SUPPLY CHAIN OPTIMIZATION CONSIDERING DISRUPTION RISKS

A Thesis in
Industrial Engineering

by
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Abstract

Following the tremendous impact that the 9/11 terror attacks had on businesses and economies, companies have become increasingly concerned about the effect of disruptions to their supply chains. Identifying the sources of disruption risks in a supply chain, quantifying and mitigating disruption risks, have become important areas of research in the last decade.

In this thesis, a combined inventory and transportation model considering disruption risks for a four-stage, global supply chain is developed. Multiple modes of transportation, each with different lead times and freight rate structure, are modeled. Disruption risk is quantified by means of risk indices that are computed separately for each site and the different transportation modes (ocean, road, rail and air) using subjective decision making tools, including AHP, ranking and Borda count methods. The risk indices are then used in a multi-objective mathematical programming model that aims at maximizing the profit of the entire supply chain, while simultaneously maximizing responsiveness and minimizing disruption risks.

Preemptive and non-preemptive goal programming methods are employed to solve the multi-objective optimization problem. The problem is illustrated using a realistic data set and the resulting solutions are analyzed. The findings and their managerial implications are also discussed. The results highlight the importance of considering disruption risks while making strategic and tactical level decisions in sourcing, production and transportation.
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Chapter 1

Introduction

1.1 Supply Chains and Supply Chain Management

A supply chain is a set of business units involved directly or indirectly in fulfilling a customer request. A supply chain consists of a connected set of activities concerned with planning, coordinating materials, parts and finished good from supplier to customer. (Chopra & Meindl 2006). The Council of Supply Chain Management Professionals defines a Supply Chain as the material and informational interchanges in the logistical process stretching from acquisition of raw materials to delivery of finished products to the end user. All vendors, service providers and customers are links in the supply chain. The Council also defines Supply Chain Management (SCM) as given below:

Supply Chain Management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies. Supply Chain Management is an integrating function with primary responsibility for linking major business functions and business processes, within and across companies, into a cohesive and high-performing business model. It includes all of the logistics management activities noted above, as well as manufacturing operations, and it drives coordination of processes and activities with and across marketing, sales, product design, and finance and information technology. (CSCMP 2011)
A typical supply chain looks as shown in Figure 1.1. While ‘chain’ is used to denote a linear flow, Figure 1.1 may convince one to call it a supply web or a supply network.

Figure 1.1 The Structure of a Typical Supply Chain (Chopra and Meindl (2006))

In the above supply chain, there are five different players or stages namely Supplier, Manufacturer, Distributor, Retailer and Customer. Hence the figure shows a five-stage supply chain. In this thesis, a four stage supply chain (Supplier → Manufacturer → Distributor → Retailer) is considered. The retailer-customer link is ignored.

Supply chains can be classified into centralized and decentralized. A centralized supply chain is one in which all the stages of the supply chain, including plants and modes of transport, are owned by the same company. Decision making is supported by complete information about all the stages. A decentralized supply chain is one in which more than one company owns the supply chain. In this case, each stage makes decisions based on what is best for that stage. In most cases, each stage doesn’t have complete information on the inventory levels or demands in the other stages. The case of a centralized supply chain is assumed in this thesis.
Supply chains can also be classified based on whether they are efficient or responsive. Responsiveness refers to the extent to which a supply chain meets customer needs and its ability to change. Efficiency focuses on resource utilization. An efficient supply chain would aim at supplying the demand at the lowest cost, while a responsive supply chain would aim at responding to a customer order as quickly as possible. Efficiency and responsiveness are considered as the key metrics of supply chain performance. The level of efficiency or responsiveness a supply chain should have depends on the type of product (functional or innovative) that flows through the supply chain.

The objective of any supply chain is to generate value by satisfying customer needs. The management of flows is very essential to the success of a supply chain. This “management of flows between and among stages in a supply chain to maximize supply chain profitability” is defined as Supply Chain Management (SCM) by Chopra and Meindl (2006). Simchi-Levi (2003) define SCM as “a set of approaches utilized to efficiently integrate suppliers, manufacturers, warehouses and stores, so that merchandise is produced at the right quantities, to the right locations, and at the right time, in order to minimize system-wide costs while satisfying service level requirements”. Both the definitions include two important aspects of supply chain – the costs and the customer. Integration of the different stages for the supply chain’s success is also emphasized in both these definitions.

However, these definitions are quite outdated. With increased environmental concern, there is more importance on sustainability and more recent definitions for SCM include such factors. “Management of raw materials and services from suppliers to manufacturer/service provider to customer and back with improvement of the social and environmental impacts explicitly considered” (New Zealand Council for Business Sustainable Development) is one such
definition. Newer definitions of supply chain include other dimensions such as globalization, supply chain risks, etc.

Traditionally, there are four drivers of supply chain namely facilities, inventory, transportation, and information. There is always a tradeoff between efficiency and responsiveness with respect to all the drivers. For instance locating more facilities close to demand regions would help increase responsiveness, but will decrease efficiency. In this thesis, two of these drivers (inventory and transportation) are considered along with disruption risks in supply chains to observe the effect of these on supply chain decisions. The tradeoff between efficiency and responsiveness is studied using Multi-criteria optimization techniques.

1.2 Supply Chain Risks

“An enterprise may have lowest overall costs in a stable world environment, but may also have the highest level of risk – if any one of the multiple gating factors kink up an elongated supply chain” – Barry (2004)

The complexity, dependency between the stages and the globalization of supply chains give rise to many unforeseen circumstances that can affect the entire network. A small disruption in any node would affect all the other stages. Typical events that cause disruption are earthquakes or other natural disasters, political instability, etc. Chopra and Sodhi (2004) categorize the different kinds of supply chain risks and list the drivers of each category as shown in Table 1.1.
Table 1.1 Supply chain risks and their drivers (Chopra and Sodhi, 2004)

<table>
<thead>
<tr>
<th>Category of risk</th>
<th>Drivers of risk</th>
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| Disruptions      | • Natural disaster  
|                  | • Labor dispute  
|                  | • Supplier bankruptcy  
|                  | • War and terrorism  
|                  | • Dependency on a single source of supply as well as the capacity and responsiveness of alternative suppliers  |
| Delays           | • High capacity utilization at supply source  
|                  | • Inflexibility at supply source  
|                  | • Poor quality or yield at supply source  
|                  | • Excessive handlings due to border crossings or to change in transportation modes  |
| Systems          | • Information infrastructure breakdown  
|                  | • System integration or extensive systems networking  
|                  | • E-commerce  |
| Forecast         | • Inaccurate forecasts due to long lead times, seasonality, product variety, short life cycles, small customer base  
|                  | • “Bullwhip effect” or information distortion due to sales promotions, incentives, lack of supply-chain visibility and exaggeration of demand in times of product shortage  |
| Intellectual property | • Vertical integration of supply chain  
|                  | • Global outsourcing and markets  |
| Procurement      | • Exchange rate risk  
|                  | • Percentage of a key component or raw material procured from a single source  
|                  | • Industry-wide capacity utilization  
|                  | • Long-term versus short-term contracts  |
| Receivables      | • Number of customers  
|                  | • Financial strength of customers  |
| Inventory        | • Rate of product obsolescence  
|                  | • Inventory holding cost  
|                  | • Product value  
|                  | • Demand and supply uncertainty  |
| Capacity         | • Cost of capacity  
|                  | • Capacity flexibility  |
In this thesis only disruption risks are considered. A good example to illustrate the effect of disruptions in supply chain is the fire in the Philips plant at Mexico in March 2000. The plant was supplying silicon chips to both Nokia and Sony Ericsson. While Nokia had alternate suppliers, this plant served as Ericsson’s sole supplier. Philips assured Ericsson and Nokia that production would be delayed by less than a week. When it became clear that production would actually be compromised for months, Ericsson was faced with a serious shortage. Nokia had already begun to get parts from alternative sources and redesigning its phones, but Ericsson's position was much worse as both production of current models and the launch of new ones were held up. As a result of this Ericsson lost its position in the mobile phone market in North America.

The 9/11/2001 attacks disrupted many supply chains in almost all industries. The U.S. government enforced stricter custom and border security regulations that delayed cross-border shipments. This led to closure of five of Ford’s plants for many days.

When Katrina struck the gulf coast, there were severe shortages of fuel, agricultural produces and other food items. The fuel prices are said to have risen by more than 20% following the hurricane.

The recent economic depression is another incident that posed a challenge to managers. In a survey by Capgemini consultants in 2009, managers were asked about the most influencing factors on the supply chain agenda in 2009. 65% of the respondents answered that the financial crisis was the most important, followed by meeting (changing) customer requirements and sustainability.
Another recent example would be the earthquake in Japan early in 2011 that caused severe disruptions to the electronic component supply chain, which in turn affected several automobile companies in various parts of the world. The floods in Thailand in 2011 disrupted the supply chains of external hard drives. Prices of external hard drives went up by at least 10% within the first three weeks of the flood. Seagate passed former market leader Western Digital Corp., which suffered heavy losses in the devastating floods. Seagate claimed 38% of HDD market share, compared with Western Digital's 23% (Mearian, 2012).

The above incidents throw light on the importance of supply chain disruption risks. Despite the importance, many firms do not pay much attention to handling disruption risks. 82% of companies are concerned about supply chain resiliency, yet only 11% are actively managing this risk (Aberdeen group, 2006). Ravindran et al. (2010) find that supplier risk doesn’t appear in the list of top three factors affecting supplier selection. Only quality, cost and delivery were considered important. In this thesis, the transportation route is selected considering disruption risks apart from responsiveness and efficiency.

1.3 Research Statement

The basic idea for this thesis was drawn from Vijayaragavan (2008). In his thesis, Vijayaragavan considers a four-stage centralized supply chain. The stages are connected by different means of transportation such as air, train, road and water. The optimal transportation routing policy is developed.
The problem that this thesis will address is stated as follows:

Given an existing supply chain network, (that is, a set of suppliers, manufacturing plants, distribution centers and retailers and their capacities); and locations in terms of distances between subsequent stages and the infrastructure of the transportation network that connects these units, and the forecasted demand at retailer locations,

1. What quantity of the total demand should be allotted to each unit in each stage in order to simultaneously minimize the cost, maximize responsiveness and minimize total disruption risk?

2. Which transportation route should be chosen so as to minimize the cost, maximize responsiveness and minimize total disruption risk?

This problem is a tactical supply chain problem because it is a planning/allocation problem that is constrained by the decisions made at the strategic level. Also the decisions are made with medium demand uncertainty, because the problem assumes availability of forecasted demand. Moreover, such decisions are not very expensive to reverse compared to, say, location of a plant or selection of suppliers.

Companies have to find the right combination of preventive and reactive measures to achieve the optimal level of supply chain security (PwC, 2011). Reacting to crisis situations is not enough; supply chains have to be more proactive in their measures to avoid disruption. This model aims at providing a more proactive approach in terms of inventory and transportation related decision.

In practice, such decisions are made by more than one decision maker and hence this work assumes the case of multiple decision makers for the process of quantifying the disruption
risks. To quantify the risks, two kinds of disruption risk scores are developed – node risk index and link risk index. As the name suggests, node risks deal with site location risks and link risks deal with risks related to the transportation modes used between nodes. In order to compute the indices, the following methods can be used:

- Rating method
- Pair-wise comparison using Borda Count
- Analytical Hierarchy Process

The risk indices are then used in a mathematical model to determine the time period and the quantity of products that should be shipped from each node using the different modes of transportation to satisfy demand and capacity constraints. The objectives will be to maximize profit, maximize responsiveness and minimize risk. The solution to the mathematical model, for a given set of objective weights, will provide the shipping quantities during the different time periods and the optimal choice of transportation modes. The results from the model will be compared with those from a four-stage model that did not consider risk.

Consider the four stage supply chain shown below with several suppliers, two manufacturers and two distribution centers that serve multiple retailers.
Assumptions:

- A global, centralized, 4-stage supply chain network
- Each stage is connected to the next by 4 modes of transport, namely, air, road, rail and ship. The shipping time depends only on the mode chosen.
- The model is a multi-period model and the forecasted demand at the retailer for the next few periods is known.
- There are several raw materials but only one finished product that flows in the chain.

Inputs to the mathematical model:

- Risk score for each node and link
- Capacities at supplier and manufacturer plants, DCs and the transportation modes.
• Feasible distribution options for the suppliers- manufacturers, manufacturers – DC and DC-retail stores networks.
• Forecasted demand at the retailers for the next few periods
• Cost components (Raw material cost, production cost, Transportation and Inventory holding costs)
• Time taken for manufacturing
• Bill of materials (No. of different parts required to make one unit of the finished product)
• Selling price

Mathematical Model

Objective:

Determine the optimal transportation and inventory policy that

• Maximizes the total supply chain profit
• Maximizes the responsiveness (Minimizes the total number of back orders at the retailers)
• Minimizes the disruption risk

Constraints:

• Demands at the retailers
• Capacities of the suppliers, manufacturers, DCs, retailers and transportation modes
• Inventory Balance constraints
Output:

- Production and distribution plans (mode of transportation) for the entire supply chain
- Shipping quantities and inventories in the supply chain at different time periods

The advantage of this model is that it considers disruption risks explicitly in making production, inventory and transportation related decisions in addition to efficiency and responsiveness.

1.4 Thesis Outline

Chapter 2 presents a comprehensive review of the literature in the areas of Multi-criteria optimization techniques and modeling supply chain risks. In Chapter 3, the development of the risk index and the mathematical optimization model are presented. The model is solved for a realistic set of data in Chapter 4. The thesis concludes with the analysis of the results and directions for future research in Chapter 5.
Chapter 2

Literature Review

The 9/11 attacks spurred a lot of questions relating to handling disruptions in the supply chain. Since then, a lot of work has been done on modeling disruptions, risk quantification, studying propagation of risks within the supply chain, supplier selection considering risks, risk mitigation in supply chain, etc. This chapter reviews the literature in these areas.

In this chapter, some of the articles from the literature in Supply Chain Risk Management (SCRM) are discussed in detail. Section 2.1 deals with articles that take a qualitative approach to SCRM, while Section 2.2 summarizes articles that are quantitative in nature.

2.1 Qualitative models on Supply Chain Disruption Risks

Hendricks and Singhal (2003) attempt to quantify in terms of shareholder value, the loss due to supply chain glitches. They measure the effect of supply chain glitches on shareholder wealth, with a focus on glitches that resulted in production or shipment delays. They test various hypotheses related to glitches and conclude based on stock price changes before and after 519 publicly announced glitches. This is done using regression methods. They find that the larger firms experience a lesser negative market reaction and smaller companies with more prospective for growth experience a higher negative reaction. They also suggest the use of forecasting tools and business performance analytics to predict glitches and the use of other special software for reducing the time to detect and resolve glitches.

Later in 2005, Hendricks and Singhal (2005) again studied the effect of supply chain glitches on operational performance. The research methodology is very similar to their earlier
work. They estimate an average loss of over $250 million in shareholder value per company per glitch and an average reduction of 10% in stock-market prices. Also there is a 14% increase in inventory, every time a glitch occurs. These numbers emphasize the need to have proper risk mitigation strategies in place for any supply chain.

Zsidisin (2003) analyzes supply chain risks such as operation, production, product quality and manufacturing technology and discusses a number of strategies and techniques that can minimize supply chain disruption risk and its impact. He also discusses, through a case study, the organizational definitions, classifications and sources of supply risk and their outcomes. He also proposes an all-encompassing, “grounded” definition of supply risk.

Christopher and Peck (2004) deal with resilience in the context of health care and defense supply chains. They categorize risks into three major categories – Risks that are internal to the firm, risks that are external to the firm but internal to the supply chain network, and other risks that are external to the network and arise from the environment of the supply chain. In the second half of the paper, the authors talk about four key principles that help in building supply chain resilience, namely, supply chain reengineering, supply chain collaboration, agility, and creating a supply chain risk management culture within the organization. Figure 2.1 (Christopher and Peck 2004) summarizes their discussion on these principles.
Craighead et al. (2007) discuss the impact of various characteristics related to the design of a supply chain such as density, complexity and node criticality on the severity of disruptions. For instance, in a supply chain that is ‘less dense’, the probability of a disruption affecting several of its entities is less, compared to one that is denser. The responses from participants in various industries including retail, pharmaceuticals, and logistics are used to substantiate the claims made. Similarly, the second half of the paper deals with the mitigation capabilities of a supply chain namely, recovery capability and warning capability.
2.2 Quantitative models on Supply Chain Disruption risks

Snyder et al. (2006), in their tutorial on planning for disruptions in supply chain networks, present a broad range of models for designing supply chains that are resilient to disruptions. Two categories of models are presented here – models in which the network is built from scratch, and models in which the existing network is modified to prevent disruptions at some facilities. The latter class of models, called fortification models, aims at enhancing the reliability of the network by investing in protection and security measures. The models presented, are further classified based on the optimization model used (facility location or network design) and the measure of risk used in optimization (expected cost or worst-case cost). The tutorial also discusses the pros and cons of each category. For instance, with respect to worst-case cost models, the criticism is that they are overly conservative. This is because the resulting solution plans against the one worst-case scenario which may be disastrous, but yet have a very low likelihood of occurrence. On the other hand, models that use expected cost fare well in the long run but perform poorly for certain (worst-case or near worst-case) scenarios. The tutorial ends with directions for future research in development of network design models considering disruption risks.

Wu et al. (2007) use a Petri net-based model to study the propagation of disruptions in the supply chain. Petri net is a “graphical and mathematical modeling tool for describing and analyzing concurrent and asynchronous events, distributed and parallel systems, conflicts and resource sharing”. DA_NET, the disruption analysis network developed by the authors, is a slight development from petri net and helps to study the propagation of disruptive events by showing the states that are reachable from a given initial “marking”. The model is then applied to an electronic manufacturer’s supply chain in which two parts flow, and the results are discussed.
Blackhurst et al. (2008) develop a risk assessment and monitoring methodology for measuring supplier risk in the automotive industry. Their method involves the use of multi-criteria scoring methods to create separate risk scores for the suppliers and the parts. They consider quality and disruption factors, and several subcategories under each factor. The risk indices are tracked continuously over time to determine trends in risk. The authors consider the example of a disc-brake system and compute the part and supplier risk indices for it. They discuss the operational issues associated with using such an index (choosing number of categories and subcategories, frequency for updating these indices, etc.) and provide directions for future work.

