to check the correctness of the results. For example, the additional costs on manufacture arcs are set to be extremely high such that an optimal solution will surely protect manufacture arcs. The layout of the example network is shown in Figure 6.2, where for simplicity, each arc is indexed with a number. All computational experiments in this section were performed on a Dell OPTIPLEX 990, Intel Core i5-2500, 3.30GHz, RAM 8GB/CPLEX 12.5. After implementing the data in **LNFD** model, we find that the solution is indeed optimal. Tables 6.3

and 6.4 present the list of parameters and Table 6.5 show some key variables in the results. Note that the budget B_c=50, and B_u=50, while the budget H is 105.

Table 6.3: List of commodity parameters

k	f_k	s^k	t^k	k	f_k	s^k	t^k
PA	1	A’	M	**CB**	20	B	M
PB	1	B’	M	**P_1**	30	M	P_1
SX_1	1	X_1	P_1	**P_2**	20	M	P_2
SX_2	1	X_2	P_2	**CX_1**	15	P_1	X
SY_1	1	Y_1	P_1	**CX_2**	10	P_2	X
SY_2	1	Y_2	P_2	**CY_1**	15	P_1	Y
CA	15	A	M	**CY_2**	10	P_2	Y

Table 6.4: List of arc parameters

arc	1	2	3	4	5	6	7	8	9	10	11
o_{ij}	2	1	1	2	2	2	100	100	15	15	80
d_{ij}	1	1	1	1	2	2	150	150	10	10	100
c_{ij}	5	5	5	5	5	5	10	10	10	10	10
e_{ij}	5	5	5	5	5	5	15	15	10	10	10
arc	12	13	14	15	16	17	18	19	20	21	22
o_{ij}	80	90	90	0	0	2	3	2	2	2	3
d_{ij}	80	90	85	0	0	1	1	1	1	1	1
c_{ij}	10	10	10	0	0	5	5	5	5	5	5
e_{ij}	10	10	10	0	0	5	5	5	5	5	5

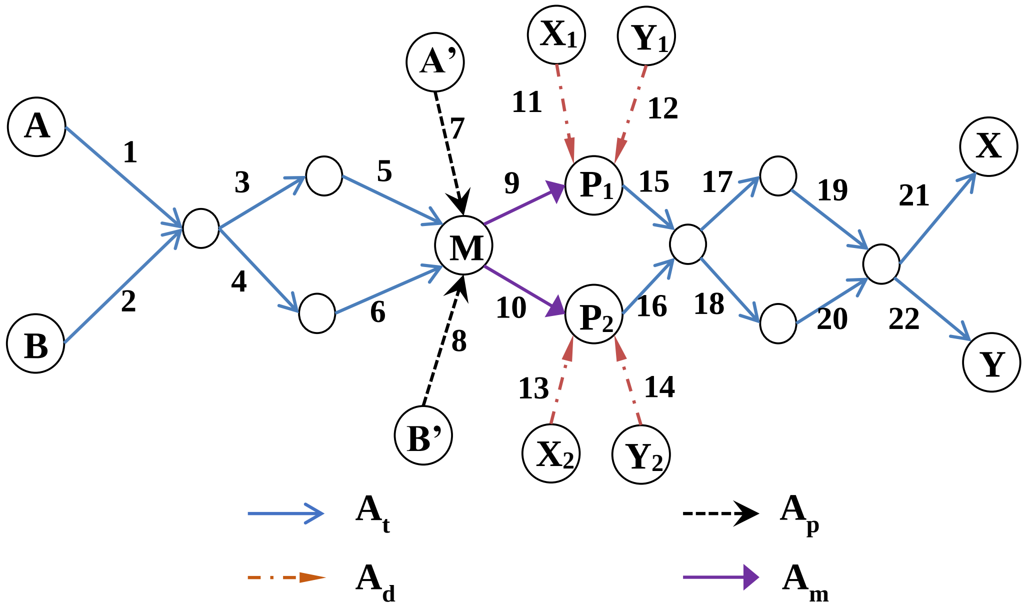


Figure 6.2: Network structure of the first test case

Table 6.5: Key variables in the results

	1	2	3	4	5	6	7	8	9	10	11
π_{ij}	15	20	35	0	70	0	150	150	300	200	100
λ_{ij}	0	0	0	0	70	0	150	150	300	200	100
r_{ij}	0	0	0	0	1	0	1	1	1	1	1
	12	13	14	15	16	17	18	19	20	21	22
π_{ij}	80	90	85	0	0	50	0	50	0	25	25
λ_{ij}	80	90	85	0	0	50	0	50	0	0	0
r_{ij}	1	1	1	0	0	1	0	1	0	0	0

The results showed that $\lambda_{ij}=\pi_{ij}r_{ij}, \quad \forall(i,j)\in\mathbf{A}$ holds and the optimal solution suggests protecting those arcs that have higher π_{ij}/e_{ij} ratio. More specifically, if we sort π_{ij}/e_{ij} in a descending order, the arcs with higher ratios would be arc 9, 10, 5, 7, 8, 11, 17, 19, 13, 14 and 12, and the values of r_{ij} suggest protecting these arcs. Table 6.6 presents the π_{ij}/e_{ij} ratio for some arcs in the example network, and the arcs that are not listed in the table are those with zero π_{ij} value. In this example, manufacture arcs 9 and 10 are the most critical arcs and are protected first, followed by transportation arc 5 and purchase contract arcs 7 and 8. After that, if we still have protection budget remaining, we can proceed to protect sales contract arc 11 and two transportation arcs 17 and 19. If we increase the budget H, more arcs would be protected.

Table 6.6 also provides evidence showing that protective strategies developed based on the vulnerability information derived from bi-level network interdiction model are often suboptimal. Since π_{ij} is the dual variable of the attacker's decision variable x_{ij}, it actually indicates the attacker's gain if one unit of interdiction variable x_{ij} is allowed, and thus it can be regarded as a vulnerability indicator. If protections are built based on this vulnerability indicator π_{ij}, then the optimal solution would be different, which turns out to be suboptimal. As will be further discussed in the sensitivity analysis, the cost efficiency of protecting arc (i, j), i.e. the π_{ij}/e_{ij} ratio, is the new indicator of how critical an arc is in our problem.

Table 6.6: The π_{ij}/e_{ij} ratio for some arcs

Arc	9	10	5	7	8	11	17	19	13	14	12	3	21	22	2	1
π_{ij}	300	200	70	150	150	100	50	50	90	85	80	35	25	25	20	15
π_{ij}/e_{ij}	30	20	14	10	10	10	10	10	9	8.5	8	7	5	5	4	3
r_{ij}	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
Arc type	$\mathbf{A_m}$	$\mathbf{A_m}$	$\mathbf{A_t}$	$\mathbf{A_p}$	$\mathbf{A_p}$	$\mathbf{A_d}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_d}$	$\mathbf{A_d}$	$\mathbf{A_d}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$

6.4.2 Sensitivity analysis

In this section, sensitivity analysis is conducted by changing budget B_c, B_u and H, using a larger network with 28 nodes, 28 arcs, 4 suppliers, 4 retailers and 2 products. The network layout of this test case is presented in Figure 6.3, and the detailed data of this example network are presented in Appendix E. The results are presented in Tables 6.8, 6.9, 6.10, 6.11 and Figures 6.4, 6.5, 6.6. Note that the base case is B_c=30, B_u=25 and H=50. If one budget is changing, the other two are fixed to be the same as in the base case. Table 6.7 summarizes some key variables in the base case results. From these results, we can see that when budget B_c=30, B_u=25 and H =50, the optimal arcs to protect are arcs 5, 6, 8, 11, 12 and 23.

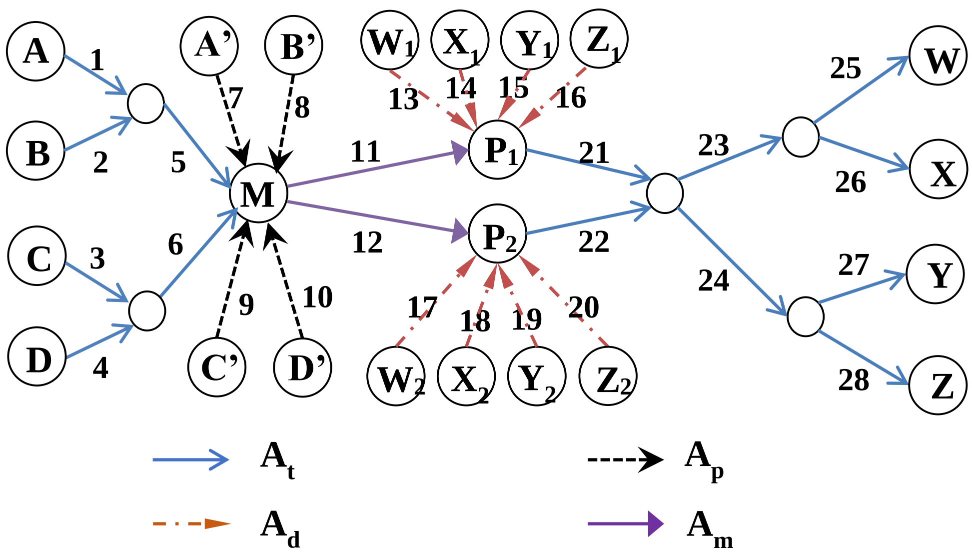


Figure 6.3: Network structure of the second test example

Table 6.7: Key variables in the base case results

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
π_{ij}	0	5	0	0	45	35	0	60	0	30	255	155	0	0
λ_{ij}	0	0	0	0	45	35	0	60	0	0	255	155	0	0
r_{ij}	0	0	0	0	1	1	0	1	0	0	1	1	0	0

	15	16	17	18	19	20	21	22	23	24	25	26	27	28
π_{ij}	0	0	0	0	0	0	0	0	35	35	0	0	0	0
λ_{ij}	0	0	0	0	0	0	0	0	35	0	0	0	0	0
r_{ij}	0	0	0	0	0	0	0	0	1	0	0	0	0	0

Table 6.8: Results under different values of B_c

B_c	20	25	30	35	40
Obj.	3000	3060	3120	3160	3200
Solution	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23

