Modeling, Analysis, and Design of Supply Chain Networks with the Integration of Nonlinear Cost of Quality Functions

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ABSTRACT

Modeling, Analysis, and Design of Supply Chain Networks with the Integration of Nonlinear Cost of Quality Functions

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Due to the complexity of the supply chain, sourcing and distribution activities within the supply chain require a fair deal of orchestrating in order to eliminate delays and other inefficiencies. For this reason, researchers have worked effortlessly to incorporate a wide range of parameters in the modeling of the supply chain. The parameters integrated have touched many important issues. As important, issues pertaining to quality are of great importance in organizations. Some literature has discussed quality from the perspective of the supply chain and acknowledged the lack of a consistent vision pertaining to quality throughout the supply chain. With many industries today on the quest of improving their quality systems, finding ways to reduce nonconformities and failure of products is crucial. In industries such as the aerospace industry, the variable production cost is considerably high; hence producing extra parts to compensate for defectives would be a costly option. While Cost of Quality (COQ) is a very good indicator of how much poor quality is costing a company, the literature lacks a work that aims at integrating COQ into Supply Chain Network Design (SCND). This thesis aims at exploring the challenges in doing so and introduces a comprehensive supply chain model that minimizes a series of costs, in which COQ is integrated.

The inclusion of COQ is done through the integration of quadratic quality function. The overall supply chain is mathematically modeled producing a nonlinearity in the objective function and in the constraints. Hence this thesis solves a constrained binary nonlinear programming problem. Further, this work integrates binary entities, to allow for assignable/set-up costs, into the model and introduces seven solution procedures to solve the model. A real life supply chain network is used to extract relevant results. The real life supply chain is in the domain of the aerospace industry and has an *n* level Bill of Material (BOM). Heuristics have been introduced to solve Binary Quadratic Programming (BQP) problems before. A majority of these heuristics are geared towards unconstrained problems where feasibility might not be a concern. Alternatively in the COQ model, constraints bind the objective function making feasibility a criterion for optimality. Therefore, the seven solution procedures entertain a feasibility check mechanism and one of the seven solution procedures is a hybrid solution procedure formulated to tailor for the special topography of the feasible solution region of the problem.

I dedicated this work

to my always loving mother,

to Maya,

and my strong and patient father

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I would like to thank my loving mother. She taught me what she knows best: Love. I thank her for her love, care, and the scarifying of herself for others. She did not get to live her dreams so we would live them. I hope this doctorate would be a token for her struggle. She is a strong woman and her strength has made miracles happen. I thank my father for planting in me the spirit of analytical thinking. I thank him for teaching me patience and I thank him for letting me be me.

I thank Maya for helping me without intending to help me; for supporting me without intending to support me; for loving me without intending to love me. Her spontaneity and free thinking has really brought the best in me. She brings out in me goodness, realism, and calmness. She is the type of a person that makes an impact without intending so and never cares to be acknowledged for anything. Maya ana be7ebek keteer.

Table of Contents

List of Figures

List of Tables

List of Symbols

Nonlinear Model

B	- Set of component types required for one product
I	- Set of suppliers
J	- Set of plants
K	- Set of Customers
P	- Set of Products
$S_{i,b}$	- Number of good components b manufactured at supplier i; $i \in I, b \in B$
$ST_{i,b}$	- Number of total components b manufactured at supplier i; $i \in I, b \in B$
$SG_{i,j,b}$	- Number of good components b shipped from supplier i to plant j; $i \in I, j \in J, b \in B$
$X_{j,p}$	- Number of good products p produced at plant j; $j \in J, k \in K$
$XT_{j,p}$	- Number of total products p produced at plant j; $j \in J, p \in P$
$XG_{j,k,p}$	- Number of good products p shipped from plant j to customer k; $j \in J, k \in K, p \in P$
$y_{i,b}$	- Percentage of defectives at supplier i for component b; $i \in I, b \in B$
$yp_{j,p}$	- Percent of defectives at plant j for product p; $j \in J, p \in P$
$PcC_{i,b}$	- Cost of producing one component b at supplier i; $i \in I, b \in B$
$\Pr C_{j,k}$	- Cost of producing one product at plant j for customer k; $j \in J, k \in K$
$TrC_{i,j,b}$	- Cost of transporting component b from supplier i to plant j;

$i \in I, j \in J, b \in B$

$fcoq_{y_{i,b}}$ - Total cost of quality (including prevention and appraisal costs) for supplier i per good component b as a function of y_i, the level of proportion of non-quality components. This is equivalent to the total cost of quality in figure 1; $i \in I, b \in B$.

$fcoq_{yp_{j,p}}$ - Total cost of quality (including prevention and appraisal costs) for supplier i per good products p as a function of yp_j, the level of proportion of non-quality components. This is equivalent to the total cost of quality in figure 1; $j \in J, p \in P$.

$TC_{j,k,p}$ - Transportation cost of transporting a product p from plant j to customer k; $j \in J, k \in K, p \in P$.

$D_{k,p}$ -Number of products demanded by customer k for product p; $k \in K, p \in P$

$SCap_{i,b}$ - Capacity of Supplier i for component b; $i \in I, b \in B$

$PCap_{j,p}$ - Allowable production capacity at plant j for product p; $j \in J, p \in P$

N_b - Number of components b required to make a product p; $b \in B, p \in P$

$AD_{i,b}$ - Maximum acceptable proportion of defective of component b at supplier i; $i \in I, b \in B$.

$AD_{j,p}$ - Maximum acceptable proportion of defective of product p at supplier j; $j \in J, p \in P$.

Binary Nonlinear Model

V	- Group of Vendors.
S	- Group of Subcontractors.
R	- Set of raw material types.
M	- Set of semi-finished product types
C	- Set of finished products
P	- Set of all product types
D	- Set of Clients
$SucV$	- Function that returns all vendors for the set of immediate successors of raw material type $p \in R$.
$SucS$	- Function that returns all subcontractors for the set of immediate successors of product type $p \in M$.
Suc	- Set of immediate successors of product type $p \in P$
$fix_{i,p}$	- Fixed cost associated to the assignment of product $p \in P$ to node $i \in V \cup S$.
$\Pr C_{i,p}$	- Unit production cost of product $p \in P$ manufactured at node $i \in V \cup S$.
$t_{i,j,p}$	- Unit transportation cost of product $p \in P$ from node $i \in V \cup S$ to node $j \in SucV \cup SucS \cup D$.
$fcoq_{i,p}$	- Function that returns the cost of quality for product $p \in P$ manufactured at link $i \in V \cup S$ at a percent of defective of $y_{i,p}$.
$Cap_{i,p}$	- Maximum number, capacity, of product $p \in P$ that can be manufactured at link $i \in V \cup S$.

$Dem_{j,p}$ - Demand of product $p \in C$ manufactured at client $j \in D$.

$g_{pp'}$ - Number of product $p \in P \mid C$ required to manufacture one unit of product $p' \in Suc$

$X_{i,p}$ - Number of product $p \in P$ manufactured at facility $i \in V \cup S$

$XT_{i,j,p}$ - Number of product $p \in P$ transported from node $i \in V \cup S$ to node $j \in SucV \cup SucS \cup D$.

$XG_{i,p}$ - Number of good product $p \in P$ manufactured at facility $i \in V \cup S$

$Z_{i,p}$ - Binary variable which equals 1 if product $p \in P$ is assigned to node $i \in V \cup S$, or zero otherwise.

$y_{i,p}$ - Percent of defectives for product $p \in P$ manufactured at link $i \in V \cup S$.

List of Acronyms

AHP	- Analytical Hierarchy Process
BOM	- Bill of Materials
BQP	- Binary Quadratic Problems
COQ	- Cost of Quality
DC	- Distribution Center
GA	- Genetic Algorithm
GIS	- Geographical Information System
GLS	- Global Logistic System
LS	- Local Search
MAUT	- Multi-Attribute Utility Theory
MIP	- Mixed Integer Programming
MIQP	- Mixed Integer Quadratic Programming
MOSA	- Multi-Objective Simulated Annealing
MP	- Mathematical Programming
MRP	- Material Requirements Planning
OEM	- Original Equipment Manufacturer
P&G	- Procter & Gamble
PDN	- Production Distribution Network
SSA	- Sample Average Approximation
SC	- Supply Chain
SCM	- Supply Chain Management
SCND	- Supply Chain Network Design

SCOR	- Supply Chain Operations Reference
SCQM	- Supply Chain Quality Management
SDP	- Stochastic Dynamic Programming
SGA	- Singlephase Genetic Algorithm
SM	- Stochastic Model
TS	- Tabu Search
VNS	- Variable Neighborhood Search
WIP	- Work-In-Process

Chapter 1

Background and Contribution

1.1 Background

In this introduction, a background is presented on the supply chain. The presentation includes definitions and a framework of the supply chain, supply chain management, supply chain network design, and cost of quality.

1.1.1 The Supply Chain

A supply chain consists of all stages involved, directly and indirectly, in fulfilling a customer request. The supply chain not only includes the manufacturer and suppliers, but also transporters, warehouses, retailers, and customer themselves (figure 1.1). The main objective of the supply chain is to maximize the overall value generated. Value is defined here as the difference between what the final product is worth to the customer and the cost the supply chain expends in fulfilling customer requirements (Chopra and Meindl 2001).

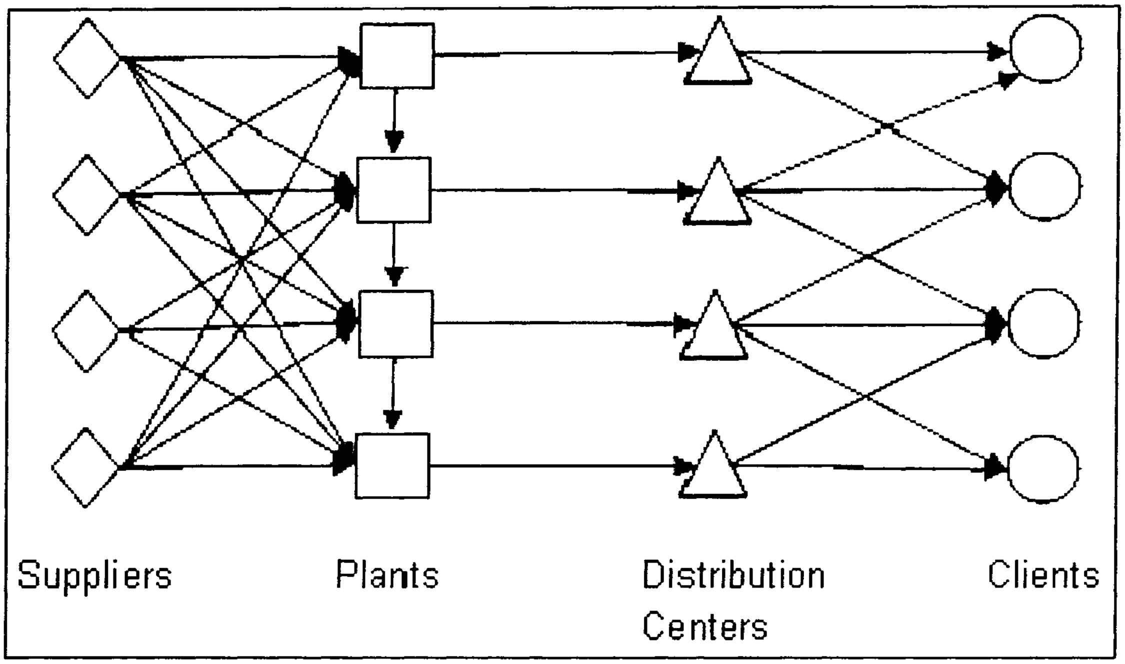


Figure 1.1: An example of a supply chain.

Govil and Proth (2002) define the supply chain as a global network of organizations that cooperate to improve the flows of material and information between suppliers and customers at the lowest cost and the highest speed; the objective of the supply chain is customer satisfaction. They assert that five major activities take place within the supply chain at the strategic level. The five activities are:

- The **buy** activity which includes the task of buying raw materials, components, resources, and services.
- The **make** activity which concerns creating products or services.
- The **move** activity which concerns transportation products within and outside the supply chain.
- The **store** activity which concerns the work-in-process and raw material when it is waiting for transportation or transformation.
- The **sell** activity which concerns all market-oriented activity.

Alternatively, Beamon (1998) suggests that a supply chain may be defined as an integrated process of various business entities interacting with each other; those business entities can be categorized in four categories: suppliers, manufacturers, distributors and retailers. Min and Zhou (2002) explain that the interactions between these entities insure the delivery of vital business processes and they described these vital processes as the following:

1. Acquiring raw materials and parts,
2. Transforming raw materials and parts into finished products,
3. Adding value to these products,
4. Distributing, and promoting these products, to retailers and in-turn to customers,
5. And facilitating information exchange among these entities.