Ji and Zhu (2008), in their work, develop a mathematical model that combines operational and disruption risks. The total cost that has to be spent on each strategy so as to maximize the total expected profit of the supply chain is determined. The model considers the effectiveness of each strategy in mitigating both operational and disruption risks. The paper also includes an in-depth discussion of risk mitigation strategies with examples mostly in the context of Chinese industries.

Manuj and Mentzer (2008) provide a comprehensive survey of the literature in the area of supply chain risks. Their findings are based on interviews conducted with supply chain executives across eight different manufacturing companies. Different sources of risk events such as currency rate fluctuations, forecast errors, etc. are defined based on the responses to the interview. The authors then present a qualitative model of global supply chain risk management strategies. The model focuses on three antecedent factors – Temporal focus, supply chain flexibility and supply chain environment, which affect the selection of risk management strategies such as postponement, speculation, hedging, etc. The model also considers the impact
of the risk management strategies on cost, inventory, fill rate, etc. The outcomes are influenced by the complexity of the supply chain. The different strategies and the outcomes are all discussed in detail.

Ravindran et al. (2010) develop a method for supplier selection considering supply chain risks. The model, developed for a global IT company, is a two-phase 1. In the first phase, the suppliers are “prequalified” using various MCSP techniques such as AHP, Borda Count and Rating methods. This helps in reducing the large list of potential suppliers to a smaller one. In phase 2, a multi-objective model is developed considering risk, lead time and price. The risks are classified as VaR (Value-at-Risk) and MtT (miss-the-target) risks. In the case of VaR type risk function, impact is the probability distribution of loss due to a risk event and occurrence is the probability distribution of the number of risk events during a planning period. The impact function is modeled using generalized extreme value distributions. For the MtT type risk function, impact represents the loss due to deviation from a performance target value and occurrence is the distribution of that performance measure. Here, the impact function is modeled using Taguchi’s loss function. The authors present a case study in which VaR Risk is used to model disruption due to floods and MtT risk is used to model quality problems. The model is solved using four variants of Goal Programming methods. The case study illustrates the use of General Extreme Value Distributions (GEVD) for developing the VaR type risk functions. The solutions from the different GP models are compared and the results are discussed.

Schmitt (2011) develop the model for a multi-echelon system and assume that disruptions can occur at any echelon. The model incorporates a “stochastic mixture” of both backordering and lost sales to make it more practical. DCs hold reserve inventory (called “strategic inventory stock”) for a part or the whole of the supply chain. The model evaluates the impact of different
flow strategies on the expected service level of the entire network. These strategies are then compared for their effectiveness in mitigating disruption risk. The model is analyzed with the help of a numerical example. It is found that proactive strategies, (such as holding inventory in a DC which might itself be disrupted) cannot help achieve very high service levels. Reactive backup strategies are also required. Other analyses with respect to service level and the time taken for a DC having backup inventory to respond to a disruption, effects of holding inventory upstream from the DCs, optimal inventory to be held provide meaningful insights.

Bilsel and Ravindran (2012) present various methods to quantify disruption risks in supply chains. These methods combine ideas from probability and statistics with concepts in reliability engineering. There is an elaborate discussion on the use of Generalized Extreme Value distribution (GEVD) for quantifying impact functions and on modeling the occurrence. The impact and occurrence functions are then aggregated to develop the disruption risk function. The authors discuss methods for convolution of several GEVD variables (where each GEVD variable represents an extreme event) using numerical examples. The paper also discusses methods, using ideas from Markov chains, to detect disruptive events. A mean first passage time (MFPT) matrix is developed from the steady state probabilities of the states. The matrix is used to quantify disruptions in several ways. For instance, the MFPT values can be used as an objective function in an optimization model or the values can represent the time it takes for the news of a disruption to travel from one node to another. The paper ends with a complete conceptual framework for recovering from a disruption risk that includes all the methods discussed in the paper.

Ravindran and Warsing (2013) provide an overview of supply chain risks in Chapter 7 of their textbook. The authors discuss methods for risk identification, risk classification and risk assessment. In risk classification, risks are grouped under different categories depending on the
source, impact, internality and manageability of the risk events. Depending on the type of risk, different risk management and mitigation strategies are also discussed. Best practices in supply chain risk management in industries are presented as examples. The chapter also presents ideas of VaR risks and MtT risks to model supply chain risks. Detectability of risk events is discussed and a model based on Markov Chain theory is presented for risk detectability. A conceptual model of risk recovery is presented next. The chapter concludes with the development of optimization models for supplier selection incorporating VaR and MtT type risks.

Baghalian et al. (2013) develop a stochastic mathematical model for designing a network of multi-product supply chain comprising several capacitated production facilities, distribution centers and retailers in markets under uncertainty. This model considers demand-side and supply-side uncertainties simultaneously, which makes it more realistic in comparison to models in the existing literature. In this model, a discrete set as potential locations of distribution centers and retailing outlets are considered. They investigate the impact of strategic facility location decisions on the operational inventory and shipment decisions of the supply chain using a path-based formulation, which includes supply-side uncertainties that are possible disruptions in manufacturing plants, distribution centers and their connecting links. The resultant model, which incorporates the cut-set concept in reliability theory and the robust optimization concept, is a mixed integer nonlinear programming problem. To solve the model and attain global optimality, a transformation based on the piecewise linearization method is used. The model outputs are illustrated by the use of several numerical examples including a real-life case study from the agro-food industry.

Samvedi et al. (2013) discuss quantification of risks in a supply chain using a method that integrates fuzzy AHP and fuzzy TOPSIS. The authors classify risks into 4 categories – supply
risk, demand risk, process risk, and environmental risk. Supply risks refer to the risks emanating from the suppliers while demand risk refers to the risk due to fluctuations in demand of the product. The internal risks such as (labor strike, machine failures, etc.) are classified under process risks. Political instability, economic downturns and other external risks are classified under environmental risks. The importance of each category is determined using fuzzy AHP. The scores for each category are developed using fuzzy TOPSIS and then consolidated to form one single risk index value using the weights from fuzzy AHP. The method is discussed using a case study based on the Indian textile industry.

Shu et al. (2013) examine the control of production disruption risk related to supply chain and investigate the uncertainty of production in supply chain enterprises for the purpose of achieving optimal profits in supply chain, based on the Generic Bill of Materials (GBOM) approach. A GBOM describes demand for materials and their proportional relationships to a family of products. The mathematical model described in the paper aims at maximizing the supply chain profit. Managing production disruption risk is included as a constraint while designing the network. This is done by using the idea that the probability that the materials provided by upstream enterprises will be sufficient to satisfy the production demand of downstream enterprises is above a certain threshold value $\alpha$. The constraints are modeled as goal constraints and solved using a smart integrating algorithm that includes genetic algorithm, neural networks and simulated annealing. The model is one of the first attempts to consider disruptions due to uncertainties in the final customer demand and productions at the different stages of the supply chain.

The most recent and closely-related literature is by Kungwalsong (2013). Her dissertation presents a framework (Figure 2.2) for disruption risk assessment for both facilities and
transportation links. A disruption risk score is calculated as the product of hazard score, vulnerability score (for facility/transportation link) and a risk management practice score. The disruption risk score is then plotted on an x-y plane to form a disruption matrix (Hazard score on x-axis, Vulnerability score on y-axis, Risk management Practice score indicated by the use of symbols). The matrix gives decision makers an easy way to visualize the relative risk of all identified hazards.

![Disruption Risk](image)

**Figure 2.2 Disruption Risk Factors (Kungwalsong 2013)**

In this framework, a strategic level network design model with objectives of maximizing profit, minimizing unfulfilled demand, minimizing delivery time, minimizing disruption risks at facilities and in transportation is developed. The model is solved for a realistic case, using various Goal Programming approaches, and the different solutions are analyzed. To support the strategic level model, a multi-period tactical level model is built with maximizing profit as the sole objective. While the strategic model aims at enhancing supply chain robustness, the tactical model aims at improving the supply chain’s resiliency. The tactical model enables decision
making related to procurement, production and distribution. The dissertation also provides a framework for carrying out a vulnerability analysis and risk mitigation analysis on the network.

2.3 Basis for this Thesis

This thesis is an extension of Vijayaragavan’s (2008) Master’s thesis. In his work, Vijayaragavan considers a four-stage centralized supply chain. He develops a multi-period model that has two objectives – Minimizing total cost and maximizing responsiveness. The total cost is the sum of inventory holding and transportation costs. To maximize the responsiveness, the cumulative backorders at each stage is minimized. The model assumes multiple modes of transportation between stages and different lead times for each. Constraints in the model include demand at the retailer, capacity constraints at different stages and the transportation modes, quantity discount constraints, inventory balance constraints, etc. He also considers the number of units of each raw material that is required to build the final finished product. The model gives the shipment quantities for each time period through each transportation mode. The model is solved using preemptive and non-preemptive goal programming methods and the managerial implications are discussed.

This thesis will add an additional dimension of disruption risk to the problem solved by Vijayaragavan (2008). Disruption risk indices are developed for each site and each link and incorporated into the model as a separate objective.

Models in the literature primarily focus on a specific function of the supply chain such as sourcing, supplier selection or design aspects such as facility location. In this thesis, an attempt is being made to take the focus from the supplier to the entire supply chain by incorporating disruption risks into a combined inventory and transportation model. The methods to quantify the
risks, factors to be considered by the decision maker and the mathematical model are discussed in the next chapter.

Table 2.1 gives a summary of related research and the contributions of this thesis for comparison.
### Table 2.1 Summary of Important Articles Related to this Thesis

<table>
<thead>
<tr>
<th>Article</th>
<th>Level of decision making</th>
<th>Objectives</th>
<th>Supply Chain decisions</th>
<th>Risk Management dimensions</th>
<th>Solution Approach(es)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wu et al. (2008)</td>
<td>Strategic</td>
<td>Minimize supply chain disruption</td>
<td>Network design</td>
<td>Disruption Propagation</td>
<td>Petri Nets</td>
</tr>
<tr>
<td>Blackhurst et al. (2008)</td>
<td>All levels</td>
<td>-</td>
<td>Supplier Evaluation/ Monitoring</td>
<td>Risk Assessment and Risk Monitoring</td>
<td>Multi-criteria Scoring (Ranking) Methods</td>
</tr>
<tr>
<td>Ravindran et al. (2010)</td>
<td>Strategic</td>
<td>Minimize total purchasing cost, Minimize average lead time, Minimize VaR and MtT type risks</td>
<td>Supplier Selection</td>
<td>Disruption Risk Quantification</td>
<td>GEVD, Goal Programming Methods</td>
</tr>
<tr>
<td>Bilsel and Ravindran (2012)</td>
<td>Strategic</td>
<td>-</td>
<td>Supplier Selection</td>
<td>Disruption risk quantification/Risk recovery</td>
<td>GEVD, Markov Chain</td>
</tr>
<tr>
<td>Baghalian et al. (2013)</td>
<td>Strategic</td>
<td>Maximize expected profit</td>
<td>Network design</td>
<td>Supply chain resiliency</td>
<td>Robust optimization</td>
</tr>
<tr>
<td>Samvedi et al. (2013)</td>
<td>Strategic</td>
<td>-</td>
<td>-</td>
<td>Disruption Risk Quantification</td>
<td>Integrated fuzzy AHP and fuzzy TOPSIS</td>
</tr>
<tr>
<td>Shu et al. (2013)</td>
<td>Strategic</td>
<td>Maximizing profit (Production disruption modeled as constraint)</td>
<td>Network design</td>
<td>Production Disruptions</td>
<td>Combination of GA, SA and Neural Networks</td>
</tr>
<tr>
<td>Kungwalsong (2013)</td>
<td>Strategic and Tactical</td>
<td>Maximizing profit, Minimizing unfulfilled demand, Minimizing delivery time, Minimizing disruption risks at facilities and in transportation</td>
<td>Network design</td>
<td>Risk Assessment, Vulnerability Analysis, Risk Mitigation Analysis</td>
<td>Goal Programming Methods</td>
</tr>
<tr>
<td>Vijayaragavan (2008)</td>
<td>Strategic/Tactical</td>
<td>Minimize cost, Maximize sum of backorders at all stages (Maximize Responsiveness)</td>
<td>Inventory and transportation</td>
<td>Not included</td>
<td>Goal Programming Methods</td>
</tr>
<tr>
<td><strong>This thesis</strong></td>
<td>Strategic/Tactical</td>
<td>Maximize Profit, Minimize backorders at retailers, Minimize disruption risk</td>
<td>Inventory and transportation</td>
<td>Disruption Risk Assessment/ Quantification</td>
<td>Ranking Methods, AHP, Goal Programming Methods</td>
</tr>
</tbody>
</table>
Chapter 3

Problem Description and Model formulation

3.1 Problem Description

The following assumptions are used for the supply chain network under consideration (Figure 3.1):

• The supply chain is centralized

• There are four supply chain stages – Supplier, Manufacturer, Warehouses and Retailers

• Every player in a stage is connected to another player in the subsequent stage by means of four modes of transportation – Rail, Road, Ocean and Air

A multi-period, multi-objective mathematical model is developed for this supply chain considering disruption risks, in addition to cost and responsiveness. The objective of the model is to find an optimal inventory and transportation policy (how much should be shipped through each mode for every period).
First, a disruption risk index is developed (Section 3.2) for each of the nodes and links (transportation modes) in the supply chain network, considering various drivers of disruption. There are several approaches to quantify risk including the use of simulation, use of probabilistic models and others. In this thesis, ranking methods such as Borda Count, Pair-wise comparison, and AHP (described in Section 3.3) are used to quantify risk. *This quantification is based on the decision makers’ perceptions of the frequency of occurrence and the impact of the disruption to the supply chain.*

Next, a multi-objective mathematical model is developed in which the disruption indices are explicitly incorporated. The model aims at choosing a transportation and inventory policy that simultaneously minimizes risk and cost, while increasing the responsiveness of the entire
supply chain. The formulation of these objective functions is explained in detail in Section 3.4. The complete model with other supply chain constraints is also presented in Section 3.4.

3.2 Disruption Risk Indices

In this work, the disruption risks are classified into two types – *Node risk* and *link risk*.

*Node risk* or *site risk* refers to disruptions that arise in a supplier’s facility, manufacturing site, warehouse, or retail store. Typical incidents that cause disruption of a node would be fire, labor unrest, a natural disaster at a location, or a terrorist attack in the country where a manufacturing site is located.

On the other hand, *link risk* refers to the risks associated with the different transportation modes. For instance, labor strike at a harbor, extreme weather conditions such as snowfall, floods or a major traffic accident on a highway can disrupt the flow of goods through the respective link.

3.2.1 Node risks

Node risks or location-based risks can arise out of various natural or man-made events ranging from a delayed delivery of parts by supplier to a massive fire or earthquake. Many such incidents were discussed in detail in Chapter 1.

Chopra and Sodhi (2004) mention the drivers of supply chain disruption risks as

- Natural disaster,
- Labor dispute,
- Supplier bankruptcy,
- War and terrorism (geo-political),
- Dependency on a single source of supply as well as the capacity and responsiveness of alternative suppliers

These drivers can be looked at as the primary source of most node-based risks.

World Economic Forum’s (2012) survey respondents ranked the exogenous disruptions most likely to provoke significant and systemic effects on supply chain or transport networks (Figure 3.2). Their report discusses each of these triggers in detail with pointers on how to handle them to mitigate their impacts.

**Figure 3.2 Triggers of Global Supply Chain Disruptions (World Economic Forum 2011)**

Yang (2006) classifies these risks as VaR (Value-at-Risk) type risks. VaR-type risks are caused by events such as earthquakes, floods, fires, regulation changes, wars, sudden departure of key personnel, etc. These events do not occur frequently. But when they occur, they can create a significant impact on firms. While Yang (2006) uses these risks only to quantify supplier risks, they can be extended to quantify node risks at all stages.
While the incidents that cause node risks are the same across all the stages, their impacts on the supply chain depend on the stage where they occur and their severity. For instance, a fire in a manufacturing plant impacts the supply chain more adversely than a fire in one of the supplier locations. It is relatively easier to have back up suppliers than to have back up manufacturing plants. Wu et al. (2007) study this propagation of node-based risks within the supply chain using Petri-net.

Node risk incidents can be mitigated by considering them at various levels of supply chain decision making, such as location decisions, supplier selection, etc. Risk management must be looked at by the organizations as a part of their culture. The recent text by Ravindran and Warsing (2013) discusses risk quantification and risk mitigation strategies in a supply chain.

3.2.2 Link risks
The disruption of a link can occur due to natural disasters, labor disputes, terrorist activities, and infrastructure failures, etc. Supplier-related or manufacturer-related disruptions that could shut down a plant (bankruptcy) or drastically reduce capacity (fire at Philips plant in Mexico) are classified as node risks and discussed in 3.2.1. These types of disruptions not only stop the flow of goods within the supply chain, but also hinder the production of goods, whereas a transportation disruption stops only the flow of goods and, in that sense, is probably less severe. Giunipero and Eltantawy (2004) mention that a potential transportation disruption is a source of risk, and that it could “quickly cripple the entire supply chain”. Supply chain and transport disruptions are no longer seen as the purview only of operational risk managers. Changes to governance models in the wake of the 2008 global financial crisis and other major disruptions have pushed organizations to review their own approaches to identifying and mitigating systemic risks. C-suite level leadership and corporate boards are increasingly understanding and being
held accountable for the many aspects of organizational risk. (World Economic Forum, 2012). Therefore, the impacts due to disruptions of transportation links are quite significant on the supply chain. More than 90% of those surveyed by the World Economic Forum indicate that supply chain and transport risk management has become a greater priority in their organization over the last five years. Wilson (2007) also notes that transportation disruptions have received less attention than supply chain disruptions. He further mentions that the uniqueness of a transportation disruption is its specificity, distinctive in that *goods in transit have been stopped, although all other operations of the supply chain are intact*. For that reason, a transportation disruption arises when the material flow is interrupted between two echelons in a supply chain, temporarily stopping the transit of these goods, regardless of the source of the disruption. An interesting conclusion from the paper is that a transportation disruption between the tier 1 supplier and the warehouse, in a traditional supply chain (and not one with Vendor Managed Inventory (VMI)) has the greatest impact on the supply chain, creating a “ripple effect” both downstream and upstream, creating relatively high increases in inventory levels and goods in transit, and resulting in unfilled customer orders.