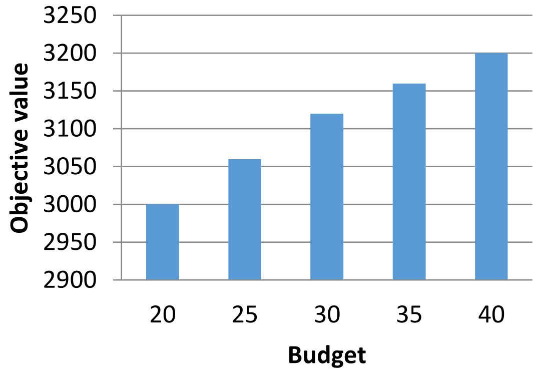


Figure 6.4: Objective values under different values of B_c

Table 6.9: Results under different values of B_u

B_u	15	20	25	30	35
Obj.	3090	3105	3120	3130	3135
Solution	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23	5, 6, 8, 11, 12, 23

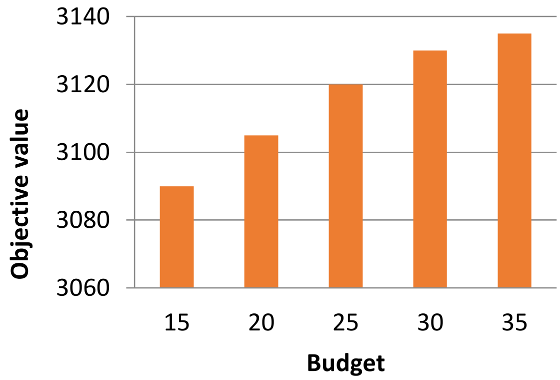


Figure 6.5: Objective values under different values of B_u

Table 6.10: Results under different values of H

H	30	35	40	45	50
Obj.	3215	3180	3140	3130	3120
Solution	5, 11, 12, 23	5, 11, 12, 23, 24	5, 6, 11, 12, 23, 24	2, 5, 6, 11, 12, 23, 24	5, 6, 8, 11, 12, 23
H	55	60	65	70	75
Obj.	3080	3070	3050	3010	3000
Solution	5, 6, 8, 11, 12, 23, 24	2, 5, 6, 8, 11, 12, 23, 24	5, 8, 10, 11, 12, 23, 24	5, 6, 8, 10, 11, 12, 23, 24	2, 5, 6, 8, 10, 11, 12, 23, 24

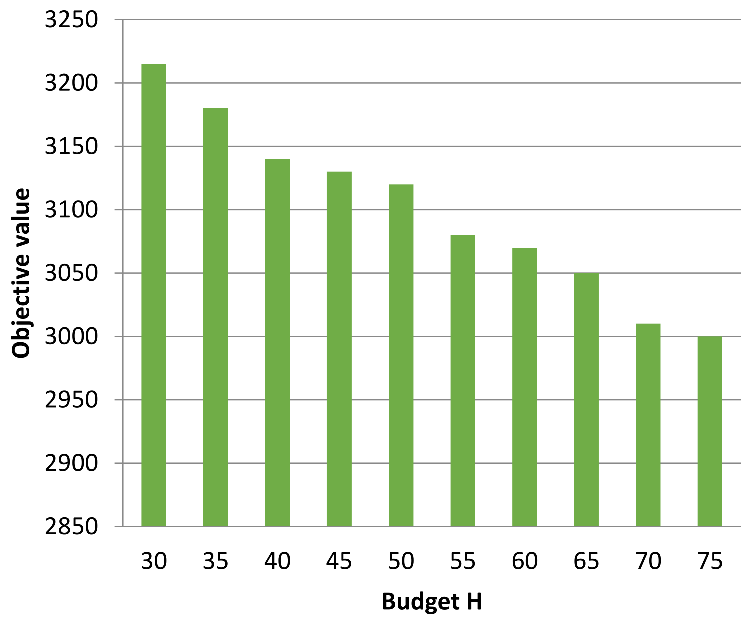


Figure 6.6: Objective values under different values of H

The results show that changing the values of B_c and B_u will not affect the solution of r_{ij}, but as the interdiction budget B_c or B_u grows, the objective value or the overall cost will increase accordingly. However changing the values of H will not only change the objective value but also affect the solution of r_{ij}, as protection budget H grows, the optimal objective value drops accordingly. The reason is that our method systematically identifies the optimal arcs to protect according to the protection budget H, regardless of how big or small the interdiction budgets are. This can also be explained by examining the formulation of **LNFD**, in which the interdiction budget B only appears in the objective function. Essentially, if attackers have more budgets, they can affect more unprotected arcs in the network. Similarly, if the company has more protection budget, we can protect more arcs from attacks, thus bringing down the overall cost. In fact, this procedure is quite close to real world cases, in which the defenders do not know the attackers' budget and therefore the decisions are solely based on the property of the network and the protection budget.

Table 6.11 presents the π_{ij}/e_{ij} ratio for some arcs in the second test example. From the results in Table 6.10 and Table 6.11 we can see that as the protection budget H grows, our method chooses arcs that with higher π_{ij}/e_{ij} ratio to protect first. More specifically, when H=30, the company is suggested to protect arcs 5, 11, 12 and 23, because arcs 11, 12 and 5 are the three arcs that with the highest π_{ij}/e_{ij} ratio, and protecting them will cost 25 units of money, while the remaining 5 units are invested in the protection of arc 23 which has the highest π_{ij}/e_{ij} ratio among arcs that cost 5 units to protect. When H=50, the company is suggested to protect arcs 5, 6, 8, 11, 12 and 23. This is because protecting arc 8 will produce a 60-unit cost decrease which is larger than the total cost decrease brought by protecting arc 10 or protecting arcs 24 and 2. Hence, when there is not enough budget to protect both arcs, our method will choose the arc with the larger π_{ij} as long as the protection budget H is not exceeded, though the chosen arc may have a smaller π_{ij}/e_{ij} ratio.

Table 6.11: The π_{ij}/e_{ij} ratio for some arcs in the 2rd test example, when H=50

	11	12	5	6	23	24	8	10	2
π_{ij}/e_{ij}	25.5	15.5	9	7	7	7	4	2	1
e_{ij}	10	10	5	5	5	5	15	15	5
Arc type	$\mathbf{A_m}$	$\mathbf{A_m}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_p}$	$\mathbf{A_p}$	$\mathbf{A_t}$

During the sensitivity analysis, we find that the π_{ij} value will change as protection budget H changes. This can be explained by analyzing the economic meanings of each variable. If we look closely at the economic meanings of each dual variable, we find that π_{ij} indicates the attacker's gain if one unit of interdiction variable x_{ij} is allowed (i.e. arc (i, j) can be interdicted); and β is the attacker's gain if one more unit of interdiction budget is allowed. Therefore, π_{ij}/e_{ij} ratio represents the reduction of attacker's gain per unit of money spent on protecting arc (i, j), which can be considered as the cost efficiency of protecting arc (i, j). As the protection budget H increases, more arcs will be fortified, which leads to the decrease of attacker's marginal gain β if one unit of interdiction budget is allowed. The decrease in β will then lead to the increase in π_{ij}, as seen in constraints (6.16). The economic explanation is that as few arcs can be interdicted, the marginal gain of being able to attack an arc π_{ij} will grow. In the extreme cases where the protection budget H is large enough to allow for fortifications in all arcs, the value of β will become 0, since increasing interdiction budget will not bring any benefit for the attacker, and the value for each π_{ij} is the attacker's marginal gain if only arc (i, j) can be interdicted in the network. Therefore, the π_{ij}/e_{ij} ratio when H is large enough to protect all the arcs can be used as an indicator of how critical an arc is in the supply chain network. Table 6.12 presents the π_{ij}/e_{ij} ratios when protection budget H is 225. Note that arcs 21and 22 in the second test example are auxiliary arcs that have no usage cost, which is used to represent that the products are ready for shipment. Since the two auxiliary arcs do not have physical meanings, they cannot be attacked, and therefore the π_{ij}/e_{ij} ratios are set to be 0.

Table 6.12: The π_{ij}/e_{ij} ratio for arcs in the 2rd test example, when H=225

	11	**12**	**5**	**8**	**6**	**23**	**24**	**10**	**7**	**9**	**13**	**18**	**14**	**15**
π_{ij}/e_{ij}	30	20	12	12	10	10	10	10	8	8	8	8	7	5.3
e_{ij}	10	10	5	15	5	5	5	15	15	15	10	10	10	15
Arc type	$\mathbf{A_m}$	$\mathbf{A_m}$	$\mathbf{A_t}$	$\mathbf{A_p}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_p}$	$\mathbf{A_p}$	$\mathbf{A_p}$	$\mathbf{A_d}$	$\mathbf{A_d}$	$\mathbf{A_d}$	$\mathbf{A_d}$

	16	**19**	**17**	**2**	**3**	**20**	**25**	**28**	**1**	**4**	**26**	**27**	**21**	**22**
π_{ij}/e_{ij}	5.3	5	4	4	3	3	3	3	2	2	2	2	0	0
e_{ij}	15	10	15	5	5	10	5	5	5	5	5	5	0	0
Arc type	$\mathbf{A_d}$	$\mathbf{A_d}$	$\mathbf{A_d}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_d}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$	$\mathbf{A_t}$

According to Table 6.12, the most critical arcs in this example network are two manufacture arcs (arcs 11, 12) followed by a transportation arc (arc 5), and a purchasing contract arc (arc 8). The solution indicates that these arcs should be protected with the highest priority. If company has more protection budget, several transportation arcs (arcs 6, 23, 24)and purchase contract arcs (arcs 10, 7, 9) should also be protected. These results can give supply chain managers some useful information about which parts of the supply chain are vulnerable and need more managerial attention. For example, the company can improve the welfare of the workers to prevent strikes from happening so that the manufacturing process is protected; if the purchase contract with supplier D is very likely to be affected, the company should use multiple suppliers to get the raw material originally provided solely by supplier D.

In fact, the above observation about π_{ij}/e_{ij} has a theoretical foundation. THEOREM 2 illustrates why the π_{ij}/e_{ij} ratios when H is large and β=0 can be considered as indicators of the critical level of arcs in a supply chain network.

THEOREM 2. If H is large enough, the value of β will be zero, and π_{ij} will reach its maximum value for each arc (i, j).

Proof.

If H is large enough, most of the r_{ij} will become 1, i.e. majority of the arcs in the supply chain would be fortified. In such a circumstance, the attackers will have no more arc to interdict even though they have remaining interdiction budget, and as β is the attacker's marginal gain if one unit of interdiction budget is allowed, β will become zero.

If β=0, constraint (6.16) becomes:

$$\pi_{ij} - \sum_{k \in \mathbf{K}} d_{ij} \alpha_{ij}^{k} \geq 0 \quad \forall (i, j) \in \mathbf{A} \tag{6.25}$$

Since constraints (6.18) and (6.19) only ensures $\lambda_{ij} = \pi_{ij} r_{ij}, \quad \forall (i, j) \in \mathbf{A}$ but do not affect the value of π_{ij}, and the objective function (6.14) is to be minimized, we have $\pi_{ij} = \sum_{k \in \mathbf{K}} d_{ij} \alpha_{ij}^{k}, \quad \forall (i, j) \in \mathbf{A}$.

