Global Supply Chain Network Design Incorporating Disruption Risk

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ABSTRACT

Supply chain networks have expanded globally in today's business environment due to cost efficiencies, advanced technology, and market growth. This expansion makes the supply chains more vulnerable to disruption risks in different countries. A disruption in one country can cause serious global impacts. In this article, we formulate a multi-criteria optimization model for supporting strategic supply chain network design decisions. The model considers disruption risk of supply chain components (i.e., facilities and transportation links) as well as profit and customer responsiveness as conflicting criteria. This consideration is important since disruption at any supply chain component may lead to the disruption of the entire supply chain network. We apply goal programming (GP) techniques to handle multiple and conflicting network design objectives. We also present a numerical example to illustrate how to incorporate disruption risk when making strategic supply chain decisions. The results demonstrate how supply chain network designs that over emphasize profit may include inexpensive supply chain components with high disruption risk. Therefore, more attention must be paid to managing potential disruptions and designing supply chain networks that balance profit and risk. We discuss tradeoffs among multiple design solutions and identify opportunities for future research.

Keywords: *Disruption Risk, Goal Programming, Multi-Criteria Optimization, Supply Chain Disruption, Supply Chain Network Design*

INTRODUCTION

Supply chain networks have expanded globally in today's business environment. The geographies, regulations, and ecosystems associated with different countries have increased the complexity associated with global supply chain management and made the global supply chain more vulnerable to disruptions (Ravindran & Warsing, 2013). Disruption in one country can significantly impact global supply chains. From a supply chain risk perspective, disruption risks due to natural disasters in each country or region are varied; for instance, Asia experiences high economic losses from earthquake, tsunami, and floods, while America's economic

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Table 1. Disruptive events and their financial impacts (from Kungwalsong and Ravindran, 2012)

Year	Country	Event	Impact
2002	United states	West coast port strike	\$11-\$22 billion
2008	Thailand	Airport closure	\$8.5 billion
2010	Worldwide	Piracy and hijacking of ships	\$7-\$12 billion
2011	Japan	Earthquake/tsunami	\$210 billion
2011	Thailand	Floods	\$30 billion
2011	New zealand	Earthquake	\$20 billion
2011	United states	Tornado	\$15 billion
2011	Australia	Floods	\$7 billion
Annual	Egypt	Ship re-routed to avoid piracy	\$642 million from suez canal fees

losses are primarily due to storms and hurricanes (Guha-Sapir, 2012). The vulnerability of supply chain components to disruptions also differs based on their roles in the supply chain network (Kungwalsong & Ravindran, 2012; 2013). Risk identification and mitigation strategies also vary among countries. Countries with efficient, transparent, and accountable governments engage in both pre-disaster planning and post-disaster recovery planning, making them better able to respond to natural disasters than the countries with corrupt governments (Kellenberg & Mobarak, 2008; Stromberg, 2007; Ye & Abe, 2012). A study by The Harvard Business Review Analytic Services (Harvard Business Review, 2011) showed that natural disasters have been among the significant risks over the last three years. Furthermore, the International Disaster Database (2012) indicates that natural disasters have occurred more frequently in recent decades. Supply chain network designs that emphasize cost and customer satisfaction seem inadequate for supply chain resiliency in such complex environment. Plausible disruptions should be considered in order to design a robust value-creating network (Klibi & Martel, 2012). Table 1 presents examples of significant disruptive events and their financial impacts to global supply chains.

Supply chain decisions can be classified as strategic, tactical, and operational, and disruptions should be treated differently for each level. In this paper, we focus specifically on strategic supply chain network design decisions and demonstrate how to incorporate disruption risks in order to balance disruption risk and business efficiency. We apply the disruption risk assessment framework proposed by Kungwalsong and Ravindran (2012; 2013) to quantify the disruption risk score of each facility and transportation link based on hazard, vulnerability, and risk management factors. The quantified risk scores are used as input parameters for the supply chain network design model. We formulate a multi-criteria optimization model to support strategic supply chain network design decisions. The model considers profit, customer responsiveness (demand fulfillment and delivery), and disruption risk of supply chain components (i.e., facilities and transportation links) as the design criteria. Goal Programming (GP) techniques are used to handle the multiple conflicting objectives. Using the model, companies can evaluate tradeoff between benefits and risks among various design solutions.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 introduces the multi-criteria optimization model for supporting supply chain network design decisions. Section 4 discusses solution techniques and presents a numerical example of the supply chain network design problem. Sections 5 and

6 contain managerial insights and directions for future work.

LITERATURE REVIEW

Supply chain risks can be classified into two broad categories: internal risks, such as operations, management strategies, and employees; and external risks, such as natural environment, manmade disasters, governments, and business competitors (Ravindran & Warsing, 2013; Waters, 2007). In this paper, we focus on external risks from manmade and natural disasters. We review several studies on supply chain management decisions, including the supplier selection problem, the facility location problem, and the supply chain network design problem in order to understand how disruption risk is integrated into these strategic supply chain decisions.

Supplier Selection Problem

Disruption risks in the context of the supplier selection problem are evaluated based on: the vulnerability of suppliers and countries (Chan et al., 2008; Lee, 2009), risk events (Levary, 2008); business performance (Wu & Olson, 2008), and occurrence and impact (Bilsel, 2009; Ravindran et al., 2010; Yang, 2007). The disruption risks are integrated when selecting suppliers through both qualitative and quantitative assessment approaches, as described below.

Chan et al. (2008) developed a multi-criteria model for a global supplier selection problem. The selection criteria were cost, quality, service performance, supplier profiles, and risk factors, in which each criterion also included several sub-criteria. The sub-criteria for risk included geographic location, political stability, foreign policies, exchange rates, economic position, terrorism and crime rate. A fuzzy set concept was used to capture the vagueness of a decision maker's preference. Criteria and sub-criteria weights were determined using Analytic Hierarchy Process (AHP). Similarly, Lee (2009) proposed a fuzzy analytic hierarchy process (FAHP) model to select suppliers based on four criteria: benefits, opportunities, costs, and risks associated with candidate suppliers. The sub-criteria for risk were capacity limit, price variation, financial profile, performance, reputation, and environment controls.

Levary (2008) applied the AHP method to evaluate and rank the foreign suppliers based on possible risks: supplier reliability, country risk (e.g., political risk, risk associated with natural or manmade disaster, currency risk), reliability of transportation companies, and reliability of a supplier's suppliers. Wu and Olson (2008) measured supplier risks in terms of quality acceptance levels and the number of late deliveries, which follow exponential and lognormal distributions, respectively. The authors applied three models: chance-constrained programming (CCP), data envelopment analysis (DEA), and multi-objective programming (MOP) to evaluate supply chain risks associated with the supplier selection decision. The study confirmed that all three models can be used to evaluate supplier selection decisions under uncertainty, as they allowed decision makers to perform trade-off analysis among multiple objectives.

Gaonkar and Viswanadham (2004) developed two mathematical models to handle supply chain risks: a strategic-level deviation management model and a strategic-level disruption management model. The strategic-level deviation management model is an integer quadratic optimization model adapted from the Markowitz's mean-variance model for portfolio optimization (Markowitz, 1959). The model determines an optimal supplier selection to minimize both the expected cost of operating the entire supply chain and the risk of variation in total supply chain cost. The strategic-level disruption management model is a mixed-integer programming optimization model, adapted from the credit risk minimization model in financial portfolio management (Markowitz, 1959). The model determines an optimal supplier selection to minimize the expected shortfall, given the expected probabilities for various supplier disruption scenarios.

Yang (2007) defined risks into two types: Miss-the-Target (MtT) Risk and Value-at-Risk (VaR). MtT-type risks refer to any missed target performances from suppliers that happen frequently but have low impact, such as delivery time, defective rate, etc. The VaR-type risks refer to rare events with high impact that may disrupt suppliers, such as earthquakes, floods, fires, wars, etc. The author quantified risk as a function of probability of occurrence and impact. The probability of occurrence was quantified using the Poisson distribution while the impact was quantified using the Extreme Value distribution. The quantified risk values were incorporated into a strategic supplier selection model and a supply chain optimization model. Bilsel (2009) developed multi-criteria supplier selection models for the strategic items under two sourcing strategies; single-sourcing and multiple-sourcing. Risk values of potential suppliers are quantified as a function of impact, occurrence, and detectability; impact and occurrence are quantified using the methods proposed by Yang (2007); and detectability is quantified using the Markov Chain theory. The author included a risk mitigation strategy by assigning backup suppliers. The model consists of four objectives: minimize total operation costs, maximize product quality, minimize procurement lead-time, and minimize losses due to disruption risks. GP techniques are used to solve the models. In addition, Ravindran et al. (2010) proposed a risk-adjusted supplier selection model. The model pre-qualifies suppliers to reduce the number of potential suppliers into a manageable size. The evaluation process considers 14 factors, including risks. The model allocates order quantities to the selected suppliers by considering price, lead-time, risk of disruption due to natural events (VaR-type risk), and quality risk (MtT-type risk). MtT-type risk and VaR-type risk are estimated using the models developed by Yang (2007) and Bilsel (2009). The multi-criteria optimization model is solved using GP techniques. The value path approach (VPA) is used to present different solutions with respect to the four objectives. The VPA allowed a decision maker to visualize the trade-offs among different decisions. This study also incorporated quantity discounts in the model, which was applied to a real problem of a global IT company.