In January 2012, the white house released USA’s National Strategy for Global Supply Chain Security to strengthen global supply chains and to protect them (White House, 2012). The primary focus of this strategy was to enable secured movement of goods by strengthening the transportation links. The report highlights the following goals:

- Promote efficient and secure movement of goods
- Foster a resilient supply chain

It also outlines the approaches through which they intend to achieve these goals to secure supply chains.
The chances of link disruptions are dependent on the mode of transportation, environmental conditions, delays, customs, terrorist attacks, and so on. Figure 3.3 (Skorna et al. 2011) shows the claims made to one of Europe’s largest transportation insurance company. The sample consisted of 7,284 claims made in 2005 – 2008 as a result of incidents in transportation. In this sample, the insurance holder was either a logistics service provider or the shipper. It is important to note that this data set is not representative for the entire transportation insurance industry, as it is certainly affected by the specific customer base of the particular insurance provider. Still, it provides some clues for the identification of the current major pain points in transportation.

Figure 3.3 plots the cause of incidents vs. the mode of transportation. The size of the circles indicates the number of cases. The color of the circles indicates the loss in millions of dollars. The authors investigate the relationship between the modes of transport and the causes of incidents.
The authors make the following observations from Figure 3.3:

- Truck, ship, and air cargo transportation operations are most vulnerable to disruptions. Most incidents (both in terms of frequency and total loss) involve truck, ship and air cargo modes of transportation.
- Cargo theft (includes also pilferage), rough handling, and environmental conditions (including condensation, contamination with fresh or sea water, fire, or natural disasters) are the most salient causes for disruptions in transportation (again, both in terms of
frequency and total loss). Changes in temperatures also seem to pose a significant threat to transportation. The average loss per incident is highest for incidents caused by changes in temperatures, followed by collision, and extreme environmental conditions.

- Cargo theft and rough handling are particularly important issues for the modes of truck, ship, and air cargo, while environmental conditions are a significant threat to in-transit storage. An interesting finding is that cargo theft is also a major problem in air cargo business.

Railroad transportation is by far one of the safest ways to transport freight. Railways are a preferred means of transportation in many Asian and European countries, where road networks are either sparse or not well-maintained. Railways are also preferred in shipment of hazardous substances, mostly gases and liquids. The time taken for shipment between two points is higher in railroad compared to air transportation.

Air transportation, by its nature, bears high risk. Apart from that, it is affected by many of the drivers mentioned at the beginning of this section such as Environment, War and terrorism, labor disputes. The volcanic ash spread in 2010 severely affected movements of freight and people through air transportation for several weeks. Labor strikes at airports have in the past caused severe delays to movement of cargo. Intensified security measures following the 9/11 attacks also contribute to the time delays.

*Risks exclusive to ocean transportation*

Ocean transportation definitely plays an important role in international trade and is constantly on the increase. According to the Suez Canal Authority, 7.5% of world sea trade is carried via the Suez Canal. The initial reactions to the extraordinary 11 September 2001 attacks on the New
York World Trade Center Towers by Al’Qaeda operatives focused on the air transportation system. However, as the level of sophistication, organization and financing involved in the Al’Qaeda attacks became apparent, governments quickly intensified their scrutiny of the ocean sector, and for good reason. The sector is characterized by an extremely diverse international labor force, transporting a vast range of goods whose provenance, description and ownership are often left remarkably vague (UNECE, 2003). This is a system where international transport chains involve thousands of intermediaries, on vessels registered in dozens of countries that sometimes choose not to uphold their international responsibilities and where some vessel owners can and do easily hide their true identities using a complex web of international corporate registration practices. Furthermore, this system had already displayed certain vulnerabilities in the past, especially with respect to its use for the illegal smuggling of drugs or banned goods. And yet this system remains absolutely essential for continued world trade and prosperity. For all of these reasons, the international transport of goods by sea quickly moved to the fore of the international agenda to combat terrorism. Thus the security measures for maritime transportations were tightened, which made international trade through water more difficult.

Apart from the complications associated with customs procedures and the delays due to security measures, the role of seaports in ocean transportation is being actively studied. The port is the point where both the land and sea interfaces come into play. There is a whole body of literature on port management and how it causes disruptions in supply chain. The increasing amalgamation and assimilation of ports into supply chains (Pettit and Beresford, 2009) has only increased the potential of ports causing disruptions in supply chains. Port accidents, equipment-failures at ports, congestion, inadequate labor, breach of security, labor strikes are all common causes for disruptions at the ports. These issues are widely dealt with in port management.
literature. Loh and Thai (2012) discuss many of these issues and present a systematic framework for managing port-related risks.

At sea, the modern day pirates have made a spectacular comeback, especially in the Gulf of Aden. Armed with GPS technology, satellite phones and rocket-propelled grenades their attacks are becoming bolder. Despite an international navy task force in the region, merchant ships are required to take defensive precautions, travel in convoys or avoid one of the world’s busiest shipping lanes all together, making a detour of many thousands of miles (Matthey, 2010).

PwC (2011) gives the primary and secondary routes that connect the major gateway regions and maps the terrorism and threat conditions in these regions. The decision maker has to keep in mind these routes and the associated levels of terrorism in these routes while assigning scores to the routes in the next stage of this model.
The purpose of discussing these risks in depth is to guide the decision maker towards making an informed decision while assigning values to the risk indices that are used in the mathematical model.

**Figure 3.4** Ocean Sea routes and Crucial Choke Points (PwC, 2011)
3.3 Computation of Disruption Risk Indices

In this section, the methods used to estimate the disruption risk indices are discussed for both the node and the link risks. It is to be noted that these indices are time-variant and do not stay constant throughout the planning horizon due to the following:

- Weather related disruptions are seasonal.
- Political instabilities and terrorist attacks do not happen throughout the year
- Occurrences of events, such as customs delays at a port, labor unrest, etc., are not uniform through the year

We will now do a review of the methods used to compute disruption risk indices in this thesis.

3.3.1 Methods for Computing Risk Indices (Ravindran and Warsing 2013)

There are several methods that can be used to compute the risk indices. Four of them, namely,

- Rating method
- Ranking method (Borda count)
- Pair-wise comparison using Borda count and
- the AHP,

are used in this thesis to compute the risk indices. It is to be noted that these methods, except AHP, require scaling of criteria, in the case that the criteria values are not comparable.

A brief explanation of the methods follows. More information on these methods can be obtained from Chapter 6 of the textbook by Ravindran and Warsing (2013).
3.3.1.1 Rating Method

Rating is one of the simplest and most widely used ranking methods under conflicting criteria. First, an appropriate rating scale is agreed to (e.g. from 1 to 10, where 10 is the most important and 1 is the least important selection criterion). The scale should be clearly understood by the DM to be used properly. Next, using the selected scale, the DM provides a rating $r_j$ for each criterion, $C_j$. The same rating can be given to more than one criterion. The ratings are then normalized to determine the weights of the criteria $j$. Assuming $n$ criteria:

$$W_j = \frac{r_j}{\sum_{j=1}^{n} r_j} \text{ for } j = 1, 2, \ldots, n$$

Note: $\sum_{j=1}^{n} W_j = 1$

Next, a weighted score of the criteria is calculated for each alternative as follows:

$$S_i = \sum_{j=1}^{n} W_j f_{ij}, \quad \forall i = 1, \ldots, K$$

where, $f_{ij}$’s are the criteria values for alternative $i$. The alternatives are then ranked based on their scores. The alternative with the highest score is ranked first. Rating method requires relatively little cognitive burden on the DM.

3.3.1.2 Ranking Method (Borda Count)

The method is as follows:

- The $n$ criteria are ranked 1(most important) to $n$ (least important)
  - Criterion ranked 1 gets $n$ points, 2$^{nd}$ rank gets $n-1$ points, and the last place criterion gets 1 point.
- Weights for the criteria are then calculated as follows:
  - Criterion ranked 1 = $\frac{n}{s}$
Criterion ranked 2 = \( \frac{n - 1}{s} \)

\( s \) last criterion=\( \frac{1}{s} \)

where, \( s \) is the sum of all the points = \( \frac{n(n+1)}{2} \)

The criterion with the most points gets the highest rank, followed by the criterion with the second highest points gets the second rank and so on.

The method requires relatively more inputs from the DM and hence has higher cognitive burden.

3.3.1.3 Pair-wise Comparison using Borda Count

When there are many criteria, it might be difficult for a DM to rank order them precisely. In practice, pair-wise comparison of criteria is used to facilitate the criteria ranking required by the Borda count. Here, the DM is asked to give the relative importance between two criteria \( C_i \) and \( C_j \), whether \( C_i \) is preferred to \( C_j \), \( C_j \) is preferred to \( C_i \) or both are equally important. When there are \( n \) criteria, the DM has to respond to \( \frac{n(n-1)}{2} \) pair-wise comparisons. Based on the DM’s response, the criteria rankings and their weights can be computed, following the steps given below:

**Step 1:** Based on the DM’s response, a pair-wise comparison matrix, \( P_{(n \times n)} \), is constructed, whose elements \( p_{ij} \) are as given below:

\( p_{ii} = 1 \) for all \( i = 1, 2, \ldots, n \)

\( p_{ij} = 1, p_{ji} = 0, \) if \( C_i \) is preferred to \( C_j \) (\( C_i > C_j \))

\( p_{ij} = 0, p_{ji} = 1, \) if \( C_j \) is preferred to \( C_i \) (\( C_i < C_j \))
\( p_{ij} = p_{ji} = 1 \) if \( C_i \) and \( C_j \) are equally important.

**Step 2:** Compute the row sums of the matrix \( P \) as, \( t_i = \sum_j p_{ij} \) for \( i = 1, 2, \ldots, n \)

**Step 3:** Rank the criteria based on the \( t_i \) values and compute their weights, \( W_j = \frac{t_j}{\sum_i t_i} \), \( \forall j = 1, 2, \ldots, n. \)

Saari, D.G. (unpublished) proves that among the positional rules, pair-wise comparison using Borda Count is the only reliable method. For all other rules such as plurality voting, anti-plurality voting, all data sets suffer some kind of distortion and cannot provide reliable rankings.

### 3.3.1.4 The Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Saaty (1980), is a multi-criteria decision making method for ranking alternatives. Using AHP, the DM can assess not only quantitative but also various qualitative factors in the ranking process. AHP can enable the DM to represent the interaction of multiple factors in complex and un-structured situations. AHP does not require the scaling of criteria values.

#### Basic Principles of AHP

- Design a Hierarchy: Top vertex is the main objective and bottom vertices are the alternatives. Intermediate vertices are criteria / sub-criteria (which are more and more aggregated as you go up in the hierarchy).

- At each level of the hierarchy, a paired comparison of the vertices criteria/sub-criteria is performed from the point of view of their “contribution (weights)” to each of the higher-level vertices to which they are linked.
• Uses both rating method and comparison method. A numerical scale 1-9 (1-equal importance; 9-most important).

• Uses pair-wise comparison of alternatives with respect to each criterion (sub-criterion) and gets a numerical score for each alternative on every criterion (sub-criterion).

• Computes total weighted score for each alternative and ranks the alternatives accordingly.

A more detailed explanation of all of these methods, and the AHP in particular, can be obtained from Chapter 6 of the textbook by Ravindran and Warsing (2013).

In the subsequent sections (Sections 3.3.2 – 3.3.6), node and link risks are calculated using these methods. It is to be noted that the methods are chosen just for the purpose of illustration. Any of the methods can be used for calculating any of the node/link risk indices.

3.3.2 Computation of Node Risk Indices
We use the Analytic Hierarchy Process (AHP) to compute the (site) risk indices of three manufacturers, M1, M2 and M3. The following disruption risk factors are considered in this example:

1. Environmental (Natural disasters, weather, pandemic)

2. Geopolitical risks (Terrorism, import/export restrictions, etc.)

3. Technological risks (Disruption of information flow, loss of data, etc.)

4. Labor Issues/Strikes

5. Raw material shortage
It is to be noted that natural disasters, weather and pandemic can be treated as sub-factors under the Environmental factor and AHP provides a way to compute their weights separately. Similarly, under natural disasters, one can include several sub-sub-factors such as earthquakes, forest fires, floods, volcanic ash, etc. and compute the weights for each of them separately.

*Step 1: Pair-wise comparison of disruption risk factors*

In the matrix shown below, each factor is compared with another and a number is given based on the DM’s strength of preference using the degree of importance scale given in Table 3.1.

**Table 3.1** Degree of Importance Scale in AHP

<table>
<thead>
<tr>
<th>Degree of Importance</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
</tr>
<tr>
<td>3</td>
<td>Weak importance of one over other</td>
</tr>
<tr>
<td>5</td>
<td>Essential or strong importance</td>
</tr>
<tr>
<td>7</td>
<td>Demonstrated Importance</td>
</tr>
<tr>
<td>9</td>
<td>Absolute Importance</td>
</tr>
<tr>
<td>2,4,6,8</td>
<td>Intermediate values between two adjacent judgments</td>
</tr>
</tbody>
</table>

For instance, $A_{12} = 5$ indicates that according to the DM, disruptions arising out of Environmental factors are as essential or strongly important as disruptions arising out of geopolitical risks.
The matrix is normalized by dividing each entry by the corresponding column sum. The resulting $A_{\text{norm}}$ matrix is shown below.

$$
A_{(5 \times 5)} = \begin{bmatrix}
1 & 5 & 4 & 3 & 3 \\
1 & 5 & 1 & 3 & 2 \\
1 & 4 & 3 & 1 & 2 \\
1 & 3 & 2 & 2 & 1 \\
1 & 3 & 2 & 1 & 1 \\
\end{bmatrix}
$$

Step 2: Normalized weights for the disruption factors

The normalized weights are obtained by averaging the entries of the normalized matrix, row-wise.

$$
A_{\text{norm}} = \begin{bmatrix}
0.472 & 0.682 & 0.444 & 0.333 & 0.333 \\
0.094 & 0.136 & 0.333 & 0.222 & 0.222 \\
0.118 & 0.045 & 0.111 & 0.222 & 0.222 \\
0.157 & 0.068 & 0.056 & 0.111 & 0.111 \\
0.157 & 0.068 & 0.056 & 0.111 & 0.111 \\
\end{bmatrix}
$$

Step 3: Consistency check of the pair-wise comparison

The consistency check is done as shown below. The Consistency Index (CI) and the Consistency Ratio (CR) are computed from the value of $\lambda_{\text{max}}$. 

$$
W = \begin{bmatrix}
0.453 \\
0.202 \\
0.144 \\
0.101 \\
0.101 \\
\end{bmatrix}
$$
\[
A W = \lambda_{\text{max}} W = \begin{bmatrix}
2.641 \\
1.127 \\
0.727 \\
0.525 \\
0.525
\end{bmatrix}
\]

\[
\lambda_{\text{max}} = \text{Average} \left( \frac{2.641}{0.453}, \frac{1.127}{0.202}, \frac{0.727}{0.144}, \frac{0.525}{0.101}, \frac{0.525}{0.101} \right) = 5.380
\]

\[
\text{Consistency Index} = \frac{5.380 - 5}{5 - 1} = 0.095
\]

\[
\text{Consistency Ratio} = \frac{0.095}{1.11} = 0.09 < 0.1
\]

Hence, the Decision Maker is consistent.

\textbf{Step 4: Pair-wise comparison of manufacturers with respect to each disruption risk factor}

In order to carry out the pair-wise comparisons, Saaty’s degree of importance scale described in Table 3.1 is used again.

Environmental Factor:

In the matrix below $A_{12} = 2$ indicates that disruptions due to weather lie between 1 (Equal importance of M1 and M2) and 3 (Weak importance of M1 over M2) on the Saaty’s scale (Table 3.1). This can either be due to the impact caused by the disruptions, or the frequency of occurrence or a combination of the both as perceived by the DM.

\[
A_1 = \begin{bmatrix}
1 & 2 & 4 \\
\frac{1}{2} & 1 & 2 \\
\frac{1}{4} & \frac{1}{2} & 1
\end{bmatrix}
\quad A_{\text{norm}} = \begin{bmatrix}
0.571 & 0.571 & 0.571 \\
0.286 & 0.286 & 0.286 \\
0.143 & 0.143 & 0.143
\end{bmatrix}
\quad S_1 = \begin{bmatrix}
0.571 \\
0.286 \\
0.143
\end{bmatrix}
\]
Geopolitical Risk:

\[ A_2 = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} \\ 2 & 1 & \frac{1}{3} \\ 3 & 3 & 1 \end{bmatrix} \quad S_2 = \begin{bmatrix} 0.159 \\ 0.252 \\ 0.589 \end{bmatrix} \]

Technological Risk:

\[ A_3 = \begin{bmatrix} 1 & \frac{1}{7} & \frac{1}{3} \\ 7 & 1 & 3 \\ 3 & \frac{1}{3} & 1 \end{bmatrix} \quad S_3 = \begin{bmatrix} 0.088 \\ 0.669 \\ 0.243 \end{bmatrix} \]

Labor Issues:

\[ A_4 = \begin{bmatrix} 1 & \frac{1}{4} & \frac{1}{7} \\ 4 & 1 & \frac{1}{2} \\ 7 & 2 & 1 \end{bmatrix} \quad S_4 = \begin{bmatrix} 0.082 \\ 0.315 \\ 0.603 \end{bmatrix} \]

Raw material Shortage:

\[ A_5 = \begin{bmatrix} 1 & 3 & 5 \\ \frac{1}{3} & 1 & 3 \\ \frac{1}{5} & \frac{1}{3} & 1 \end{bmatrix} \quad S_5 = \begin{bmatrix} 0.633 \\ 0.260 \\ 0.106 \end{bmatrix} \]

Matrices \( A_1 \) – \( A_5 \) were all tested for consistency, similar to matrix \( A \), and were found to be consistent.
Step 5: Computing the risk index for each manufacturer

The final step is computing the risk index of each manufacturer. It is obtained by multiplying matrices S and W. Matrix S is obtained by placing matrices $S_1$ – $S_5$ as columns of the matrix S, in that order. Matrix W was computed in Step 2.

$$TS = SW = \begin{bmatrix} 0.571 & 0.159 & 0.088 & 0.082 & 0.633 \\ 0.286 & 0.252 & 0.669 & 0.315 & 0.260 \\ 0.143 & 0.589 & 0.243 & 0.603 & 0.106 \\ 0.453 \\ 0.202 \\ 0.144 \\ 0.101 \\ 0.101 \end{bmatrix} \begin{bmatrix} 0.453 \\ 0.202 \\ 0.144 \\ 0.101 \\ 0.101 \end{bmatrix} = \begin{bmatrix} 0.376 \\ 0.335 \\ 0.290 \end{bmatrix}$$

As per the resulting matrix, the Disruption Risk Index for M1 = 0.376, M2 = 0.335 and M3 = 0.290. In other words, M1 has higher chances of causing disruption (37.6%) in the supply chain than M2 (33.5%), who has a higher chance than M3 (29%). These values are denoted by $RM_{11}$, $RM_{21}$ and $RM_{31}$ in the optimization model where RM stands for Risk of Manufacturer, the first subscript denotes Manufacturer 1 and the second subscript denotes the time period for which the index is computed.