To best achieve those processes, one needs to strategically choose, locate, coordinate, and manage the entities of the supply chain (i.e. suppliers, manufacturers, distributors, and retailers). Hence, a strategic plan needs to be put in place to link all the supply chain entities in a manner that best chooses, locates, and manages them; and this could be done through the faculty of supply chain management.

1.1.2 Supply Chain Management

Supply Chain Management (SCM) could be defined as the configuration, coordination, management and improvement of supply chain operations. Alternatively Copacino (1997) refers to SCM as the art of managing the flow of materials and products from source to user. The logistic system includes the total flow of material from the acquisition of raw material to delivery of finished products to the ultimate users. The logistic system includes the activities of sourcing and purchasing, capacity planning, technology solution, operations management, production scheduling, and material requirements planning (MRP), distribution planning and management of warehouse operations, inventory management and inbound and outbound transportation. Logistic is a term that is interrelated to supply chain management. The logistics concept is defined as the integrated management of the forecasting, inventory-control, transportation, warehousing, order-entry and customer service, and production planning functions. One of the great benefits of supply chain management is the integration of suppliers, manufacturers, distributors and customers. All these entities behave as if they are part of the same company. Mentzer et al. (2001) define supply chain management as the systematic, strategic coordination of the traditional business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole. And Hugos (2003) defines SCM as the coordination of production, inventory, location, and transportation among the participants in a supply chain to achieve the best mix of responsiveness and efficiency for the market being served. Consequently, supply chain management aims at increasing value to the end customer while decreasing operational costs all across the supply chain. Copacino (1997) speaks of seven principles of supply chain management. The seven principles are as the following:

1. Begin with the customers by understanding the customers' needs and requirements.
2. Manage logistic assets across the whole supply chain, not just the organization.
3. Organize customer management by aligning suppliers' fulfillment processes with customers' buying processes.
4. Integrate sales and operations planning as the fundamentals of a highly responsive supply chain.
5. Leverage manufacturing and sourcing for flexible and efficient operations.
6. Focus on strategic alliance and relationship management across the supply chain.
7. Develop customer-driven performance measures.

These principles are of great importance. The success of the implementation of integrating the cost of quality into the supply chain network design highly depends on how well the supply chain nodes share information and logistic assets. Operational costs could be shared across the supply chain if a strong strategic management of the supply chain is present. While this thesis is concerned with the supply chain network design, the understanding of the concept of supply chain management is vital. Further, supply chain network design could be expressed as part of the overall scope of SCM.

1.1.3 Supply Chain Network Design

The network design of a supply chain aims at identifying and coordinating key suppliers, manufacturers, distributors, and retailers to maximize its profits. Among many suppliers, many manufacturing plants, many distributors, and many retailers, one can optimize the supply chain network to achieve the best cost effective network of suppliers, manufacturers, distributors, and retailers, while still satisfying business constraints. A Supply Chain Network Design (SCND) is a modeling module that aims at optimizing an organization's resources; one of the ways this is done is through the minimization of the overall cost of the supply chain's operations. The cost is minimized by evaluating different combination scenarios of facility functions (i.e. suppliers, manufacturers, distribution centers, and retailers), and different processes decisions within a supply chain.

Why is it so important to design the supply chain network? The recent paradigm shift to the integrated supply chain, the ultimate success of a firm may depend on its ability to link supply chain members seamlessly. These members include manufacturers, distributors, customers, or suppliers (Min and Zhou 2002). Marbert and Venkataramanan (1998) commented on the Supply Chain Design as an important phase in establishing the overall configuration of the chain by looking into the future two to five years, determining the number of facilities, distribution center (DC) locations, transportation modes, product design, vendor support, and many other factors.

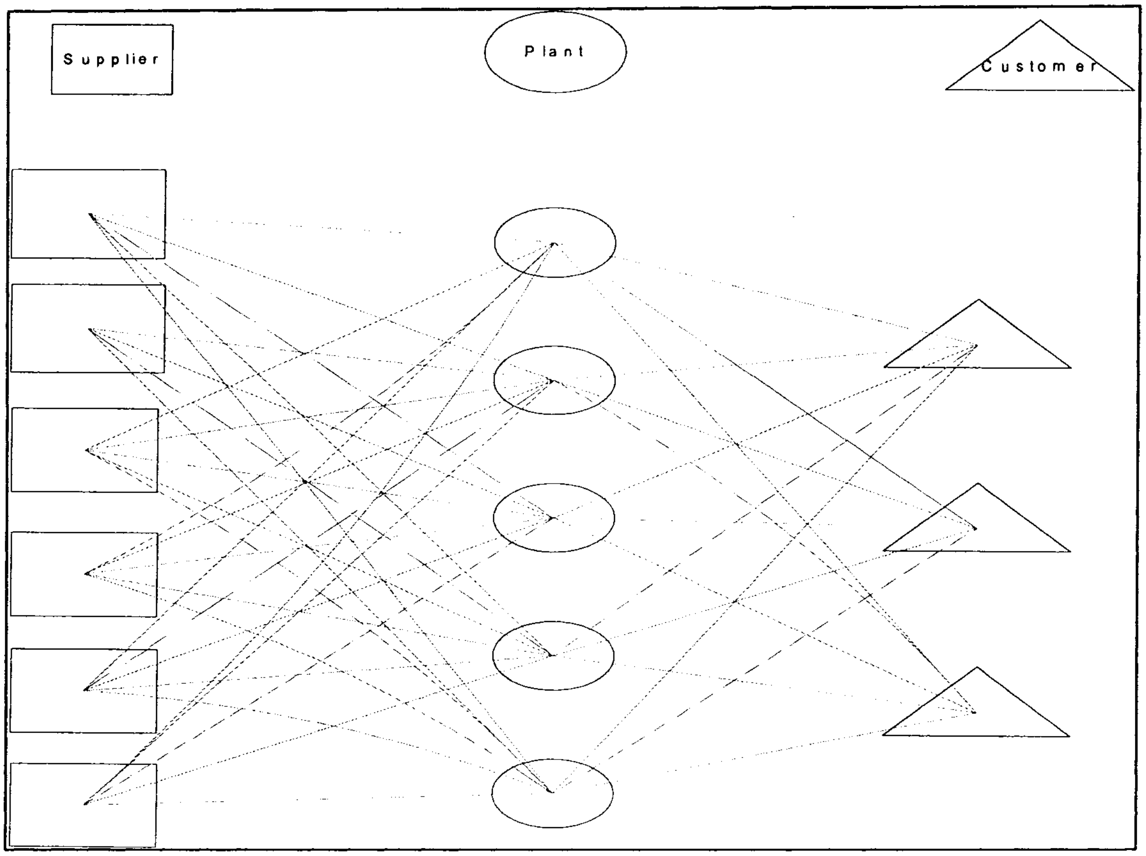


Figure 1.2: Three echelon supply chain network

This work builds on the fundamentals of SCND and integrates cost of quality into the overall supply chain design along with other operational costs within the supply chain. At first, this study models a three echelon supply chain consisting of suppliers, plants, and customers (figure 1.2). Later, the work models a real life supply chain where the supply chain echelons are entwined. In both cases, this work designs a network that minimizes operational costs along with the cost of quality.

1.1.4 Cost of Quality (COQ)

The quality of the products being produced at facilities with in the supply chain is of great importance. If parts procured at the supply chain nodes are not up to the quality standards required, then additional time and cost are incurred in correcting this. Building on this, quality impacts on cost and the responsiveness of the supply chain and hence quality is an important factor in supply chain network design.

> "*Quality is an important factor in the value-adding process involved in the production and delivery of products along the supply chain. The production of defect-free components and parts that meet the requirements of customers along the supply chain is critical for the quality of the final products. Sustaining quality efforts throughout the chain also has significant implications for reducing costs.*" (Forker et al. 1997).

A quality cost is defined as the expenditure incurred by the producer, by the user and by the community, associated with product or service quality (BS 4778 1991); and a quality-related cost is defined as the expenditure incurred in defect prevention and appraisal activities plus the losses due to internal and external failure (BS 4778 1991). By another definition, quality-related costs are defined as those costs incurred in ensuring and assuring satisfactory quality as well as the losses incurred when satisfactory quality is not achieved (BS EN ISO 1995).

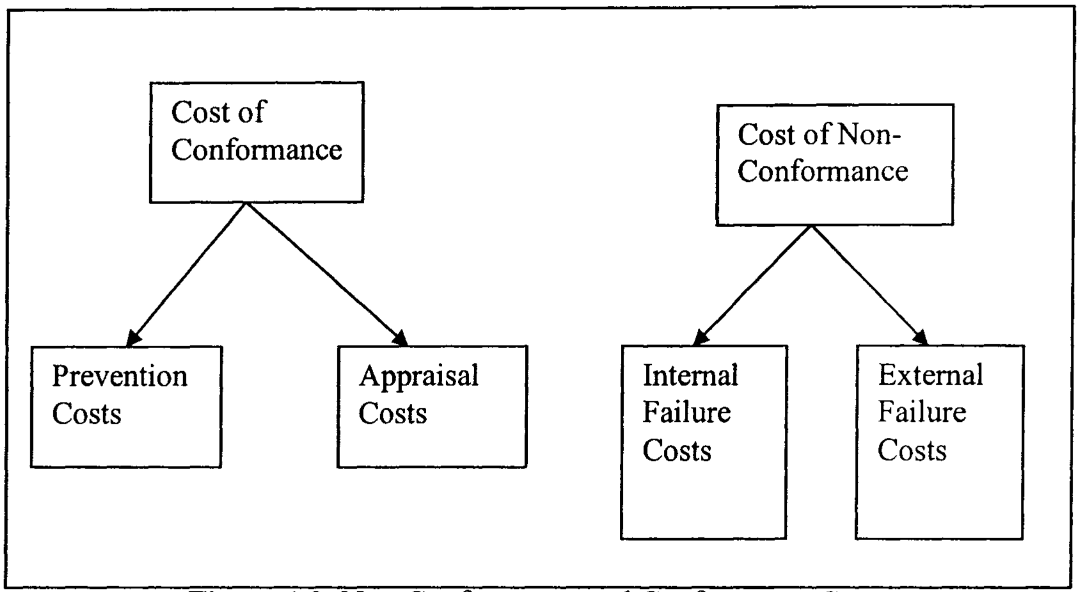


Figure 1.3: Non-Conformance and Conformance Costs

Quality costs are categorized into prevention, appraisal, and failure costs. Prevention and appraisal costs are costs incurred to insure conformance. Failure costs are costs incurred due to nonconformance (figure 1.3). In more details, quality costs are categorized and defined as the following (Campanella 1999).

- Prevention Costs: The costs of all activities specifically designed to prevent poor quality in products or services. Examples are the costs of new product reviews, quality planning, supplier capability surveys, process capability evaluations, quality improvement team meetings, quality improvement projects, quality education and training.
- Appraisal Costs: The costs associated with measuring, evaluating or auditing products or services to assure conformance to quality standards and performance requirement. These include the costs of incoming and source inspection/test of purchased material; in-process, ore service audits; calibration of measuring and test equipment; and the cost of associated supplies and materials.

- Failure Costs: The cost resulting from products or services not conforming to requirement or customer/user needs. Failure costs are divided into internal and external failure cost categories
    - Internal Failure Costs: Failure costs occurring prior to delivery or shipment of the product, or the furnishing of a service, to the customer. Examples are the costs of scrap, rework, re-inspection, retesting, material review, and down grading.
    - External Failure Costs: Failure costs occurring after delivery or shipment of the product, and during or after furnishing of a service, to the customer. Examples are the costs of processing customer complaints, customer returns, warranty claims, and product recalls.
- Total Quality Costs: The sum of the above costs. It represents the difference between the actual cost of a product or service and what the reduced cost would be if there were no possibility of substandard service, failure of products, or defects in their manufacture.

Alternatively, the cost of quality for an organization can be defined as any cost incurred due to either bad quality or efforts to ensure good quality. More specifically, COQ is the sum of four generally agreed upon categories: prevention, appraisal, internal failure, and external failure. The first two represent discretionary or control costs and the last two categories reflect consequential or failure costs (Gupta and Campbell 1995).