Facility Location

Disruption risks in the context of the facility location problem are usually represented in monetary terms, such as lost sales cost and transportation cost. Some studies employed scenario analysis to select locations that minimize financial and transportation impacts, assuming that facilities may fail with given probabilities (Drezner, 1987; Snyder & Daskin, 2005; Snyder et al., 2006). Other facility location studies aimed to identify the most vulnerable facilities, facilities that may be fortified, and possible mitigation strategies (Aryanezhad et al., 2010; Church & Scaparra, 2006; Church et al., 2004; Peng et al., 2011). The following facility location studies consider disruption risks.

Drezner (1987) proposed a mathematical model based on the assumption that facilities may fail with a given probability. Unreliable facilities were located in order to minimize an expected travel distance between customers and the facilities. Similarly, Snyder and Daskin (2005) formulated an incapacitated fixed-charge location model problem (UFLP) and p-median problem to minimize transportation costs. The authors assumed that all facilities have the same probability of failure. Snyder et al. (2006) provided multiple facility location models and supply chain network design models considering facility disruptions. The models minimized the weighted sum of two objectives: the cost of the system when no disruptions occur and the expected transportation cost when facing disruptions, which allowed decision makers to analyze trade-off between the two costs. However, the models assumed that the disruption probabilities for the facilities were equal.

Church et al. (2004) proposed the median facility interdiction model and the covering facility interdiction model to determine the set of emergency response facilities which, if disabled, will disrupt service delivery the most. Church and Scaparra (2006) formulated a model to determine the best facilities to fortify, assuming that a supply chain network has resources to prevent disruptions. Aryanezhad et al. (2010) proposed a location-inventory model with random disruptions of distribution centers (DCs). The authors examined impacts of the facility disruptions on facility location and inventory decisions. The model suggested assigning multiple DCs, a primary DC and backup DCs to each customer in order to cope with disruptions. The model was a non-linear integer programming problem, which aimed to minimize costs associated with location, transportation, lost sales, and inventory. A genetic algorithm was used to solve the proposed model. Peng et al. (2011) formulated a mixed-integer programming model to design a reliable logistics network under facility disruptions. The model objective was to minimize cost when no disruptions occur, while reducing the disruption risk using the p-robustness criterion. The authors proposed a hybrid meta-heuristic algorithm based on genetic algorithms, local improvement, and the shortest augmenting path method.

Supply Chain Network Design

Various aspects of disruption risks in supply chain network design decisions have been addressed in the literature. Some studies considered facility and country conditions as decision criteria (Klibi & Martel, 2012; Portillo Bollat, 2009). Other studies applied disruptive scenario analysis to study disruption impacts (Snediker et al., 2008; Solo, 2009; Wilson, 2007), to identify critical infrastructures (Jiang, 2011; Matisziw, 2009), and to evaluate risk mitigation strategies (Schmitt & Singh, 2009).

Portillo Bollat (2009) formulated a resilient global supply chain network design optimization model and integrated disruption risk as one of the design criteria. In the study, the supply chain disruption risks were evaluated from facility-specific and country-specific factors. The facility factor represented each facility's performance characteristics, as well as frequency of natural disasters. The country-specific factor was measured based on a company's internal weighted average cost of capital (WACC). The WACC represents an estimate of the domestic cost of capital excluding inflation, based on US-denominated bonds that are used to determine the spread between the United States and foreign countries. The author applied a qualitative assessment approach for assessing the disruption risk. Klibi and Martel (2012) proposed a risk modeling approach, called a three-phase hazard model, to generate plausible future supply chain scenarios. Phase-1 estimates supply chain network uncertainty based on multi-hazards, vulnerability sources, and exposure levels; Phase-2 estimates hazard arrival, intensity, and duration; Phase-3 assesses impact and recovery time. The future uncertainty scenarios are generated using a Monte Carlo approach. The authors applied the risk modeling approach to characterize future supply chain scenarios for two business cases. In case 1, the risk model was used to generate future scenarios for a two-echelon North-American distribution network. The future scenarios were generated to cover a 1-year planning horizon with daily working period under random customer orders and natural catastrophes at distribution centers. In case 2, the risk model was used to generate future scenarios for the Canadian Armed Forces to support its worldwide humanitarian, peacekeeping, and peace enforcement missions. The future scenarios were generated to cover a 10-years planning horizon with weekly working periods under natural catastrophes and global conflicts.

Wilson (2007) studied the effect of a transportation disruption on supply chain performance for a five-echelon supply chain, which consists of the retailer, the warehouse, the tier-1 supplier, the tier-2 supplier, and the raw material supplier. The author compared the disruption effect between a traditional supply chain system and a vender managed inventory (VMI) system using system dynamics simulation. The study found that the greatest impact occurred when transportation was disrupted between the tier-1 supplier and the warehouse. In the traditional structure, the retailer, warehouse, and tier-1 supplier experienced the greatest inventory fluctuations and had the most goods in transit to their facilities. These impacts were less severe in the VMI structure because the tier-1 supplier determined the number of items to be shipped to the warehouse based on customer demand. However, both structures yielded the same number of unfilled orders due to transportation disruptions. Snediker et al. (2008) developed a decision support system for mitigating network disruption. The decision support system examined the effects of different network disruption scenarios using an interdiction model. The authors developed an interface, which allowed visualization of the network and flows. The decision support system also allowed users to analyze mitigation strategies with respect to the disruptive scenarios. Solo (2009) developed a two-phase multi-objective optimization model to solve a supply chain network design and distribution problem. The first phase provided strategic decisions such as supplier selection, plant construction, production capacity level, and plant and warehouse operating schedules. A multi-period mixed integer programming model was developed to maximize supply chain profit. The optimal solutions from this phase were used as inputs for the tactical model. The second phase provided tactical decisions such as supplier selection for non-critical raw materials, material order allocation, shipping, and storage quantities, finished product production, and an optimal profit. A multi-period, mixed integer linear goal programming model was developed with multiple objectives that included minimizing unsatisfied demand, meeting or exceeding profit goal, and minimizing overall supply chain response time. Disruption was not integrated when making the design decisions, but it was considered in the tactical model to study the transportation disruptions.

Matisziw et al. (2009) applied simulation for evaluating the vulnerability to disruptions of nodes or links in a communication network. The evaluation processes consisted of: (i) setting up a network topology and network attributes; (ii) selecting the scenarios of facilities being disrupted; (iii) assessing impacts of network performance for all scenarios; and (iv) finding origin-destination pairs that are still connected after disruption has occurred in order to plan for security. Two mitigation strategies considered were protecting the network components (nodes) and adding new links to the network. Jiang (2011) assessed supply chain risks based on various risk factors related to procurement, demand, production, finance, and management. The objective of the study was to measure their impact on the supply chain under various scenarios to help a manager identify possible areas of improvement against potential risks. Finally, Schmitt and Singh (2009) quantified the supply chain disruption risk of a consumer products company using simulation techniques. In their model, the supply chain consisted of suppliers, manufacturing plant, packaging plant, and distribution centers. A Monte Carlo simulation was used to study risk profiles, while a Discrete Event Simulation (DES) was used to estimate flow of material and network interactions. The inter-arrival times of disruptive events were exponentially disturbed, while duration of disruption was represented by a lognormal distribution. Backup facility, flexible production sizing, and inventory level were used as mitigation strategies.