Similar approaches can be adopted to calculate site risks at supplier and distributor locations as well. Also, as mentioned earlier, these indices are subject to several seasonal variations such as weather, market conditions, political issues, etc. Thus it is important that these indices be reviewed periodically and updated, so as to ensure that the decisions made are not based on information that is obsolete.

3.3.3 Computation of Link Risk Indices for Ocean

For transportation links, disruptions can arise from three possible sources:

- Disruptions inherent in the mode of transportation
- Disruptions due to the route chosen
Disruptions caused by the carrier/freight forwarder

For transportation by ocean, the following disruption factors are considered.

Inherent to the mode of transportation:

- Wetting (damaged due to water)
- Sweating (damage due to the evaporation of other cargo or packaging materials in the same vessel)
- Damage (abrasion, collision, dint, tear, cracking, scratching, bending etc.)

Disruptions due to the chosen route:

- Congestion at the destination port
- Import/Export restrictions at the origin/destination ports
- Environmental factors (Weather, Natural disasters, Pandemic)
- Labor Issues at the ports/port closures
- Water Levels

Disruptions caused by the carrier/freight forwarder:

- Presence of transshipment (Presence of transshipment points on the route implies increased chances of disruption)
- Bad Quality of containers/pallets used for shipping
- Inability to get customs documentation ready on time
- Absence of anti-theft/tracking devices in the containers to ensure safety of cargo
To illustrate the procedure to compute the disruption risk index for ocean transportation, the rating method is employed. Consider the ocean link connecting manufacturer M1 to distributor D1. In this method, the decision maker assigns a rating from 1 to 10 for every disruption risk factor, 10 being very important and 1 being extremely insignificant (Table 3.2).

Table 3.2 Score for Ocean M1 – D1 (Rating Method)

<table>
<thead>
<tr>
<th>Risk Factor</th>
<th>Ratings</th>
<th>Weights for factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetting</td>
<td>3</td>
<td>3/52 = 0.058</td>
</tr>
<tr>
<td>Sweating</td>
<td>6</td>
<td>0.115</td>
</tr>
<tr>
<td>Damage</td>
<td>4</td>
<td>0.077</td>
</tr>
<tr>
<td>Port Congestion</td>
<td>6</td>
<td>0.115</td>
</tr>
<tr>
<td>Import/Export Restrictions</td>
<td>5</td>
<td>0.096</td>
</tr>
<tr>
<td>Environmental factors</td>
<td>7</td>
<td>0.135</td>
</tr>
<tr>
<td>Labor Issues</td>
<td>3</td>
<td>0.058</td>
</tr>
<tr>
<td>Water Levels</td>
<td>3</td>
<td>0.058</td>
</tr>
<tr>
<td>Transshipment</td>
<td>2</td>
<td>0.038</td>
</tr>
<tr>
<td>Container Quality</td>
<td>4</td>
<td>0.077</td>
</tr>
<tr>
<td>Customs Documentation</td>
<td>3</td>
<td>0.058</td>
</tr>
<tr>
<td>GPS/anti-theft devices</td>
<td>6</td>
<td>0.115</td>
</tr>
</tbody>
</table>

Table 3.2 gives the ratings for each of the risk factors considered for ocean links M1 – D1 and their corresponding weights. Following this, each of the ocean links is evaluated against the disruption risk factors and the decision maker assigns scores again. Higher score implies more risk for that factor for that ocean link. The scores to calculate disruption risk index for the ocean link connecting M1 and D1 is shown in Table 3.3.
Table 3.3 Ocean Link M1 – D1 scored against the Risk Factors

<table>
<thead>
<tr>
<th>Risk Factor</th>
<th>Score for Ocean link M1 – D1 (Lower the better)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetting</td>
<td>5</td>
</tr>
<tr>
<td>Sweating</td>
<td>6</td>
</tr>
<tr>
<td>Damage</td>
<td>2</td>
</tr>
<tr>
<td>Port Congestion</td>
<td>8</td>
</tr>
<tr>
<td>Import/Export Restrictions</td>
<td>7</td>
</tr>
<tr>
<td>Environmental factors</td>
<td>4</td>
</tr>
<tr>
<td>Labor Issues</td>
<td>5</td>
</tr>
<tr>
<td>Water Levels</td>
<td>8</td>
</tr>
<tr>
<td>Transshipment</td>
<td>2</td>
</tr>
<tr>
<td>Container Quality</td>
<td>4</td>
</tr>
<tr>
<td>Customs Documentation</td>
<td>9</td>
</tr>
<tr>
<td>GPS/anti-theft devices</td>
<td>3</td>
</tr>
</tbody>
</table>

It is important to understand the difference between the risk factor ratings and their scores. While the ratings represent the relative importance of risk factors to the disruption indices, the scores help to quantify the DM’s perception of how good or bad the manufacturer performs against each risk factor. A higher rating indicates how important that risk factor is, in computing the risk index, while a higher score indicates higher risk of the manufacturer for that particular risk factor.

Risk index of ocean Link connecting manufacturer M1 and distributor D1 = 0.058*5 + 0.115*6 + ……+0.115*3 = 5.269

In order to scale the Risk Index (so that they all lie between 0 and 1), the final index is divided by 10. Therefore the Risk Index for the Ocean Link connecting manufacturer M1 to distributor D1 = 0.527.
3.3.4 Computation of Link Risk Indices for Road

Road transportation is used in countries where the Rail is not suited for domestic/in-land transportation. In the US, the presence of a good road network augments such a situation. Over-the-road transportation of cargo is provided by trucks over short and medium distances. In 2011, trucks moved 9.2 billion tons of freight, or about 67 percent of all freight tonnage transported domestically within the United States. Motor carriers collected $604 billion in revenues, or about 81 percent of total revenue earned by all domestic transport modes (SelectUSA report).

The disruption factors associated with road are as given below.

**Inherent to the mode of transportation:**

- Road crashes
- Drivers’ strike

**Disruptions due to the chosen route:**

- Environmental factors (Weather, Natural Disasters, Pandemic)
- Highway congestion
- Thefts

**Disruptions caused by the carrier/freight forwarder:**

- Use of unreliable trucks
- Irresponsible/rash drivers
- Absence of anti-theft/tracking devices in the containers to ensure safety of cargo

We will use pair-wise comparison using Borda count to illustrate the computation of the risk index for a road link connecting manufacturer M1 and distributor D1. In pair-wise comparison using Borda count, the factors are compared pair-wise and the decision maker indicates which factor is more important as shown in Table 3.3. For example, between road
crashes and drivers’ strikes, road crashes are considered more important than drivers’ strikes. Hence a value of 1 is entered against drivers’ strike in row 1. However, between crashes and congestion, congestion is considered more important. Therefore, a value of 0 is entered against congestion in row 1.
Table 3.4 Pair-wise comparison of Risk factors for Road link M1 – D1

<table>
<thead>
<tr>
<th></th>
<th>Crashes</th>
<th>Drivers' strike</th>
<th>Environmental</th>
<th>Congestion</th>
<th>Thefts</th>
<th>Reliable trucks</th>
<th>Responsible drivers</th>
<th>Anti-theft devices</th>
<th>Sum</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crashes</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td>0.167</td>
</tr>
<tr>
<td>Drivers' strike</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>5</td>
<td>0.139</td>
</tr>
<tr>
<td>Environmental</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>0.111</td>
</tr>
<tr>
<td>Congestion</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>7</td>
<td>0.194</td>
</tr>
<tr>
<td>Thefts</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.028</td>
</tr>
<tr>
<td>Reliable trucks</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>0.083</td>
</tr>
<tr>
<td>Responsible drivers</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>0.056</td>
</tr>
<tr>
<td>Anti-theft devices</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>8</td>
<td>0.222</td>
</tr>
</tbody>
</table>

Using the pair-wise comparison matrix, weights are calculated for each disruption factor as shown in Table 3.4 for the road link between manufacturer M1 and distributor D1.
The road link under consideration, M1 – D1, is evaluated against the disruption factors in a scale of 1 to 10, a higher number indicating a higher prevalence of that factor. The scores of the disruption risk factors are shown in Table 3.5, a higher number indicates more risk for that factor.

**Table 3.5** Evaluation of road link M1-D1 using Pair-wise comparison

<table>
<thead>
<tr>
<th>Disruption Risk Factors</th>
<th>Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crashes</td>
<td>3</td>
</tr>
<tr>
<td>Drivers' strike</td>
<td>5</td>
</tr>
<tr>
<td>Environmental</td>
<td>4</td>
</tr>
<tr>
<td>Congestion</td>
<td>5</td>
</tr>
<tr>
<td>Thefts</td>
<td>6</td>
</tr>
<tr>
<td>Reliable trucks</td>
<td>3</td>
</tr>
<tr>
<td>Responsible drivers</td>
<td>6</td>
</tr>
<tr>
<td>Anti-theft devices</td>
<td>7</td>
</tr>
</tbody>
</table>

The risk index for the road link connecting manufacturer 1 and distributor 1 is calculated as the weighted sum \( = 3 \times 0.167 + 5 \times 0.139 + \ldots + 7 \times 0.222 = 4.917 \)

Again for the purpose of scaling, the index is divided by 10 and the Risk index for the link M1 – D1 is 0.492

### 3.3.5 Computation of Link Risk Indices for Air

Air transportation is used for both domestic and international shipments when time is the constraining factor. Air is the fastest mode of transportation between any two points on the globe, but is also the most expensive. Following are the disruption factors that can be considered for air transportation:
Disruptions due to the chosen route:

- Environmental factors (Weather, Natural Disasters, Pandemic)
- Airport congestion
- Import/Export restrictions
- Airport labor strike

Disruptions caused by the carrier/freight forwarder:

- Delays from improper Customs documentation
- Non-availability of flights to dispatch the cargo

We will use the Borda count method to illustrate the computation of the risk index for the air link between manufacturer M1 and distributor D1. In Borda count, the risk factors are rank ordered by the decision maker (1 – most important, 2- next important, and so on). Weights are calculated by dividing the individual rankings by the sum of the rankings. The weights and the rankings of the disruption risk factors for air are shown in Table 3.6.

Table 3.6 Weights for the Disruption Risk Factors for Air using Borda Count

<table>
<thead>
<tr>
<th>Disruption Risk Factors</th>
<th>Ranking</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental factors</td>
<td>1</td>
<td>0.048</td>
</tr>
<tr>
<td>Airport congestion</td>
<td>3</td>
<td>0.143</td>
</tr>
<tr>
<td>Import/Export restrictions</td>
<td>2</td>
<td>0.095</td>
</tr>
<tr>
<td>Airport Labor strike</td>
<td>4</td>
<td>0.190</td>
</tr>
<tr>
<td>Customs documentation</td>
<td>5</td>
<td>0.238</td>
</tr>
<tr>
<td>Flights unavailable</td>
<td>6</td>
<td>0.286</td>
</tr>
</tbody>
</table>
The air link under consideration, say the air link connecting manufacturer M1 and distributor D1, is evaluated under all these disruption risk factors. Table 3.7 shows the scores for the disruption risk factors, a higher number indicates more risk for that factor.

**Table 3.7 Disruption Risk Index for Air link M1-D1 using Borda Count**

<table>
<thead>
<tr>
<th>Disruption Risk Factors</th>
<th>Scores for air link connecting M1- D1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental factors</td>
<td>4</td>
</tr>
<tr>
<td>Airport congestion</td>
<td>5</td>
</tr>
<tr>
<td>Import/Export restrictions</td>
<td>7</td>
</tr>
<tr>
<td>Airport Labor strike</td>
<td>6</td>
</tr>
<tr>
<td>Customs documentation</td>
<td>4</td>
</tr>
<tr>
<td>Flights unavailable</td>
<td>6</td>
</tr>
</tbody>
</table>

The risk index for the air link = 4*0.48 +5*0.143+….+6*0.286 = 5.381. In order to scale it to a value between 0 and 1 we divide the score by 10. The risk index for the air link connecting M1 with D1 is 0.538.

### 3.3.6 Computation of Link Risk Indices for Rail

Rail is cheaper compared to road, but it takes longer to ship. The disruption risk factors for rail are as follows:

**Disruptions due to the chosen route:**

- Environmental factors (Weather, Natural Disasters, Pandemic)
- Railroad congestion
• Railway labor strike

Disruptions caused by the carrier/freight forwarder:

• Delays due to non-availability of carts/coaches to load the cargo

• Damages due to improper storage/loading; Bad Quality of coaches, etc.

Using these and any other possible factors causing disruptions in rail transportation, one can compute the risk indices for the rail links using AHP, Pair-wise comparison or Borda count methods. The risk indices are scaled to a value between 0 and 1 for use in the optimization model.

In the subsequent section, an optimization model is developed that specifically considers risk as an objective function.
3.4 Mathematical model

3.4.1 Assumptions

- The supply chain is centralized.
- There are four modes of transportation between each stage – Air, Road, Rail and Ocean and each mode has a different transit time and risk index.
- Backorders are allowed only at the retailer.
- Demand is satisfied only if it is profitable.
- Finished goods are immediately shipped to distributors. No inventory is held at the plants.
- For shipping through rail and ocean, no quantity discounts are assumed. Total cost is the product of the number of containers and cost per container.
- For shipping through road and air, all-unit quantity discounts are assumed.
- The forecasted monthly demands and the cost of shipping are assumed to be known.

3.4.2 Indices

\( n \) – Raw material type, \( n = 1, 2, \ldots, N \)

\( s \) – Supplier, \( s = 1, 2, \ldots, S \)

\( m \) – Manufacturer, \( m = 1, 2, \ldots, M \)

\( d \) – Distributor, \( d = 1, 2, \ldots, D \)

\( r \) – Retailer, \( r = 1, 2, \ldots, R \)

\( i \) – Mode of transportation, \( i = 1 \) (Air), 2 (Road), 3(Rail), 4(Ocean)

\( t \) – Time period, \( t = 1, 2, \ldots, T \)
$g, h, k, e, f, v$ – indices to describe the different price break points of the quantity discount cost structure.

### 3.4.3 Input Parameters

- **$S$** No. of suppliers
- **$M$** No. of manufacturers
- **$D$** No. of distributors
- **$R$** No. of retailers
- **$T$** No. of time periods
- **$N$** No. of raw materials
- **$T$** No. of time periods in the planning horizon
- **$SP$** Selling price of one unit of finished good
- **$PC$** Cost of producing one unit of finished product
- **$MIC$** Inventory holding cost per unit per period at manufacturer locations
- **$DIC$** Inventory holding cost per unit per period at distributor locations
- **$LT$** Production lead time at the manufacturer
- **$a_n$** no. of units of raw material ‘$n$’ needed to produce one unit of the finished product
- **$RMC_{ns}$** Cost of procuring one unit of raw material ‘$n$’ from supplier ‘$s$’
- **$RS_{st}$** Risk index of supplier ‘$s$’ during time period ‘$t$’
- **$RM_{mt}$** Risk index of manufacturer ‘$m$’ during time period ‘$t$’
- **$RDC_{dt}$** Risk index of distributor ‘$d$’ during time period ‘$t$’
\( RTSM_{smi} \) Risk index of transportation mode ‘i’, linking supplier ‘s’ to manufacturer ‘m’, during time period ‘t’

\( RTMD_{mdit} \) Risk index of transportation mode ‘i’, linking manufacturer ‘m’ to distributor ‘d’, during time period ‘t’

\( RTDR_{drit} \) Risk index of transportation mode ‘i’, linking distributor ‘d’ to retailer ‘r’, during time period ‘t’

\( MCAP_m \) Capacity of manufacturer ‘m’

\( DCAP_d \) Capacity of distributor ‘d’

\( SMMAX_{ism} \) Maximum quantity of raw material that can be shipped from supplier ‘s’ to manufacturer ‘m’ through mode ‘i’

\( MDMAX_i \) Maximum quantity of finished goods that can be shipped from manufacturer m to distributor ‘d’ through mode ‘i’

\( DRMAX_i \) Maximum quantity of finished goods that can be shipped from supplier ‘s’ to manufacturer ‘m’ through mode ‘i’

\( DEM_{rt} \) Forecasted demand for retailer ‘r’ during time period ‘t’

\( A_{ism} \) Lead time from supplier ‘s’ to manufacturer ‘m’ through mode ‘i’

\( B_{imd} \) Lead time from manufacturer ‘m’ to distributor ‘d’ through mode ‘i’

\( C_{idr} \) Lead time from distributor ‘d’ to retailer ‘r’ through mode ‘i’

\( CR \) Cost of shipping one container through rail

\( CM \) Cost of shipping one container through ocean transportation

\( CPR \) Capacity of a pallet for rail transportation
$CCR$ Capacity of a container for rail transportation

$CPM$ Capacity of a pallet for ocean transportation

$CCM$ Capacity of a container for ocean transportation

$MEI_{nm}$ Inventory of raw material ‘n’ at manufacturer ‘m’ at the end of planning horizon

$DEI_{d}$ Inventory of finished goods at distributor ‘d’ at the end of planning horizon

$MI_{nm}$ Initial Inventory of raw materials at Manufacturer

$DI_{d}$ Initial Inventory of finished goods at distributor ‘d’

### 3.4.4 Decision Variables

$X_{nsmit}$ Quantity of raw material ‘n’ shipped from supplier ‘s’ to manufacturer ‘m’, using mode ‘i’, in period ‘t’

$Y_{mdit}$ Quantity of finished goods shipped from manufacturer ‘m’ to distributor ‘d’, using mode ‘i’, in period ‘t’

$Z_{drit}$ Quantity of finished goods shipped from distributor ‘d’ to retailer ‘r’, using mode ‘i’, in period ‘t’

$Q_{mt}$ Total quantity produced starting at time period ‘t’ (This will be ready for shipping at the end of period ‘t+LT’ from manufacturer ‘m’)

$MI_{nm}$ Inventory of raw material ‘n’ at manufacturer ‘m’ at the end of time period ‘t’

$DI_{dt}$ Inventory of finished goods at distributor ‘d’, at the end of time period ‘t’

$BO_{rt}$ Backorders at the retailer ‘r’, at the end of time period ‘t’
$NCR_{smt}$ - No. of containers through rail, sent from supplier ‘s’ to manufacturer ‘m’, in time period ‘t’

$NCR_{mdt}$ - No. of containers through rail, sent from manufacturer ‘m’ to distributor ‘d’, in time period ‘t’

$NCR_{drt}$ - No. of containers through rail, sent from distributor ‘d’ to retailer ‘r’, at the end of time period ‘t’

$NCM_{smt}$ - No. of containers through ocean, sent from supplier ‘s’ to manufacturer ‘m’, at the end of time period ‘t’

$NCM_{mdt}$ - No. of containers through ocean, sent from manufacturer ‘m’ to distributor ‘d’, in time period ‘t’

$NCM_{drt}$ - No. of containers through ocean, sent from distributor ‘d’ to retailer ‘r’, in time period ‘t’

$a^g_{sm2t}, p^h_{md2t}, y^k_{dr2t}, \delta^e_{sm1t}, \delta^f_{md1t}, \delta^v_{dr1t}$ - Binary variables used to model the flat regions in the quantity discount structure

3.4.5 Objective Functions

**Objective 1:** Profit is given by difference between revenue from sales and the total costs incurred (sum of raw material procurement, transportation, production and inventory holding costs).
Maximize Profit

= Revenue from sales

− (Raw material procurement cost + Production cost

+ Transportation cost + Inventory holding cost at DC)

The demand is met only if it is profitable. The assumption here is that all the units shipped to a retailer in a time period are sold out.