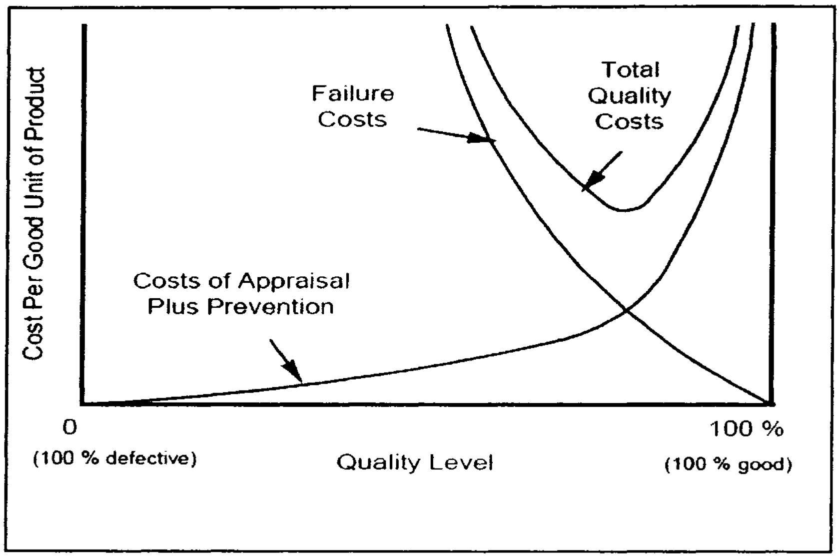


Figure 1.4: Juran's model of optimum quality costs

The effect of prevention and appraisal on failure is presented in figure 1.4, which is suggested by Juran (1979). One can observe that as the quality level rises, failure costs decline while appraisal plus prevention costs increase. Hence, an optimum quality level exists, and the tradeoff of improving quality level beyond optimal will increase the total cost, thus decrease financial gains. In a more classical view, a pursuit to a zero defects objective is economically not viable. As one can see, to reach a 100 % conformance (zero defects), the increase of costs of prevention plus appraisal is non-bounded, thus impossible to achieve. In other terms, zero defects cannot be achieved and if achieved it would be at an enormous cost.

A more modern view of COQ speaks of zero defect approach, which aims at bringing percent of defectives, y, to almost zero. For the purpose of this research, percent of defectives, y, is the portion of defective products in a given lot of products. While the modern `Zero Defect' approach to quality control does not encourage trade-offs in quality level, economic trade-offs do exist throughout industry and the assessment of quality economics can be beneficial in many instances (De Ruyter et al. 2002).

1.2 Motivation, Contribution and Thesis Structure

1.2.1 Motivation

The integration of COQ is critical especially in situations where suppliers are scarce; it is important to separate the quality cost of suppliers or subcontractors from the direct cost of the product so that the non-quality costs can be monitored over time and quality be improved while minimizing costs. One example is the case in the aerospace industry where an engine manufacturer has a limited pool of qualified suppliers or subcontractors. The latter are relatively small in size as the volume of engines produced is quite low. When introducing a new engine, the manufacturer must coach and train the suppliers and subcontractors to manufacture and assemble parts using the right technology. They will monitor the suppliers' production process to ensure that capacity as well as quality issues are being considered and addressed. The suppliers must have their production process validated and put in place an accredited quality program. The engine manufacturer will sometime choose a supplier with a higher cost knowing that this supplier has an advantageous COQ structure and hence better quality. Thus, the manufacturer would gain in having a model that explicitly considers COQ in choosing the suppliers. In other domains, managers are still interested in knowing the proportion of the operational cost that is due to preventive or corrective measures. When implementing the integration of COQ into SCND, supply chain nodes (i.e., production facilities) that provide good quality products with low COQ are favored, and hence are chosen in the optimal network design.

1.2.2 Contribution

This work makes a significant addition to the supply chain research. The contribution of the work is highlighted by the integration of Cost of Quality (COQ) into Supply Chain Network Design (SCND). COQ is integrated in a form of quadratic functions that simulate the convex function, which dictates the behavior of COQ, presented by Juran (1989) (see figure 1.4). The convex functions are function of the percent of defectives, y, and y is also a decision variable in the objective function of the mathematical programming model. Consequently, the integration of COQ function produces a nonlinear model. Hence, another contribution of this research is the formulation of a methodology that solves the nonlinear model. The methodology is based on a gradient search method and takes advantage of the convexity of the model. To validate the model with a real life case, data is obtained from a leading company in the Aerospace industry. The data includes assigned costs and hence binary variables are consequently required. To deal with this practicality, binary variables are incorporated in the model. Further, the company's Bill of Material (BOM) is an n level BOM and the model would also need to be revised to cater for an n level BOM. The result is a binary nonlinear model that serves a n BOM levels. Seven solution procedures are introduced to solve the problem, one of which is a hybrid solution procedure designed to solve the model effectively. The seven solution procedures are compared on two criteria, which are: accuracy and computational expense. The hybrid solution procedure takes advantage of the topography of the problem and it contributes to the literature by the novelty of coupling k-opt and 1-opt solution procedures. The hybrid solution procedure achieves accuracy and lesser computational intensity. Alternatively, the contribution is highlighted in figure 1.5; the initial contribution is that of the incorporation of COQ into SCND resulting in a nonlinear model. Then, convexity of the model is proved and a gradient search method is utilized to successfully solve the model. Afterward, the model is revised to account for an *n* level BOM and binary variables are incorporated to allow for the possibility of assignable based costs at all the different supply chain nodes; the result is a binary nonlinear model. Consequently, the seven solution procedures are used to solve the model and one of these solution procedures is especially designed to cater to the special characteristics of the model.

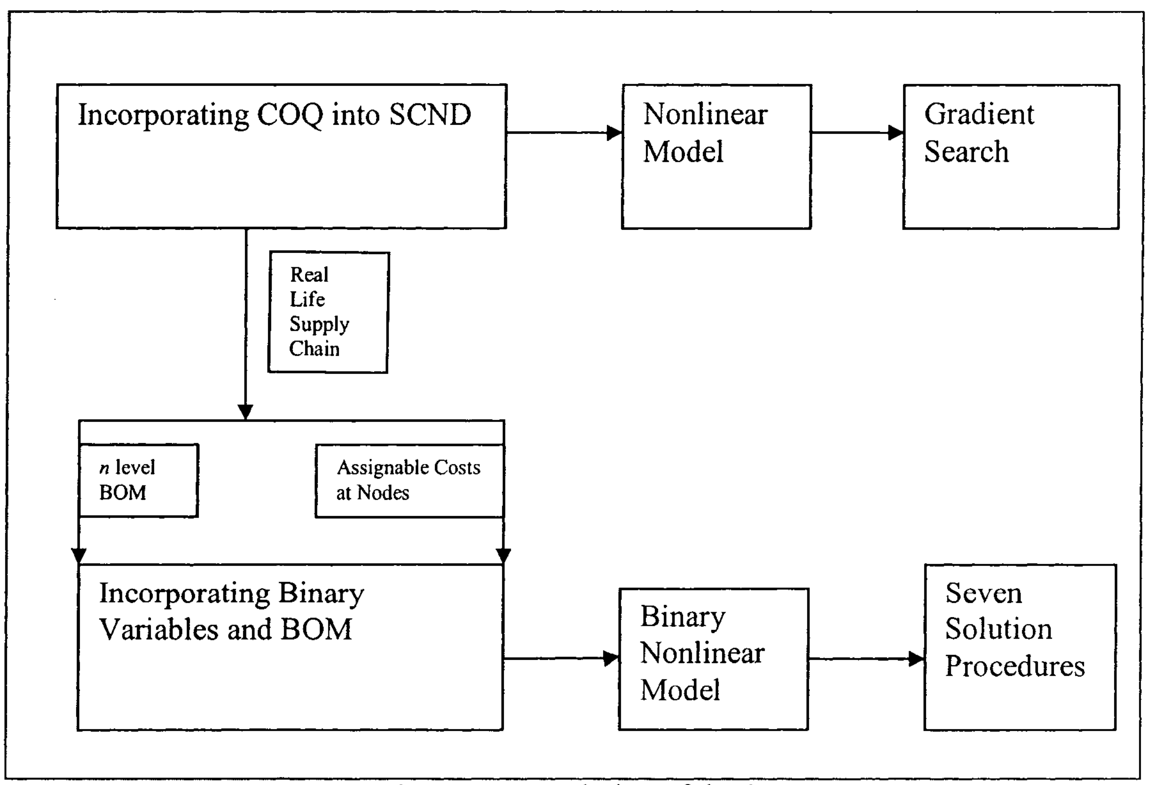


Figure 1.5: Evolution of thesis

1.2.3 Thesis Structure

The thesis is structured in a manner as to underscore the important steps in its evolution (figure 1.6). First, the motivation of the thesis is emphasized in Chapter 2. The first section of Chapter 2 goes into in-depth analysis of the concept of the supply chain; and then the practical implications and applicability of this work is discussed. The modeling of the supply chain within the framework of this thesis applies to vertically integrated supply chains where the ownership of, all supply chain entities, all network's nodes, belong to one organization. However, Chapter 2 stresses that the applicability could be expanded to supply chains where the ownership does not belong to one party. The first section of the chapter comments on the recent trends of the supply chains. It also comments on the move towards stronger relationships with the suppliers and the sharing of information among all the supply chain facilities which makes a holistic approach to supply chain network design very possible. Thus recently, information is shared between suppliers and producers. Furthermore, when the real case supply chain case is contested, costs of production at the vendors are available to the organization, owner of the final product supplied to the client. In summary, Chapter 2 reasons that the model proposed in this thesis could be also used for non-vertically integrated organizations as long as their partners are well integrated in the context of the supply chain. Moving forward, Chapter 2 presents a literature review on supply chain modeling and the state of the art in that discipline. Constructing on that, an elaboration is made on the presence of quality consideration in the supply chain and the novelty of the idea of integrating COQ into SCND.

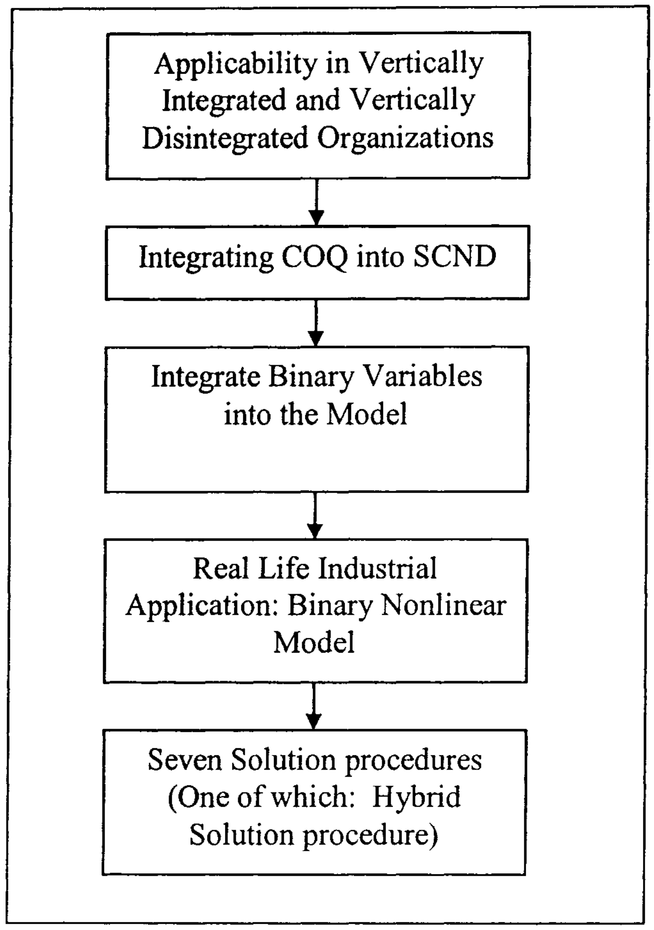


Figure 1.6: Structure of thesis

Chapter 3 presents the model and explains it thoroughly. Chapter 3 also elaborates on the challenges arising in the model. Assertions are made on the nonlinearities in the objective function. In a later section within the chapter, the convexity of the model is evaluated and then proved; also an illustration is made in regard to the significance of convexity in the later development of a solution methodology. Following, a gradient methodology is introduced to solve the model effectively. A lower bound is introduced and the results fall within less than 1% of the lower bound. A comparison between a model with COQ integrated and one with out is then presented; the purpose of this is to show the significant contribution of integrating

COQ. Chapter 4 assesses the importance of having binary variables to quantify the opening and closing of facilities and also assignable based costs. Binary variable are then integrated into the model and the model in turn is revised. The solution methodology presented in Chapter 4 is a genetic based solution procedure. The solution procedure is used to solve the model with the results shown and discussed. Chapter 5 introduces a real-life supply chain network. The model is then revised to account for an *n* level Bill of Materials (BOM). Later in the chapter, six more solution procedures are introduced with four of them being local search solution procedures. The fifth solution procedure is a simulated annealing-based solution procedure and the sixth solution procedure is a hybrid solution procedure that is formulated with special attention to the topography of the model. All seven solution procedures are assessed and reviewed in the chapter. A lower bound is also constructed and all seven solution procedures are contrasted against the lower bound. The chapter ends with a remark on the contribution of the hybrid solution procedure. The last piece of the thesis is the conclusion which summarizes the work and discusses the possibility of further research.

Chapter 2

Scope of Research and Literature Review

2.1 Scope of Research

In this section the evolution of the supply chain is discussed with real insight into the functionality of the supply chain. Also, the motivation of this research is conferred.

2.1.1 Evolution of the Supply Chain

In the early decades of the 20^{th} century, companies ran almost all production operations within its facilities. For example, FORD made everything from the steel that goes into the car to the cotton used in the car's interior. This is not the case any longer, as companies have been going through a process of vertical disintegration. Vertical disintegration is the externalization of specified activities performed in production while vertical integration is the internalization of all operational activities.