Opportunities for Improvement

Most papers have focused on facility disruptions and ignored transportation disruptions when making strategic supply chain decisions. Examples of transportation disruptions include the 2002 US West Coast port lockout, the 9/11 terrorist attack, the 2008 Thailand airport closure, and piracy attacks and robberies in the South China Sea and other maritime passages. These transportation disruptions can significantly impact global supply chains (Kungwalsong & Ravindran, 2013; Ravindran & Warsing, 2013; Wilson, 2007). In addition, disruption risks are characterized and integrated into strategic decision-making processes based on one of two broad perspectives: risk (e.g., risk type, occurrence, and impact) and vulnerability (e.g., supplier condition, political condition, etc.). These perspectives may be insufficient for understanding the causes of supply chain disruptions. Another factor that is important but has not been mentioned in the literatures is the availability of risk management practices. Wai and Wongsurawat (2013) highlighted that risk mitigation strategies such as backup warehouses and Enterprise Risk Management (ERM) systems were key factors that saved Western Digital's production facilities in Thailand after a massive flood that lasted for 46-days. Hence, companies should consider risk, vulnerability, and availability of risk management practices to effectively manage disruption risks in today's global supply chain environments.

In this article, we formulate a multi-criteria supply chain network design model that considers disruption risk as one of the design criteria. We consider both facility disruptions and transportation disruptions when making supply chain strategic decisions. These disruptions are evaluated separately. We assess the disruption risk assuming that supply chain disruptions are influenced by risk events, vulnerability of supply chain components, and risk management practices (Kungwalsong & Ravindran, 2012; 2013). We summarize the differences between our model and other studies in Table 2.

MATHMATICAL FORMULATION

Problem Environment

A physical representation of a supply chain network consists of facilities (e.g., suppliers, manufacturing plants, distribution centers, demand zones), and transportation links. In a global supply chain network, facilities are located in different countries and multiple transportation links transport items between facilities. A typical global supply chain network is shown in Figure 1.

Suppliers and manufacturing facilities are usually located in developing countries, where infrastructures, labor cost, and business incentives are attractive to investors. However, from a risk management perspective, efforts to mitigate the impact of disaster risks in developing countries are less than in developed countries (Kahn, 2005; Kellenberg & Mobarak, 2008; Gaiha et al., 2010). The authors have pointed out that developing countries often under-invest in protection, whereas developed countries may lower their exposure to disaster risks by improving the quality of institutions, educations, or access to medical care which allows them to respond to natural disasters better than corrupt governments (Amendola et al., 2008; Kellenberg & Mobarak, 2008; Stromberg, 2007; Ye & Abe, 2012). Therefore, the supply chain network design decision should balance benefit and risk.

Design Criteria and Model Assumptions

This article considers a traditional supply chain network that consists of candidate suppliers, possible manufacturing plant and distribution center locations, and customer zones. Items can be transported between facilities using multiple transportation links. The suppliers supply raw materials to the plants for producing finished products. The plants produce finished products using the raw materials purchased from the suppliers and ship to the DCs or the customer zones. The DCs are used to distribute finished products to customer zones. Demands at the customer zones can be satisfied from either the direct shipment from the plants or via the DCs.

Since disruptions may occur to either facilities or transportation links, a company wants to design a global supply chain network that satisfies five objectives: maximize profit (Z_1), maximize demand fulfillment or minimize unfulfilled demand (Z_2), minimize delivery time (Z_3), minimize facility disruption risk (Z_4), and minimize transportation link disruption risk (Z_5). The design criteria are shown in Figure 2:

The last two objectives are used to enhance the robustness of the global supply chain network. A supply chain network that consists of low-risk facilities/transportation links should be more robust than a network that consists of high-risk facilities/transportation links. We formulate a multi-criteria optimization model

Table 2. The comparison between our model and other studies (from Kungwalsong, 2013)

Authors	Description of the study (e.g., methodology and objective)	Consideration of risk	Decision maker's preference	Disrupted components
Supplier selection problem				
Gaonkar and Viswanadham (2004)	Mixed integer linear programming model to minimize expected cost and cost variance	Risk event (occurrence and impact)	Not included	Facility and transportation
Chan et al. (2008)	Multi-criteria selection problem and fuzzy AHP	Vulnerability (Location, political instability, foreign policies, exchange rate, economic, crime rate)	Included	Facility
Levary (2008)	Ranking method and AHP to select the most reliable suppliers	Vulnerability (reliability of transportation, supplier's suppliers, country risk)	Included	Facility and transportation
Lee (2009)	Multi-criteria problem and fuzzy AHP considering benefit, opportunity, cost, and risk	Price variation, financial profile, capacity, supplier reputation, and environment	Included	Facility
Yang (2007), Bilsel (2009), Ravindran et al. (2010)	Multi-criteria optimization model considering cost, lead time, quality, and disruption risk	Risk event (occurrence and impact)	Included	Facility
Facility location problem				
Drezner (1987)	P-median and (p, q)-center problem to minimize the expected demand-weighted travel distance and cost	Risk event (occurrence and impact)	Not included	Facility
Snyder and Daskin (2005)	P-median problem to minimize the weighted sum of cost and expected failure cost	Risk event (occurrence and impact)	Not included	Facility
Snyder et al. (2006)	P-median and R-covering problems to minimize the expected cost	Risk event (occurrence and impact)	Not included	Facility
Church et al. (2004)	P-median and R-covering problems to minimize the service delivery	Risk event (occurrence and impact)	Not included	Facility
Aryanezhad et al. (2010)	Nonlinear location-inventory model considering costs, lost sales, and inventory	Risk event (occurrence and impact)	Not included	Facility
Peng et al. (2011)	Mixed integer linear programming model to minimize cost	Risk event (occurrence and impact)	Not included	Facility
Supply chain network design problem				
Wilson (2007)	Simulation model	Occurrence of a transportation disruption	Not included	Transportation

continued on following page

Table 2. Continued

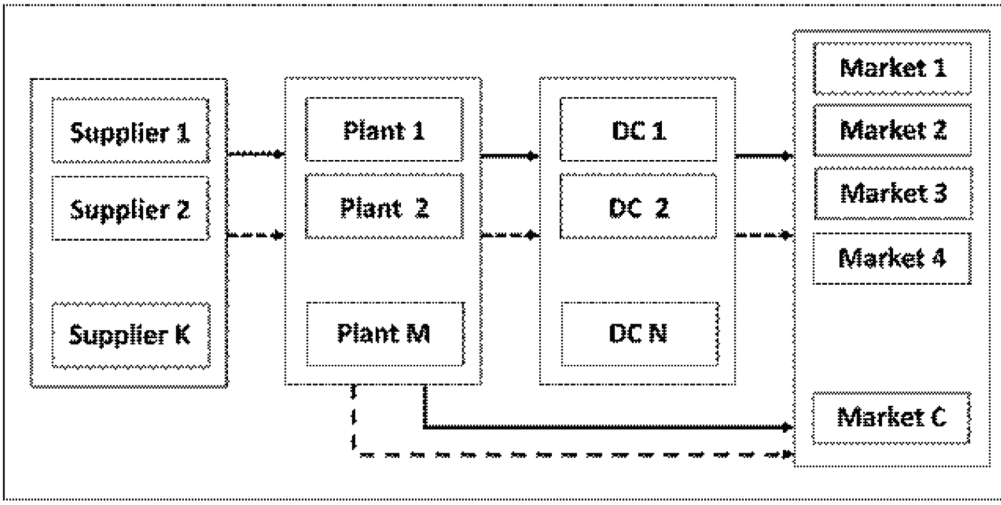
Authors	Description of the study (e.g., methodology and objective)	Consideration of risk	Decision maker's preference	Disrupted components
Portillo Bollat (2009)	Multi-criteria model considering profit, customer service, risk, strategic measure	Facility risk, country risk	Included	Facility
Schmitt and Singh (2009)	Simulation model to study the impact of facility disruption to the demand fulfillment	Risk event (occurrence and impact)	Not included	Facility
Solo (2009)	Multi-criteria model considering profit, shortage, and time	Occurrence of a transportation disruption	Included	Transportation
Jiang (2011)	Scenario analysis using AHP	Procurement, production, finance, and management	Included	Facility
This paper	Multi-criteria model considering profit, demand fulfillment, delivery time, and disruption risks of facility and transportation link	Risk event, vulnerability of supply chain component, and availability of risk management practice	Included	Facility and transportation

to make the following decisions: (i) supply chain network structure, including which suppliers, manufacturing plants, and DCs to use; (ii) production and distribution planning, including which plants should produce which finished products, and which plants or DCs should distribute finished products to which customers; and (iii) transportation selection, including which transportation links should be used to ship items between facilities.