In comparison, when β>0, we will have $\pi_{ij} = \sum_{k \in \mathbf{K}} d_{ij} \alpha_{ij}^{k} - c_{ij} \beta, \quad \forall (i, j) \in \mathbf{A}$. Hence, when β=0, π_{ij} will reach its maximum for each arc (i, j). □

From THEOREM 2, we can see that when H is large and β=0, $\pi_{ij} = \sum_{k \in \mathbf{K}} d_{ij} \alpha_{ij}^{k}, \quad \forall (i, j) \in \mathbf{A}$, which can be considered as the attacker's best possible gain of interdicting arc (i, j). While in cases when H is not large enough, the values of π_{ij} for some arc might be smaller or even zero, as shown in Table 6.11. Therefore, the π_{ij}/e_{ij} ratios when H is large and β=0 would be a better representation of the cost efficiency of protecting each arc.

6.4.3 Solution time

Next, we check whether our model is capable of solving real world size problems of large size. Let n be the number of arcs in the network, and so the computational complexity of model **LNFD** is O(n^2). We use some larger networks to test the model: one with 6 suppliers, 6 retailers, 3 products, 47 nodes and 50 arcs, one with 10 suppliers, 9 retailers, 4 products, 81 nodes and 93 arcs, one with 20 suppliers, 18 retailers, 6 products, 184 nodes and 221 arcs, and one with 40 suppliers, 38 retailers, 8 products, 382 nodes and 469 arcs. Table 6.13 compares the solution time of network examples with different sizes, and all network examples are solved to optimality. For simplicity, we will subsequently refer to network examples with different sizes according to the numbers of suppliers and retailers. For example, the previous network example we have used that has 6 suppliers and 6 retailers is referred to as '6×6' network.

Table 6.13: Comparison of solution time and cuts applied for different size networks

Problem size (# of supplier × # of retailer)		6×6	10×9	20×18	40×38
Number of constraints		2272	5780	31282	130726
Number of variables	**binary**	50	93	221	469
	others	2253	6327	36689	158525
Implied bound cuts		12	17	49	162
Flow cuts		7	18	64	207
Mixed integer rounding cuts		9	20	83	169
Gomory fractional cuts		4	11	24	33
Average Solution time(s)	**Total**	0.18	0.39	1.26	3.85
	Root	0.18	0.38	0.53	0.69
	Branch & cut	0	0.01	0.73	3.17

From the results, we can see that for the smaller networks like "6×6" and "10×9", almost all the solution time is spent on root node processing, while the parallel branch & cut phase almost takes no time. The solution times for "20×18" and "40×38" are above 1 second, and the parallel branch & cut phases take longer time as the network grows larger, but overall the solution times are still very short. This implies that our MIP model is not a hard one which will generate billions of nodes in the branch & cut tree even with a small amount of variables. If we apply a real world problem for a large size manufacturing company, it would be a '50×50' network and above, which has over 1000 different types of commodities, and the number of constraints is estimated to be over 800,000. In fact, CPLEX is capable of handling large MIP problems with hundreds of thousands of constraints and variables, given that the MIP model is not an extremely hard one. Thus it is reasonable to conclude that our model can handle real world size problems.

6.5 Case Study

In this section, we discuss a case study about outsourcing the vaccine supply chain in South Africa, which was originally presented in PATH (2011). As the new vaccines become more bulky and more expensive, the Ministry of Health in South Africa can no longer afford to have inefficient and ineffective vaccine supply chains. In 2003, the South Africa National Department of Health (DOH) decided to outsource the vaccine supply chain and logistic system to a 3PL (third-party logistic) provider called 'Biovac Institute' in the private sector, since compared to public systems, the 3PL providers have more incentives in utilizing the available resources and technologies, minimizing wastage of resources, and achieving economy of scale. The vaccines in South Africa are imported from foreign countries and will be shipped to the airport in the capital city Johannesburg. The major responsibility of Biovac Institute is to manage the vaccine arrival and transfer, vaccine storage at all levels of the supply chain, as well as vaccine distributions.

Among the nine provinces in South Africa, the Western Cape Province has a unique agreement that requires Biovac to manage its in-province vaccine supply chain. For the rest of the eight provinces, Biovac's duty is just to deliver the vaccine to the provincial warehouse, because the warehousing and transportation of vaccines in these eight provinces are managed by provincial departments of health. The South Africa National DOH consider the Western Cape vaccine supply chain system as a pilot project, which can provide guidance to other provinces that wish to outsource their vaccine supply chain. Therefore, Biovac considers the service in Western Cape as highly important, and cannot afford to have any significant disruption event happening to the supply system.

One of the advantages of the Western Cape's vaccine supply chain is that it is streamlined, which means the number of touch points for vaccines before reaching their final destinations is decreased. A streamlined vaccine supply chain decreases the lead time, raises efficiency by holding less buffer stock, and minimizes the risk to vaccines due to fewer touch points. In particular, the Western Cape supply chain bypasses the district-storage level compared to other provinces. All vaccines are stored in Biovac's Pineland facility located in Cape Town. In practice, Biovac distributes directly to 131 health centers out of 277 in Western Cape, while the other 146 health centers prefer to transport their vaccines from the district hospital to their facilities at their own expense, which means Biovac just needs to distribute their vaccines to the corresponding district hospitals. A possible reason for such preference is that these districts prefer to have control over their stock of vaccines so that they can reallocate vaccines from the district level to ensure no stock out occurs in any of their health centers. The vaccine supply chain structure is shown in Figure 6.7. Note that WCDH stands for Western Cape Department of Health.

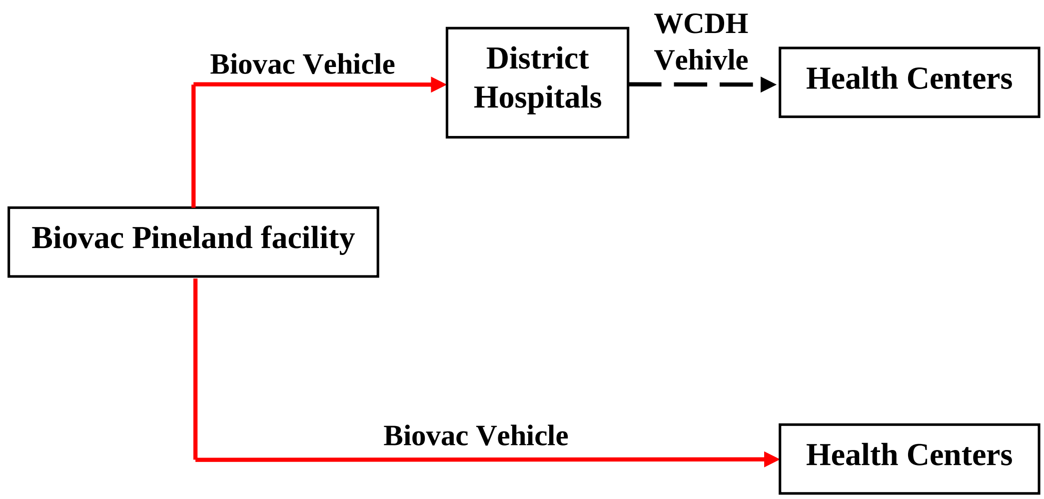


Figure 6.7: The Western Cape vaccine supply chain structure

Table 6.14 presents the South Africa national vaccination schedule in 2010. From the table, we can see that there are in total eight types of vaccines in the South Africa supply chain. The demand for each type of vaccine varies in each month, and such information is communicated through monthly email reports between Biovac and WCDH. Biovac imposes a minimum order size of $120.

Table 6.14: South Africa national vaccination schedule in 2010

Vaccine(doses per FIC)	Birth	6 wks.	10 wks.	14 wks.	9 mo.	18 mo.	6 yrs.	12 yrs.
BCG(1)	X							
OPV(2)	X	X						
DTP-IPV-Hib(4)		X	X	X		X		
Measles(2)					X	X		
Hep B(3)		X	X	X				
Rotavirus(3)		X						
Pneumococcal (3)		X		X	X			
Td(2)							X	X

Biovac has identified three major risks from intentional attacks in the Western Cape vaccine supply chain system. The first risk comes from internal dissatisfied labors, who will cause temperature failure in the cold chain storage and lead to large amount of spoiled vaccines. To prevent such internal attacks, Biovac plans to develop a temperature monitoring system and link the bonus of employees to the number of accidents they have in their duty, and employees with zero accident will be rewarded. The second and third types of risks come from terrorists or enemies, who will cut off transportation routes or create explosions to destroy Biovac facilities, vehicles and vaccine stocks. The protection strategy against these two types of risk is to prepare emergency inventory in vaccine storage facilities at each level, and employ armed guards to protect facilities and vehicles on the road. Now Biovac wants to identify the most critical links in their supply chain to protect, given a protection budget of $15000.

In order to apply our approach to solve Biovac's problem, certain transformation is needed in terms of the problem network structure. In particular, we add in some auxiliary nodes and arcs to the supply chain network. Sorting nodes and arcs are added to the network between Biovac's Pineland facility and each destinations, to represent the vaccine management and sorting process before the vaccines are delivered to their destinations. Entry inspections nodes and storage arcs are added before the vaccines are stored in local facilities, so that we can model the protection of facilities. Figure 6.8 illustrates the reformed network structure for Biovac's vaccine supply chain. In practice, temperature failure disruptions can happen both in the sorting stage and transportation stage, but since the protective measures for such kind of disruption work directly on the employees, their effect will cover both sorting and transportation stages. So for simplicity we assume that the temperature failure disruptions will only happen on sorting arcs and the corresponding protective measures will be implemented on sorting arcs only. Disruptions from terrorists/enemies cutting off the transportation route are assumed to happen only on transportation arcs, and the corresponding protective measure that can be implemented is to have emergency inventories at local warehouses. Storage facilities are most likely to be the target of extreme events like explosions, which are assumed to happen on storage arcs in the reformed network, and Biovac can fortify storage facilities by placing armed guards around the facilities.