The mid-1970's to present time period was highlighted by continuous process technology, spread of flexible manufacturing systems, influence of Japanese style management, increase in network structures, and dynamic environment (Desai and Mukherji 2001). Humphreys et al. (2005) point out that during the past fifteen years there has been a significant trend for firms and public organizations to externalize a wide range of functions that formerly might have been carried out in-house. On the same note, Prahalad and Harnel (1990) mention that in recent years, there has been a shift in manufacturing companies away from vertical integration toward smaller, leaner operations (Prahalad and Harnel 1990; Piercy et al. 1997). Organizations have downsized, focused on core competencies, and attempted to achieve competitive advantage by leveraging their suppliers' capabilities and technologies (Kannan and Tan 2002). By exploiting suppliers' capabilities, improvements in product quality, quicker integration of technological breakthroughs, and shorter new product development leadtimes are the expected outcomes (Ragatz et al. 1997).

While vertical disintegration has been the highlight of the new generation of corporate structuring, the activities which are now disintegrated still require monitoring. In simpler terms, all the value-added and non-value added activities still need to be monitored even when done elsewhere within the supply chain. Hence, the concept of integrating the supply chain and building stronger relations with suppliers comes about.

In the implementation of integrating quality costs into the supply chain, operational costs at all entities within the supply chain need to be procured. With the trend of stronger relationships between suppliers and producers in sight, managers have access to suppliers' production data and products' quality characteristics. This data can be used to build a network that includes suppliers, manufactures, and distributors. This network will have the costs incurred at the suppliers along with costs of production elsewhere. Cost of Quality (COQ) is a cost indicator that infers the amount an organization incurs to insure good quality products and also incurs if products do not meet good quality specifications. As parts are procured from the suppliers, it would be very productive to know the COQ of those parts in order to infer the amount a firm spends on quality non-conformance. In knowing the cost of quality, managers would be able to distinguish the difference between the actual cost of production and the reduced cost if there were no possibility of a substandard quality level. This work asserts the idea of integrating COQ as a decision parameter within the supply chain. In the case where the supply chain is integrated, costs are obtained for all the supply chain nodes. In lesser integrated supply chain networks, the concept of supply chain integration would be of assistance as it targets the coordination of processes within the supply chain. Correspondingly, the literature review supports the idea that supply chain integration becomes an extension to the vertical integration concept as will be discussed in section 2.1.2. Through stronger suppliers' evaluations and supply chain integration one ends up with a vertically integrated supply chain where procuring operational costs from all the supply chain nodes is attainable. Thus, the applicability of integrating COQ into SCND is extended also to vertically disintegrated organizations.

2.1.2 Vertical Disintegration and Supply Chain Integration

Before, it was common to run all operations concerned with a specific product in-house. Currently, companies are disintegrating some of their business and acquiring needed functions from external suppliers. An important advantage of vertical disintegration is flexibility. Vertical disintegration is advantageous in responding quickly to new product development opportunities that require a novel set of technical capabilities. Risk associated with uncertainties in the future could be better dealt with in organizations that are less vertically integrated; risk would be shared between the organization and other partners while in vertical organizations the risk remains the burden of the organization. As advantages are numerous to vertical disintegration, disadvantageous are also evident. Organizations that are vertically disintegrated do not have strong control over quality and delivery of products. Also shortages and other production miscalculations are difficult to prevent in vertically disintegrated organizations. Furthermore, information pertaining to actual cost of production at the suppliers is no longer available or is difficult to attain.

Given the advantages and disadvantages of vertical disintegration, one could build-on both phenomena to arrive at a comprehensive model. To remedy the disadvantages of vertical disintegration while still maintaining the advantages of vertical integration, one could initialize a model that bases itself on stronger relationships with the suppliers and better integrates the supply chain. At first, the formation of stronger and longer relationships with suppliers would insure collaboration among supply chain entities and pave the way for this model. Later, the concept of using COQ as a parameter in supply chain management would be introduced. Further, one could integrate COQ into the supply chain to formulate an operational network and to enable analysis and clearer observations of all activities with in the supply chain.

2.1.2.1 Strong Relations with the Suppliers

It is widely accepted that in order to compete and survive, firms must seek, build up and maintain relationships with capable suppliers and extract the maximum value through such relationships (Carr and Pearson 1999; Dyer J.H. 1996). Bullington K. and Bullington F. (2005) stress that many writers (Deming 1986; Hanan 1986; Bhote 1989; Poirier and Houser 1993; Dixon and Porter 1994; Dobler and Burt 1996; Dyer 1996;

Rackham et al. 1996; Simchi-Levi et al. 2000; Wagner et al. 2002; McHugh et al. 2003) have praised the concept of long-term customer-supplier relationships.

Deming (1986) emphasizes the importance of long term relationships with single sources suppliers in the discussion of his fourth principle for management: "end the practice of awarding business based on price alone." With external spent accounting for up to sixty to seventy percent of companies' external budgets in many industries (Heberling et al. 1992), firms have to work through suppliers to facilitate and realize significant cost savings and can no longer limit such efforts to their firm's boundaries. The performance demonstrated by the supplier on a day-to-day basis is influential (Tan et al. 1998). Firms can face a variety of problems such as suppliers failing to provide demanded products, supplier not performing up to expectations, and quality of firm's supplier base not being competitive. Companies have adopted approaches to deal with these problems such as supplier switching (i.e., searching for alternative sources of supply and sourcing the product from a more capable supplier), vertical integration, and supplier development (i.e., supporting the supplier in enhancing the performance of their products and services or improving the supplier's capabilities). The third option is becoming the most effective as the option of supplier switching might not be viable due to high switching cost and the second requires substantial investment (Wanger 2006). Supplier development incites closer work with suppliers to provide good quality products to the end customer. To achieve this, supplier evaluations have been heavily used; in those, the suppliers are evaluated at criteria of interest to the producers.

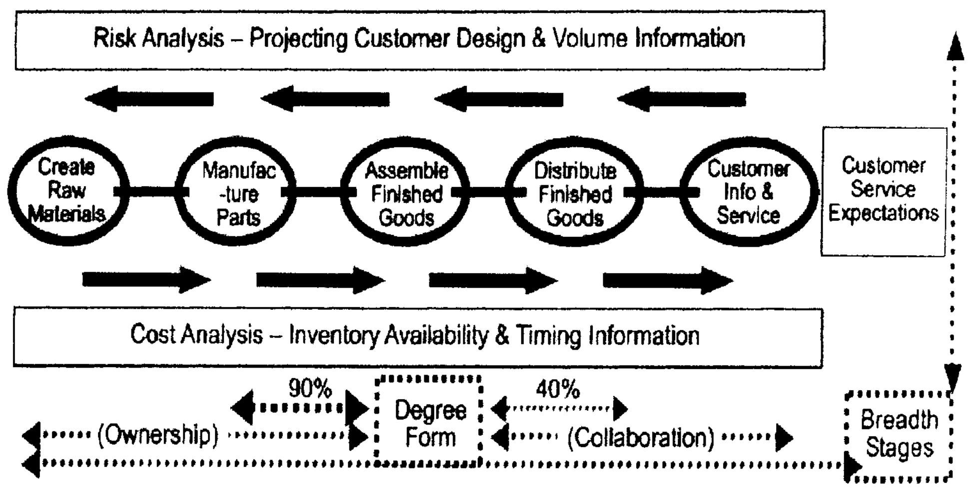
Firms now expect suppliers to attain and maintain established standards of product quality, service, distribution, promotion, and partnering. In 2002, Simpson et al.

examined criteria on which suppliers were evaluated. Criteria such as quality and process control, continuous improvement, facility environment, customer relationship, delivery, inventory and warehousing, ordering, financial conditions were on top of the list of categories for supplier characteristics included in the evaluation. Further their results suggest that quality, physical distribution, and relational factors are key considerations in the supplier evaluation process (Simpson et al. 2002). With comprehensive supplier evaluations, information pertaining to operational attributes including production cost and COQ can be fetched. Operational costs and COQ at the suppliers are great indicators of operational efficiency. Evaluating suppliers using operational cost values would reduce rework cost and production cost per unit in the log term. Since organizations' quality performance depends on the weakest link of its supply chain partners, COQ and operational costs should be looked into insightfully and suppliers should be evaluated accordingly. However, in order for operational information to be obtained, the supply chain needs to be integrated.

2.1.2.2 Integrating the Supply Chain

Various supply chain integration aspects have been studied by many researchers in the past. Lummus et al. (1998) state that the increase in global competition had made supply chain efficiencies surface and be more evident to management. Also the increase in specialization of products and processes has generated an inefficient or disintegrating effect, which must be counterbalanced by greater integration (Lummus et al. 1998). Stonebraker and Liao (2006) argue that the development of the integrated supply chain is the most significant contribution to the delivery of goods and services in the past decade. Supply chain management has been a major source of competitive advantage in the USA and, increasingly in the global economy. Their work pursued the notion that supply chain integration is an extension and application of vertical integration theory; it models the variable of an integrated manufacturing and distribution supply chain (Stonebraker and Liao 2006).

Integrating the supply chain could be thought of as the coordination and integration of processes within the supply chain. The development of the integrated supply chain comes about from the economic theory of vertical integration (Harrigan 1985). Stonebraker and Liao (2006) pursue the notion that supply chain integration is an extension and application of vertical integration theory; it models the variables of an integrated manufacturing and distribution supply chain. Hence if an organization is not vertically integrated, one can reap the benefits of vertical integration by integrating the supply chain. In figure 2.1, Harrigan (1985) illustrate an integrated supply chain with the platform of vertical integration overlaid. The figure draws the parallel between both phenomenon of vertical integration and integrating the supply chain. The supply chain once integrated looks very similar to a vertically integrated organization.



Note: The four Harrigan (1985) dimensions of stages, breadth, degree and form are superimposed in dotted lines

Figure 2.1: A parallel between vertical integration and integrating the supply chain (Harrigan 1985).

Integrating the supply chain aims at building closer collaboration between all the different supply chain nodes (i.e. facilities). This type of collaboration is needed for the procurement of cost data and other information pertaining to supply chain network design. In doing so, the supply chain would resemble a vertically integrated organization.

2.1.3 Integration of COQ

The procurement of operational cost data, and specifically COQ data, could be achieved in vertically integrated supply chains. When an organization owns all the supply chain entities, the procurement of any data is achievable; hence, the procurement of COQ data at different nodes within the supply can be done. Alternatively, for supply chains that are not vertically integrated, the task might prove to be challenging. But given the evolution of stronger supplier relationships and consequently the evolution of supply chain integration, the task becomes simplified.

Through stronger collaboration with external suppliers, COQ data can be attained. In a similar manner, production costs can be attained. It has been noted in the literature review (2.1.2) that supply chain integration would simulate a vertically integrated network and hence the acquiring of cost data would be achievable. Both COQ and production costs compliment each other as they give a complete picture of operational activities; a clear picture that gives insight into which costs are value added and which ones are not. Further, when combining both figures, managers would have a better knowledge of the value added activity costs in comparison to the total production costs. Certain suppliers could be running operations at a low production cost, and in turn selling at a lower price, but yet incurring a high COQ. The high COQ could be due to high failure costs. These suppliers could be spending a lot of resources on rework and repair-costs; costs that do not add any value to the product. Hence, sourcing work to these suppliers might not be advisable in the long run. Such conclusions could only be drawn if both COQ and operational costs are analyzed.

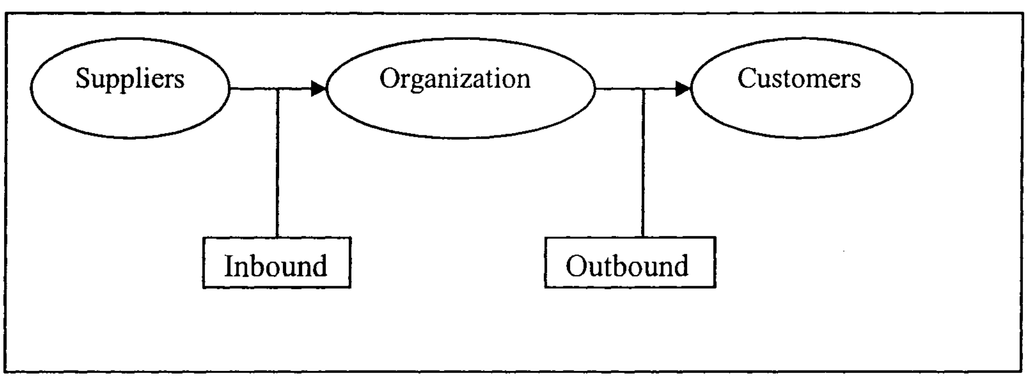


Figure 2.2: Supply chain scenario 1.