Revenue from sales = \( SP \sum_{t=1}^{T} \sum_{i=1}^{4} \sum_{r=1}^{R} \sum_{d=1}^{D} Z_{dri(t-c_{idr}-1)} \)

Raw material procurement cost = \( \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{i=1}^{4} \sum_{r=1}^{R} \sum_{d=1}^{D} (RMC_{ns} X_{nsmit}) \)

Production Cost = \( PC \sum_{t=1}^{T} \sum_{m=1}^{M} Q_{mt} \)

Inventory holding cost at DC = \( DIC \sum_{t=1}^{T} \sum_{d=1}^{D} DI_{dt} + MIC \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{n=1}^{N} MI_{nmt} \)

Container transportation costs

= \( CR * \left( \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{s=1}^{S} NCR_{smt} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{m=1}^{M} NCR_{mdt} + \sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{d=1}^{D} NCR_{drt} \right) \)

+ \( CM * \left( \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{s=1}^{S} NCM_{smt} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{m=1}^{M} NCM_{mdt} + \sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{d=1}^{D} NCM_{drt} \right) \)
Quantity discount costs

\[
\begin{align*}
&= \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{s=1}^{S} \sum_{n=1}^{N} \sum_{e=1}^{E} (X_{nsm1t} \cdot VC_{e-1} + \delta_{sm1t}^e \cdot FC_e) \\
&\quad + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{m=1}^{M} \sum_{f=1}^{F} (Y_{md1t} \cdot VC_{f-1} + \delta_{md1t}^f \cdot FC_f) \\
&\quad + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{m=1}^{M} \sum_{v=1}^{V} (Z_{dr1t} \cdot VC_{v-1} + \delta_{dr1t}^v \cdot FC_v) \\
&\quad + \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{s=1}^{S} \sum_{n=1}^{N} \sum_{g=1}^{G} (X_{nsm2t} \cdot VC_{g-1} + \alpha_{sm2t}^g \cdot FC_g) \\
&\quad + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{m=1}^{M} \sum_{h=1}^{H} (Y_{md2t} \cdot VC_{h-1} + \beta_{md2t}^h \cdot FC_h) \\
&\quad + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{m=1}^{M} \sum_{k=1}^{K} (Z_{dr2t} \cdot VC_{k-1} + \gamma_{dr2t}^k \cdot FC_k)
\end{align*}
\]

Objective 2:

Responsiveness of the supply chain is measured in terms of the cumulative number of backorders at the retailer through the planning horizon. Higher the number of backorders implies that the time to respond is high and this in turn implies low responsiveness.

Maximize Responsiveness = Minimize backorders at the retailer = Minimize \(Z_2\)

\[
= \sum_{t=1}^{T} \sum_{r=1}^{R} BO_{rt}
\]
Objective 3:

This objective represents the quantity-weighted risk of the supply chain. It is calculated as the sum of the product of the disruption risk indices and the number of units passing through the corresponding node/link.

Minimize Total Risk

\[
\begin{align*}
&= \sum_{t=1}^{T} \left\{ \sum_{s=1}^{S} \left( RS_{st} \sum_{i=1}^{4} \sum_{m=1}^{M} \sum_{n=1}^{N} X_{ntsmit} \right) + \sum_{m=1}^{M} \left( RM_{mt} \sum_{i=1}^{4} \sum_{d=1}^{D} Y_{mdit} \right) \right. \\
&\quad + \sum_{d=1}^{D} \left( RDC_{dt} \sum_{i=1}^{4} \sum_{r=1}^{R} Z_{dr} \right) + \sum_{i=1}^{4} \sum_{m=1}^{M} \sum_{s=1}^{S} \left( RTSM_{ntsmit} \sum_{n=1}^{N} X_{ntsmit} \right) \\
&\quad \left. + \sum_{i=1}^{4} \sum_{d=1}^{D} \sum_{m=1}^{M} (RTMD_{mdit} \cdot Y_{mdit}) + \sum_{i=1}^{4} \sum_{r=1}^{R} \sum_{d=1}^{D} (RTDR_{dr} \cdot Z_{dr}) \right\}
\end{align*}
\]

3.4.6 Constraints

1. Total quantity produced starting at time ‘\(t\)’ and available for shipping at the end of period ‘\(t+LT\)’ from manufacturer ‘\(m\)’:

\[
Q_{mt} = \sum_{i=1}^{4} \sum_{d=1}^{D} Y_{mditi(t+LT)} \quad \forall m \forall t = 1, 2, \ldots, T
\]

2. Flow constraint at manufacturer:

\[
MI_{ntm(t-1)} + \sum_{i=1}^{4} \sum_{s=1}^{S} X_{ntsmit(t-A_{ism})} = MI_{ntm} + a_n Q_{mt} \quad \forall n, \forall m, \forall t
\]

3. Manufacturer raw material storage capacity:
\[
\sum_{n=1}^{N} MI_{nmt} \leq MCAP_m \forall m, \forall t
\]

4. Manufacturer's production capacity: \( Q_{mt} = 0 \) when \( t = 0 \)

\[
Q_{mt} \leq PMCAP_m \forall m, \forall t
\]

5. Restricting shipping units out of Manufacturing plants:

Units can be shipped from manufacturing plants only after the production lead time.

\[
\sum_{t=1}^{LT} \sum_{i=1}^{4} \sum_{d=1}^{D} \sum_{m=1}^{M} Y_{mdit} = 0
\]

6. Flow constraint at distributor: \( Y_{mdit} = 0 \) when \( t = 0 \)

\[
DI_{d(t-1)} + \sum_{i=1}^{4} \sum_{m=1}^{M} Y_{mdi(t-B_{imd})} = DI_{dt} + \sum_{i=1}^{4} \sum_{r=1}^{R} Z_{dr(it)} \forall d, \forall t
\]

7. Capacity constraint at distributor:

\[
DI_{dt} \leq DCAP_d \forall d, \forall t
\]

8. Demand constraint at Retailer

\[
\sum_{i=1}^{4} \sum_{d=1}^{D} Z_{dri(t-c_{idr})} = DEM_{rt} + BO_{r(t-1)} - BO_{rt} \forall r, \forall t
\]

9. Minimum demand to be satisfied for Retailers

This constraint is to obtain realistic bounds on the disruption risk objective. In the absence of this constraint, when a single objective optimization problem to minimize disruption risk is executed, the model tends to ship quantities towards the end of the planning horizon just
to meet the ending inventory conditions. This does not make practical sense. Therefore, with the sole purpose of inducing production and transportation from period 1 into the network, irrespective of the objective being optimized, this constraint is included in the model.

A new variable $Unmet_{rt}$ represents the unmet demand at each retailer at the end of time period ‘t’ and is defined as the absolute difference between the backorders of the current and the previous time period.

$$Unmet_{rt} = |BO_{rt} - BO_{r(t-1)}|$$

$Unmet_{rt}$ is unrestricted, but can be expressed as the sum of two positive integers as follows:

$$Unmet_{rt} = Unmet^+_{rt} - Unmet^-_{rt}$$

$$Unmet^+_{rt} = BO_{rt} - BO_{r(t-1)}$$

$$Unmet^-_{rt} = BO_{r(t-1)} - BO_{rt}$$

$$Unmet^+_{rt}, Unmet^-_{rt} \geq 0$$

A measure, $UR_r$, is given as an input for each retailer. $UR_r$ represents the maximum allowable backorders as a percentage of the forecasted demand of the entire planning horizon for retailer ‘r’.

$$\frac{Unmet^+_{rt} - Unmet^-_{rt}}{\sum_{t=1}^{T} Dem_{rt}} \leq UR_r, \forall t = 1, 2,...$$
10. Cost constraints for truck shipment from supplier to manufacturer

\[ l_{sm}^{g-1} \alpha_{smt}^{g} \leq TX_{smt}^{g} \leq l_{sm}^{g} \alpha_{smt}^{g} \forall g, \forall s, \forall m, \forall t \]

\[ \sum_{g=1}^{G} TX_{smt}^{g} = \sum_{n=1}^{N} X_{nsm2t} \]

\[ \sum_{g=1}^{G} \alpha_{smt}^{g} \leq 1 \forall s, \forall m, \forall t \]

where \( l_{sm}^{g} \) represents the upper limit of weight break \( g \) used in calculating freight through truck from supplier to manufacturer. \( TX_{smt}^{g} \) represents the number of units of raw material shipped from supplier ‘\( s \)’ to customer ‘\( m \)’ in time period ‘\( t \)’ in weight break ‘\( g \)’.

11. Cost constraints for truck shipment from manufacturer to distributor

\[ l_{md}^{h-1} \beta_{mdt}^{h} \leq TY_{mdt}^{h} \leq l_{sm}^{g} \beta_{mdt}^{h} \forall h, \forall m, \forall d, \forall t \]

\[ \sum_{h=1}^{H} TY_{mdt}^{h} = Y_{md2t} \]

\[ \sum_{h=1}^{H} \beta_{mdt}^{h} \leq 1 \forall m, \forall d, \forall t \]

12. Cost constraints for truck shipment from distributor to retailer

\[ l_{dr}^{k-1} \gamma_{drt}^{k} \leq TZ_{drt}^{k} \leq l_{dr}^{k} \gamma_{drt}^{k} \forall k, \forall d, \forall r, \forall t \]

\[ \sum_{k=1}^{K} TZ_{drt}^{k} = Z_{dr2t} \]
\[ \sum_{k=1}^{K} \gamma^h_{drt} \leq 1 \ \forall d, \forall r, \forall t \]

13. Cost constraints for air shipment from supplier to manufacturer

\[ L_{sm}^{e-1} \alpha_{smt}^e \leq AX_{smt}^e \leq L_{sm}^{e} \alpha_{smt}^e \forall g, \forall s, \forall m, \forall t \]

\[ \sum_{e=1}^{E} AX_{smt}^e = \sum_{n=1}^{N} X_{nsmt} \]

\[ \sum_{e=1}^{E} \alpha_{smt}^e \leq 1 \ \forall s, \forall m, \forall t \]

14. Cost constraints for air shipment from manufacturer to distributor

\[ L_{md}^{f-1} \beta_{mdt}^h \leq AY_{mdt}^h \leq L_{md}^{f} \beta_{mdt}^h \forall h, \forall m, \forall d, \forall t \]

\[ \sum_{f=1}^{F} AY_{mdt}^f = Y_{mdt} \]

\[ \sum_{f=1}^{F} \beta_{mdt}^f \leq 1 \ \forall m, \forall d, \forall t \]

15. Cost constraints for air shipment from distributor to retailer

\[ L_{dr}^{v-1} \gamma_{drt}^v \leq AZ_{drt}^v \leq L_{dr}^{v} \gamma_{drt}^v \forall k, \forall d, \forall r, \forall t \]

\[ \sum_{v=1}^{V} AZ_{drt}^v = Z_{drt} \]

\[ \sum_{v=1}^{V} \gamma_{drt}^v \leq 1 \ \forall d, \forall r, \forall t \]
16. Cost constraints for rail shipment from supplier to manufacturer

\[ \sum_{n=1}^{N} X_{nsmt} \leq CCR * NCR_{smt} \forall s, \forall m, \forall t \]

17. Cost constraints for rail shipment from manufacturer to distributor

\[ \frac{Y_{mdt}}{CPR} \leq CCR * NCR_{mdt} \forall m, \forall d, \forall t \]

18. Cost constraints for rail shipment from distributor to retailer

\[ \frac{Z_{drt}}{CPR} \leq CCR * NCR_{drt} \forall d, \forall r, \forall t \]

19. Cost constraints for ocean shipment from supplier to manufacturer

\[ \sum_{n=1}^{N} X_{nsmt} \leq CCM * NCM_{smt} \forall s, \forall m, \forall t \]

20. Cost constraints for ocean shipment from manufacturer to distributor

\[ \frac{Y_{mdt}}{CPM} \leq CCM * NCM_{mdt} \forall m, \forall d, \forall t \]

21. Cost constraints for ocean shipment from distributor to retailer

\[ \frac{Z_{drt}}{CPM} \leq CCM * NCM_{drt} \forall d, \forall r, \forall t \]

22. Ending Inventory constraints

\[ MI_{nm} \geq MEI_{nm} \forall n, \forall m \]

\[ DI_{d} \geq DEI_{d} \forall d \]

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23. Other constraints

\[ X_{nsmt}, Y_{mdit}, Z_{drt}, Q_{mt}, M_{nmt}, D_{it}, BO_{rt}, NCA_{smt}, NCA_{mdt}, NCA_{drt}, NCM_{smt}, NCM_{mdt}, NCM_{drt} \]

\[ \geq 0 \text{ and are integers for } \forall n, \forall s, \forall m, \forall d, \forall r \forall i, \forall t \]

\[ \alpha_{sm2t}^g, \beta_{md2t}^h, \gamma_{dr2t}^k, \delta_{sm1t}^e, \delta_{md1t}^f, \delta_{dr1t}^w \in \{0,1\} \]

3.5 Solution Methodology

In chapter 4, the model proposed in Section 3.4 is solved using a realistic example, optimizing each of the objectives separately. Following this, the model will be solved using Non-preemptive Goal Programming (NPGP) approach (with varying sets of weights on the three objectives) and also using Preemptive Goal Programming approach by varying the Decision Makers’ ordinal priorities of the three objectives. The results from these models will be analyzed to illustrate the tradeoffs and managerial insights.
Chapter 4

Illustrative Example

In this Chapter, an example is developed with realistic data to analyze the model and understand its implementation and managerial implications better. The example problem is solved using Goal Programming (GP) methods (preemptive and non-preemptive). The chapter begins with an explanation of the example problem and the input parameters. The second section carries a brief discussion of the two GP methods used in this thesis. The third and fourth sections discuss the results of the preemptive and the non-preemptive GP solutions, respectively. The solutions are compared using the Value Path approach in the final section.

4.1 Example Data Set

Consider the supply chain network described in Chapter 3. There are four stages – Supplier, Manufacturer, Distributor and Retailer. The stages are connected with one another by means of four modes of transportation – Air, Ocean, Rail and Road. In this example, the time unit is weeks and the planning horizon is set as 15 weeks. We illustrate the model with the network parameters listed in Table 4.1.

Table 4.1 Supply Chain Network Parameters

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>No. of suppliers</td>
<td>4</td>
</tr>
<tr>
<td>$M$</td>
<td>No. of manufacturers</td>
<td>2</td>
</tr>
<tr>
<td>$D$</td>
<td>No. of distributors</td>
<td>3</td>
</tr>
<tr>
<td>$R$</td>
<td>No. of retailers</td>
<td>7</td>
</tr>
</tbody>
</table>
The cost components that are involved in calculating the profit objective, namely, the selling price/unit, the production cost/unit, and the inventory holding costs are presented in Table 4.2.

**Table 4.2 Cost components in USD**

<table>
<thead>
<tr>
<th>Description</th>
<th>Notation</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selling price of one unit of finished good</td>
<td>$SP$</td>
<td>$240 USD</td>
</tr>
<tr>
<td>Cost of producing one unit of finished product</td>
<td>$PC$</td>
<td>$25 USD</td>
</tr>
<tr>
<td>Inventory holding cost at manufacturer locations</td>
<td>$MIC$</td>
<td>$0.5/unit/week</td>
</tr>
<tr>
<td>Inventory holding cost at distributor locations</td>
<td>$DIC$</td>
<td>$0.5/unit/week</td>
</tr>
</tbody>
</table>

We assume that two different types of raw materials ($a_1$ and $a_2$) are required to build the finished product. One unit of $a_1$ and two units of $a_2$ go into producing one unit of the finished product. The costs of procuring raw material from the different suppliers are given in Table 4.3.