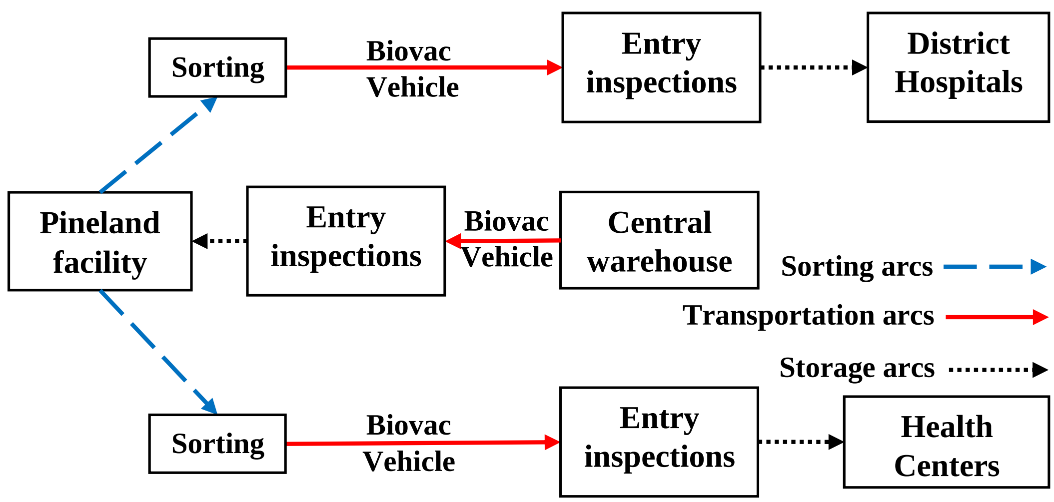


Figure 6.8: Reformed network structure for Biovac

Define $\mathbf{A}_D$ as the set of sorting arcs, $\mathbf{A}_T$ as the set of transportation arcs, and $\mathbf{A}_S$ as the set of storage arcs. Then B_D, B_T, and B_S are the interdiction budgets for temperature failure incidents, blocking transportation routes, and explosion attacks, respectively. The remaining notations are consistent with those in the **LNFD** Model. The cost for disrupting sorting arcs is set to 1, and the budget for temperature failure disruptions is set to the number of sorting arcs. In other words, all sorting arcs can be disrupted simultaneously in the worst case, since in this Biovac case it is generally easy for dissatisfied employees to make such temperature failure incidents happen. Therefore Biovac should pay significant amount of attention to this kind of internal attacks. The monthly demand data for each type of vaccines is based on the monthly report from Biovac to WCDH, and therefore the solution of the model changes monthly. The vaccine demand data in this model is estimated in US dollars, and among the six districts in Western Cape, the city of Cape Town has the highest vaccine demand of $27000 due to its dense population, followed by Cape Winelands($5700), Eden($4200), West Coast($2800), Overberg($1800), and Central Karoo($500). Hospitals and Health Centers in Cape Town, Cape Winelands and Overberg receive delivery service from Biovac, while the vaccines for West Coast, Eden, and Central Karoo districts are delivered to their District Hospitals. The costs of transportation are estimated by the distance between Pineland facility and destinations, and the average cost of transportation per kilometer for Biovac in 2010 (PATH, 2011). The costs on sorting arcs are estimated from the cold chain management costs and salary of management staff, and the costs on storage arcs mainly consists of packaging and labeling costs (PATH, 2011). Details of the problem data can be found in Appendix F. The **LNFD** formulation of Biovac's problem is as follows:

$$\min_{\mathbf{r},\boldsymbol{\pi},\boldsymbol{\alpha},\beta} TC = \sum_{k\in\mathbf{K}} \sum_{(i,j)\in\mathbf{A}} o_{ij}\alpha_{ij}^k + \mathrm{B}_D\beta_D + \mathrm{B}_T\beta_T + \mathrm{B}_S\beta_S + \sum_{(i,j)\in\mathbf{A}} \pi_{ij} - \sum_{(i,j)\in\mathbf{A}} \lambda_{ij} \tag{6.26}$$

$$s.t \quad \sum_j \alpha_{ij}^k - \sum_j \alpha_{ji}^k = \begin{cases} f_k, & i = s^k \\ 0, & i \neq s^k, t^k \\ -f_k, & i = t^k \end{cases} \quad \forall k \in \mathbf{K} \quad \forall i \in \mathbf{N} \tag{6.27}$$

$$c_{ij}\beta_D - \sum_{k\in\mathbf{K}} d_{ij}\alpha_{ij}^k + \pi_{ij} \geq 0 \quad \forall (i,j) \in \mathbf{A}_D \tag{6.28}$$

$$c_{ij}\beta_\mathrm{T} - \sum_{k\in\mathbf{K}} d_{ij}\alpha_{ij}^k + \pi_{ij} \geq 0 \quad \forall (i,j) \in \mathbf{A}_T \tag{6.29}$$

$$c_{ij}\beta_\mathrm{S} - \sum_{k\in\mathbf{K}} d_{ij}\alpha_{ij}^k + \pi_{ij} \geq 0 \quad \forall (i,j) \in \mathbf{A}_S \tag{6.30}$$

$$\sum_{(i,j)\in\mathbf{A}} e_{ij} r_{ij} \leq \mathrm{H} \tag{6.31}$$

$$\lambda_{ij} - \pi_{ij} \leq 0 \quad \forall (i,j) \in \mathbf{A} \tag{6.32}$$

$$\lambda_{ij} - r_{ij} \sum_{k\in\mathbf{K}} f_k d_{ij} \leq 0 \quad \forall (i,j) \in \mathbf{A} \tag{6.33}$$

$$r_{ij} \in \{0,1\} \quad \forall (i,j) \in \mathbf{A} \tag{6.34}$$

$$\boldsymbol{\alpha} \geq 0, \beta_D \geq 0, \beta_T \geq 0, \beta_S \geq 0, \boldsymbol{\pi} \geq 0, \boldsymbol{\lambda} \geq 0 \tag{6.35}$$

The protection budget of Biovac is set to be \$15000. By solving the above mathematical model to optimality, the solution we obtained suggests that Biovac should protect all the sorting arcs by implementing the temperature monitoring system and rewarding employees with zero temperature accidents, and Biovac should also protect some storage arcs by employing armed guards to protect storage facilities and to secure the vaccine transferring process. The arc with the highest π_{ij}/e_{ij} ratio is the storage arc flowing into Pineland facility, followed by the sorting arcs and some storage arcs flowing into district hospitals. Figure 6.9 briefly illustrates the optimal protection strategies suggested by our approach. No transportation arc is protected according to the solution under $15000 budget. This is because the loss due to transportation disruption is relatively small compared to the other two disruption types, and the corresponding protective measure of having buffer inventory costs more than that of the other two protective measures, in other words, the π_{ij}/e_{ij} ratio of transportation arcs in Biovac's case is relatively small. Moreover, the protective measure of having buffer inventory works against Biovac's competitive advantage of streamlined supply chain. The vaccines' cold chain storage management process and some of the important vaccine storage facilities such as the Pineland facility, three district hospitals, and major hospitals in Cape Town are suggested to be secured or fortified. This is because the consequences of disruptions in these two areas are unaffordable to Biovac, while the corresponding protective measures are relatively easy to be implemented, i.e. the π_{ij}/e_{ij} ratios of these arcs are the highest, and therefore should be protected with first priority. From this case study of Biovac's vaccine supply chain, we can conclude that the proposed approach can be applied to effectively solve a real world problem.

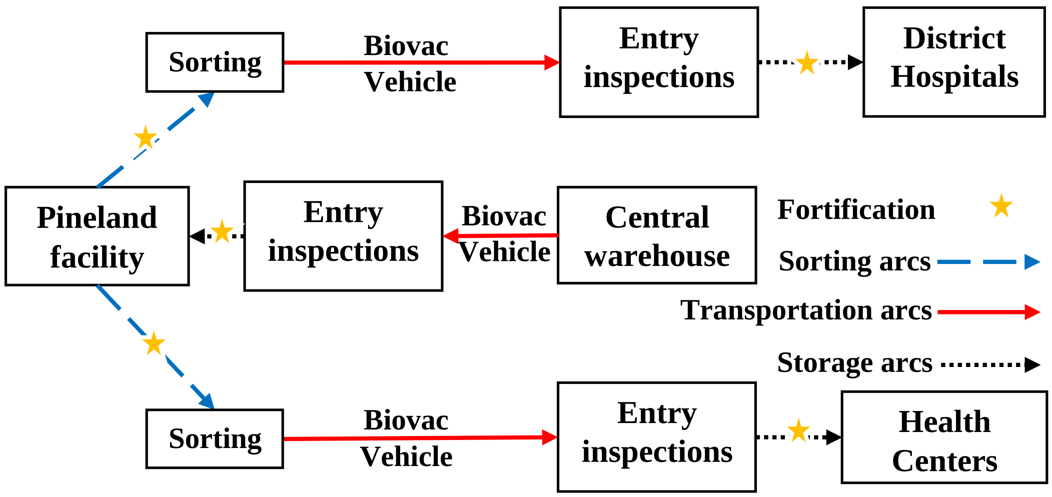


Figure 6.9: The optimal protection strategies suggested by the solution of **LNFD**

6.6 Recommended Applications

The optimal solution of **LNFD** can provide supply chain managers with useful information in the strategic decision making process. If the optimal solution suggests protecting more purchase contract arcs and upper stream transportation arcs, supply chain managers should be more focused on building the robustness of material supply. For example, companies can have multiple suppliers to make sure that the flow of supply will not easily be interrupted. If more sales contract arcs and lower stream transportation arcs are suggested to be protected, companies then should make more efforts in boosting the responsiveness of the supply chain, because rapid reactions are needed to deal with changing customer needs and unsatisfied demand. To sum up, companies should adjust their supply chain strategies according to the protection suggestions. The weaknesses within the supply chain network identified by our approach could also serve as a guideline for the redesign of network structure such that the new supply chain system is more robust against intentional attacks and worst case disruptions.

This research provides practitioners, supply chain managers and government agencies a useful tool that can automatically suggest where to allocate protection resources so that loss is minimized. Besides supply chain applications, our model can also be applied to the protection of critical infrastructures such as pipelines used for oil or gas transportation. The method proposed is also capable of solving problems in military fields, for instance, how to allocate defensive facilities so that national security is ensured. The advantage of this approach is that no detailed information about the opponents' interdiction budget is needed, which means practitioners could readily know the optimal protection plan based on the supply chain network and typical operational data, without having to know the opponents' interdiction budget.