The design of the supply chain network is based on the following assumptions:

1. A multinational corporation wants to design a supply chain network for new products. A set of potential suppliers, plant locations, DCs, and transportation links are available; hence, the decisions focus on the network structure and distribution planning.
2. The candidate suppliers, plants, and DCs that are located in developing countries may have lower costs and higher disruption risk value than those in developed countries.
3. When items (raw materials or finished products) are shipped internationally, additional cost due to tariffs and fees should be taken into accounted. In this study, the import fees apply to raw materials that arrive at the plants because suppliers and plants are located in different countries. It is expressed as a percentage of total raw material cost. Tariffs do not apply when finished products are shipped from plants to the company-owned DCs; however export fees apply to finished products that are shipped directly from plants to customers in different countries. Export fees are calculated as a percentage of the total revenue at plants.
4. Products can be shipped directly from the plants to the customer zones if the demand meets minimum level. The direct shipment may reduce the number of transshipments, however the shipment from the plants to the customers may take longer time compare to the shipment from DCs. The use

Figure 1. A global supply chain network



of direct shipment or ship via DC is one of the model decisions.

5. Business environments are deterministic. In addition, all relevant prices and costs are given in U.S. dollars (USD).
6. Disruption risk score for facilities (suppliers, plants, and DCs) and transportation links are pre-determined by the company and may vary based on facility location. Disruption risk scores are determined using the disruption risk assessment framework proposed by Kungwalsong and Ravindran (2012; 2013), as shown in Figure 3, and used as input parameters in the supply chain network design model.

Multi-Criteria Optimization Model

The notations, parameters, and the decision variables used to formulate the model are listed as follows.

Indices

I Set of raw materials
J Set of finished products
K Set of raw materials suppliers
M Set of manufacturing plants
N Set of distribution centers
C Set of customer zones
f Origin facilities $\left(f \in \left\{K \cup M \cup N\right\}\right)$

Figure 2. Supply chain network design criteria

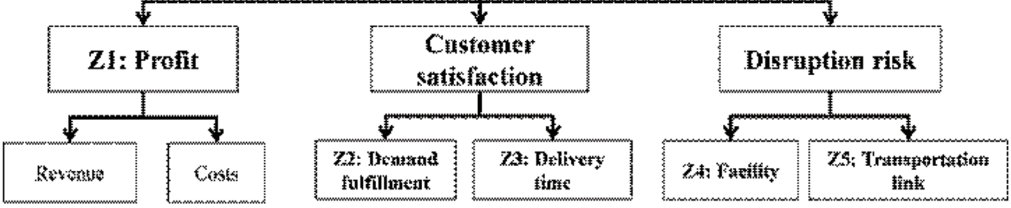
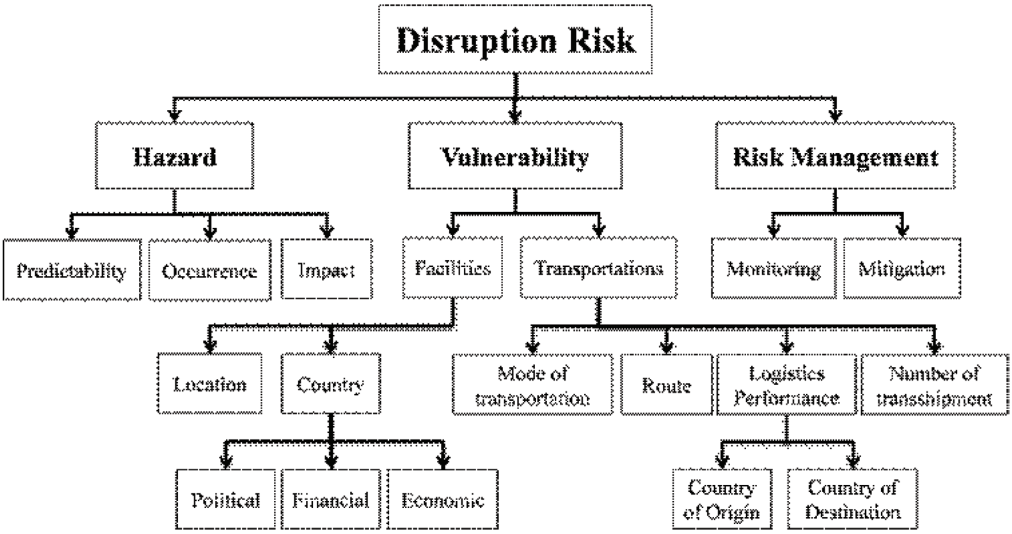


Figure 3. Disruption risk factors (from Kungwalsong and Ravindran, 2012; 2013)



d Destination facilities $(\mathrm{d} \in \{M \cup N \cup C\})$

u_{fd} Transportation links between facilities f and d

p Raw material or finished product $(\mathrm{p} \in \{I \cup J\})$

Parameters

D_{jc} Forecasted demand of product j to customer c (units)

f_{jc} Fraction of demand of product j to customer c that a company desires to satisfy

b_{ij} Quantity of raw material i to produce one unit of product (units)

RMD_i Quantity of raw material i required $(RMD_i = \sum_j b_{ij} \sum_c D_{jc})$ (units)

FSC_f Fixed cost of selecting facility f (\$)

FC_{pf} Fixed cost when selecting item p from facility f (\$)

FSC_{pfd} Fixed cost when assigning item p between facilities f and d (\$)

SP_{jc} Selling price of product j to customer c (\$/unit)

MC_{ik} Cost of raw material i from supplier k (\$/unit)

S_j Space required at a distribution center to store one unit of product j (unit space)

SC_{jn} Cost of handling finished product j at a distribution center n (\$/unit space)

PC_{jm} Production cost of finished product j at plant m (\$/unit)

FTC_{ufd} Fixed cost of selecting link u between facilities f and d (\$)

TC_{pufd} Unit shipping cost of item p via link u from facility f to facility d (\$/unit)

LT_{ufd} Average lead-time of transportation link u between facilities f and d (time)

CAP_f Capacity of facility f (unit)

CAP_{pf} Capacity of item p at facility f (unit)

MIN_{pf} Minimum quantity of item p at facility f (unit)

$MIND$ Minimum order to allow direct shipment from plants to customers (unit)

CAP_{ufd} Capacity of link u between facilities f and d (unit)

VaR_f Disruption risk score of facility f

VaR_{ufd} Disruption risk score of transportation link u between facilities f and d

ϕ_m Percentage of fees applied to the variable purchasing cost at plant m

∂_m Percentage of fees applied to the revenue of plant m

Decision Variables

X_f Binary variable equals to 1 if facility f is selected; 0 otherwise.

X_{pf} Binary variable equals to 1 if item p is assigned to facility f; 0 otherwise.

X_{pfd} Binary variable equals to 1 if item p is transferred between facilities f and d; 0 otherwise.

X_{ufd} Binary variable equals to 1 if link u is used to ship items between facilities f and d; 0 otherwise

Q_{pufd} Quantity of item p shipped via transportation link u between facilities f and d (unit)

Y_{jm} Quantity of product produced at plant m (unit)

W_{jc} Quantity of unfulfilled demand of product j to customer c (unit)

σ_f Fraction of items handled by facility f

δ_{ufd} Fraction of items handled by links μ connecting facilities f and d

The multi-criteria optimization model consists of five objective functions as follows:

Objective 1: Maximize Profit

Maximize $Z_1 =$

$$\left(\sum_{c\in C}\sum_{m\in M} SP_{jmc}\sum_{u\in U_{mc}} Q_{jumc} + \sum_{c\in C}\sum_{n\in N} SP_{jnc}\sum_{u\in U_{nc}} Q_{junc}\right)$$

$$-\left(\sum_{f\in F} FSC_f X_f\right)$$

$$-\left(\sum_{k\in K}\sum_{i\in I} FC_{ik}X_{ik} + \sum_{k\in K}\sum_{i\in I} MC_{ik}\sum_{m\in M}\sum_{u\in U_{km}} Q_{iukm}\right)$$

$$-\left(\sum_{m\in M}\sum_{j\in J} FC_{jm}X_{jm} + \sum_{m\in M}\sum_{j\in J} PC_{jm}Y_{jm}\right)$$

$$-\left(\sum_{n\in N}\sum_{j\in J} FC_{jn}X_{jn} + \sum_{n\in N}\sum_{j\in J} S_j SC_{jn}\sum_{m\in M}\sum_{u\in U_{mn}} Q_{jumn}\right)$$

$$-\left(\sum_{d\in D}\sum_{f\in F}\sum_{u\in U_{fd}} FTC_{ufd}X_{ufd} + \sum_{d\in D}\sum_{f\in F}\sum_{u\in U_{fd}}\sum_{p\in P} TC_{pufd}Q_{pufd}\right)$$

$$-\left(\sum_{d\in D}\sum_{f\in F}\sum_{u\in U_{fd}} FSC_{pfd}X_{pfd}\right)$$

$$-\left(\sum_{m\in M}\phi_m\sum_{k\in K}\sum_{i\in I} MC_{ik}\sum_{u\in U_{km}} Q_{iukm} + \sum_{m\in M}\partial_m\sum_{c\in C}\sum_{j\in J} SP_{jc}\sum_{u\in U\in} Q_{jumc}\right)$$