**Table 4.3 Raw material cost ($RMC_{n,z}$) at the suppliers in USD/unit.**

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Raw material 1</th>
<th>Raw material 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>40.66</td>
<td>41.91</td>
</tr>
<tr>
<td>S2</td>
<td>36.83</td>
<td>37.60</td>
</tr>
<tr>
<td>S3</td>
<td>37.84</td>
<td>43.83</td>
</tr>
<tr>
<td>S4</td>
<td>38.08</td>
<td>41.66</td>
</tr>
</tbody>
</table>

The production lead time at the manufacturing units is assumed to be two weeks. The Manufacturers’ capacities to hold inventory of raw material and finished goods are presented in Tables 4.4 and 4.5 respectively. The boundary conditions related to the initial and final inventory of raw materials at the manufacturing plants are given in Table 4.6.

**Table 4.4 Capacity of Manufacturer ($MCAP_m$) to Store Raw Material Inventory in no. of units**

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>2,841</td>
</tr>
<tr>
<td>M2</td>
<td>2,418</td>
</tr>
</tbody>
</table>
Table 4.5 Manufacturer’s Production Capacity ($PMCAP_m$) in no. of units

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>1,077</td>
</tr>
<tr>
<td>M2</td>
<td>1,162</td>
</tr>
</tbody>
</table>

Table 4.6 Initial and Ending Inventory of Raw Material for Manufacturers

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Initial Inventory ($MII_{nm}$)</th>
<th>Ending Inventory ($MEI_{nm}$), ∀n</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>500 for n = 1</td>
<td>100</td>
</tr>
<tr>
<td>M2</td>
<td>500 for n = 1</td>
<td>100</td>
</tr>
</tbody>
</table>

The capacity of the DC to hold finished good inventory is listed in Table 4.7. The boundary conditions relating to the initial and ending inventory at the DCs are listed in Table 4.8.

Table 4.7 Capacity of DC to hold Finished Goods ($DCAP_d$) in no. of units

<table>
<thead>
<tr>
<th>Distributor</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>791</td>
</tr>
<tr>
<td>D2</td>
<td>609</td>
</tr>
<tr>
<td>D3</td>
<td>716</td>
</tr>
</tbody>
</table>

Table 4.8 Initial and Ending Inventory of Finished Goods for DC

<table>
<thead>
<tr>
<th>Distributor</th>
<th>Initial Inventory ($DII_d$)</th>
<th>Ending Inventory ($DEI_d$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>750</td>
<td>50</td>
</tr>
<tr>
<td>D2</td>
<td>750</td>
<td>50</td>
</tr>
<tr>
<td>D3</td>
<td>750</td>
<td>50</td>
</tr>
</tbody>
</table>

Table 4.9 gives the forecasted demand at the retailers for the next fifteen time periods. It is to be noted that these values can be updated as and when they change, and the model can be re-run with the updated values to capture the effect of changing forecasts.
### Table 4.9 Forecasted Demand ($DEM_r$) at the Retailers in no. of units

<table>
<thead>
<tr>
<th></th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
<th>R5</th>
<th>R6</th>
<th>R7</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>T1</strong></td>
<td>166</td>
<td>201</td>
<td>207</td>
<td>245</td>
<td>233</td>
<td>195</td>
<td>195</td>
</tr>
<tr>
<td><strong>T2</strong></td>
<td>239</td>
<td>237</td>
<td>249</td>
<td>154</td>
<td>158</td>
<td>206</td>
<td>207</td>
</tr>
<tr>
<td><strong>T3</strong></td>
<td>171</td>
<td>210</td>
<td>243</td>
<td>208</td>
<td>219</td>
<td>172</td>
<td>172</td>
</tr>
<tr>
<td><strong>T4</strong></td>
<td>153</td>
<td>202</td>
<td>216</td>
<td>167</td>
<td>204</td>
<td>189</td>
<td>182</td>
</tr>
<tr>
<td><strong>T5</strong></td>
<td>220</td>
<td>241</td>
<td>191</td>
<td>243</td>
<td>193</td>
<td>230</td>
<td>190</td>
</tr>
<tr>
<td><strong>T6</strong></td>
<td>150</td>
<td>229</td>
<td>234</td>
<td>191</td>
<td>227</td>
<td>157</td>
<td>164</td>
</tr>
<tr>
<td><strong>T7</strong></td>
<td>157</td>
<td>184</td>
<td>166</td>
<td>242</td>
<td>208</td>
<td>227</td>
<td>154</td>
</tr>
<tr>
<td><strong>T8</strong></td>
<td>193</td>
<td>203</td>
<td>158</td>
<td>215</td>
<td>157</td>
<td>164</td>
<td>175</td>
</tr>
<tr>
<td><strong>T9</strong></td>
<td>157</td>
<td>227</td>
<td>180</td>
<td>194</td>
<td>186</td>
<td>194</td>
<td>170</td>
</tr>
<tr>
<td><strong>T10</strong></td>
<td>192</td>
<td>240</td>
<td>174</td>
<td>160</td>
<td>218</td>
<td>217</td>
<td>192</td>
</tr>
<tr>
<td><strong>T11</strong></td>
<td>152</td>
<td>154</td>
<td>184</td>
<td>200</td>
<td>205</td>
<td>244</td>
<td>160</td>
</tr>
<tr>
<td><strong>T12</strong></td>
<td>167</td>
<td>240</td>
<td>189</td>
<td>181</td>
<td>205</td>
<td>242</td>
<td>216</td>
</tr>
<tr>
<td><strong>T13</strong></td>
<td>241</td>
<td>161</td>
<td>242</td>
<td>186</td>
<td>192</td>
<td>245</td>
<td>177</td>
</tr>
<tr>
<td><strong>T14</strong></td>
<td>174</td>
<td>186</td>
<td>228</td>
<td>247</td>
<td>216</td>
<td>176</td>
<td>150</td>
</tr>
<tr>
<td><strong>T15</strong></td>
<td>153</td>
<td>185</td>
<td>174</td>
<td>177</td>
<td>152</td>
<td>238</td>
<td>156</td>
</tr>
</tbody>
</table>

The transportation capacities are set to 1000 units using all modes of transportations, between all stages, in all time periods (Table 4.10). The lead time is assumed to be one week if shipped using air, two if shipped through road, three if shipped through rail and four if shipped using ocean between all stages in all the time periods (Table 4.11).

### Table 4.10 Transportation Capacities

<table>
<thead>
<tr>
<th></th>
<th>Air ($i = 1$)</th>
<th>Road ($i = 2$)</th>
<th>Rail ($i = 3$)</th>
<th>Ocean ($i = 4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier to Manufacturer ($SMMAX_i$)</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
</tr>
<tr>
<td>Manufacturer to Distributor ($MDMAX_i$)</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
</tr>
<tr>
<td>Distributor to Retailer ($DRMAX_i$)</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
</tr>
</tbody>
</table>
Table 4.11 Transportation Lead Times Associated with the Different Modes of Transportation

<table>
<thead>
<tr>
<th></th>
<th>Air ((i = 1))</th>
<th>Road ((i = 2))</th>
<th>Rail ((i = 3))</th>
<th>Ocean ((i = 4))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suppliers to Manufacturers ((A_{im}))</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Manufacturer to Distributor ((B_{mid}))</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Distributor to Retailer ((C_{idr}))</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

For shipments that are made through air and road, an (all-unit) quantity discount cost structure is assumed. In all unit quantity discounts, the entire shipment is charged at a lower price based on the shipment quantity. In the example in (Table 4.12), if the number of units shipped through road is between 1 and 499, the cost is $1.36/unit. If the number of units shipped is between 500 and 999, the shipping cost is $1.1/unit for all the units that are being shipped. If the number of units shipped is 1000 or more, the shipping cost is $0.92/unit for all the units that are being shipped.

In the transportation industry, the practice of *over declaring* the weight of a shipment (or the no. of units in a shipment) is very common, in order to take advantage of the all-unit quantity discount. For instance, in this example, if the number of units being shipped is 410 units, the cost according to the all-unit quantity discount structure in Table 4.12 is $1.36/unit*410 units = $557.6. However, an intelligent shipper would instead declare the number of units in the shipment as 500 and pay $1.1/unit*500 units = $550 and make a savings of $7.6. This practice is termed as *over declaring*.

A breakpoint is the threshold value in each quantity break beyond which it makes sense to over declare. In other words, if your shipment quantity is greater than the breakpoint, over declaring will result in cost savings. Breakpoints can be calculated for each quantity break. Figure 4.1 shows the plots of the cost structure prior to, and post over declaration. It can be seen
how the “flat regions” of the over declared cost structure helps in bringing in savings. The modified cost structure with the break points included is given in Table 4.13. Croxton et al. (2003) discuss the practice of over declaration and the method to compute the breakpoints for each quantity break in detail. They also discuss mathematical modeling methods used to model such cost structures.

Table 4.12 Nominal Freight Rate Structure for Transportation in all Stages through Road and Air

<table>
<thead>
<tr>
<th>Road:</th>
<th>Air:</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quantity (no. of units)</strong></td>
<td><strong>Cost (USD/unit)</strong></td>
</tr>
<tr>
<td>1-499</td>
<td>1.36</td>
</tr>
<tr>
<td>500-999</td>
<td>1.1</td>
</tr>
<tr>
<td>&gt;=1000</td>
<td>0.92</td>
</tr>
</tbody>
</table>

Table 4.13 Freight Rate Structure (Post Over Declaration) for Transportation in all Stages through Road and Air

<table>
<thead>
<tr>
<th>Road:</th>
<th>Air:</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quantity (no. of units)</strong></td>
<td><strong>Cost</strong></td>
</tr>
<tr>
<td>1 – 404</td>
<td>$1.36/unit</td>
</tr>
<tr>
<td>405 – 499</td>
<td>$550</td>
</tr>
<tr>
<td>500 – 836</td>
<td>$1.1/unit</td>
</tr>
<tr>
<td>837 – 1000</td>
<td>920</td>
</tr>
</tbody>
</table>
A similar cost structure is assumed for shipments through air. The transportation costs are assumed to be the same across the network, between all the stages.

For shipments through ocean and rail, shipping containers are used. Charges for this are incurred on a per container basis (Table 4.14). The finished goods are placed in pallets, which are then loaded onto the containers. We assume that each pallet can hold ten units of the finished goods and each container can hold up to ten pallets (Table 4.15).

**Table 4.14 Transportation Costs for Rail and Ocean**

<table>
<thead>
<tr>
<th>Description</th>
<th>Notation</th>
<th>Cost in USD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of shipping one container through rail</td>
<td>$CR$</td>
<td>$2,000</td>
</tr>
<tr>
<td>Cost of shipping one container through ocean</td>
<td>$CM$</td>
<td>$1,500</td>
</tr>
</tbody>
</table>
Table 4.15 Pallet and Container capacities for shipments through Rail and Ocean

<table>
<thead>
<tr>
<th>Description</th>
<th>Notation</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity of a pallet for rail</td>
<td>CPR</td>
<td>10 units</td>
</tr>
<tr>
<td>Capacity of a container for rail</td>
<td>CCR</td>
<td>10 pallets</td>
</tr>
<tr>
<td>Capacity of a pallet for ocean</td>
<td>CPM</td>
<td>10 units</td>
</tr>
<tr>
<td>Capacity of a container for ocean</td>
<td>CCM</td>
<td>10 pallets</td>
</tr>
</tbody>
</table>

The risk indices for the different nodes and links are computed using one or more of the methods described in Section 3.3.1 of this thesis. For the sake of brevity, the calculations are not repeated for every node and link. Only the final values are presented in Tables 4.16 – 4.17. Similar to the forecasted retailer demands, the risk indices can also be changed any time during the planning horizon. The model can be rerun using the updated risk indices to capture the effect of the changing indices on the inventory and transportation policies for the forthcoming time periods. This approach is known as the rolling horizon implementation of the model. In this example, it is assumed that the risk indices remain constant over the planning horizon for all the nodes and links in the network.

Table 4.16 Facility Risk Indices

a) Risk Indices for Suppliers \((RS_{si})\)

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Risk Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>4.494</td>
</tr>
<tr>
<td>S2</td>
<td>8.636</td>
</tr>
<tr>
<td>S3</td>
<td>4.357</td>
</tr>
<tr>
<td>S4</td>
<td>3.690</td>
</tr>
</tbody>
</table>

b) Risk Indices for Manufacturers \((RM_{mt})\)

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Risk Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>2.641</td>
</tr>
<tr>
<td>M2</td>
<td>1.016</td>
</tr>
</tbody>
</table>
c) Risk Indices for Distributors \((RDC_{dt})\)

<table>
<thead>
<tr>
<th>Distributor</th>
<th>Risk Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>7.607</td>
</tr>
<tr>
<td>D2</td>
<td>4.535</td>
</tr>
<tr>
<td>D3</td>
<td>2.955</td>
</tr>
</tbody>
</table>

**Table 4.17** Link/Transportation Risk Indices

a) Risk Indices for Links between Suppliers and Manufacturers \((RTSM_{mit})\)

<table>
<thead>
<tr>
<th></th>
<th>Air ((i = 1))</th>
<th>Road ((i = 2))</th>
<th>Rail ((i = 3))</th>
<th>Ocean ((i = 4))</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1 – M1</td>
<td>5.989</td>
<td>8.247</td>
<td>9.559</td>
<td>1.625</td>
</tr>
<tr>
<td>S1 – M2</td>
<td>7.837</td>
<td>1.653</td>
<td>2.057</td>
<td>2.768</td>
</tr>
<tr>
<td>S2 – M1</td>
<td>4.210</td>
<td>7.886</td>
<td>1.845</td>
<td>2.869</td>
</tr>
<tr>
<td>S2 – M2</td>
<td>6.299</td>
<td>1.713</td>
<td>4.185</td>
<td>6.121</td>
</tr>
<tr>
<td>S3 – M2</td>
<td>8.476</td>
<td>3.041</td>
<td>5.914</td>
<td>7.195</td>
</tr>
<tr>
<td>S4 – M1</td>
<td>3.775</td>
<td>1.285</td>
<td>1.282</td>
<td>9.701</td>
</tr>
<tr>
<td>S4 – M2</td>
<td>6.229</td>
<td>7.470</td>
<td>3.219</td>
<td>5.021</td>
</tr>
</tbody>
</table>

b) Risk Indices for Links between Manufacturers and DCs \((RTMD_{mit})\)

<table>
<thead>
<tr>
<th></th>
<th>Air ((i = 1))</th>
<th>Road ((i = 2))</th>
<th>Rail ((i = 3))</th>
<th>Ocean ((i = 4))</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1 – DC2</td>
<td>5.324</td>
<td>6.722</td>
<td>5.066</td>
<td>3.341</td>
</tr>
<tr>
<td>M1 – DC3</td>
<td>4.589</td>
<td>6.145</td>
<td>6.746</td>
<td>8.462</td>
</tr>
<tr>
<td>M2 – DC1</td>
<td>5.546</td>
<td>3.047</td>
<td>8.458</td>
<td>4.418</td>
</tr>
<tr>
<td>M2 – DC2</td>
<td>5.305</td>
<td>2.904</td>
<td>9.287</td>
<td>1.393</td>
</tr>
<tr>
<td>M2 – DC3</td>
<td>8.351</td>
<td>6.354</td>
<td>8.663</td>
<td>9.503</td>
</tr>
</tbody>
</table>
c) Risk Indices for Links between DCs and Retailers ($RTDR_{dir}$)

<table>
<thead>
<tr>
<th></th>
<th>Air ($i = 1$)</th>
<th>Road ($i = 2$)</th>
<th>Rail ($i = 3$)</th>
<th>Ocean ($i = 4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC1 – R1</td>
<td>7.378</td>
<td>6.746</td>
<td>8.828</td>
<td>7.748</td>
</tr>
<tr>
<td>DC1 – R2</td>
<td>5.425</td>
<td>2.045</td>
<td>3.299</td>
<td>7.478</td>
</tr>
<tr>
<td>DC1 – R3</td>
<td>5.166</td>
<td>8.616</td>
<td>8.535</td>
<td>1.898</td>
</tr>
<tr>
<td>DC1 – R5</td>
<td>7.302</td>
<td>5.670</td>
<td>2.910</td>
<td>6.765</td>
</tr>
<tr>
<td>DC1 – R6</td>
<td>3.408</td>
<td>3.756</td>
<td>9.678</td>
<td>6.778</td>
</tr>
<tr>
<td>DC1 – R7</td>
<td>3.930</td>
<td>4.266</td>
<td>9.087</td>
<td>8.659</td>
</tr>
<tr>
<td>DC2 – R1</td>
<td>4.689</td>
<td>2.895</td>
<td>4.553</td>
<td>9.048</td>
</tr>
<tr>
<td>DC2 – R2</td>
<td>5.771</td>
<td>2.286</td>
<td>2.313</td>
<td>8.879</td>
</tr>
<tr>
<td>DC2 – R3</td>
<td>7.639</td>
<td>7.552</td>
<td>2.835</td>
<td>2.149</td>
</tr>
<tr>
<td>DC2 – R4</td>
<td>1.839</td>
<td>2.447</td>
<td>3.811</td>
<td>7.736</td>
</tr>
<tr>
<td>DC2 – R5</td>
<td>4.221</td>
<td>6.975</td>
<td>5.302</td>
<td>2.987</td>
</tr>
<tr>
<td>DC2 – R6</td>
<td>1.923</td>
<td>2.089</td>
<td>1.078</td>
<td>2.841</td>
</tr>
<tr>
<td>DC2 – R7</td>
<td>8.347</td>
<td>9.471</td>
<td>9.392</td>
<td>1.055</td>
</tr>
<tr>
<td>DC3 – R1</td>
<td>6.421</td>
<td>4.189</td>
<td>9.185</td>
<td>9.786</td>
</tr>
<tr>
<td>DC3 – R2</td>
<td>3.084</td>
<td>3.350</td>
<td>9.513</td>
<td>8.626</td>
</tr>
<tr>
<td>DC3 – R3</td>
<td>4.048</td>
<td>2.242</td>
<td>5.116</td>
<td>8.006</td>
</tr>
<tr>
<td>DC3 – R4</td>
<td>3.740</td>
<td>6.284</td>
<td>4.525</td>
<td>3.163</td>
</tr>
<tr>
<td>DC3 – R5</td>
<td>9.806</td>
<td>3.924</td>
<td>1.904</td>
<td>3.956</td>
</tr>
<tr>
<td>DC3 – R6</td>
<td>2.503</td>
<td>6.128</td>
<td>3.252</td>
<td>5.616</td>
</tr>
<tr>
<td>DC3 – R7</td>
<td>5.589</td>
<td>1.147</td>
<td>5.763</td>
<td>1.546</td>
</tr>
</tbody>
</table>

4.2 Goal Programming Solutions (Ravindran and Warsing (2013), Masud and Ravindran (2008, 2009))

The problem dealt with in the thesis has multiple, conflicting criteria. For instance, increasing the profits (decreasing expenditure) might result in increasing backorders and hence decrease responsiveness. Or, the least expensive route might not necessarily be the route with the least disruption risk score. Such scenarios are often encountered in the context of solving supply chain optimization problems. Goal programming is often used in such cases to simultaneously optimize several conflicting criteria.
Goal programming (GP) falls under the class of methods that use completely pre-specified preferences of the DM in solving the Multi-criteria Mathematical Programming (MCMP) problems. In goal programming, all the objectives are assigned target levels for achievement and a relative priority on achieving those levels. Goal programming treats these targets as *goals to aspire for* and not as absolute constraints. It then attempts to find an optimal solution that comes as “close as possible” to the targets in the order of specified priorities.