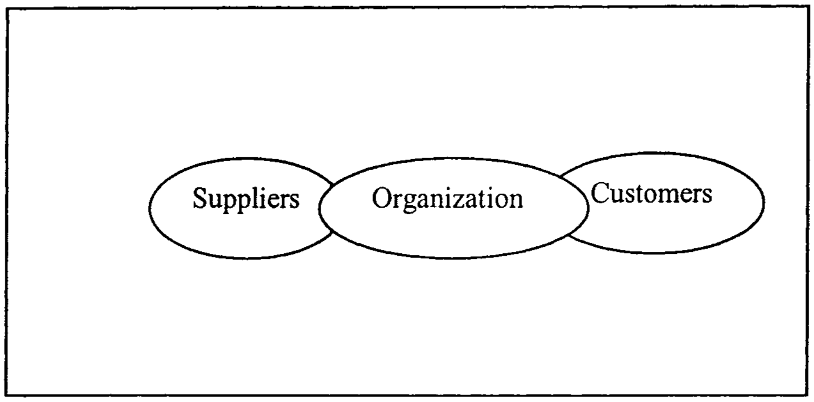


Figure 2.3: Supply chain scenario 2.

The case for better integrating the supply chain is illustrated in figure 2.2 and 2.3. In figure 2.2 and 2.3, the contrast between two different scenarios, one with traditional non-integrated supply chain and one with integration, is evident. In figure 2.2, the organization becomes the system, where suppliers and customers are effectively external to the system. Only information pertaining to procurement is transferred from suppliers to the organization as an inbound information flow, all other information is non-visible to the organization. The second scenario illustrated in figure 2.3, the suppliers and the organization become an integrated system and all information is interchanged. Correspondingly through stronger relationships with the suppliers, supplier evaluations and integration of the supply chain, scenario 2, the integrated model, can be achieved. Once this model is achieved, the road would be paved for the integration of COQ into SCND and the model can be implemented through designing the supply chain network to include COQ and operational costs.

A primary concept of reporting COQ is to infer what proportion of quality cost is allocated to prevent nonconformance and what portion is a result of nonconformance.

As mentioned before failure costs are due to nonconformities that already have occurred and preventive and appraisal costs are costs incurred to prevent nonconformities from happening in the first place. From the Juran's graph, figure 1.4, of COQ against percent of defectives, one can infer an optimal COQ. Percent of defective has also a bearing on production, as you eventually have to remedy defective products by rework or replacement resulting in additional costs. Hence, managers would realize an optimal quality cost figure that reduces defectives and in turn reduces COQ.

While supply chain network design problems have been addressed before by a number of researchers on the basis of operation costs, the idea of incorporating the cost of quality into the network design is lacking in research. Knowing that most supply chain models employ some form of a cost variable, it is advantageous if one can find a cost indicator for quality which can be incorporated into the supply chain modeling. With stronger relationships with suppliers, managers are able to obtain operational cost data, including COQ. Given a supply chain with COQ integrated into it, managers can asses the corresponding weights of important operational parameters such as quality and production cost. In this case production costs even at external suppliers are of interest as these costs explicate the component of value added activities to those which are non-value adding. Managers can reward suppliers spending more money on value-adding activities and not on corrective action. COQ and production cost are complimentary as they reveal waste and other non-value added activities. Hence, by integrating both costs into the supply chain, managers would have more insight into supply chain operations. In the subsequent sections, the SCND literature is reviewed. Many of the literature surveys within SCND literature suggest that no work to this date had sought the integration of

COQ into the supply chain network design as will be discussed in the next section, and since COQ is a cost indicator and can be integrated into the supply chain, a mathematical model is developed and presented in the Chapter 3.

2.2 Literature Review

A supply chain network design model aims at determining the location of production, stocking, and sourcing facilities, and paths, which the product(s) take. Such models are of large scale and require strong computational power (Min and Zhou 2002). The earliest work in this area was by Geoffrion and Graves and can be traced back to 1974. They introduce a multi-commodity logistics network design model for optimizing the flow of finished products from plants to distribution centers. Crainic and Rousseau (1986) discuss the subject of network design in freight transportation. They present a review of service network design modeling efforts and mathematical programming development for network design. They reflect on the complexity of transportation systems involving many human and material resources and which display intricate relationships and tradeoffs among the various decisions and management policies affecting their different components. They further present network design models and discuss heuristics used to obtain solutions of good quality. A number of heuristics aim to avoid mathematical programming techniques for the mixed-integer formulation but are not very successful for the capacitated models. Alternatively, the model presented in this work is capacitated.

Later, Breitman and Lucas (1987) present comprehensive models of a production-distribution system. The system they provided was named PLANETS. PLANETS is a framework that decides what products to produce, where and how to produce these products, and which market to target with these products. PLANETS was an ambitious system which modeled almost the whole scope of the supply chain. Some parts of their project were implemented successfully at General Motors. Camm et al. (1997) present a model analyzing Procter & Gamble's (P&G) supply chain. Their work seeks improving the efficiency of all work processes and eliminating non-value added costs at P&G. The developed methodology involves mathematical modeling. More specifically, they developed a model, which lumps integer programming, network optimization, and geographical information system (GIS) together. The modeling strategy decomposed the overall supply-chain problem into two easily solvable sub-problems: a distribution-location problem and a product-sourcing problem. In the first problem, distribution location attributes were determined and then inputted into the production sourcing problem for results (Camm et al. 1997).

As a general look at papers published with regards to supply chain modeling, Beamon presents his 1998 review of the literature of supply chain modeling. He classifies supply chain models into four categories:

- Analytical Deterministic Models
- Analytical Stochastic Models
- Economic Models
- Simulation Models

For the analytical models, Beamon notes the works of Cohen and Lee (1989), Newhart et al. (1993), Arntzen et al. (1995), Voudouris (1996), and Camm et al. (1997). For the stochastic models, he notes the works of Cohen and Lee (1988), Svoronos and Zipkin (1991), Lee and Billington (1993), and Pyke and Cohen (1993). Beamon highlights the works of Christy and Grout (1994), for the economic models and Towill (1991) for the simulation models.

Pivotal to the modeling approach of this thesis two works are explored. Arntzen et al. (1995) provide a deterministic model for supply chain network design. The model went as far as considering duty and, more specifically, options for avoiding drawback duty charges. In their paper, the objective function minimizes a combination of cost and time elements. The function minimizes such cost elements as purchasing, manufacturing, pipeline inventory, transportation between different plants or sites, and duty costs. The time elements in the objective functions are manufacturing lead and transit times. Implementation of this models resulted in magnificent savings at Digital Equipment Corporation as the paper claims. Secondly, Vidal and Goetschalckx (2000) develop a Mixed Integer Programming model (MIP) that models a Global Logistic System (GLS). The model attempts to include supplier reliability in the design. Supplier reliability is modeled using historic data to estimate the probability that a supplier will send shipments on time. They also study the effect of exchange rates, changes in demand, and international transportation lead times, on the model.

Reviews are numerous in the domain of supply chain modeling. Goetschalckx et al. (2002) present a review of integrated strategic and tactical models and design algorithms. They comment on the history of tactical models (Geoffrion and Graves 1974;

Geoffrion et al. 1978, 1982; Cohen and Lee 1985; Brown et al. 1987; Cohen and Moon 1991; Goetschalckx et al. 1994; Cole 1995). As time went, the models became more sophisticated. They mention Cohen et al. (1989) model which presented many feature, in an international supply chain model, such as duties, tariffs, and differential tax rates among countries, random fluctuation of currency exchange rates, and the existence of constraints not included in single-country models, such as local content rules. The inclusion of these factors made the model more tangible to real life situations. As a result of these inclusions, Cohen et al. (1989) present a preliminary formulation of a normative model that is a dynamic, nonlinear mixed integer programming (MIP) formulation. In the area of quadratic models, Goetschalckx et al. (2002) comment on a model presented by Hodder and Dincer (1986). Hodder and Dincer present a mixed integer quadratic programming model that combines plant location variables and product flow variables with financial variables. In the formulation, random variables are included in the objective function. These variables represent the sale price of products and the fixed costs at plants; the variables are solved using approximation procedures. The review continues to mention the work of Cohen and Kleindorfer (1993). Cohen and Kleindorfer's work describes a normative model for the operations of a global organization that includes decisions of location, capacity, product mix, material flow, and cash flow. Also the work of Huchzermeier and Cohen (1996) is highlighted as they develop a stochastic dynamic programming formulation to analyze global manufacturing strategies. The review concludes by commenting on the benefits of distribution system as illustrated by Geoffrion and Powers (1995). Geoffrion and Powers report typical cost reductions range from 5% to 15% in a historical perspective on strategic distribution systems design.

The modeling approach in supply chain network design shares some relevance with facility location problems. Klose and Drexl (2003) summarize continuous location models, network location models, mixed-integer programming models, and applications. They state that location-allocation models cover formulation which range in complexity from simple linear, single-stage, single-product, un-capacitated, deterministic models to non-linear probability models. Algorithms include local search and other mathematical programming based approaches. They segment their review into continuous location models, network location models, and mixed-integer programming models. In their work they commented on the following models:

- Un-capacitated, single-stage models
- Capacitated, single stage models
- Multi-stage models
- Multi-product models
- Dynamic models
- Probabilistic models
- Hub location models
- Routing location models
- Multi-objective location models

For each of the above categories, Klose and Drexl (2003) illustrate a mathematical modeling notation. The notation includes the objective function and its corresponding constraints and a generic model is conceived for each of the categories. Since the topic of this thesis is mainly concerned with the mixed-integer programming segment, focus is placed on this segment.

Further they illustrate a mathematical generic modeling notation. The notation includes the objective function and its corresponding constraints. In their review, a similar pattern of modeling supply chain networks using mathematical programming could be observed; however it is quite evident that there is a gap in literature for quality consideration in facility location problems. More importantly their review did not mention any attempt to integrate some form of quality nonconformance cost that would measure an important aspect of customer dissatisfaction.

Wang et al. (2005) stress that most of the published work has focused on high level strategic aspects of the supply chain and resulted in generic guidelines for business executives rather than specific tools for plant managers. The paper presents a methodology that a plant manager can use to select suppliers based on the type of outsourced components. Decisions are made based on supply chain operations reference Supply Chain Operation Reference (SCOR). The analytical hierarchy process (AHP) is used as the decision making mechanism. Qualitative aspects of the decision are addressed using AHP. Due to the presence of not only qualitative but also quantitative aspects of a decision making process, the paper integrates preemptive goal programming with AHP to handle the problem.

Sachan and Datta (2005) examine the state of logistics and supply chain management research in 442 papers published from 1999 to 2003 in three primary journals in logistics. They assess the state of art of research by examining the research design, number of hypothesis testing, research methods, data analysis techniques, data sources, level of analysis and country of authors. In their work, they also compare new trends with old ones. The current research has failed to look at that perspective of the Supply Chain Management (SCM) which has the objective of integrating all the firms in the value chain and treat them as a single entity. They also stress that major problems targeted in research were inventory management, network optimization, facility layout and locations and demand forecasting. Recently researchers are tackling problems such as, how functions within a company can be integrated, how companies can coordinate their activities, and the chain of customer service to customer satisfaction to customer value. Hence, future prospects arise in integrating novel elements into the overall supply chain modeling such as factors which assess customer satisfaction. Since COQ measures nonconformance cost which triggers customers' dissatisfaction, it is a novel and relevant factor to integrate.

In recent studies, Jayaraman and Ross (2003) present PLOT, which is a production, logistics, outbound, and transportation design system. The overall system produces near optimal distribution system utilizing simulated annealing. In their work, the objective function minimizes fixed costs to open warehouses and cross-docks, costs to transport products from warehouses to cross-docks and costs to supply products from cross-docks to satisfy the demand of customers. Melo et al. (2005) work focus on the strategic design of supply chain networks. They propose a mathematical framework that captures dynamic planning horizon, generic supply chain network structure, external supply of materials, inventory opportunities for goods, distribution commodities, facility configuration, availability of capital for investments, and storage limitations. Santoso et al. (2005) present a stochastic programming model and solution algorithm for solving supply chain network design problems. They use a methodology of Sample Average Approximation (SAA) scheme with an accelerated bender decomposition algorithm. Their objective function minimizes total investment and operational costs. Amiri (2006) considers the problem of designing a distribution network that involves determining simultaneously the best sites of both plants and warehouses and the best strategy for distributing the product from the plants to the warehouses and from the warehouses to the customers. A common objective in designing such a distribution network is to determine the least cost system design such that the demands of all customers are satisfied without exceeding the capacities of the warehouses and plants. Further, Amiri's study represents a significant improvement over past research by presenting a unified model of the problem that includes the numbers, locations, and capacities of both warehouses and plants as variables to be determined in the model (Amiri 2006). Based on recent work, it is quite important to take into consideration customer satisfaction as it is an important ingredient in designing a supply chain. Cost of Quality has not been integrated so far due to the lack of emphasis on customer satisfaction in the raw physical design of supply chain networks and the difficulty of doing so.