6.7 Summary

This chapter presents a quantitative method for identifying the optimal protection strategies against intentional attacks or worst case disruptions in supply chain. We consider the supply chain system as a directed graph and define different functional components in the system as nodes and arcs. Based on these definitions, we developed a tri-level optimization problem to identify the optimal arcs to protect, given a budget for performing protective activities. A MIP model **LNFD** is proposed to solve the tri-level problem, and is proved to be equivalent to the tri-level problem. It is shown in the numerical studies that model **LNFD** can efficiently solve small to medium size problems and is also capable of solving large size problems. In addition, the optimal solution is found to be independent of the interdiction budget, which matches reality well because in most cases, decision makers have little information on how much money or resources the opponents plan to use. The proposed method can provide supply chain managers with useful information in the strategic decision making process and can serve as a guideline for the redesign of supply chain network structure.

Chapter 7 Conclusion

7.1 Introduction

This research has presented a framework for strategic supply chain planning under multiple criteria and uncertainty, and two quantitative approaches for the strategic decision making in supply chain subjected to disruption risks. The research focus is on making the strategic level decisions in supply chain partner selections and protection planning against worst case disruptions.

This research has proposed an efficient quantitative approach for strategic decision making in supply chain partner selections with considerations of disruption risks, which complements existing methodologies by considering the combination of trade-off options and supply chain level performance requirements to allow for a wider range of choices and potentially better supply chain structures. The supply chain level performance requirements are developed based on a detailed definition of four supply chain performance indices: disruption index, flexibility index, quality index, and innovation index. In practice, the values of performance indices are determined by evaluating historical data and applying Analytic Hierarchy Process (AHP) approaches. The supply chain level requirements are then modeled by enforcing a performance threshold on each of the performance index. Trade-off options are enabled once supply chain level performance requirements are implemented, by enforcing the performance index of certain parts of the supply chain to meet a target value. The trade-off constraints and supply chain level performance requirements constraints are integrated into a mixed integer programming model, which allows for supply chain characteristic diversifications in the supply chain designing process. In order to model the risk considerations in supply chain designing, Conditional Value-at-Risk (CVaR) is introduced and incorporated into a Min-risk model as an objective function to be minimized. The number of variables and constraints in the Min-risk Model grows exponentially with the number of potential supply chain partners, which can lead to large size problems that are difficult to solve. To overcome the computational issues, a new decomposition scenario management approach is proposed to reduce the number of disruption scenarios to be considered in solving the problem. Numerical results have shown that the proposed decomposition scenario management approach can provide near optimal solutions for the supply chain partner selection problem when minimizing risk is the objective. By comparing the results of Min-risk model under different confidence levels with that of the basic model for supplier selection, it is shown that the solutions of Min-risk model are in line with real world observations, indicating that the proposed Min-risk model can be applied to support the decision making in supply chain partner selections and design problems when minimizing the risk is the first priority. Case studies on a European chemical company and an Indian TMT bar company have further validated the applicability of the proposed methods in solving realistic problems.

This study has also proposed a method for the protection planning against worst case disruptions in supply chains. To consider potential intentional attacks or worst case disruptions in supply chain, possible disruption scenarios due to intentional attacks are examined, followed by a novel definition of supply chain networks on graphs, which allows for the modeling of disruptions on financial flows and information flows. The protection problem is then modeled as a tri-level defender-attacker-user optimization model. By using duality theory and standard linearization techniques, the tri-level problem is transformed into a mixed integer programming model which can be solved readily using commercial software. By comparing the solution values of some key variables in numerical analysis, we reconfirm a previous finding that protection decisions based on the solution of traditional bi-level interdiction models may be suboptimal due to its dependence on attacker's interdiction budget, and find that the solution of our approach is based on the cost efficiency of protecting each arc, which is independent of the attacker's budget. The weaknesses of the supply chain system identified by our approach could also serve as a guideline for the redesign of network structure such that the new supply chain system is more robust against intentional attacks or worst case disruptions. A case study of a South African third party logistics company in vaccine industry is presented showing that the proposed approach can be applied to solve realistic problems.

7.2 Main Contributions

This thesis presented a decision framework for strategic supply chain planning under multi-criteria and risk consideration. This research also proposed a novel definition of supply chain networks on graphs, which considers all types of flows in supply chain and enables the modeling of disruptions on financial flows and information flows. The application of this new definition for the protection planning problems in this thesis has proven that it can be used to effectively model realistic problems in supply chain.

This thesis also presented a decision framework for strategic planning in supply chain, which is a closed-loop system with a self-adjusting capability, and is useful in maintaining the competitive advantage and achieving sustainable value creation for the company. Supply chain disruptions are considered as an external factor that can affect this closed-loop and self-adjusting system. Based on this decision framework, this thesis proceeds to discuss the strategic decision making in supply chain under disruption risks.

This thesis derived a quantitative approach for the supply chain partner selection problems under disruption risks, and this new approach complements existing methods by considering both supply chain level requirements and trade-off options to enable diversification in supply chain characteristics, which can effectively assist in achieving the supply chain strategic alignment. The new approach can also be extended to consider the risk concerns of decision makers by incorporating Conditional Value-at-Risk into the model, which provides solutions with minimum disruption risk to the decision maker. The method proposed for solving the protection planning problem against worst case disruptions manages to consider all three types of flow disruptions and provides a practical way of identifying the weak spots in supply chain.

This thesis also developed a new algorithm called 'Decomposition Scenario Management' approach for effective scenario reductions. This new algorithm is focused on reducing the number of scenarios in LP or MIP problems, and numerical results have proven that it is more efficient and more accurate than the original scenario management approach.

The proposed approaches can provide managers and practitioners in supply chain with useful information in the strategic decision making process. Based on the suggestions of the proposed supply chain partner selection approach, decision makers can identify good quality suppliers, vendors or service providers and develop strategic partnerships with them to enhance the strategic alignment of the supply chain, which is critical to the competitiveness of the company. In terms of fortification strategies in supply chain, companies can adjust the characteristics of the supply chain or even reconsider the supply chain strategy according to the protection suggestions. The weak spots within the supply chain network identified by our approach could also serve as a guideline for the redesign of network structure such that the new supply chain system is more robust against intentional attacks and worst case disruptions.

In summary, the work in Chapter 4 and 5 present new methodologies for supply chain partner selection with trade-offs options and supply chain partner selection under risk considerations with a novel scenario reduction algorithm, which addresses the first research gap identified in Section 2.7. Chapter 6 discusses a supply chain fortification methodology using a tri-level network interdiction model, which is developed based on a novel graph representation of supply chain networks that allows for the definition of various types of intentional disruptions. The work in Chapter 6 addresses the second and third research gaps identified in Section 2.7.

7.3 Limitations and Future Work

While the proposed approaches for strategic decision making in supply chain under disruption risks have addressed the identified research gaps in the literature, several new research questions emerged. This section presents a discussion of the limitations of this research and some interesting research directions remain to be considered in the future.

In the process of modeling the supply chain partner selection problem, the material supply and product demand are assumed to be constant values estimated from historical data, since the uncertainty factors are modeled in the disruption index and quality index. After the partner selection phase, however, it will be unrealistic to have the assumptions of constant supply and demand when decision makers need to design the detailed network structure of the supply chain. Hence, one possible future extension is to discuss the optimal strategies in the next phase of partner selections, i.e. supply chain structure design. In particular, stochastic programming can be applied to cope with supply and demand uncertainties, and the decision outputs of the approach are the optimal number and location of manufacturing plants, warehouses, and distribution centers to maximize profitability. Trade-off options and supply chain level performance requirements can be modeled in the supply chain network design model to allow for more design possibilities and potentially better combinations of plants, DCs, and warehouses. Demand-side and supply-side uncertainties should be considered simultaneously in designing the supply chain network. Scenario reduction approaches such as the forward selection (FS) and backward reduction (BR) heuristics (Dupacova et al., 2003), clustering algorithms (Latorre et al., 2007), and importance sampling approach (Papavasiliou and Oren, 2013) can be applied to reduce the number of scenarios in the stochastic formulation of supply chain network design.

The supply chain performance measures considered in this research are cost, disruption risk, flexibility, quality, and innovation capability, all of which are focused on the profitability and competitiveness of the supply chain. The increasing concerns about global climate change and pollution issues have prompted decision makers to consider the environmental impacts in supply chain designing, and social responsibilities such as labor conditions, and improving healthcare and education of population are also very important to the social sustainability of the supply chain. Future research extensions can discuss the quantitative definitions of performance measurements for environmental factors and social factors, and incorporate these factors into supply chain partner selection and structure design approaches. Environmental performance measures can be examined from aspects such as greenhouse gas emissions, waste, energy use, material recovery etc., while social performance measures can be examined from work conditions, societal commitment, as well as customer issues (Eskandarpour et al., 2015). According to the review in Eskandarpour et al. (2015), still very few published models handle the economic, environmental and social dimensions simultaneously. It would be interesting to investigate the relationship between economic factors and environmental/social factors, and compare the impacts of these factors on supply chain decisions and the resulting competitiveness. Multi-objective optimization models can be applied to simultaneously consider the economic, environmental and social objectives of the company, and the Pareto-optimal front we get from solving the multi-objective optimization model can be used to analyze the trade-offs between different objectives. Furthermore, the impacts of supply chain disruptions on the environmental and social objectives of the supply chain need to be discussed, since certain types of disruptions like accidents and disasters will lead to severe consequences that affect multiple dimensions of supply chain performances. For example, the oil spill accidents in maritime transportation can lead to catastrophic environmental problems (Jenkins, 2000); fire accidents would not only bring economic losses, but also cause environmental and social issues such as the air pollutions and unemployment issues. The challenge in this research direction is to develop a comprehensive definition of environmental performance and social performance in supply chain, and to investigate how the disruptions in supply chain will impact the environmental and social performances.

In the approach developed for protection planning against worst case disruptions, the protection option on each arc is represented by an estimated protection cost, while the possibility that one arc can have multiple protection options is not considered. One possible research direction is to develop an approach to consider alternative protection strategies on the same arc to allow for more realistic models. For example, for the transportation links within the supply chain, companies can either choose to fortify them by having emergency inventories and improving the welfare of employees, or choose to outsource the logistics to a 3PL provider. Furthermore, it would be interesting to investigate how alternative protection strategies will impact the supply chain performance. In other words, the strategic decisions in protection planning against worst case disruptions in supply chain are more than identifying optimal parts to fortify, the options of choosing the optimal fortification methods should also be implemented in the decision making approach.

In the protection planning model, the supply and demand are assumed to be constant numbers. However, in reality the supply and demand are subjected to change, and how to deal with uncertainties in supply and demand is one of the most important topics in supply chain management problems. Therefore, another possible future extension is to incorporate supply and demand uncertainties with the protection planning model using stochastic programing or robust optimization techniques to allow for a holistic risk management strategy. The challenge for such an extension would be to formulate a valid mathematical programming model to combine both the consideration of uncertainties and the consideration of worst case disruptions from intentional attacks or disastrous incidents, and to deal with the resulting complex formulations and discover efficient algorithms to solve the problem.