Profit is the difference between revenue and total cost. The first component represents the revenues from plants and DCs. Next are the facility location cost; raw material purchasing cost, which consists of fixed purchasing cost and variable cost; production cost, which consists of fixed cost of producing a specific product at a specific plant and variable production cost; distribution center cost, which consists of the fixed operating cost and variable cost calculated based on the space used; transportation cost, which consists of fixed transportation cost and variable cost based on shipping quantities; additional fixed administration cost that may occur when assigning an item between facilities; and the cross-sourcing cost incurred at plants when raw materials are imported from suppliers and finished products are exported to customers.

Objective 2: Minimize Unfulfilled Demand of All Finished Products among All Customers

Minimize $Z_2 .= \sum_{c \in C} \sum_{j \in J} Wjc$

Objective 3: Minimize Delivery Time

Minimize $Z_3 . = \left(\sum_{c \in C} \sum_{m \in M} \sum_{u \in U_{mc}} LT_{umc} \sum_{j \in J} Q_{jumc} \right) + \left(\sum_{c \in C} \sum_{n \in N} \sum_{u \in U_{nc}} LT_{unc} \sum_{j \in J} Q_{junc} \right)$

The delivery time consists of two components, the delivery time from plants to customer zones and the time from DCs to customer zones. Even though the value does not represent the true delivery time to customers, it provides a useful measure of responsiveness in terms of volume-weighted lead-time. If a link with a long travel time carries a huge amount of demand, then the delivery time value will be high. Hence, the customer demand should be allocated to each link in such a way that the total delivery time is minimal.

Objective 4: Minimize Facility Disruption Risk

Minimize $Z_4 = \sum_{f \in F} VaR_f \sigma_f$

The disruption risk of facilities depends upon the quantity (flow) handled by a particular facility (σ_f). Hence, items should be allocated to each facility in such a way that the disruption risk value is minimal. The σ_f is unknown values representing the fraction of items handled by each location f. The variables $\sigma_k, \sigma_m, \sigma_n$ are determined as follows:

$$\sigma_k = \frac{\sum_{m \in M} \sum_{u \in U_{km}} \sum_{i \in I} Q_{iukm}}{\sum_{i \in I} \sum_{j \in J} bij \sum_{c \in C} D_{jc}}$$

$$\sigma_m = \frac{\sum_{j \in J} Y_{jm}}{\sum_{c \in C} \sum_{j \in J} D_{jc}}$$

$$\sigma_n = \frac{\sum_{c \in C} \sum_{u \in U_{nc}} \sum_{j \in J} Q_{junc}}{\sum_{c \in C} \sum_{j \in J} D_{jc}}$$

Objective 5: Minimize Transportation Link Disruption Risk

Minimize $Z_5 .= \sum_{d \in D} \sum_{f \in F} \sum_{u \in U_{fd}} VaR_{ufd} \delta_{ufd}$

The disruption risk for transportation links depends upon the quantity (flow) handled by each transportation link (δ_{ufd}). Hence, items should be allocated to each transportation link in such a way that the disruption risk value is minimal. The δ_{ufd} are unknown values representing the fraction of items carried by each transportation link u between origin facility (f) and destination facility (d). The variables $\delta_{ukm}, \delta_{umn}, \delta_{unc}$ are determined as follows:

$$\delta_{ukm} = \frac{\sum_{i \in I} Q_{iukm}}{\sum_{i \in I} \sum_{j \in J} bij \sum_{c \in C} D_{jc}}$$

$$\delta_{umn} = \frac{\sum_{j \in J} Q_{jumn}}{\sum_{c \in C} \sum_{j \in J} D_{jc}}$$

$$\delta_{unc} = \frac{\sum_{j \in J} Q_{junc}}{\sum_{c \in C} \sum_{j \in J} D_{jc}}$$

Since the disruption risk score value of a facility or a transportation link is determined from a qualitative assessment (Kungwalsong & Ravindran, 2012; 2013), the score itself does not have meaning. However, it can be used to compare the disruption risks between different supply chain design networks.

Model Constraints

$$\left(\sum_{m\in M}\sum_{u\in U_{mc}} Q_{jumc} + \sum_{n\in N}\sum_{u\in U_{nc}} Q_{junc}\right) + W_{jc} = D_{jc} \quad \forall j\in J, \forall c\in C \tag{1}$$

$$W_{jc} \le \left(1 - f_{jc}\right) D_{jc} \quad \forall j\in J, \forall c\in C \tag{2}$$

$$X_{pf} \le X_f \quad \forall p\in P, \forall f\in K\cup M\cup N \tag{3}$$

$$X_{pfd} \le X_{pf} \quad \forall p\in P, \forall f\in K\cup M\cup N, \forall d\in M\cup N\cup C \tag{4}$$

$$X_{ufd} \le X_{pfd} \quad \forall u\in U_{fd}, \forall p\in P, \forall f\in K\cup M\cup N, \forall d\in M\cup N\cup C \tag{5}$$

$$MIN_{ik} X_{ik} \le \sum_{m\in M}\sum_{u\in U_{km}} Q_{iukm} \le CAP_{ik} X_{ik} \quad \forall i\in I, \forall k\in K \tag{6}$$

$$\sum_{m\in M}\sum_{k\in K}\sum_{u\in U_{km}} Q_{iukm} \ge RMD_i \quad \forall \mathrm{i}\in \mathrm{I} \tag{7}$$

$$MIN_{jm} X_{jm} \le Y_{jm} \le CAP_{jm} X_{jm} \quad \forall j\in J, \forall m\in M \tag{8}$$

$$\sum_{j\in J} b_{ij} Y_{jm} \le \sum_{k\in K}\sum_{u\in U_{km}} Q_{iukm} \quad \forall i\in I, \forall m\in M \tag{9}$$

$$\sum_{j\in J} b_{ij} \sum_{m\in M} Y_{jm} \le \sum_{m\in M}\sum_{k\in K}\sum_{u\in U_{km}} Q_{iukm} \quad \forall i\in I \tag{10}$$

$$\sum_{c\in C} f_{jc} D_{jc} \le \sum_{m\in M} Y_{jm} \le \sum_{c\in C} D_{jc} \quad \forall j\in J \tag{11}$$

$$\sum_{n\in N}\sum_{u\in U_{mn}} Q_{jumn} + \sum_{c\in C}\sum_{u\in U_{mc}} Q_{jumc} \le Y_{jm} \quad \forall j\in J, \forall m\in M \tag{12}$$

$$\sum_{j\in J} S_j \left(\sum_{m\in M}\sum_{u\in U_{mn}} Q_{jumn}\right) \le CAP_n X_n \quad \forall n\in N \tag{13}$$

$$\sum_{c\in C}\sum_{u\in U_{nc}} Q_{junc} \le \sum_{n\in N}\sum_{u\in U_{mn}} Q_{jumn} \quad \forall j\in J, \forall n\in N \tag{14}$$

$$\sum_{p\in P} Q_{pufd} \le CAP_{ufd} X_{ufd} \quad \forall u\in U_{fd}, \forall p\in P, \forall f\in K\cup M\cup N, \forall d\in M\cup N\cup C \tag{15}$$

$$\sum_{p\in P} Q_{pufd} \ge MIND\left(X_{ufd}\right) \quad \forall u\in U_{fd}, \forall p\in P, \forall f\in K\cup M\cup N, \forall d\in M\cup N\cup C \tag{16}$$

$$Q_{jumc} \ge MIND\left(X_{umc}\right) \quad \forall j\in J, \forall u\in U_{mc}, \forall m\in M, \forall c\in C \tag{17}$$