In regard to quality in the supply chain, Roethlein and Ackerson (2004) analyze through a case study, four business entities in a connected supply chain whose final products are life safety systems. They are a large, diversified manufacturing and service company with locations in over 100 countries around the world. This case study has shown how four different entities within a manufacturing supply chain interact with each other. Each entity presented has unique manufacturing, quality and corporate goals. Although the ultimate goal of some entities was customer satisfaction or end-customer satisfaction, this was not constant throughout the chain, and nor were customer preferences identified to all entities. True partnerships did not exist in this connected supply chain. Working relationships and continual business contracts seem to be the norm. Quality goals and objectives were communicated and interpreted differently at the different levels in the supply chain. Fynes et al. (2005) suggest that by developing and engaging in deep partnership types of supply chain relationships, suppliers can improve supply chain performance. This requires frequent communication and cooperation on issues such as product and process design, quality and scheduling, all of which is evidenced by increased adaptation on the part of both buyer and supplier. Despite its importance and implications for supply chains, Sila et al. (2006) mention that Supply Chain Quality Management (SCQM) has not been sufficiently covered in the literature. One of their main findings was that although companies believed that SCQM would have a positive impact on the quality of the final product, they did not fully implement this concept. The results also showed that although companies included their major customers in their quality initiatives, they did not include their major suppliers. Hence, a better system that integrates all entities within the supply chain could improve the implementation of SCQM. Literature concerning quality in the supply chain is scarce and the three authors cited urge more research in this domain. COQ, which is modeled explicitly into SCND in this thesis, is advantageously a quality indicator and also a customer dissatisfaction indicator. However, two challenges arise when modeling COQ in the supply chain. The first is the challenge of the modeling itself; this challenge arises in defining mathematical relationships between COQ and other operational costs. The second challenge arises in the complexity of solving the model due to the nonlinearity nature of the supply chain model resulting from the integration of COQ. These two challenges precluded the integration of a non-conformance quality cost into the supply chain modeling in the past.

In Table 2.1 and 2.2, the literature discussed is categorized and analyzed.

Table 2.1 : Reviewed paper in supply chain modeling: Part I

Author	Type of Paper	Inclusion of a quality cost	Modeling Approach	Solution Methodology
Amiri (2006)	SCND	-	MP	Scatter Search Approach
Arntzen (1995)	SCND	-	MIP	Non Traditional
Beamon (1998)	Review of SCND	-	-	-
Breitman and Lucas (1987)	SCND	-	Mathematical Representation	Not Reported
Camm et al. (1997)	SCND	-	MP	Merging Integer Programming
Crainic and Rousseau (1986)	SCND	-	MIP	Decomposition and column generation
Cohen and Lee (1989)	SCND	-	MP	-
Cohen and Kleindorfer (1993)	SCND	-	Multi-Stochastic Programming	No Procedure is reported
Cohen et al. (1989)	SCND	-	NMIP	Model Simplifications
Fynes et al. (2005)	SC Analysis	-	-	-
Geoffrion and Graves (1974)	SCND	-	MP	Benders decomposition
Geoffrion and Powers (1995)	Historic Review	-	-	-
Goetschalckx et al. (2002)	Review of SCND	-	-	-

Table 2.2 : Reviewed papers in supply chain modeling: Part II.

Author	Type of Paper	Inclusion of a quality cost	Modeling Approach	Solution Methodology
Hodder and Dincer (1986)	SCND	-	MIQP	Approximation Procedure
Huchzermeier and Cohen (1996)	SCND	-	SDP	Option Pricing Methodology
Jayaraman and Ross (2003)	SCND	-	MIP	Simulated Annealing
Klose and Drexl (2003)	SC Models Review	-	-	-
Lee and Billington (1993)	SCND	-	SM	Simple Search Heuristic
Melo et al. (2005)	SCND	-	MIP	Branch and Bound Procedure
Pyke and Cohen (1993)	SCND	-	SM	Approximation Procedure
Roethlein and Ackerson (2004)	SC Analysis	-	-	-
Sachan and Datta (2005)	Review of SCM	-	-	-
Sila et al. (2006)	SC Analysis	-	-	-
Svoronos and Zipkin (1991)	SCND	-	SM	Approximate Method
Towill (1991)	SCND	-	SM	Simulation Model
Vidal and Goetschalckx (2000)	SCND	-	MIP	Commercial Software
Voudouris (1996)	SCND	-	MP	Fixation and Approximation Methods

Table 2.1 and 2.2 illustrate the gap in research for a supply chain network model designed to integrate COQ. Referring to the table, among the entries no work looked into integrating COQ into SCND. Tables 2.1 and 2.2 also illustrate the modeling approach and solution methodology of pivotal papers in SCND. The solution procedure of this work is quite different than those discussed in the table as will be later discussed in subsequent chapters; in addition, the local search procedures used in this work have not be utilized in the supply chain modeling literature. Acronyms and other brief explanatory statements are present in the table and could be explained as follows

- NMIP: Nonlinear Mixed Integer Programming.
- Non Traditional: Non traditional methods including elastic constraints, row factorization, cascaded problem solution, and constraint-branching enumeration.
- MIP: Mixed Integer Programming
- Merging Integer Programming: Merging integer programming, network optimization models, and a geographical information system (GIS).
- MP: Mathematical Programming
- MIQP: Mixed Integer Quadratic Programming
- SDP: Stochastic Dynamic Programming
- SM: Stochastic Model
- Model Simplification: Authors simplify the model by fixing variables. By fixing these variables, the model is transformed into a more tractable linear MIP model.

Based on this review, some ideas could be brought forward. First, one could integrate a form of a quality indicator that would measure the quality performance of the supply chain. While there are many different indicators of quality, COQ has a unique characteristic as it is a cost measurement and thus could be integrated into the SCND along other cost parameters. Second, it is critical that the supply chain subsidiaries perceive similar quality goals and hence run at a similar vision of quality standings and hence alternatively run at optimal quality levels. Third, the modeling of COQ into the supply chain would insure that quality is communicated throughout the supply chain.

An important conclusion that could be drawn from Table 2.1 and 2.2 is that the inclusion of a quality cost parameter is lacking in literature. Furthermore, two primary motivations could be summarized in Chapter 2. The first motivation is the evolution of the integration of the supply chain which insures cooperation of all the supply chain nodes and in turns assures the sharing of operational cost data. The second motivation is the evident lack of models, in research, that integrates a quality cost. This gives a strong platform for the modeling of COQ into SCND which is discussed in Chapter 3.

2.3 Review on Solution Procedures

In this section the solution procedures used in this thesis are commented-on in the context of the supply chain modeling literature. The overall literature is tabulated in Table 2.3.

2.3.1 Gradient Search Methodology

Concerning the use of the gradient search methodology for supply chain sourcing problems, Ettl et al. (2000) develop a supply network model that takes into account the bill of materials, lead times, cost data, and demand information and fetches the best-stock level at each store. In solving the model the gradients are derived in explicit forms and a conjugate gradient routine is used to search for the optimal solution. Haoxun and Chengbin (2003) present a heuristic approach to solve a supply chain model with multi-item and multilevel capacitated lot sizing problem. The heuristic employs Lagrangian relaxation with local search. The problem is relaxed and approximately solved linearly and the Lagrange multipliers are updated using a sub-gradient method. Lashine et al. (2006) formulate a mixed integer linear programming model and solve it using Lagrange relaxation and sub-gradient search for the location/allocation module. Their results show a deviation in the objective function value that varies between 0.29 and 2.05 percent from the optimum value. In contrast, this work presents a gradient solution methodology and the gradients are in this case those of the COQ functions (i.e. quality functions).

2.3.2 Genetic Algorithm

Syarif et al. (2002) stress the importance of finding a network strategy that can give the least cost of the physical distribution flow. They consider a mixed integer linear programming model where choices of facilities to be opened are applicable. They propose a spanning tree based genetic algorithm by using Prufer number representation. They further compare their results with those of traditional matrix based genetic algorithm. Tong and O'Grady (2004) comment on the difficulty of finding a suitable methodology to meet the complexity of real-world supply chains. In their work, a network-based approach, called extended Trans-Nets, is presented. A constraint-based genetic algorithm is utilized to search for improvements in the design that satisfy the constraints imposed on the system. Altiparmak et al. (2006) propose a new solution procedure based on genetic algorithms to find the set of Pareto-optimal solutions for multi-objective supply chain network design problem. Their work handles multi-objectives and allows the managers to make decisions based on greater number of alternative solutions. Two different weight approaches are implemented in their work as they propose a solution procedure that encompasses them. Data from a company are used to carry an experiment study in which the effects of weights approach on the performance of the proposed solution procedure are studied. Their proposed solution procedure is compared to simulated annealing.

Sha and Che (2006) introduce multiphase mathematical approach for the design of a supply chain network. Their proposed approach is based on the genetic algorithm (GA), the analytical hierarchy process (AHP), and the multi-attribute utility theory (MAUT). The approach satisfies simultaneously the preferences of the suppliers and the customers at each level in the network. To illustrate the efficiency of the approach, a case study is analyzed with good results affirmed. The performance of their proposed approach is put to the test by a comparative numerical experiment against the common single phase genetic algorithm (SGA) with their approach outperforming the SGA. Chen et al. (2007) stress the importance of planning a production-distribution network (PDN) where the key player needs to create an environment in which the partnership with suppliers is nurtured; the key player has to consider the constraint of the autonomous suppliers also seeking maximum profits as their business goals. They incorporate alternative design features in the PDN design model and formulate the problem for key player's PDN design with alternative design features (KPDN/ADF) as a bi-level programming problem. An extended genetic algorithm is used to solve the KPDN/ADF problem. Their experimentation demonstrates satisfactory results.

2.3.3 Simulated Annealing

As one of the solution procedures used in this research is Simulated Annealing (SA). Some relevant papers have been published in the implementation of SA in the supply chain literature. Azevedo and Sousa (2000) address the problem of planning the incoming customers' orders which would be produced in a distributed multi-site and multi-stage production system. The application of their work was in the semiconductor industry. They present an approach based on simulated annealing as well as a specially designed heuristic. In their work the performance of SA is assessed through computational experiments. Jayaraman and Ross (2003) introduce a system that generates globally feasible, near optimal distribution system design and utilization strategies utilizing the SA methodology. They discuss two significant contributions they made to SA literature. First, they extend the horizon of applications available in research by studying a new combinatorial problem that includes cross-docking in the supply chain. Second, they evaluate the computational performance under a variety of problem scenarios and variety of SA control parameter settings. Masouri (2006) introduces a multi-objective simulated annealing (MOSA) solution approach. The solution approach is applied to a bi-criteria sequencing problem where there is a requirement to coordinate fixed set-ups between two successive stages of the supply chain and the application is in a flow shop environment. Unlike the problem proposed in this paper, there are two objectives in the model. One objective is the minimization of the setup cost and the other is the maximization of the number of set-ups between the two successive stages. Daniel and Rajendran (2005) present simulation-based heuristic methodologies, one where a simulated annealing heuristic is proposed to compute the installation base-stock levels for different installations in a serial supply chain. The objective of the work is to compute installation base-stock levels in a serial supply chain so as to minimize the total supply chain cost. Later in the paper a simulation is used to evaluate the base stock-levels fetched by the simulated annealing heuristic.

2.3.4 Local Search Methods

Haoxun and Chengbin (2003) present a heuristic approach that employs Lagrangian relaxation with local search to solve a supply chain model with multi-item and multilevel capacitated lot sizing problem. The problem is relaxed and approximately solved linearly and the Lagrange multipliers are updated using a sub-gradient method. Syarif and Gen (2003) consider the production/distribution planning of a multi-stage structure. Their work involves making choices in regard to the opening of facilities and the production/distribution network design to satisfy demand. They propose a method call hybrid spanning which utilizes the Prufer number and as an improvement tool for their proposed method, they develop a local search technique. Yeh (2005) proposes a revised mathematical model and develops an efficient hybrid heuristic algorithm combining greedy method and linear programming technique and three local searches. He demonstrates by preliminary computational experiments the efficiency and performance of his proposed methodology. Higgins et al. (2006) study the supply chain of the sugar industry in Australia where the planning of the supply chain is quite complex and is done through the use of a mixed-integer programming. The model is employed to obtain a base schedule and a rescheduling tool. Using the Australian sugar industry as a case study, Higgins et al. introduce a mathematical model and two meta-heuristics based on local search. The two meta-heuristics are based on neighborhood search; mainly a tabu search (TS) heuristic and a variable neighborhood search (VNS) are introduced. In this thesis, a 1-opt and k-opt search methods are used to solve the model. The literature within SCND lacks solution methodologies that implement a 1-opt or k-opt methodologies. Alternatively, 1-opt and k-opt have been used to solve unconstrained binary quadratic programming; in this research the 1-opt and k-opt search procedures are modified to solve constrained SCND problems. The 1-opt and k-opt solution procedures are powerful tools to search local regions and are flexible to programming requirements and have shown good results as will be discussed in Chapter 5.

Table 2.3 : Review on the solution procedures used in this thesis.