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Appendix A

The AHP is a structured technique for organizing and analyzing complex decisions, which is based on three basic functions: structuring complexity using hierarchies, measurements on a ratio scale, and synthesis. Figure A.1 illustrates the hierarchy structure of the AHP approach. The AHP helps decision makers find solutions that best suit their goal and their understanding of the problem. It provides a comprehensive and rational framework for structuring a decision problem, representing and quantifying its elements, relating those elements to overall goals, and evaluating alternative solutions. The AHP can be applied to a wide variety of decision situations, such as selection of alternatives, resource allocation, ranking, conflict resolution, quality management etc., and the procedure of the AHP can be summarized as:

1. Define the problem.
2. Structure a hierarchy to model the problem, which contains decision goals, attributes, criteria, sub-criteria, activities, alternatives etc.
3. Establish weights among the elements of the hierarchy by making a series of judgments based on pairwise comparisons of the elements at each level of the hierarchy.
4. Synthesize these judgments to yield a set of overall weights for the hierarchy. Check the consistency of the judgments, revise the pairwise comparison matrices until the inconsistencies are within acceptable limits if necessary.

5. Combine the weights to obtain global weights for the alternatives using hierarchical composition.
6. Come to a final decision based on the results of this process.

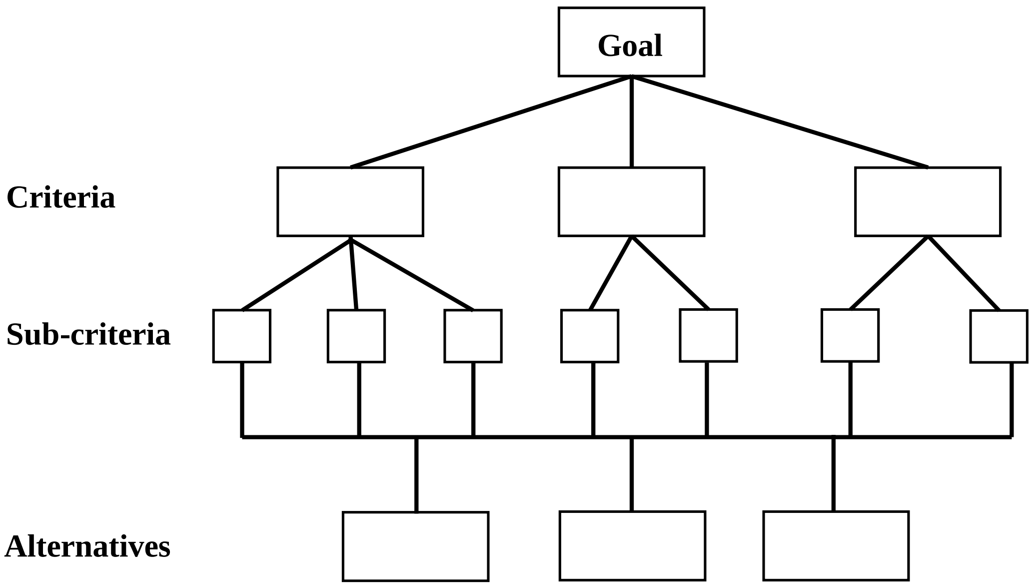

Figure A.1: The hierarchy structure of the AHP approach

Appendix B

Table B.1: Notation, description and value for optimization model in European supply chain case

Notation	Description and Value
f	the total demand for product per month; f=56000
f_t	the demand local facility t can handle per month; f_1=6000, f_2=8000, f_3=3000, f_4=6000, f_5=5000, f_6=6000, f_7=6000, f_8=6000, f_9=6000, f_{10}=5000, f_{11}=3000, f_{12}=5000, f_{13}=10000, f_{14}=10000, f_{15}=6000, f_{16}=5000, f_{17}=6000, f_{18}=8000
v_t	cost of upgrading and establishing facilities in local facility t (100 \$); v_1=5000, v_2=5000, v_3=5000, v_4=5000, v_5=8000, v_6=8000, v_7=8000, v_8=8000, v_9=6000, v_{10}=6000, v_{11}=6000, v_{12}=8000, v_{13}=0, v_{14}=0, v_{15}=5750, v_{16}=6500, v_{17}=6400, v_{18}=6800
e_t	unit cost of shipping product from central DC to local facility t (\$); e_1=6.7, e_2=6.8, e_3=4, e_4=4.9, e_5=6.1, e_6=6, e_7=6.1, e_8=8.1, e_9=6.7, e_{10}=11, e_{11}=19, e_{12}=19, e_{13}=5.6, e_{14}=0, e_{15}=7.5, e_{16}=13, e_{17}=7.5, e_{18}=6.6
P_{cDC}	the probability of disruption in central DC; P_{cDC}=0.01
P_t^T	the probability of disruption in local facility t; P_1^T=0.01, P_2^T=0.03, P_3^T=0.05, P_4^T=0.05, P_5^T=0.05, P_6^T=0.01, P_7^T=0.03, P_8^T=0.05, P_9^T=0.01, P_{10}^T=0.01, P_{11}^T=0.04, P_{12}^T=0.02, P_{13}^T=0.01, P_{14}^T=0.01, P_{15}^T=0.05, P_{16}^T=0.05, P_{17}^T=0.05, P_{18}^T=0.01
ρ_{cDC}	the flexibility score of central DC; ρ_{cDC}=0.95
ρ_t^T	the flexibility score of local facility t; ρ_1^T=0.85, ρ_2^T=0.9, ρ_3^T=0.75, ρ_4^T=0.8, ρ_5^T=0.7, ρ_6^T=0.95, ρ_7^T=0.75, ρ_8^T=0.8, ρ_9^T=0.85, ρ_{10}^T=0.7, ρ_{11}^T=0.8, ρ_{12}^T=0.95, ρ_{13}^T=0.95, ρ_{14}^T=0.95, , ρ_{15}^T=0.95, ρ_{16}^T=0.9, ρ_{17}^T=0.9, ρ_{18}^T=0.95
Q_{cDC}	quality score of central DC; Q_{cDC}=0.97
Q_t^T	quality score of local facility t; Q_1^T=0.85, Q_2^T=0.85, Q_3^T=0.9, Q_4^T=0.7, Q_5^T=0.6, Q_6^T=0.85, Q_7^T=0.65, Q_8^T=0.95, Q_9^T=0.9, Q_{10}^T=0.95, Q_{11}^T=0.6, Q_{12}^T=0.9, Q_{13}^T=0.9, Q_{14}^T=0.97, Q_{15}^T=0.95, Q_{16}^T=0.9, Q_{17}^T=0.95, Q_{18}^T=0.95
P_{risk}	the disruption risk threshold index for the supply chain; P_{risk}= 0.9
P_{flex}	The flexibility threshold index for the supply chain; P_{flex}= 0.8
Q	the quality threshold index for the supply chain; Q=0.8

Appendix C

Table C.1: Notation, description and value for models in Indian company's case

Notation	Description and Value
f	the total demand for product per month (ton); f=14400
f_t	the demand for product from distributor t per month (ton); f_1=3600, f_2=3600, f_3=3600, f_4=3600, f_5=3600, f_6=3600, f_7=3600, f_8=3600
a_i	supply capacity of raw material for supplier i (ton); a_1=18000, a_2=24000, a_3=30000, a_4=15000
b_i	minimum order quantity of supplier i (ton); b_1=3000, b_2=6000, b_3=5000, b_4=3000
d	demand for raw material per month; d= 21000
c_i	cost of purchasing and shipping material from supplier i per ton ($); c_1=440, c_2=440, c_3=420, c_4=450
v_t	cost of establishing partnerships with distributor t (100$); v_1=1500, v_2=2000, v_3=5000, v_4=5000, v_5=5000, v_6=6500, v_7=6000, v_8=5600
q_i	fixed cost of ordering material from supplier i ($); q_1=6000, q_2=5000, q_3=4500, q_4=5000
e_t	cost of shipping product from plant to distributor t per ton ($); e_1=15.5, e_2=19, e_3=17, e_4=17.5, e_5=19, e_6=19, e_7=23, e_8=19
P_i^S	the probability of disruption in supplier i; P_1^S=0.02, P_2^S=0.01, P_3^S=0.05, P_4^S=0.02
P_t^T	the probability of disruption in distributor t; P_1^T=0.05, P_2^T=0.02, P_3^T=0.03, P_4^T=0.01, P_5^T=0.05, P_6^T=0.01, P_7^T=0.01, P_8^T=0.01
P_m	the probability of disruption in manufacturing plant; P_m=0.01
Q_i^S	quality score of supplier i; Q_1^S=0.9, Q_2^S=0.8, Q_3^S=0.98, Q_4^S=0.95
Q_t^T	quality score of distributor t; Q_1^T=0.75, Q_2^T=0.85, Q_3^T=0.98, Q_4^T=0.9, Q_5^T=0.95, Q_6^T=0.9, Q_7^T=0.9, Q_8^T=0.9
P_{risk}	the disruption risk threshold index for the supply chain; P_{risk}= 0.85
Q	the quality threshold index for the supply chain; Q=0.8
P_{riskT}	the disruption risk threshold index for distributors; P_{riskT}= 0.95
Q_T	the quality threshold index for distributors; Q=0.9
Mn	the minimum number of suppliers; Mn=2
k_{risk}	the weight of material disruptions compared to product disruptions; k_{risk}=0.6
k_q	the weight of quality in the material supply stage; k_q=0.4