$$X_f, X_{pf}, X_{pfd}, X_{ufd} \in \left\{0,1\right\} \tag{18}$$

$$Q_{pufd}, Y_{jm}, W_{jc}, \sigma_f, \delta_{ufd} \ge 0 \tag{19}$$

Constraint (1) ensures that customer demands are satisfied. Constraint (2) allows the company to specify different level of customer responsiveness, especially when shortages occur due to disruptions. Constraint (3) states that item can be assigned to a facility only when the facility is selected. Constraint (4) ensures that origin facilities can respond to demand for an item at a destination facility if the item is available. Constraint (5) ensures that a transportation link can be used if the item is shipped between the facilities. Constraint (6) ensures that a total order placed with a supplier meet the minimum order requirement but does not exceed the available capacity. The binary variable X_{ik} is used to activate the constraint for supplier k. Constraint (7) ensures that each material purchased from suppliers is sufficient for production. Constraint (8) ensures that the production quantity meets the minimum production requirement but does not exceed the capacity. Constraints (9) and (10) ensure that the production quantity at each plant is limited by the availability of raw materials. Constraint (11) forces the production quantity to meet the minimum demand fulfillment target but not to produce more than the forecasted demand. Constraint (12) ensures that a shipment from a plant does not exceed its production quantity. Constraint (13) ensures that total storage space used at a distribution center does not exceed its available space. Constraint (14) ensures that the total number of products shipped out of a DC does not exceed availability. Constraints (15) and (16) ensure that the quantity of an item shipped between facilities meets the minimum shipping quantity, but does not exceed the capacity of the selected transportation link. In addition, constraint (17) states that a direct shipment between a plant and customers is allowed if a shipment meets a minimum quantity. Finally, constraints (18) and (19) ensure binary and non-negativity conditions, respectively.

SOLUTION APPROACH

The mathematical model formulated in this paper is a multi-criteria mathematical programming problem (MCMP). We use Goal Programming (GP) to handle the multiple and conflicting objectives. Goal programming uses pre-specified preferences of the decision maker to solve MCMPs. In this approach, target levels for achievement are obtained for all objectives. In addition, the relative importance of achieving the different targets are also specified. These target values are treated as goal constraints that the decision maker desires to achieve. However, they may or may not be achievable. The goal programming approach attempts to find an optimal solution that comes as close to the targets as possible based on the decision makers' preferences.

The objective function in GP is to minimize deviations from the target values. There are four types of GP formulations: (i) Preemptive Goal Programming (P-GP); (ii) Non-preemptive Goal Programming (NP-GP); (iii) MinMax Goal Programming (or Tchebysheff GP); and (iv) Fuzzy Goal Programming. These formulations are different based on how the objective functions are prioritized and target deviations are treated. A detailed description of GP methods can be found in Masud and Ravindran (2008). In this paper, we apply the P-GP and the NP-GP formulations to solve the supply chain network design model.

Preemptive Goal Programming (P-GP) Model

In P-GP, the objective functions are ranked based on the ordinal preferences of the decision maker. In other words, the higher priority goals are achieved before the lower priorities are considered. In addition, deviations from target values associated with each objective are minimized in the sequence of priorities (Masud & Ravindran, 2008). Suppose the decision maker assigns profit as the most important objective, followed by delivery time to customer, facility disruption risk, transportation disruption risk, and demand fulfillment (i.e., $Z_1 > Z_3 > Z_4 > Z_5 > Z_2$). Variables d_r^- and d_r^+ represent how far the solution deviates from each goal or target value. The P-GP formulation for the supply chain network design problem is as follows:

Min z =
$P_1 d_1^- + P_2 d_3^+ + P_3 d_4^+ + P_4 d_5^+ + P_5 d_2^+$.(20)

Subject to

$Z_1 - d_1^+ + d_1^-$ = Profit target (21)

$Z_2 - d_2^+ + d_2^-$ = Unfulfilled demand target (22)

$Z_3 - d_3^+ + d_3^-$ = Delivery time to customer target (23)

$Z_4 - d_4^+ + d_4^-$ = Facility disruption risk target (24)

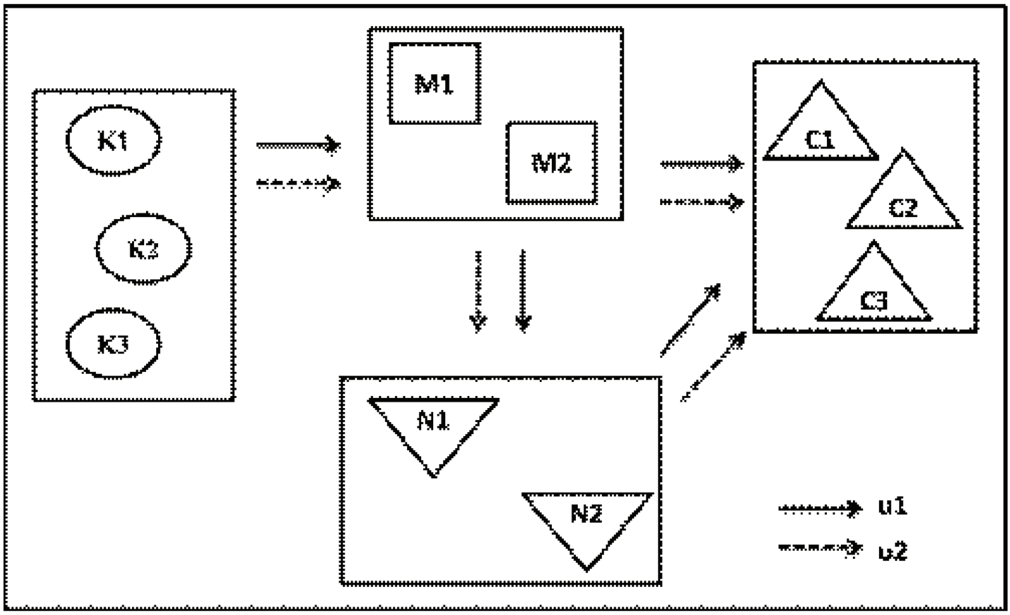
$Z_5 - d_5^+ + d_5^-$ = Transportation link (25)

Disruption risk target

. $d_r^+, d_r^- \geq 0$ i=1,..., 5 (26)

Constraints (1) – (19) stated earlier will also be included in this model. To determine the optimal solution from the P_GP model, a sequence of optimization problems must be solved.

Figure 4. Example of a global supply chain network



Non-Preemptive Goal Programming (NP-GP) Model

In NP-GP, numerical weights are used to indicate the relative importance of the objective functions. Several methods exist for estimating criteria weights, such as simple rating method, pair-wise comparison method, and Analytical Hierarchy Process (AHP). It is important to note that the objectives must be scaled due to differences in units and the magnitude of the objectives (Masud & Ravindran, 2008). The NP-GP formulation for the supply chain network design problem is as follows:

Min z =

$$.\, W_1 d_1^- + W_2 d_2^+ + W_3 d_3^+ + W_4 d_4^+ + W_5 d_5^+$$

The NP-GP model is subjected to the constraints (1) – (19) and (21) – (26). To scale each objective, the objective function is divided by the target value such that the new right-hand-side value is 1. The advantage of NP-GP is that only a single objective optimization problem has to be solved.

Criteria Weights for NP-GP Models

To obtain weights of the decision criteria, rating method and AHP are used in this paper. For the rating method, the decision maker assigns a score for each criterion (scale of 1-10) and normalizes the score to obtain the weights (Masud & Ravindran, 2008). AHP is the process of comparing criteria in pairs to judge which criterion is preferred and the intensity of preference (Portillo Bollat, 2009; Ravindran et al., 2010). For AHP, it is important to test the consistency of the decision maker. The main difference between these two methods is that the rating method does not include the preference intensity.

In our example, the non-preemptive weights from the simple rating method for profit, unfulfilled demand, delivery time, facility disruption risk, and transportation disruption risk are 0.45, 0.10, 0.25, 0.10, and 0.10, respectively. The non-preemptive weights from the AHP for those objectives are 0.572, 0.056, 0.260, 0.056, and 0.056, respectively. Next section presents the results from the GP models. The models are

Table 3. Summary of disruption risk scores for facilities

Facility	Disruption risk score
Supplier K1	8.739
Supplier K2	16.824
Supplier K3	15.202
Plant M1	12.066
Plant M2	9.524
DC N1	6.475
DC N2	4.947

coded and solved using LINGO 13.0 optimization software.