Author	Inclusion of a quality cost	Modeling Approach	Solution Methodology
Altiparmak et al. (2006)	-	MP	Genetic Algorithm
Azevedo and Sousa (2000)	-	MP	Simulated Annealing
Chen et al. (2007)	-	Bi-level Programming	Genetic Algorithm
Daniel and Rajendran (2005)	-	MP	Simulated Annealing
Ettl et al. (2000)	-	MP	Conjugate Gradient Routine
Haoxun and Chengbin (2003)	-	MP	Sub-gradient Search and Local Search
Higgins et al. (2006)	-	MIP	Local Search Meta-heuristics
Jayaraman and Ross (2003)	-	MP	Simulated Annealing
Lashine et al. (2006)	-	MIP	Sub-gradient Search
Masouri (2006)	-	MP	Multi-objective Simulated Annealing
Syarif and Gen (2003)	-	MP	Local search technique
Sha and Che (2006)	-	MP	Genetic Algorithm, AHP
Syarif et al. (2002)	-	MIP	Spanning tree based genetic algorithm
Tong and O'Grady (2004)	-	MP	Genetic Algorithm
Yeh (2005)	-	MP	Hybrid Heuristic based on Greedy Method

Chapter 3

Modeling Cost of Quality and Solution Methodology

3.1 Incorporating Cost of Quality into the Supply Chain Network Design

The model presented in this section models a three-echelon supply chain (i.e. suppliers, plants, and customers) for a multi-product system with the objective of minimizing the overall operational and quality costs. Operational costs include production and transportation costs. COQ is modeled using quality functions that are present at both the suppliers and plants. The input parameters, decision variables, and constraint parameters are explained as follows:

Sets

B: Set of component types required for one product

I: Set of suppliers

J: Set of plants

K: Set of Customers

P: Set of Products

Decision Variables

$S_{i,b}$ = Number of good components b manufactured at supplier i; $i \in I, b \in B$

$ST_{i,b}$ = Number of total components b manufactured at supplier i; $i \in I, b \in B$

$SG_{i,j,b}$ = Number of good components b shipped from supplier i to plant j; $i \in I, j \in J, b \in B$

$X_{j,p}$ = Number of good products p produced at plant j; $j \in J, p \in P$

$XT_{j,p}$ = Number of total products p produced at plant j; $j \in J, p \in P$

$XG_{j,k,p}$ = Number of good products p shipped from plant j to customer k; $j \in J, k \in K, p \in P$

$y_{i,b}$ = Percent of defectives at supplier i for component b; $i \in I, b \in B$

$yp_{j,p}$ = Percent of defectives at plant j for product p; $j \in J, p \in P$

Parameters (Input Data)

$PcC_{i,b}$ = Cost of producing one component b at supplier i; $i \in I, b \in B$

$\Pr C_{j,p}$ = Cost of producing one product p at plant j; $j \in J, p \in P$

$TrC_{i,j,b}$ = Cost of transporting component b from supplier i to plant j; $i \in I, j \in J, b \in B$

$fcoq_{y_{i,b}}$ = Cost of quality for supplier i per good component b as a function of y_i, where y_i is the level of proportion of non-quality components (i.e. percent of defectives, ratio of defectives) at supplier i for component b. This is equivalent to the total cost of quality in figure 1.4; $i \in I, b \in B$.

$fcoq_{yp_{j,p}}$ = Cost of quality for plant j per good products p as a function of yp_j, where y_{pj} is the level of proportion of non-quality components (i.e. percent of defectives or ratio of defectives) at plant j for product p. This is equivalent to the total cost of quality in figure 1.4; $j \in J, p \in P$.

$TC_{j,k,p}$= Transportation cost of transporting a product p from plant j to customer k; $j \in J, k \in K, p \in P$.

Constraints Input Data

$D_{k,p}$= Number of products demanded by customer k for product p; $k \in K, p \in P$,

$SCap_{i,b}$= Allowable production capacity at supplier i for component b; $i \in I, b \in B$

$PCap_{j,p}$= Allowable production capacity at plant j for product p; $j \in J, p \in P$

N_b= Number of components b required to make a product p; $b \in B, p \in P$

$AD_{i,b}$= Acceptable proportion of defective of component b at supplier i; $i \in I, b \in B$.

$AD_{j,p}$= Acceptable proportion of defective of product p at plant j; $j \in J, p \in P$.

The general non-linear mixed integer-programming model is as follows:

Min

$$\sum_{i\in I}\sum_{b\in B} PcC_{i,b} ST_{i,b} + \sum_{i\in I}\sum_{j\in J}\sum_{b\in B} TrC_{i,j,b} SG_{i,j,b}$$

$$+ \sum_{i\in I}\sum_{b\in B} fcoq_{y_{i,b}} S_{i,b} + \sum_{j\in J}\sum_{p\in P} fcoq_{yp_{j,p}} X_{j,p}$$

$$+ \sum_{j\in J}\sum_{p\in P} \Pr C_{j,p} XT_{j,p} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P} TrC_{j,k,p} XG_{j,k,p} \tag{3.1}$$

Subject to

$$\sum_{j \in J} XG_{j,k,p} = D_{k,p} \qquad \forall k, \forall p \qquad (3.2)$$

$$XT_{j,p} \le PCap_{j,p} \qquad \forall j, \forall p \qquad (3.3)$$

$$N_b XT_{j,p} = \sum_{i \in I} SG_{i,j,b} \qquad \forall j, \forall b, \forall p \qquad (3.4)$$

$$S_{i,b} = ST_{i,b}(1 - y_{i,b}) \qquad \forall i, \forall b \qquad (3.5)$$

$$X_{j,p} = XT_{j,p}(1 - yp_{j,p}) \qquad \forall j, \forall p \qquad (3.6)$$

$$X_{j,p} = \sum_{k \in K} XG_{j,k,p} \qquad \forall j, \forall p \qquad (3.7)$$

$$ST_{i,b} \le SCap_{i,b} \qquad \forall i, \forall b \qquad (3.8)$$

$$S_{i,b} = \sum_{j \in J} SG_{i,j,b} \qquad \forall i, \forall b \qquad (3.9)$$

$$y_{i,b} \le AD_{i,b} \qquad \forall i, \forall b \qquad (3.10)$$

$$yp_{j,p} \le AD_{j,p} \qquad \forall j, \forall p \qquad (3.11)$$

$$ST_{i,j} \ge 0, S_{i,j} \ge 0, SG_{i,j,b} \ge 0, XT_{j,k} \ge 0, X_{j,k} \ge 0, XG_{j,k,p} \ge 0, y_{i,b} \ge 0, yp_{j,p} \ge 0$$

The objective function (3.1) minimizes the following costs respectively:

1. Production cost at suppliers
2. Transportation cost from suppliers to plants
3. Total quality cost at suppliers
4. Total quality cost at plants
5. Production cost at the plants
6. Transportation cost from plants to customers

Constraint (3.2) ensures that all plants are producing enough products to meet the demand from customers. Constraint (3.3) ensures that no plant's production exceeds its capacity. Constraint (3.4) ensures that the suppliers will produce enough components for the number of products produced at the plants. Constraint (3.5) relates the number of good components shipped, from a supplier to a plant, to the total number of component produced at a supplier for a plant use. Constraint (3.6) is analogous to constraint (3.5); it relates the fraction of good products to the totals products produced at the plant. Constraint (3.7) sums the total number of good products p produced at plant j. Constraint (3.8) is a supplier capacity constraint and it ensures that supplier's capacity is not exceeded. Constraint (3.9) is analogous to constraint (3.7); it sums the total number of good component of type b produced at supplier i. Constraint (3.10) places a bound on the maximum proportion of defective allowed at the suppliers. And constraint (3.11) places a bound on the maximum proportion of defective allowed at the plants. Figure 3.1 depict the parameters within the supply chain. At the suppliers, the production cost and cost of quality are modeled. Cost of Quality is modeled through the use of quality functions as will be explained further. At the plants, the production cost and the cost of quality are also modeled. A transportation cost between the supplier and plants and between plants and customers is also modeled.

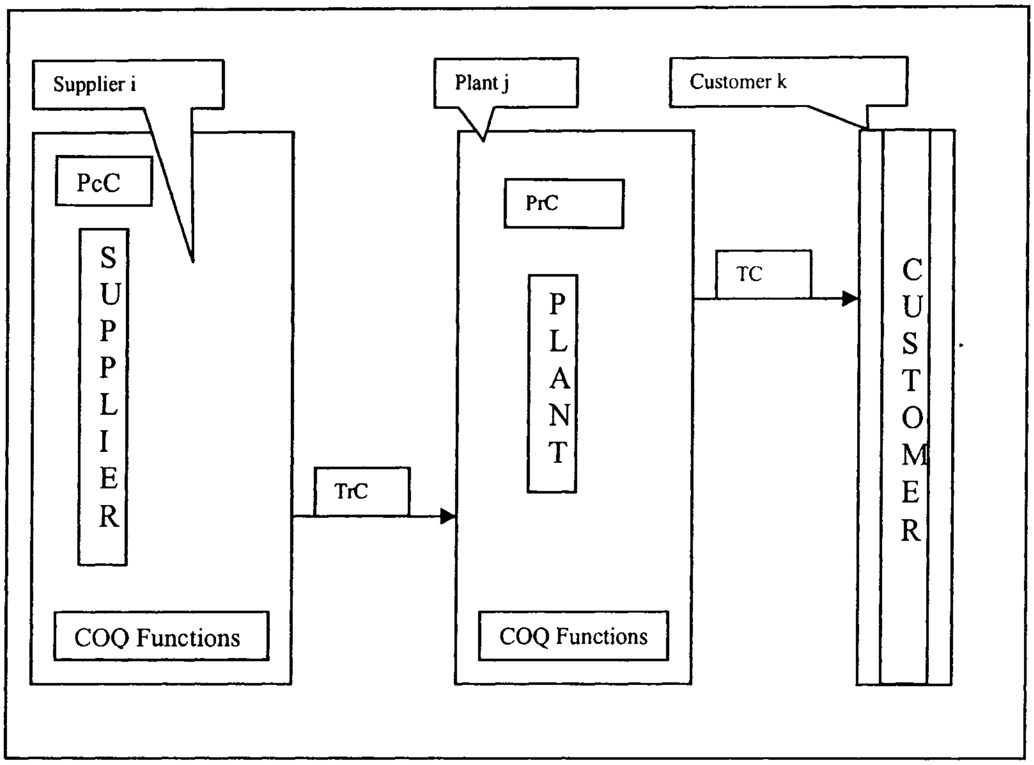


Figure 3.1 : The parameters within the supply chain model.

Graphical demonstration of how quality costs affect the overall quality conformance of a given system was presented in figure 1.4. One can observe that as the quality level rises, failure costs decline and appraisal plus prevention costs increase. One can also infer that a relationship exists between the quality of conformance percentage, (*1-y*), and prevention and appraisal costs on one hand and failure costs on the other. In this work, the total quality curve is approximated by quadratic functions and then integrated into the model. In elaboration, the total cost of quality curve is convex and can be modeled by a convex quadratic function (see figure 1.4). Correspondingly, integrating COQ into SCND results in a nonlinear mathematical programming model as the quality functions are nonlinear; hence in this chapter a methodology for solving the model is presented. Since nonlinearities exist in the objective function (3.1) and the constraints (3.5 and 3.6) of the model, knowing the shape of the objective function will assist in the formulation of a search procedure that will tailor to the topography of the model. If convexity is proven, one global minimum would occur and hence a search methodology can be formulated to find this optimum. Hence in this chapter convexity of the objective function is proven and a methodology is introduced to solve the model. Later the results are presented and discussed in illustration of the significance of integrating COQ into SCND. Furthermore, analysis of two different models, one with COQ integrated and one without is carried out. And to assess the connotation of the methodology, a lower bound is fetched for the objective function and the solution is contrasted against the lower bound.

3.2 Convexity and Gradient-Based Methodology

Knowing the topography of the objective function would be the first important step in solving the problem. Looking at the structure of the objective function, a question arises on whether it is of a special type. Among the different types of functions, there exists a special class of functions, known as convex functions; these functions exhibit an important characteristic related to the identification of maxima and minima. This characteristic reflects the fact that the graph of these functions is characterized by a single peak or valley. Alternatively, a function is convex if a line segment drawn between two points on its graph lies entirely on or above the graph. This is the case in figure 1.4, as any line drawn between any two points would lie entirely above the graph. An important property of a convex function is that any local minimum of a convex function is also a global minimum (Schmidt and Davis 1981). The COQ functions both integrated into the model at the suppliers and plants are convex as illustrated by Juran's graphical presentation (figure 1.4), where the COQ function is convex and characterized by only a single peak which is a minimum.

Importantly the usability of the COQ model can be enhanced significantly if convexity is proven. To elaborate more, there exist nonlinearities in the objective function (3.1) and in the constraints (3.5 and 3.6) of the model. Knowing the shape of the objective function will assist in the formulation of a search procedure that will tailor to its shape. If convexity of the objective function (3.1) is proven, one global minimum would occur and hence a search methodology would be formulated to find this optimum. In the search procedure, the aim is to move towards the optimal solution. The move should be in the direction of optimality. If the objective function is convex then there exists only one minimal which is a global minimum. Then, the search methodology will start at one fixed point and then seek the minimum of the convex function.