Appendix D

Min-risk model and its additional data in Indian company's case

Min $\quad \gamma + (1-\alpha)^{-1} \sum_{\beta \in \theta} P_\beta \tau_\beta$

Subject to

$$w_i \le x_i \qquad \forall i \in S$$

$$w_i d \le a_i \qquad \forall i \in S$$

$$w_i d \ge b_i x_i \qquad \forall i \in S$$

$$\sum_{i \in S} w_i = 1$$

$$\sum_{t \in T} f_t y_t = f$$

$$k_{risk} \sum_{i \in S} (1-P_i^S)(1-P_m) w_i + (1-k_{risk}) \sum_{t \in T} (1-P_t^T)\, f_t y_t / f \ge P_{risk}$$

$$k_q \sum_{i \in S} Q_i^S w_i + (1-k_q) \sum_{t \in T} Q_t^T\, f_t y_t / f \ge Q$$

$$\sum_{t \in T} (1-P_t^T)\, f_t y_t / f \ge P_{riskT}$$

$$\sum_{t \in T} Q_t^T\, f_t y_t / f \ge Q_T$$

$$\sum_{i \in S} x_i \ge 2$$

$$\gamma + \tau_\beta \ge \sum_{i \in S} q_i x_i + \sum_{i \in S} c_i w_i d + \sum_{t \in T} (v_t y_t + e_t f_t y_t) + \mathrm{c}^S \sum_{i \in S_\beta} w_i d + \sum_{t \in T_\beta} c_t^T f_t$$

$$\forall \beta \in \theta$$

$$\tau_\beta \ge 0 \qquad \forall \beta \in \theta$$

$$0 \le w_i \le 1 \qquad \forall i \in S$$

$$x_i, y_t \in \{0,1\} \qquad \forall i \in S, t \in T$$

Appendix E

Table E.1: List of commodity parameters for the second test example

k	**f_k**	**s^k**	**t^k**	**k**	**f_k**	**s^k**	**t^k**
PA	1	A’	M	CB	20	B	M
PB	1	B’	M	CC	15	C	M
PC	1	C’	M	CD	10	D	M
PD	1	D’	M	P_1	30	M	P_1
SW_1	1	W_1	P_1	P_2	20	M	P_2
SX_1	1	X_1	P_1	CW_1	10	P_1	W
SY_1	1	Y_1	P_1	CX_1	5	P_1	X
SZ_1	1	Z_1	P_1	CY_1	5	P_1	Y
SW_2	1	W_2	P_2	CZ_1	10	P_1	Z
SX_2	1	X_2	P_2	CW_2	5	P_2	W
SY_2	1	Y_2	P_2	CX_2	5	P_2	X
SZ_2	1	Z_2	P_2	CY_2	5	P_2	Y
CA	10	A	M	CZ_2	5	P_2	Z

Table E.2: List of arc parameters for the second test example

arc	1	2	3	4	5	6	7	8	9	10	11	12	13	14
o_{ij}	1	1	1	1	2	2	150	200	160	180	15	18	100	100
d_{ij}	1	1	1	1	2	2	120	180	120	150	10	10	80	70
c_{ij}	5	5	5	5	5	5	10	10	10	10	15	15	10	10
e_{ij}	5	5	5	5	5	5	15	15	15	15	10	10	10	10
arc	15	16	17	18	19	20	21	22	23	24	25	26	27	28
o_{ij}	100	100	100	100	100	100	0	0	2	2	1	1	1	1
d_{ij}	80	80	60	80	50	30	0	0	2	2	1	1	1	1
c_{ij}	10	10	10	10	10	10	0	0	5	5	5	5	5	5
e_{ij}	15	15	15	10	10	10	0	0	5	5	5	5	5	5

Appendix F

Table F.1 presents the list of commodity parameters for the Biovac case study, in which we have 135 commodities. Commodity P135 represents the total amount of vaccine for Western Cape Province transported from central warehouse (node 1) to Pineland facility (node 3). P132, P133, P134 are the vaccines for the three district hospitals in West Coast, Eden, and Central Karoo. The remaining 131 commodities are the vaccines for different health centers that receive delivery services from Biovac. All the demand data are measured in terms of US dollars, and are estimated according to the population of the corresponding area.

Table F.1: List of commodity parameters for the Biovac case

k	f_k	s^k	t^k	**k**	f_k	s^k	t^k
P1	3000	3	275	P69	200	3	343
P2	3000	3	276	P70	200	3	344
P3	3000	3	277	P71	200	3	345
P4	1000	3	278	P72	200	3	346
P5	1500	3	279	P73	200	3	347
P6	1500	3	280	P74	200	3	348
P7	200	3	281	P75	200	3	349
P8	200	3	282	P76	200	3	350
P9	200	3	283	P77	900	3	351
P10	200	3	284	P78	240	3	352
P11	200	3	285	P79	120	3	353
P12	200	3	286	P80	120	3	354
P13	200	3	287	P81	120	3	355
P14	200	3	288	P82	120	3	356
P15	200	3	289	P83	120	3	357
P16	200	3	290	P84	120	3	358
P17	200	3	291	P85	120	3	359
P18	200	3	292	P86	120	3	360
P19	200	3	293	P87	120	3	361
P20	200	3	294	P88	120	3	362
P21	200	3	295	P89	120	3	363
P22	200	3	296	P90	120	3	364
P23	200	3	297	P91	120	3	365
P24	200	3	298	P92	120	3	366
P25	200	3	299	P93	120	3	367
P26	200	3	300	P94	120	3	368
P27	200	3	301	P95	120	3	369
P28	200	3	302	P96	120	3	370
P29	200	3	303	P97	120	3	371

P30	200	3	304	P98	120	3	372
P31	200	3	305	P99	120	3	373
P32	200	3	306	P100	120	3	374
P33	200	3	307	P101	120	3	375
P34	200	3	308	P102	120	3	376
P35	200	3	309	P103	120	3	377
P36	200	3	310	P104	120	3	378
P37	200	3	311	P105	120	3	379
P38	200	3	312	P106	120	3	380
P39	200	3	313	P107	120	3	381
P40	200	3	314	P108	120	3	382
P41	200	3	315	P109	120	3	383
P42	200	3	316	P110	120	3	384
P43	200	3	317	P111	120	3	385
P44	200	3	318	P112	120	3	386
P45	200	3	319	P113	120	3	387
P46	200	3	320	P114	120	3	388
P47	200	3	321	P115	120	3	389
P48	200	3	322	P116	120	3	390
P49	200	3	323	P117	120	3	391
P50	200	3	324	P118	120	3	392
P51	200	3	325	P119	120	3	393
P52	200	3	326	P120	120	3	394
P53	200	3	327	P121	120	3	395
P54	200	3	328	P122	120	3	396
P55	200	3	329	P123	120	3	397
P56	200	3	330	P124	120	3	398
P57	200	3	331	P125	120	3	399
P58	200	3	332	P126	120	3	400
P59	200	3	333	P127	120	3	401
P60	200	3	334	P128	120	3	402
P61	200	3	335	P129	120	3	403
P62	200	3	336	P130	120	3	404
P63	200	3	337	P131	120	3	405
P64	200	3	338	P132	2800	3	6
P65	200	3	339	P133	4200	3	9
P66	200	3	340	P134	500	3	12
P67	200	3	341	P135	42000	1	3
P68	200	3	342				

Table F.2 presents the arc parameters for the Biovac case, where the left most column is the index for each arc, and the top most row illustrates the arc types.

Table F.2: List of arc parameters for the Biovac case

	original cost			additional cost			interdiction cost			reinforce cost		
	sorting	trans.	storage	sorting	trans.	storage	sorting	trans.	storage	sorting	trans.	storage
1	180	2.7	18	7500	3.375	3000	1	800	800	360	1500	1050
2	180	1.35	18	7500	1.6875	3000	1	800	800	360	1500	1050
3	180	2.7	18	7500	3.375	3000	1	800	800	360	1500	1050
4	60	3.24	6	2500	4.05	1000	1	600	600	120	500	350
5	90	4.05	9	3750	5.0625	1500	1	600	600	180	750	525
6	90	4.86	9	3750	6.075	1500	1	600	600	180	750	525
7	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
8	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
9	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
10	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
11	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
12	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
13	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
14	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
15	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
16	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
17	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
18	12	5.4	1.2	500	6.75	200	1	300	300	24	100	70
19	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
20	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
21	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
22	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
23	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
24	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
25	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
26	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
27	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
28	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
29	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
30	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
31	12	6.75	1.2	500	8.4375	200	1	300	300	24	100	70
32	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
33	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
34	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
35	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70

36	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
37	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
38	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
39	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
40	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
41	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
42	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
43	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
44	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
45	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
46	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
47	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
48	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
49	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
50	12	8.1	1.2	500	10.125	200	1	300	300	24	100	70
51	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
52	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
53	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
54	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
55	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
56	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
57	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
58	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
59	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
60	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
61	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
62	12	12.15	1.2	500	15.1875	200	1	300	300	24	100	70
63	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
64	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
65	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
66	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
67	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
68	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
69	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
70	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
71	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
72	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
73	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
74	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
75	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
76	12	13.5	1.2	500	16.875	200	1	300	300	24	100	70
77	54	14.85	5.4	2250	18.5625	900	1	600	600	108	450	315
78	14.4	14.85	1.44	600	18.5625	240	1	500	500	28.8	120	84

79	7.2	14.85	0.72	300	18.5625	120	1	200	200	14.4	60	42
80	7.2	14.85	0.72	300	18.5625	120	1	200	200	14.4	60	42
81	7.2	14.85	0.72	300	18.5625	120	1	200	200	14.4	60	42
82	7.2	14.85	0.72	300	18.5625	120	1	200	200	14.4	60	42
83	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
84	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
85	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
86	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
87	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
88	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
89	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
90	7.2	20.25	0.72	300	25.3125	120	1	200	200	14.4	60	42
91	7.2	20.25	0.72	300	25.3125	120	1	200	200	14.4	60	42
92	7.2	20.25	0.72	300	25.3125	120	1	200	200	14.4	60	42
93	7.2	20.25	0.72	300	25.3125	120	1	200	200	14.4	60	42
94	7.2	22.95	0.72	300	28.6875	120	1	200	200	14.4	60	42
95	7.2	22.95	0.72	300	28.6875	120	1	200	200	14.4	60	42
96	7.2	22.95	0.72	300	28.6875	120	1	200	200	14.4	60	42
97	7.2	24.3	0.72	300	30.375	120	1	200	200	14.4	60	42
98	7.2	24.3	0.72	300	30.375	120	1	200	200	14.4	60	42
99	7.2	24.3	0.72	300	30.375	120	1	200	200	14.4	60	42
100	7.2	24.3	0.72	300	30.375	120	1	200	200	14.4	60	42
101	7.2	27	0.72	300	33.75	120	1	200	200	14.4	60	42
102	7.2	27	0.72	300	33.75	120	1	200	200	14.4	60	42
103	7.2	27	0.72	300	33.75	120	1	200	200	14.4	60	42
104	7.2	29.7	0.72	300	37.125	120	1	200	200	14.4	60	42
105	7.2	29.7	0.72	300	37.125	120	1	200	200	14.4	60	42
106	7.2	29.7	0.72	300	37.125	120	1	200	200	14.4	60	42
107	7.2	32.4	0.72	300	40.5	120	1	200	200	14.4	60	42
108	7.2	32.4	0.72	300	40.5	120	1	200	200	14.4	60	42
109	7.2	32.4	0.72	300	40.5	120	1	200	200	14.4	60	42
110	7.2	37.8	0.72	300	47.25	120	1	200	200	14.4	60	42
111	7.2	37.8	0.72	300	47.25	120	1	200	200	14.4	60	42
112	7.2	40.5	0.72	300	50.625	120	1	200	200	14.4	60	42
113	7.2	40.5	0.72	300	50.625	120	1	200	200	14.4	60	42
114	7.2	40.5	0.72	300	50.625	120	1	200	200	14.4	60	42
115	7.2	45.9	0.72	300	57.375	120	1	200	200	14.4	60	42
116	7.2	45.9	0.72	300	57.375	120	1	200	200	14.4	60	42
117	7.2	16.2	0.72	300	20.25	120	1	200	200	14.4	60	42
118	7.2	16.2	0.72	300	20.25	120	1	200	200	14.4	60	42
119	7.2	17.55	0.72	300	21.9375	120	1	200	200	14.4	60	42
120	7.2	18.9	0.72	300	23.625	120	1	200	200	14.4	60	42
121	7.2	20.25	0.72	300	25.3125	120	1	200	200	14.4	60	42