Illustrative Example

A global supply chain consists of three suppliers (K1, K2, K3), two manufacturing plants (M1, M2), two DCs (N1, N2), and three customer zones (C1, C2, C3), which are located in different countries. There are two transportation links (U1, U2) available between each pair of facilities. There are two types of raw materials (i1, i2) and two types of finished products (j1, j2). A representation of the global supply chain is shown in Figure 4.

The data used in this example are available through the hyperlink in Appendix A. From a cost perspective, supplier K3 has the lowest raw material cost, followed by suppliers K2 and K1. Plant M1 has a lower production cost than plant M2. DC N1 has a lower operating than DC N2. Transportation link U2 has a lower shipping costs and longer lead-time than link U1. In addition, the disruption risk scores for facilities (suppliers, plants, and DCs) and transportation links are pre-determined by the

Table 4. Summary of disruption risk scores for transportation links

Links between suppliers and plants	Disruption risk score	Links between plants and DCs	Disruption risk score	Links between plants and customers	Disruption risk score	Links between DCs and customers	Disruption risk score
U1_K1M1	9.49	U1_M1N1	6.33	U1_M1C1	9.49	U1_N1C1	8.26
U1_K1M2	9.49	U1_M1N2	6.33	U1_M1C2	9.49	U1_N1C2	8.26
U1_K2M1	10.90	U1_M2N1	6.33	U1_M1C3	9.49	U1_N1C3	7.19
U1_K2M2	10.90	U1_M2N2	6.33	U1_M2C1	9.49	U1_N2C1	8.26
U1_K3M1	10.90	U2_M1N1	9.24	U1_M2C2	9.49	U1_N2C2	8.26
U1_K3M2	10.90	U2_M1N2	9.24	U1_M2C3	9.49	U1_N2C3	6.28
U2_K1M1	12.78	U2_M2N1	9.24	U2_M1C1	12.78	U2_N1C1	12.78
U2_K1M2	12.78	U2_M2N2	9.24	U2_M1C2	13.86	U2_N1C2	12.78
U2_K2M1	14.68			U2_M1C3	13.86	U2_N1C3	11.12
U2_K2M2	14.68			U2_M2C1	12.78	U2_N2C1	12.78
U2_K3M1	14.68			U2_M2C2	13.86	U2_N2C2	12.78
U2_K3M2	14.68			U2_M2C3	13.86	U2_N2C3	9.72

Table 5. Supply chain network performances from goal programming techniques

Objective function	Ideal value	Target value	Solution 1 (P-GP model)	Solution 2 (NP-GP model, weights from rating method)	Solution 3 (NP-GP model, weights from AHP)
Z1: Profit ($)	109,180,410	108,634,507	108,634,508 (achieved the target)	102,825,140 (5.35% lower than the target value)	104,802,140 (3.53% lower than the target value)
Z2: Unfulfilled demand (%)	0.00	0.50	0.00 (achieved the target)	0.00 (achieved the target)	0.00 (achieved the target)
Z3: Delivery time	216000	217080	264040 (21.63% longer than the target value)	240000 (10.56% longer than the target value)	240000 (10.56% longer than the target value)
Z4: Facility disruption risk	21.20	21.30	32.75 (53.76% higher than the target value)	27.10 (27.23% higher than the target value)	28.62 (34.37% higher than the target value)
Z5: Transportation link disruption risk	18.77	18.86	32.39 (71.74% higher than the target value)	24.30 (28.84% higher than the target value)	24.24 (28.53% higher than the target value)

company using the disruption risk assessment framework proposed by Kungwalsong and Ravindran (2013). The disruption risk scores of all facilities and transportation links used in this example are provided in Tables 3 and 4. Note that a higher score value indicates a higher disruption risk.

From a disruption risk perspective, supplier K2 has the highest disruption risk score value, followed by suppliers K3 and K1. Plant M1 has a higher disruption risk score than plant M2. DC N1 has a higher disruption risk score than DC N2. Transportation link U2 has a higher disruption risk score than the link U1.

The GP approach begins with finding the ideal solutions for the five objectives. The ideal solutions are obtained by optimizing each objective independently ignoring the other objectives. For instance, an ideal profit value is obtained by maximizing profit ignoring other objectives. Similarly, an ideal facility disruption risk value is obtained by minimizing facility disruption risk and ignoring other objectives. In summary, the ideal values for profit, unfulfilled demand, delivery time, facility disruption risk, and transportation risk are given in Table 5, Column 2. Note that except for profit, the other objectives are minimized.

Once an ideal value of each objective function has been determined, the decision maker will be asked to set the target values. For the illustrative purpose, we assume that the decision maker sets the profit target value at 99.5% of the ideal profit value (0.995×109,180,410 = 108,634,507.95), the unfulfilled demand target value at 0.5% (that is 99.5% of the forecasted demands must be fulfilled), the delivery time target value at 0.5% above the ideal delivery time value (1.005×216000 = 217080), the facility disruption risk target value at 0.5% above the ideal facility disruption risk value (1.005×21.20 = 21.30), and the transportation disruption risk target value at 0.5% above the ideal transportation disruption risk value (1.005×18.77 = 18.86). The target values are summarized in column 3 of Table 5. These target values are treated as goal constraints in the multi-criteria optimization models. For the NP-GP model, we scale

Table 6. Supply chain network decisions from goal programming techniques

Supply chain network design		Solution 1 (P-GP model)	Solution 2 (NP-GP model, weights from rating method)	Solution 3 (NP-GP model, weights from AHP)
Suppliers	K1	No	Select	Select
	K2	No	No	No
	K3	Select	Select	Select
Plants	M1	Select	Select	Select
	M2	Select	Select	Select
DCs	N1	Select	No	Select
	N2	No	Select	No
Transportation links	U1	Select	Select	Select
	U2	Select	No	No
Direct shipment from plants to customers		No	No	No

the objective functions due to the differences in their units.

DISCUSSION OF RESULTS

This section discusses the objective function values and the supply chain network design decisions from the P-GP and NP-GP models, as summarized in Tables 5 and 6.

From Tables 5 and 6, the P-GP solution suggests choosing supplier K3, plants M1 and M2, distribution center N1, using transportation link U2 to ship items among suppliers, plants, and DC facilities, and using transportation link U1 to ship items from DC to customer zones. The profit and the unfulfilled demand objectives are achieved. However, the delivery time, the facility disruption risk, and the transportation disruption risk objectives are higher than their target values by 21.63%, 53.76%, and 71.74%, respectively. Since profit is the most important, supply chain network design solution includes inexpensive facilities and transportation links. The P-GP model suggests purchasing raw materials from supplier K3, which has the lowest cost among the three suppliers. Most of the finished products are produced at plant M1 because its production costs are lower than those at plant M2. Similarly, DC N1 is selected, as it is less expensive to operate than DC N2. Transportation link U2 carries higher quantity of raw materials and finished products than the link U1. There is no direct shipment from plants to customers. As a result, the P-GP solution has the highest facility disruption risk and transportation link disruption risk values compared to the NP-GP solutions.

We can study the impact of the supply chain disruption on the network design solution by examining their disruption risk score values. Supplier K3 and plant M1 have very high disruption risk values compared to the other facilities, the company should closely monitor supplier K3 and plant M1 and prepare mitigation strategies. For instance, supplier K3 is located in a developing country where risk management practices are not fully implemented, possible risk mitigation strategies could be having a backup supplier or carrying extra inventory at plants to cope with the supplier disruption. For plant M1, a company may develop a contingency plan to relocate its production to other plant facilities in order to reduce damages from a possible plant disruption. Furthermore, the company should also pay attention to the transportation link U2 from supplier K3 to

Table 7. Summary of objective function values and the scaled values

Objective function value	Solution 1 (P-GP model)	Solution 2 (NP-GP model, weights from rating method)	Solution 3 (NP-GP model, weights from AHP)
Z1: Profit ($)	1.000	1.056	1.037
Z2: Demand fulfillment (%)	1.000	1.000	1.000
Z3: Delivery time	1.100	1.000	1.000
Z4: Facility disruption risk	1.208	1.000	1.056
Z5: Transportation link disruption risk	1.336	1.002	1.000

all plants. Risk mitigation strategies such as choosing alternate transportation links and risk monitoring should help address plausible disruptions from unpredictable events, long transportation lead-times, and a large number of transshipments.