In GP, the real constraints are absolute restrictions on the decision variables, while the goals are conditions one would like to achieve but are not mandatory. For instance a real constraint given by

\[ x_1 + x_2 = 8 \]

requires all possible values of \( x_1 + x_2 \) to always equal 8. As opposed to this, a goal requiring \( x_1 + x_2 = 8 \) is not mandatory, and can choose values of \( x_1 + x_2 \geq 8 \) as well as \( x_1 + x_2 \leq 8 \). In a goal constraint, positive and negative deviational variables are introduced to represent constraint violations as follows:

\[ x_1 + x_2 + d^-_i - d^+_i = 8 \quad d^+_i, d^-_i \geq 0 \]

Note that, if \( d^-_i > 0 \), then \( x_1 + x_2 < 8 \), and if \( d^+_i > 0 \), then \( x_1 + x_2 > 8 \).

By assigning suitable weights, \( w^-_i \) and \( w^+_i \) on \( d^-_i \) and \( d^+_i \) in the objective function, the model will try to achieve the sum \( x_1 + x_2 \) as close as possible to 8. If the goal were to satisfy \( x_1 + x_2 \geq 8 \), then only \( d^-_i \) is assigned a positive weight in the objective, while the weight on \( d^+_i \) is set to zero.
4.2.1 General Goal Programming Model

A general Multiple Criteria Mathematical Programming (MCMP) problem is given as follows:

\[
\text{Max } \mathbf{F}(\mathbf{x}) = \{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})\}
\]

Subject to \(g_j(\mathbf{x}) \leq 0\) for \(j = 1, \ldots, m\)

where \(\mathbf{x}\) is an \(n\)-vector of \textit{decision variables} and \(f_i(\mathbf{x}), i = 1, \ldots, k\) are the \(k\) \textit{criteria/objective functions}.

Let \(S = \{\mathbf{x} / g_j(\mathbf{x}) \leq 0, \text{ for all } 'j'\}\)

\(Y = \{y / \mathbf{F}(\mathbf{x}) = y \text{ for some } \mathbf{x} \in S\}\)

\(S\) is called the \textit{Decision space} and \(Y\) is called the \textit{criteria or objective space} in MCMP.

In the general MCMP model presented, the assumption that there exists an optimal solution to the MCMP problem involving multiple criteria implies the existence of some preference ordering of the criteria by the DM. The Goal Programming (GP) formulation of the MCMP problem requires the DM to specify an acceptable level of achievement (\(b_i\)) for each criterion \(f_i\) and specify a weight \(w_i\) (ordinal or cardinal) to be associated with the deviation between \(f_i\) and \(b_i\). Thus, the GP model of an MCMP problem becomes:

\[
\text{Minimize } Z = \sum_{i=1}^{k} (w_i^+ d_i^+ + w_i^- d_i^-)
\]

Subject to: \(f_i(\mathbf{x}) + d_i^- - d_i^+ = b_i\) for \(i = 1, \ldots, k\)

\(g_j(\mathbf{x}) \leq 0\) for \(j = 1, \ldots, m\)

\(x_j, d_i, d_i^+ \geq 0\) for all \(i\) and \(j\)

The objective function of the GP model minimizes the weighted sum of the deviational variables. The system of equations representing the goal constraints relates the multiple criteria
to the goals/targets for those criteria. The variables, $d_i^-$ and $d_i^+$ are the deviational variables, representing the under achievement and over achievement of the $i^{th}$ goal. The set of weights ($w_i^+$ and $w_i^-$) may take two forms:

1. Pre-specified weights (cardinal)
2. Preemptive priorities (ordinal)

Under pre-specified (cardinal) weights, specific values in a relative scale are assigned to $w_i^+$ and $w_i^-$ representing the DM’s “trade-off” among the goals. Once $w_i^+$ and $w_i^-$ are specified, the goal program reduces to a single objective optimization problem. The cardinal weights could be obtained from the DM using methods such as the Rating, Borda Count, AHP, discussed in Section 3.3.1 of this thesis. However, for this method to work effectively, criteria values have to be scaled properly. Refer Section 6.3.6 of Ravindran and Warsing (2013) for more details on the different scaling methods. In reality, goals are usually incompatible (i.e., incommensurable) and some goals can be achieved only at the expense of some other goals. Hence, preemptive goal programming, which is more common in practice, uses ordinal ranking or preemptive priorities to the goals by assigning incommensurable goals to different priority levels and weights to goals at the same priority level. In this case, the objective function of the GP model takes the form

$$\text{Minimize } Z = \sum_p P_p \sum_i (w_{ip}^+ d_i^+ + w_{ip}^- d_i^-)$$

where $P_p$ represents priority $p$ with the assumption that $P_p$ is much larger then $P_{p+1}$ and $w_{ip}^+$ and $w_{ip}^-$ are the weights assigned to the $i^{th}$ deviational variables at priority $p$. In this manner, lower priority goals are considered only after attaining the higher priority goals. Thus,
preemptive goal programming is essentially a sequential, single objective optimization process, in which successive optimizations are carried out on the alternate optimal solutions of the previously optimized goals at higher priority. In addition to Preemptive and Non-Preemptive goal programming models, other approaches (Fuzzy GP, Min-Max GP) have also been proposed. Readers are directed to Section 6.4 of Ravindran and Warsing (2013) for a detailed discussion of Goal Programming along with practical case studies.

### 4.2.2 Goal Programming formulation of the problem under consideration

Following the formulations of the General GP models in the previous Section, the model explained in Section 3.4 is formulated as preemptive goal programming (PGP) and non-preemptive goal programming (NPGP) problems.

#### 4.2.2.1 Preemptive Goal Programming Formulation

Let us assume that the decision maker has the following preemptive priorities for the objective functions – Profit ($Z_1$) > Responsiveness ($Z_2$) > Risk ($Z_3$). Let $P_1$ be the preemptive priority associated with $Z_1$, $P_2$ with $Z_2$, and $P_3$ with $Z_3$. The order of importance suggests that $P_1 > P_2 > P_3$. $Z_1$ is maximized, $Z_2$ and $Z_3$ are minimized. (It is to be noted that in objective $Z_2$, responsiveness is measured in terms of the number of backorders at the retailers. Thus $Z_2$ is minimized in order to maximize responsiveness.) The PGP formulation will be as follows:

$$
\text{Minimize } Z_{PGP} = P_1 d_1^- + P_2 d_2^+ + P_3 d_3^+
$$

Subject to

$$
Z_1 + d_1^- - d_1^+ = Target_1
$$

$$
Z_2 + d_2^- - d_2^+ = Target_2
$$
\[ Z_3 + d_3^- - d_3^+ = \text{Target}_3 \]

Constraints (1) – (20) listed in Section 3.4.6

where, \(d_1^-, d_1^+, d_2^-, d_2^+, d_3^-\), \(d_3^+\) are deviational variables that represent the overachievement or underachievement of the target.

The targets are calculated based on the ideal values. Ideal values are obtained by optimizing each objective function separately (ignoring the other two objectives) to know the best value that objective can attain. Targets are calculated as a percentage of the ideal value. Typically for maximization objectives, the percentage is lesser than 100% and greater than 100% for minimization objectives. In this example, the targets are set at 100% of the ideal value for all the objectives.

Three PGP models are solved, assuming the following preemptive priorities:

- Case 1: Profit \((Z_1)\) > Responsiveness \((Z_2)\) > Risk \((Z_3)\)
- Case 2: Profit \((Z_1)\) > Risk \((Z_3)\) > Responsiveness \((Z_2)\)
- Case 3: Responsiveness \((Z_2)\) > Profit \((Z_1)\) > Risk \((Z_3)\)

4.2.2.2 Non-preemptive Goal Programming Formulation

The NPGP formulation will be as follows:

Minimize \(Z_{PGP} = w_1 d_1^- + w_2 d_2^+ + w_3 d_3^+\)

Subject to

\[ Z_1 + d_1^- - d_1^+ = \text{Target}_1 \]
\[ Z_2 + d^-_2 - d^+_2 = \text{Target}_2 \]
\[ Z_3 + d^-_3 - d^+_3 = \text{Target}_3 \]

*Constraints (1) – (20) listed in Section 3.4.6*

where, \( d^-_1, d^+_1, d^-_2, d^+_2, d^-_3, d^+_3 \) are deviational variables that represent the overachievement or underachievement of the target. The targets are calculated similar to the targets used for the PGP formulation. \( w_1, w_2, w_3 \) represent the decision maker’s weights (importance) for the objectives. The weights must add up to unity.

The goal constraints in NPGP have to be scaled. Scaling is the process of making all the targets and the objective function values comparable to each other. If this is not done, the targets that are numerically larger in value will drive the solution. The solution thus obtained will not provide the optimum solution for all the objectives. Scaling is done by dividing the left hand side of the goal constraint, by the right hand side value, usually the target for the objective. By doing so, the targets for all the objectives become unity.

For example,

\[ Z_1 + d^-_1 - d^+_1 = \text{Target}_1 \]
\[ \rightarrow \frac{Z_1}{\text{Target}_1} + \frac{d^-_1}{\text{Target}_1} - \frac{d^+_1}{\text{Target}_1} = 1 \]
\[ \rightarrow \frac{Z_1}{\text{Target}_1} + d^r_1 - d^l_1 = 1 \]
Similarly,

\[ Z_2 + d^-_2 - d^+_2 = \text{Target}_2 \rightarrow \frac{Z_2}{\text{Target}_2} + d^-_2 - d^+_2 = 1 \]

\[ Z_3 + d^-_3 - d^+_3 = \text{Target}_3 \rightarrow \frac{Z_3}{\text{Target}_3} + d^-_3 - d^+_3 = 1 \]

where \( d^-_i, d^+_i \) are the scaled deviational variables.

Thus the scaled NPGP formulation of the problem is as shown below.

**Minimize** \( Z_{PGP} = w_1d^-_1 + w_2d^+_2 + w_3d^+_3 \)

Subject to

\[ \frac{Z_1}{\text{Target}_1} + d^-_1 - d^+_1 = 1 \]

\[ \frac{Z_2}{\text{Target}_2} + d^-_2 - d^+_2 = 1 \]

\[ \frac{Z_3}{\text{Target}_3} + d^-_3 - d^+_3 = 1 \]

*Constraints (1) \( \rightarrow \) (20) listed in Section 3.4.6*

4.2.2.3 Ideal Values, Bounds and Targets

The problem has a total of 4469 variables (of which 3441 are binary variables) and 9621 constraints. The problem was coded in C++ 6.0 and solved using CPLEX 12.0 on a 4 GB RAM and 2.8 GHz processor. For problems that had feasible solutions, optimum was reached at an
average of 7 seconds. The solutions from the different single-objective optimization problems are presented in Table 4.18.

**Table 4.18** Solutions to the Single Objective Optimization Problems

<table>
<thead>
<tr>
<th>Objective</th>
<th>Max Profit (Max $Z_1$)</th>
<th>Max Responsiveness (Min $Z_2$)</th>
<th>Min Risk (Min $Z_3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of $Z_1$ when</td>
<td>$2,307,288$</td>
<td>$1,005,325$</td>
<td>$1,036,144$</td>
</tr>
<tr>
<td>Value of $Z_2$ when</td>
<td>54,668 units</td>
<td>25,718 units</td>
<td>111,264 units</td>
</tr>
<tr>
<td>Value of $Z_3$ when</td>
<td>847,120</td>
<td>1,092,499</td>
<td>214,057</td>
</tr>
</tbody>
</table>

It can be seen from this table that the Ideal solution is $(2307288, 25718, 214057)$, which is unachievable. Also, comparing rows 1 and 2 of Table 4.18, it can be seen that when $Z_2$ decreases, $Z_1$ also decreases. Therefore, it is not possible to achieve an improvement in either of these objectives without sacrificing at least one of them. This implies that objectives $Z_1$ and $Z_2$ conflict with each other. Similarly comparing rows 2 and 3, it can be seen that objectives $Z_2$ and $Z_3$ conflict with each other. Thus the problem is a multi-criteria optimization problem.

The bounds, ideal values and targets are calculated as shown in Table 4.19. Targets are taken as 100% of the ideal value for all the three objectives.

**Table 4.19** Bounds, Ideal values and Targets for the Objectives

<table>
<thead>
<tr>
<th>Objective</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
<th>Ideal Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Profit ($Z_1$)</td>
<td>1,005,325</td>
<td>2,307,288</td>
<td>2,307,288</td>
<td>2,307,288</td>
</tr>
<tr>
<td>Min Backorders ($Z_2$)</td>
<td>25,718</td>
<td>111,264</td>
<td>25,718</td>
<td>25,718</td>
</tr>
<tr>
<td>Min Risk ($Z_3$)</td>
<td>214,057</td>
<td>1,092,499</td>
<td>214,057</td>
<td>214,057</td>
</tr>
</tbody>
</table>
The solutions from the three different preemptive goal programming models are discussed in the next section.

4.2.3 Analysis of Preemptive Goal Programming Solutions

Three preemptive priorities are used to solve the problem using Preemptive GP. In Case 1, \( Z_1 > Z_2 > Z_3 \), the decision maker places higher importance on maximizing profit followed by maximizing responsiveness and finally minimizing disruption risk. In Case 2, \( Z_2 > Z_1 > Z_3 \), highest importance is placed on maximizing responsiveness, as in the case of an innovative product. The least importance is on minimizing disruption risk. In case 3, \( Z_1 > Z_3 > Z_2 \), the decision maker’s preemptive priority is maximizing profit, followed by minimizing risk and maximizing responsiveness, in that order. The other three instances (\( Z_3 > Z_2 > Z_1 \), \( Z_3 > Z_1 > Z_2 \), \( Z_2 > Z_3 > Z_1 \)) were not considered because it is very unlikely that a company would place minimizing disruption risk ahead of maximizing profits and responsiveness in its list of priorities. Also, the idea of giving the least priority to maximizing profits compared to maximizing responsiveness and minimizing disruption risks does not make practical sense. The results of Cases 1 – 3 are discussed next.

From Table 4.20, it can be seen that while the profit objective is met reasonably well (Maximum of the deviations = 56%) in all the three cases, there is extremely high deviation from the target for \( Z_2 \) (Maximum of the deviations =112%) and \( Z_3 \) (Maximum of the deviations = 410%). Though the deviations from the targets may seem very high, it does not mean that the solutions produced are of poor quality. The reason for such high deviations is because the target is equal to the vector of ideal solutions, which is unachievable. Also it can be seen that cases 1 and 3 have the same solution. Therefore, only cases 1 and 2 are considered for all analyses.
Table 4.20 Achievement of Targets in the Preemptive GP solutions

<table>
<thead>
<tr>
<th>Preemptive ordering</th>
<th>$Z_1$</th>
<th>% deviation from target</th>
<th>$Z_2$</th>
<th>% deviation from target</th>
<th>$Z_3$</th>
<th>% deviation from target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: $Z_1 &gt; Z_2 &gt; Z_3$</td>
<td>2,307,288</td>
<td>0%</td>
<td>54,668</td>
<td>112%</td>
<td>847,120</td>
<td>296%</td>
</tr>
<tr>
<td>Case 2: $Z_2 &gt; Z_1 &gt; Z_3$</td>
<td>1,005,325</td>
<td>56%</td>
<td>25,718</td>
<td>0%</td>
<td>1,092,499</td>
<td>410%</td>
</tr>
<tr>
<td>Case 3: $Z_1 &gt; Z_3 &gt; Z_2$</td>
<td>2,307,288</td>
<td>0%</td>
<td>54,668</td>
<td>112%</td>
<td>847,120</td>
<td>296%</td>
</tr>
</tbody>
</table>

4.2.3.1 Profit Objective

Figure 4.2 Profit Objectives from Preemptive GP (PGP) Models

The profits are shown in Figure 4.2. Due to the higher priority on profit in case 1, its profit is higher than that of Case 2. The percentage contribution of the different costs to the total expenditure is shown in Figure 4.3.
The striking difference between the two cases is the difference in the percentage contribution of transportation costs to the total expenditure. This can be explained by the fact that when responsiveness takes a higher priority over profit, more units are shipped to satisfy the retailer demands irrespective of whether or not, they are profitable.

4.2.3.2 Responsiveness Objective

Recall that responsiveness is measured by the number of backorders. Higher number of backorders at the retailer is indicative of low responsiveness and vice-versa. Figure 4.4 shows the comparison of the total number of backorders for every time period between cases 1 and 2. As expected, case 1 has higher or equal number of backorders over case 2 for all time periods. It is also to be noted that owing to the production and shipping delays, in both the cases, the entire first week’s demand for all the retailers are counted as backorders in both the cases. Case 2 does
not have backorders for the last four time periods while case 1 solution does not only for the last time period.