122	7.2	21.6	0.72	300	27	120	1	200	200	14.4	60	42
123	7.2	24.3	0.72	300	30.375	120	1	200	200	14.4	60	42
124	7.2	25.65	0.72	300	32.0625	120	1	200	200	14.4	60	42
125	7.2	27	0.72	300	33.75	120	1	200	200	14.4	60	42
126	7.2	32.4	0.72	300	40.5	120	1	200	200	14.4	60	42
127	7.2	33.75	0.72	300	42.1875	120	1	200	200	14.4	60	42
128	7.2	36.45	0.72	300	45.5625	120	1	200	200	14.4	60	42
129	7.2	40.5	0.72	300	50.625	120	1	200	200	14.4	60	42
130	7.2	43.2	0.72	300	54	120	1	200	200	14.4	60	42
131	7.2	48.6	0.72	300	60.75	120	1	200	200	14.4	60	42
132	168	36.72	16.8	7000	45.9	2800	1	200	200	336	1400	980
133	252	98.01	25.2	10500	122.5125	4200	1	200	200	504	2100	1470
134	30	112.59	3	1250	140.7375	500	1	200	200	60	250	175
135	--	2000	252	--	2500	210000	--	2000	1000	--	21000	840

Appendix G

The OPL data for the computational example (Base Case) in Section 4.5:

```
// Definition of supply chain partners and material types

Supplier={"a","b","c","d","e","f","g","h","a1","b1","c1","d1","e1","f1","g1","h1"
};

Material={"m1","m2","m3" };

DC={"D1","D2","D3","D4","D5","D6"};

Retailer={"u","v","w","x","y","z","x1","y1","z1","u1","v1","w1"};

// Define total demand, and demand from each potential retailer

TotalDemand=600;

Demand=[100,100,100,100,100,100,100,100,100,100,100,100];

// Define supply capacity of each supplier for each material

Capacity=[
        [500,0,0],
        [600,0,0],
        [400,0,0],
        [500,0,0],
        [550,0,0],
        [0,750,0],
        [0,700,0],
        [0,800,0],
        [0,600,0],
        [0,800,0],
        [0,650,0],
        [0,0,700],
        [0,0,800],
        [0,0,700],
```

```
        [0,0,800],
        [0,0,800]   ];
// Minimum Order Quantity, set "1" values to avoid suppliers being chosen wrongly by the model
MOQ=[
        [50,1,1],
        [100,1,1],
        [50,1,1],
        [100,1,1],
        [50,1,1],
        [1,100,1],
        [1,80,1],
        [1,100,1],
        [1,100,1],
        [1,80,1],
        [1,100,1],
        [1,1,50],
        [1,1,80],
        [1,1,80],
        [1,1,50],
        [1,1,50]  ];
// Demand for each material
DM=[1000,2000,800];
// Unit cost of purcharsing and shipping each material from each supplier
CPS=[
        [3.5,0,0],
        [3.4,0,0],
        [3.8,0,0],
        [2.8,0,0],
```

```
          [3.2,0,0],
          [0,2.4,0],
          [0,2.6,0],
          [0,2.8,0],
          [0,1.8,0],
          [0,2.1,0],
          [0,2.2,0],
          [0,0,9.2],
          [0,0,9.6],
          [0,0,9.7],
          [0,0,8.5],
          [0,0,9]  ];
// Capacity of each potential Distribution Center
CapacityDC=[300,200,400,300,400,200];
// Cost of establishing marketing channel with each retailer
CR=[500,600,550,550,500,580,400,400,450,350,400,480];
// Cost of establishing facilities in each DC
CDC=[300,200,600,240,400,160];
// Fixed ordering cost
CO=[  [50,0,0],
          [60,0,0],
          [55,0,0],
          [60,0,0],
          [55,0,0],
          [0,60,0],
          [0,70,0],
          [0,65,0],
          [0,50,0],
```

```
          [0,60,0],
          [0,55,0],
          [0,0,30],
          [0,0,30],
          [0,0,40],
          [0,0,30],
          [0,0,35]  ];
// Unit cost of shipping product from plant to retailer via DC
CS=[
          [1,1,2,2,2.5,3,1,1,2,2,2.5,3],
          [3,3,2.5,1.5,1,1,3,3,2.5,1.5,1,1],
          [2,1,1,1,1.5,2.5,2,1,1,1,1.5,2.5],
          [1,1,2,2,2.5,3,1,1,2,2,2.5,3],
          [2,1,1,1,1.5,2.5,2,1,1,1,1.5,2.5],
          [3,3,2.5,1.5,1,1,3,3,2.5,1.5,1,1]       ];
// Probability of disruption for each supplier, DC, retailer and manufacturing site
PdisS=[0.08,0.1,0.03,0.25,0.2,0.1,0.05,0.02,0.25,0.2,0.15,0.1,0.06,0.03,0.25,0.15]
;
PdisD=[0.1,0.05,0.05,0.25,0.15,0.2];
PdisR=[0.1,0.03,0.08,0.07,0.1,0.05,0.2,0.2,0.15,0.25,0.25,0.1];
PdisM=0.02;
// Flexibility score of each supplier, DC, retailer, and manufacturing site
PdelS=[0.88,0.9,0.95,0.75,0.7,0.9,0.88,0.98,0.75,0.7,0.8,0.88,0.95,0.9,0.75,0.7];
PdelD=[0.95,0.9,0.95,0.7,0.85,0.75];
PdelR=[0.88,0.95,0.88,0.9,0.9,0.95,0.7,0.85,0.88,0.75,0.78,0.9];
PdelM=0.99;
// Quality score of each supplier, DC, and retailer
QS=[0.9,0.8,0.9,0.7,0.75,0.8,0.9,0.95,0.7,0.7,0.8,0.9,0.85,0.95,0.7,0.7];
QD=[0.8,0.95,0.9,0.8,0.75,0.7];
```

```
QR=[0.9,0.9,0.95,0.9,0.88,0.95,0.8,0.7,0.7,0.7,0.78,0.8];

// Innovation score of each supplier, DC, and retailer
IS=[0.8,0.5,0.6,0.4,0.7,0.9,0.6,0.7,0.7,0.5,0.6,0.4,0.5,0.7,0.6,0.4];
ID=[0.5,0.6,0.5,0.6,0.7,0.8];
IR=[0.9,0.9,0.9,0.7,0.6,0.7,0.5,0.4,0.8,0.7,0.6,0.8];
// Threshold values
DisIndex=0.85;
ResIndex=0.75;
QIndex=0.85;
IIndex=0.65;
// Minimum number of suppliers required for each material
Mn=[2,2,1];
// Different weight values
krisk=0.65;
krsp=0.6;
kfm=0.7;
kfr=0.7;
kq1=0.4;
kq2=0.25;
kI1=0.1;
kI2=0.3;
// Number of material types
n=3;
```

Appendix H

The OPL data for the computational example in Table 5.4:

```
// Definition of supply chain partners and material types
Supplier={"a","b","c","d"};
Material={"m1","m2"};
DC={"D1","D2","D3"};
Retailer={"u","v","w"};
// Define total demand, and demand from each potential retailer
TotalDemand=300;
Demand=[150,150,150];
// Define supply capacity of each supplier for each material
Capacity=[
        [300,0],
        [300,0],
        [0,700],
        [0,900],
 ];
// Minimum Order Quantity, set "1" values to avoid suppliers being chosen
wrongly by the model
MOQ=[
        [60,1],
        [50,1],
        [1,100],
        [1,200]
 ];
// Demand for each material
DM=[400,700];
```

```
// Unit cost of purcharsing and shipping each material from each supplier
CPS=[
        [3.5,0],
        [3.2,0],
        [0,2.8],
        [0,2.4]
 ];
// Capacity of each potential Distribution Center
CapacityDC=[200,200,200];
// Cost of establishing marketing channel with each retailer
CR=[45,40,53];
// Cost of establishing facilities in each DC
CDC=[120,80,50];
// Fixed ordering cost
CO=[     [50,1],
        [20,1],
        [1,100],
        [1,80]
 ];
// Unit cost of shipping product from plant to retailer via DC
CS=[
        [1,2.5,2],
        [2.5,1,2],
        [2,2,1.5]        ];
// Probability of disruption for each supplier, DC, retailer and manufacturing site
PdisS=[0.05,0.03,0.08,0.1];
PdisD=[0.02,0.05,0.08];
PdisR=[0.1,0.01,0.05];
```

```
PdisM=0.01;
// Flexibility score of each supplier, DC, retailer, and manufacturing site
PdelS=[0.98,0.97,0.96,0.95];
PdelD=[0.972,0.967,0.985];
PdelR=[0.9,0.99,0.93];
PdelM=0.99;
// Quality score of each supplier, DC, and retailer
QS=[0.9,0.9,0.9,0.9];
QD=[0.93,0.92,0.95];
QR=[0.95,0.99,0.9];
// Innovation score of each supplier, DC, and retailer
IS=[0.9,0.9,0.9,0.95];
ID=[0.93,0.92,0.95];
IR=[0.95,0.99,0.9];
// Threshold values
DisIndex=0.85;
ResIndex=0.75;
QIndex=0.85;
IIndex=0.65;
// Minimum number of suppliers required for each material
Mn=[1,1];
// Different weight values
krisk=0.65;
krsp=0.58;
kfm=0.6;
kfr=0.7;
kq1=0.4;
kq2=0.25;
```

```
kI1=0.1;
kI2=0.3;
// Number of material types
n=2;
```