The NP-GP solution (with weights from the simple rating method) suggests choosing suppliers K1 and K3, plants M1 and M2, distribution center N2, and using transportation link U1. Direct shipment from plants to customers is not selected. Finished products are distributed to customers via DC N2. For this solution, the unfulfilled demand is achieved, while other objective values are worse than their target values. The profit is 5.35% less than its target value, while the delivery time, facility disruption risk, and transportation disruption risk are 10.56%, 27.23%, and 28.84% higher than their target values, respectively.

Another solution from the NP-GP solution (with weights from AHP) suggests choosing suppliers K1 and K3, plants M1 and M2, distribution center N1, and using transportation link U1. Direct shipment from plant to customers is not allowed. Finished products are distributed to customers via DC N1. For this network design, the unfulfilled demand is achieved. However, profit, delivery time, facility disruption risk, and transportation disruption risk goals are worse than their target values by 3.53%, 10.56%, 34.37%, and 28.53%, respectively.

The NP-GP solutions have lower disruption risk objective values than the P-GP solution because the NP-GP models consider five objectives simultaneously, while the P-GP considers one objective at a time according to their importance. The low disruption risk objective values implies that the NP-GP solutions are more robust or less susceptible to disruption than the P-GP solution. Thus, it is likely that a company will spend fewer resources to prepare and mitigate potential disruptions. On the other hand, the P-GP model focuses on designing the most profitable network, which results with the highest disruption risk network.

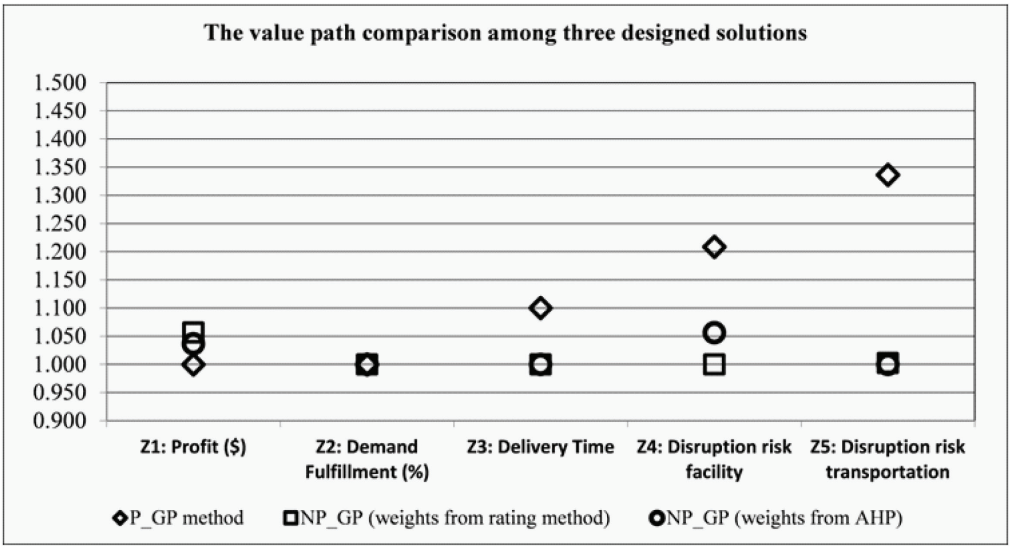
The next section provides the trade-off among the three design solutions based on their objective function values. The decision maker can evaluate how much profit the company may have to give up in order to increase the robustness (or lower the disruption risk) of the supply chain network.

Comparison of the Supply Chain Network Design Results

The P-GP and NP-GP models provide different solutions and different levels of target achievement. In order to compare the three supply chain design alternatives and their trade-offs visually, we use the value path approach (VPA) to display objective function values of different solutions. The VPA proposed by Schilling et al. (1983) is one the most efficient ways to demonstrate visually the tradeoffs among conflicting objectives.

From a set of solutions, the VPA starts with determining the best value corresponding to each objective function. The best value corresponding to a maximization objective is the highest value among all alternatives, while

Figure 5. The value path comparison for supply chain network design solutions



the best value corresponding to a minimization objective is the lowest value among all alternatives. Next, the best value is scaled to 1, while others are scaled to a value greater than 1. The larger the scaled value, the worse a method performs on that objective. A scaled value corresponding to a maximization objective is determined by dividing the best value by the achieved value, while a scaled value corresponding to a minimization objective is determined by dividing the achieved value by the best value. From Table 5, the best values for profit and demand fulfillment, which are maximization objectives, are 108,634,507.95 and 100%. The best values for delivery time, facility disruption risk, and transportation disruption risk, which are minimization objectives, are 240000, 27.10, and 24.24, respectively. Note that we replace the unfulfilled demand objective with the demand fulfillment to avoid a computational error. For the P-GP method, the achieved values for profit, demand fulfillment, delivery time to customers, facility disruption risk, and transportation disruption risk are 108634507.95, 100, 264040, 32.75, and 32.39, respectively. Hence, the scaled objective values corresponding to the P-GP solution are (108634507.95/108634507.95), (100/100), (264040/240000), (32.75/27.10), and (32.39/24.24), respectively. For the NP-GP method, with weights from the rating method, the achieved values for profit, demand fulfillment, delivery time to customers, facility disruption risk, and transportation disruption risk are 102825140, 100, 240000, 27.10, and 24.30, respectively. Hence, the scaled objective values corresponding to the NP-GP solution are obtained as (108634507.95/102825140), (100/100), (264040/240000), (32.75/27.10), and (32.39/24.30), respectively. Table 7 shows the scaled objective values for the three solutions from the GP methods.

Using the scaled values from Table 7, we plot them to provide a visual tradeoff analysis among the different solutions, as shown in Figure 5. The horizontal axis represents profit, demand fulfillment, delivery time to customers, facility disruption risk, and transportation disruption risk. The vertical axis represents the scaled objective values. In our example, the NP-GP solution (with weights from rating method) performs 10% better than the P-GP solution on delivery time to customers, 20.8% better on the facility disruption risk, and 33.6% better on the transportation disruption risk, but at the cost of 5.6% in lower profit. The NP-GP solution (with weights from rating method) performs 5.6% better on the facility disruption than the NP-GP solution (with weights from AHP), but at the cost of 1.9% in lower profit.

MANAGERIAL INSIGHT

Supply chain network design decisions are related to supplier selection, facility location, production and distribution planning, and transportation network. For a global supply chain, each facility and transportation link has its own risk and vulnerability. Once the network is designed, they cannot be changed easily and any change in the network component may impact the entire network.

This paper presented a multi-criteria optimization model to support a supply chain network design considering profit, unfulfilled demand, delivery time, disruption risk of facility, and disruption risk of transportation link as the design criteria. For the disruption risk parameters, we applied the disruption risk assessment framework proposed by Kungwalsong and Ravindran (2012; 2013) to quantify the disruption risk scores of facilities and transportation links. We applied the goal programming approach to handle the multiple-conflicting objectives and to provide the tradeoff among different design solutions.

Using a numerical example, we solved the GP problem and obtained three design solutions. The first solution, obtained by the P-GP model, was a network that highly relied on the profit objective. The network consisted of low-cost facilities and transportation links, which were prone to very high risk of disruptions. This indicates that a supply chain network design that relies heavily on maximizing profit may also create a network that is highly susceptible to disruptions.

The other two design solutions, obtained by the NP-GP models, represented networks that balance all the objectives simultaneously. These networks consisted of facilities and transportation links which had higher cost and lower risk. This indicates that the robustness of the supply chain network can be improved at the expense of profit. Thus, it is likely that a company will spend fewer resources to prepare and mitigate potential disruptions.

The illustrative example shows that the robustness of the supply chain network can be improved during the design phase by explicitly considering disruption risk as part of the objective functions.

FUTURE RESEARCH

This work can be extended in several ways. First, the multi-criteria mathematical model can be extended to incorporate other types of risk such as operational risks, financial risks, and strategic risks. Second, the robustness of supply chain network can be further improved through the redundancy and risk diversification strategies (Schmitt & Singh, 2009). Additional constraints can be added into the strategic model to have multiple facilities (e.g., suppliers and DCs). Even though the supply chain design decisions are made using disruption risk as criteria, supply chain risks still exist. Efforts can be taken to evaluate multiple disruptive scenarios in order to improve the resiliency of the supply chain at a tactical level. Finally, emphasis can be given to developing appropriate risk mitigation strategies and analyzing the tradeoffs between benefits and mitigation costs.

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APPENDIX

The parameters and LINGO codes used in this study are provided through the following hyperlink: https://www.dropbox.com/sh/iqd2xphdhe4dvz1/2WcC8E5-TL