![Figure 4.4 Total No. of backorders Vs. Time Period – PGP solutions](image)

**Figure 4.4** Total No. of backorders Vs. Time Period – PGP solutions

### 4.2.3.3 Disruption Risk Objective

As shown in Figure 4.5, Case 2 has higher value of disruption risk compared to case 1. This is explained by the fact that more units are shipped every time period between all stages in case 2 because of the higher priority assigned to responsiveness.
Figure 4.5 Disruption Risk Objective values for Cases 1 and 2 – PGP solutions

From Table 4.21, it can be seen that the average risk per unit shipped

\[
\left( \frac{\text{Quantity-weighted disruption risk}}{\text{Total no. of units shipped}} \right)
\]

is also higher for Case 2 than Case 1.

Table 4.21 Average disruption Risk per Unit Shipped

<table>
<thead>
<tr>
<th>Measure</th>
<th>Case 1</th>
<th>Case 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity-weighted disruption risk</td>
<td>847,121</td>
<td>1,092,499</td>
</tr>
<tr>
<td>Total no. of units shipped</td>
<td>90,295</td>
<td>114,018</td>
</tr>
<tr>
<td>Average risk per unit shipped</td>
<td>9.381</td>
<td>9.581</td>
</tr>
</tbody>
</table>

This metric helps to reduce the bias created by the quantity shipped in measuring the total disruption of the supply chain and to look at a single, overall metric that represents the chances of disruption of the entire supply chain, on an average. A solution that ships more number of units can appear to be more risky while using the quantity-weighted risk.
In the next section, solutions from three non-preemptive goal programming solutions are analyzed.

**4.2.4 Analysis of Non-preemptive Goal Programming solutions**

Three sets of weights \((w_1, w_2, w_3)\) for the objectives are chosen for the purpose of analysis – \((0.34, 0.33, 0.33)\), \((0.7, 0.2, 0.1)\) and \((0.3, 0.5, 0.2)\). In practice, companies do not place higher importance on minimizing risk compared to maximizing profits and responsiveness. To reflect this thought process of decision makers, in these three sets of weights, either equal or lesser importance has been assigned to the disruption risk objective compared to the other two. The first set of weights, \((0.34, 0.33, 0.33)\), represents a company that would place equal importance on maximizing profit, as it does on maximizing responsiveness and minimizing disruption risk. The second set, \((0.7, 0.2, 0.1)\), might be suited for a company that is primarily profit-driven. Consider the supply chain of a functional product, where more importance is placed on the profits than on the responsiveness. In such a case, the disruption risk objective takes the back seat with a very negligible weight. This is because, even in the event of a disruption that causes considerable production or shipping delays, the customers of innovative products tend to wait more willingly as opposed to customers of functional products. The third set of weights \((0.3, 0.5, 0.2)\) might be suited for an innovative product, in which case, the decision makers tend to place significantly greater importance on responsiveness, than on profit due to the lack of willingness to wait on the customers’ part. As explained before, in order to arrive at these weights, one or more of the ranking methods discussed in Section 3.4 of this thesis can be used. The results of the NPGP problems are presented in Table 4.22.
### Table 4.22 Results of the NPGP Problems

<table>
<thead>
<tr>
<th>Non-preemptive weights</th>
<th>$Z_1$</th>
<th>% deviation from Target</th>
<th>$Z_2$</th>
<th>% deviation from Target</th>
<th>$Z_3$</th>
<th>% deviation from Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 4: (0.34, 0.33, 0.33)</td>
<td>1,445,022</td>
<td>37%</td>
<td>33,835</td>
<td>32%</td>
<td>508,518</td>
<td>138%</td>
</tr>
<tr>
<td>Case 5: (0.7, 0.2, 0.1)</td>
<td>1,985,170</td>
<td>14%</td>
<td>27,891</td>
<td>8%</td>
<td>728,181</td>
<td>240%</td>
</tr>
<tr>
<td>Case 6: (0.3, 0.5, 0.2)</td>
<td>1,556,427</td>
<td>33%</td>
<td>25,886</td>
<td>1%</td>
<td>602,651</td>
<td>182%</td>
</tr>
</tbody>
</table>

#### 4.2.4.1 Profit Objective

Figure 4.6 shows the profits obtained in cases 4, 5 and 6. The profit increases with increasing value of $w_1$. The different expenses are analyzed to further drill down into the profits. Figure 4.7 shows the distribution of the different expenses in the three NPGP solutions.
In all the three cases, inventory costs are a very small (0.01%) part of the total expenses. Production cost percentages are similar across the three cases. The purchasing cost is higher for case 5 (69%) compared to cases 4 (61%) and 6 (61%). The transportation cost is significantly lower for case 5 (15%) compared to that of cases 4 (25%) and 6 (24%) because of the smallest...
weight on responsiveness. The split of transportation units across the different modes and stages is analyzed further in Figure 4.8.

In Case 4, where equal weights are placed on all the three objectives, air and road modes of transportation are used. Rail and ocean are used very sparsely. In case 5, where profit is given more weight, more units are shipped using road compared to air. In case 6, owing to the higher weight on responsiveness, most of the shipments are made through air, followed by road.

4.2.4.2 Responsiveness Objective (Number of backorders)

From Table 4.24, the least number of backorders is obtained in case 6 where the responsiveness objective is only given 50% of the total weight closely followed by case 5 in which responsiveness has 20% of the total weight. Figure 4.9 and 4.10 give the number of backorders across time periods and the retailers, respectively. In Figure 4.9, it is interesting to note that, the
number of backorders for the first ten weeks is very close across the three cases. This is due to the similar initial conditions and production and shipping lead times across the cases. From the eleventh week, the number of backorders varies depending on the weights given to the objectives. Clearly, case 4 has the highest number of backorders.

Figure 4.9 No. of Backorders by Time Period – NPGP solutions

In comparing the total number of backorders by retailers (Figure 4.10), it is seen that for case 4, the average number of backorders is 30% higher than the average number of backorders per retailer for the other two cases. Between cases 4 and 5, Retailers 4, 6 and 7 have exactly or almost the same number of backorders over all time periods. Comparing cases 5 and 6, Retailers 4, 5 and 7 have lower number of backorders in case 6, while retailers 1 and 2 have lower backorders in case 5. The maximum variation between cases 4 and 5 in terms of the number of backorders is seen for Retailer 5. If Retailer 5 is strategically an important retailer compared to the others, then it would be advisable for the management to not consider implementing the weights chosen in case 6. Similar analyses can be extended to other retailers too.
4.2.4.3 Disruption Risk Objective

Figure 4.11 presents the quantity-weighted disruption risk indices of the different NPGP solutions.
In case 5, the most number of units are shipped between all stages across all time periods. Because the disruption risk index heavily depends on the quantity shipped, its value is highest for case 5. Table 4.23 presents the average disruption risk for every unit shipped in the entire planning horizon. This is obtained by dividing the quantity weighted disruption risk by the total number of units shipped. Looking at this measure, it is evident that the disruption risk per unit shipped is lowest in cases 4 and 6. Even though, the overall quantity-weighted disruption risk is higher for case 6 compared to case 4, they have the same value for the average risk per unit shipped. This indicates the choice of facilities and links has been better in terms of disruption risk indices compared in case 6 compared to case 4.

**Figure 4.11** Quantity-weighted Disruption Risk for NPGP solutions

In case 5, the most number of units are shipped between all stages across all time periods.

<table>
<thead>
<tr>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qty.-weighted disruption risk</td>
<td>508,518</td>
<td>728,181</td>
</tr>
<tr>
<td>Total no. of units shipped</td>
<td>75418</td>
<td>90295</td>
</tr>
<tr>
<td>Average risk per unit shipped</td>
<td>6.74</td>
<td>8.06</td>
</tr>
</tbody>
</table>
Figure 4.12 shows the contribution of the different facilities and the links to the overall disruption risk index of the supply chain.

As it can be seen from the charts, the major contributor to the supply chain’s disruption index is the supplier. This is true in practice also. In most cases, suppliers, who are responsible for delivering several units of different types of raw materials, form the riskiest link of the supply chain. In this example, the least risky stage turns out to be the manufacturer contributing only to

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5-6% of the total risk. An important point to be noted here is that in all the three cases, the transportation risk contributes to approximately half (~45%) of the total supply chain’s risk. Firms often tend to ignore the risk involved with transportation and do not account for possible delays/disruptions in transportation links.

4.3 Comparison of Solutions using Value Path Approach (Ravindran and Warsing (2013))

The Value path approach (Schilling et al. 1983) is one of the most efficient ways to demonstrate the trade-offs among the criteria obtained by the different solutions. The display consists of a set of parallel scales; one for each criterion, on which is drawn the value path for each of the solution alternative. Value paths have proven to be an effective way to present the trade-offs in problems with more than two objectives. The value assigned to each solution on a particular axis is that solution’s value for the appropriate objective divided by the best solution for that objective. The minimum value will be one if all the objectives were to minimize. Following are some properties of the value path approach (Schilling et al. 1983):

- If two value paths representing solutions A and B intersect between two vertical scales then the line segment connecting A and B in objective space has a negative slope and neither objective dominates other.
- If three or more value paths intersect then their associated points in the objective space are collinear.
- If two paths do not intersect then one path must lie entirely above the other and is therefore inferior, if the objective were to minimize.
More information about the value path approach, with an example, is presented in Ravindran and Warsing (2013).

The results from both the preemptive and non-preemptive GP solutions are presented below in Table 4.24.

<table>
<thead>
<tr>
<th>Case</th>
<th>Method</th>
<th>Profit</th>
<th>Responsiveness</th>
<th>Disruption Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Preemptive GP</td>
<td>2,307,288</td>
<td>54,668</td>
<td>847,120</td>
</tr>
<tr>
<td>2</td>
<td>Preemptive GP</td>
<td>1,005,325</td>
<td>25,718</td>
<td>1,092,499</td>
</tr>
<tr>
<td>4</td>
<td>Non-Preemptive GP</td>
<td>1,445,022</td>
<td>33,835</td>
<td>508,518</td>
</tr>
<tr>
<td>5</td>
<td>Non-Preemptive GP</td>
<td>1,985,170</td>
<td>27,891</td>
<td>728,181</td>
</tr>
<tr>
<td>6</td>
<td>Non-Preemptive GP</td>
<td>1,556,427</td>
<td>25,886</td>
<td>602,651</td>
</tr>
</tbody>
</table>

To present these results to the DM, value path approach is used as follows.

1. The best value obtained for each criterion is computed. For the profit objective, case 1 has the maximum value ($2,307,288). For responsiveness criteria, case 2 has the least value (25,718 units). For the disruption risk objective, case 3 has the least value (508,518).

2. For each solution, the minimization objective’s actual values are divided by the best value for that objective. (For maximization objective, the best value is divided by the actual value.) For example, for case 1, the actual values of profit, responsiveness and disruption risk are 2,307,288, 54,688 and 847,120 respectively. The best values for profit, responsiveness and disruption risk are 2,307,288, 25,718 and 508,518. Therefore, the values for the Value Path Approach corresponding to case 1 are obtained as (2,307,288/2,307,288), (54,688/25,718) and (847,120/508,518) respectively. Similar
values are calculated for the other solutions under the value path approach as shown in Table 4.25. The scaled values for case 1 shown in Table 4.25 can be interpreted as follows – The 1.0 for profit indicates that it is the best value for profit amongst all the cases. A value of 2.13 for responsiveness indicates that the number of backorders for case 1 is approximately twice as much as the number of backorders for case 2. (Case 2 has the least number of backorders because it has a scaled value of 1). A scaled value of 1.67 for disruption risk indicates that the disruption risk objective has a value that is approximately 5/3 times the value of disruption risk objective for case 3. (Case 3 has the least disruption risk because it has a scaled value of 1).

<table>
<thead>
<tr>
<th>Case</th>
<th>Method</th>
<th>Profit</th>
<th>Responsiveness</th>
<th>Disruption Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Preemptive GP</td>
<td>1.00</td>
<td>2.13</td>
<td>1.67</td>
</tr>
<tr>
<td>2</td>
<td>Preemptive GP</td>
<td>2.30</td>
<td>1.00</td>
<td>2.15</td>
</tr>
<tr>
<td>4</td>
<td>Non-Preemptive GP</td>
<td>1.60</td>
<td>1.32</td>
<td>1.00</td>
</tr>
<tr>
<td>5</td>
<td>Non-Preemptive GP</td>
<td>1.16</td>
<td>1.08</td>
<td>1.43</td>
</tr>
<tr>
<td>6</td>
<td>Non-Preemptive GP</td>
<td>1.48</td>
<td>1.01</td>
<td>1.19</td>
</tr>
</tbody>
</table>

3. The graph is plotted with profit, responsiveness and disruption risk on X-axis and ratios of the objective values on the Y-axis as shown in Figure 4.13.
Figure 4.13 Value Path Graph of the GP Solutions

The Value Path graph can be used to determine dominated and non-dominated solutions simply by visual inspection. From Figure 4.8, it can be seen that none of the solutions dominate each other.

Comparing the paths of cases 1 and 2 in Figure 4.13, it can be seen that case 1 has a higher profit than case 2; case 2 has lower number of backorders compared to case 1. With respect to the disruption risk objective, case 1 has a lower value compared to case 2. Similar analyses can be performed comparing the five solutions. The value path graph reiterates the conflicting nature of the objective functions and the tradeoffs involved in choosing one solution compared to another.

From the value path graph, it is also possible to find which case has the best value for each objective. Case 1 has the best value with respect to the profit objective, case 2 for responsiveness and case 4 for disruption risk.
A lot of other tradeoff information can also be obtained from the value path graph. For example, comparing cases 2 and 4, while case 2 does better in terms of backorders (responsiveness objective) with a difference of about 32% compared to case 2, solution from case 4 exceeds that from case 2 by 70% in terms of profit and the solution from case 4 does 115% better than that from case 2 in terms of disruption risk. Such information might prove to be extremely useful in arriving at a best compromise solution that maximizes the decision maker’s utility function based on the priorities the DM has in his/her mind for the different objectives.

In the next chapter, managerial implications of the model are presented along with a summary of the conclusions and the possible extensions for future research in this direction.
Chapter 5

Conclusions and Managerial Implications

“A ship in port is safe, but that’s not what ships are built for.” - Grace Murray Hopper

The above quote summarizes the concept of supply chain risk management. May be, the safest thing to do for an enterprise’s supply chain would be to not produce or ship any products at all, but that would be akin to ships in a port! Successful businesses are the ones that take efficient decisions on the amount of risk they are willing to undertake and earn the maximum profits for that level of risk. With increasing occurrences of man-made and natural disruptions, companies are becoming aware of the benefits of risk management practices.

This thesis discusses a methodology for incorporating disruption risk while making strategic and tactical level supply chain decisions, namely, production and transportation decisions. A risk assessment method to develop risk indices for nodes and links is presented in Chapter 3. The risk indices are then used to compute the overall supply chain risk by weighting them with the quantities shipped through the nodes and links. The model considers four modes of shipping between each of the stages, each with a different lead time and a different freight rate structure. The model maximizes profit, maximizes responsiveness (minimizes sum of backorders at retailers) and minimizes the disruption risk of the supply chain network. The model is solved for a realistic set of data in Chapter 4 using preemptive and non-preemptive Goal Programming methods. The solutions are then analyzed and compared with each other using the Value Path Approach.
5.1 Managerial Insights

The aim of the work presented in this thesis is to provide a framework to incorporate disruption risks into the decision making process at the strategic and tactical levels. Using concepts presented in Chapter 3, this can be achieved in several ways. Firstly, the risk assessment method presented in Chapter 3 by itself can be used to provide several insights, without even having to use it in the optimization model. The indices can be used to develop risk mitigation plans and strategies. For instance, if the DM wants to know the most reliable (or unreliable) supplier, it can be found by simply comparing the risk indices of the suppliers alone. Accordingly, backup suppliers can be contracted to minimize delays due to supply disruptions. Also, if the organization has a supplier rating system, these indices can be directly incorporated into the rating system along with scores for other criteria such as price, lead time, quality, etc.

The transportation link indices can also be used to develop risk mitigation plans. For links with high risk indices, which are likely to face more disruptions compared to the other links, alternative or backup transportation plans can be created.

The solutions from the optimization model provide several insights for the DM. The combined inventory and transportation plan, contribution of different nodes and links to the overall disruption risk of the supply chain, the tradeoff between the objectives are all important takeaways from the model that the DM can use during decision making process.

Several insights can be obtained from the rolling horizon implementation of the model. In this thesis, the model is run for fifteen weeks at a time. The major drawback is that the model is driven by the boundary conditions on inventory, i.e., towards the end of the planning horizon, the
model ships quantities just enough to meet the boundary conditions. In practice, this is not true. Decisions on production and shipping are not driven by any sort of boundary conditions. This can be overcome by implementing the model in a rolling horizon fashion. While implementing the model in a rolling horizon fashion, the model is run at the beginning of every time period for the next fifteen weeks and the solutions given by the model are implemented only for the current time period. Thus, this method eliminates the effect that the boundary conditions have, on the solutions. Another advantage to the rolling horizon implementation is that the sensitivity of the model to changes in the risk indices and to changes in the demand forecasts can be studied. It is to be noted that both the demand values and the risk indices, were modeled as quantities that vary with time.

5.2 Directions for Future Research

There are several possible extensions to the work presented in this thesis. A major improvement to the work presented in this thesis will be the use of VaR, MtT type risk functions (explained in Chapter 2) to model disruption risk. Use of the GEVD functions to model the risk will remove the subjectivity involved in the method proposed in this thesis and make it entirely quantitative. More information on the use of VaR and MtT type risk functions can be found in Ravindran and Warsing (2013) and Bilsel and Ravindran (2012).

Modeling responsiveness using stock-out probability or fill rate criteria instead of the number of backorders at the retailer would also provide a different perspective to analyze the model. Decreasing the number of backorders indirectly increases profits, thus making the two objectives less conflicting. Using other measures of responsiveness might improve the
conflicting nature of the two objectives and hence may produce results that are vastly different from the results presented in this thesis.

Another possible extension would be to use stochastic demands and lead times. In this thesis, we have assumed these to be deterministic. This can be done by making suitable assumptions on the probability distribution of demand and lead time. This would make the model closer to scenarios encountered in actual practice.
REFERENCES


Suez Canal Authority. http://www.suezcanal.gov.eg/