Juran classical model (figure 1.4) depicts COQ as a function of the quality level and since the quality level is the complimentary of the ratio of defectives, one can simulate the COQ curve as a function of the ratio of defectives. To simulate Juran's quality representation, quadratic functions are simulated to represent the behavior of COQ corresponding to y (ratio of defectives). The quadratic functions are of the form: $fcoq = ay^2 - by + c$, where a, b, c are constants and y is the ratio of defectives.

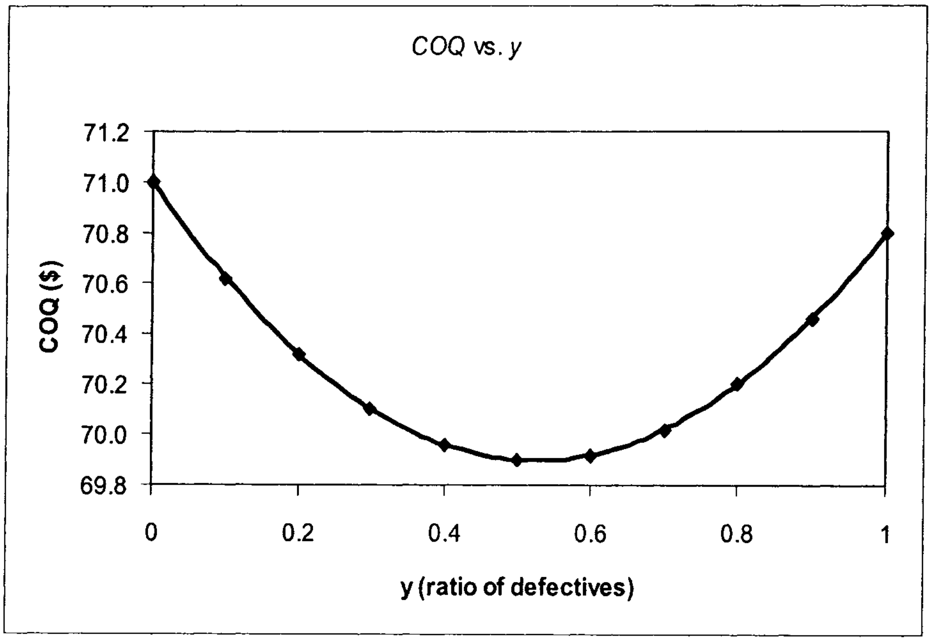


Figure 3.2 : An example of a supply chain node illustrating COQ behavior corresponding to changes in y.

In figure 3.2, an example of a supply chain's quality function that takes the form of $fcoq = 4y^2 - 4.2y + 71$. Starting at y equals zero, the y is increased and by this increase the value of COQ decreases until it reaches its global minimum. The $fcoq$ functions used in this research are all in the form $fcoq = ay^2 - by + c$ and hence are convex as coefficient a is positive by definition and any line drawn between any two points on the graph lie entirely above the graph. As for the objective function (3.1), convexity needs to be evaluated. Given that the objective function is convex, the solution methodology could be tailored to the convexity of the objective function and in order for this to happen convexity needs to be proven. Hence, the next section is dedicated to proving the convexity of the objective function.

3.2.1 Convexity

The model is challenging to solve as it contains nonlinearities both in the objective function and in the constraint set. Nevertheless, the model does have some special structure which enables a solution methodology to be developed. One important special structure is that the objective function (3.1) is convex as demonstrated in the following proposition as well as its proof.

Proposition: The objective function (3.1) is convex.

Proof

The nonlinear terms in expression (3.1) are:

$$\sum_{i\in I}\sum_{b\in B} fcoq_{y_i,b} S_{i,b}$$

And

$$\sum_{j\in J}\sum_{p\in P} fcoq_{yp_{j,p}} X_{j,p} .$$

All other terms are linear and hence convex. Let us first examine $fcoq_{y_i,b} S_{i,b}$. It is given that $fcoq_{y_i,b}$, the COQ function at supplier i for component b is convex (see figure 1.4 and 3.2). Hence, $fcoq_{y_i,b} S_{i,b}$ is convex since $S_{i,b}$ is positive. Now define F to be an mxn matrix where m is the number of suppliers and n the number of components in the BOM.

$$F = \begin{pmatrix} fcoq_{1,1}(.) & \cdots & fcoq_{1n}(.) \\ \vdots & \ddots & \vdots \\ fcoq_{m1}(.) & \cdots & fcoq_{mn}(.) \end{pmatrix}$$

Similarly *Y* is the *mxn* matrix given below:

$$Y = \begin{pmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{m1} & \cdots & S_{mn} \end{pmatrix}$$

It follows that $F^i Y^{iT}$ is convex in *Y* since each of the terms $fcoq_{y_{i,b}} S_{i,b}$ in the sum is convex. Consequently FY^T is convex. By the same analogy $\sum_{j\in J}\sum_{p\in P} fcoq_{yp_{j,p}} X_{j,p}$ is convex and hence expression (3.1) (i.e. objective function) is convex because the sum of convex functions is convex (Schmidt and Davis 1981).

3.2.2 Gradient-Based Search Solution Procedure

This model is hard to solve for the following reasons:

1. The total cost of quality function $(fcoq_{y_i})$ in the objective function is a function of *y* and is non-linear;
2. The term $(fcoq_{y_i})$ is a function of *y* and is multiplied by *S* in the objective function; this results in the multiplication of *y* and *S* which are both decision variables creating another non-linearity in the objective function.
3. Constraints 5 and 6 involve a multiplication of two unknown quantities $(ST_{i,b} * y_{i,b})$ as also $(XT_{j,p} * yp_{j,p})$ and is hence non-linear.

If the y values are fixed, then all above issues disappear and the model becomes a linear one. Hence, if y is fixed and then iterated, the model can be solved linearly by successive fixations of y. If initial values of the y vector are introduced and then the model is solved linearly, then incrementing y in a manner as to seek optimality can solve the problem. To elaborate, when y is incremented, the model is solved linearly again and this procedure is repeated until optimality is reached. The key point here is to formulate a gradient approach which guarantees that each iterate of y gets closer to the optimal solution.

As discussed previously the objective function, f, is convex. If f is differentiable at x, then a vector $d \in \Re^n$ is a descent direction for f at x if it is within 90° of $-\nabla f(x)$, i.e.,

$$-\nabla f(x)T^d > 0$$

The definition of the derivative says that

$$f(x+\alpha d) = f(x) + \alpha \nabla f(x)^T d + o(\alpha)$$

If d is a descent direction, and α >0 is sufficiently small, then $x^{k+1} = x^k + \alpha^k d^k$ reduces the value of the objective f. This observation forms the basis of line search methods: at the iterate x^k, choose a descent direction d^k and search along this direction for a point $x^{k+1} = x^k + \alpha^k d^k$, with α^k >0, that has a smaller objective value. Choosing the correct α is important to guarantee faster convergence (Kolda *et al.,* 2003) but before discussing this it is important to investigate the search methodology more closely.

Gradient methods are specified in the form,

$$x^{k+1} = x^k + \alpha^k D^k \nabla f(x^k)$$

For steepest descent $D^k = I$ (where $k = 0,1,.....$) is chosen where I is the n x n identity matrix (Bertsekas 1995). For the purpose of this research, the steepest descent method is employed to fetch the iterate of y. In choosing a good stepsize, at each iterate the following is conducted (Hillier and Liberman, 2001):

$$y^{k+1} = y^k + \alpha^k \nabla f(y^k)$$, where

α^k is the step size and is a positive value that minimizes $f(y^k + \alpha^k \nabla f(y^k))$; that is,

$$f(y^k + \alpha^{k*} \nabla f(y^k)) = \min_{\alpha^k} f(y^k + \alpha^k \nabla f(y^k))$$

Note that $f(y^k + \alpha^k \nabla f(y^k))$ is simply $f(x)$ where

$$y_i^{k+1} = y_i^k + \alpha(\frac{\partial f}{\partial y_i})$$

and these expressions for the y_i involve only constants, as the problem is fixed each time and solved then linearly; hence, $f(x)$ becomes a function of just the single variable α, (Hillier and Liberman, 2001).

Building on this, the gradient search procedure first starts at y equals zero and solves the model linearly to produce $f(y)$. Then the stepsize is fetched by finding a step size, α, that minimizes $f(y+\alpha d)$. When the value of $f(y+\alpha d)$ approaches that of $f(y)$, the solution cannot be improved anymore, as the stepsize approaches zero and the minimum is intuitively achieved. Consequently, as the objective function has been proven to be convex: this minimum is a global one.

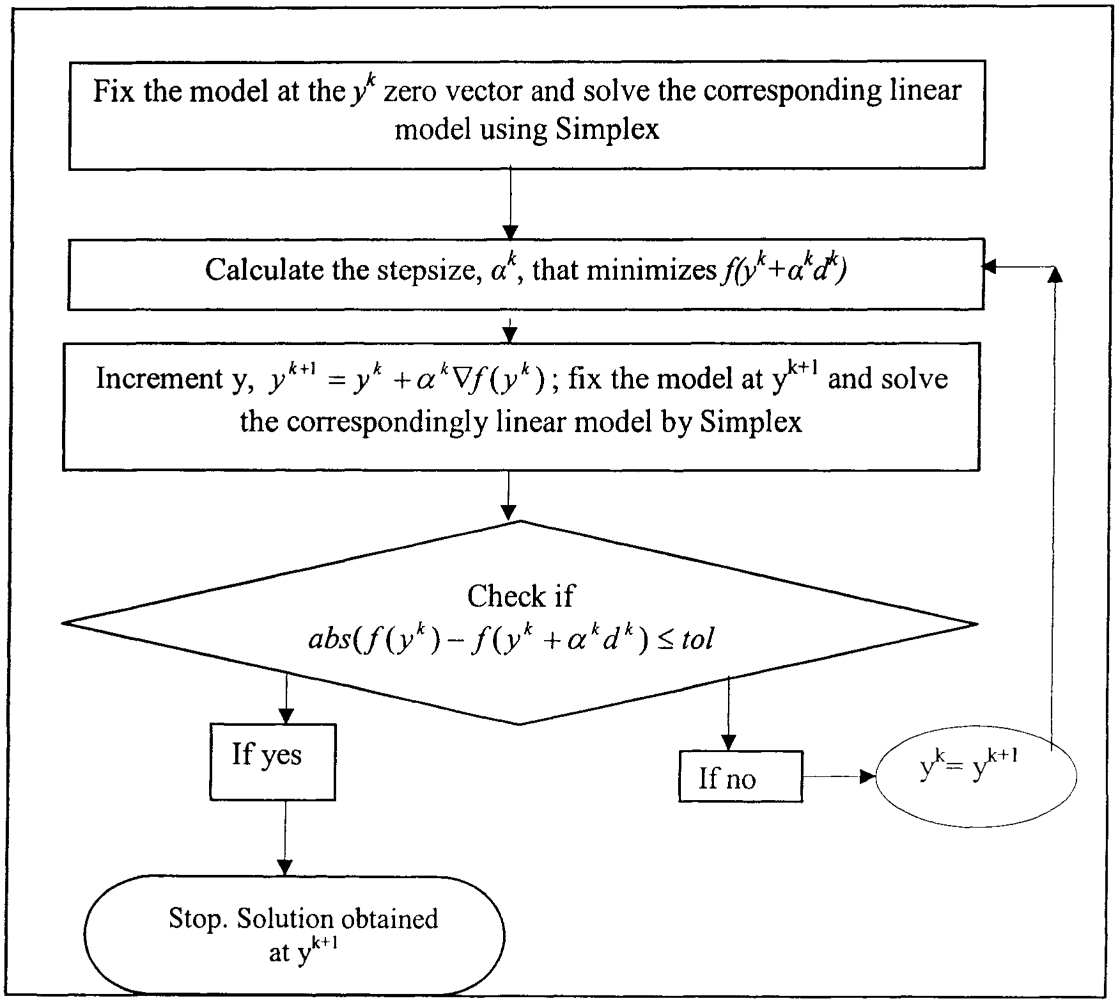


Figure 3.3 : Flow chart of the gradient-based search method.

Figure 3.3 illustrates the steps in the methodology. At first the y^k elements are set to zero and here the y^k elements represent y and yp defined in section 3.1 and in the list of symbols. By setting y^k to zero the model becomes linear and is solved in-turns by the simplex method. Then, the stepsize, α^k that minimizes $f(y^k + \alpha^k d^k)$, is calculated. y is incremented and the model is fixed at the new y and is in-turns solved linearly, by the simplex method and thus two solutions are obtained: $f(y^{k+1})$ and $f(y^k + \alpha^k d^k)$ for y^{k+1} and y^k respectively. And then the stopping criterion of

$abs(f(y^{k+1}) - f(y^k + \alpha^k d^k)) < tolerance$ is evaluated. Hence, the solution methodology will be as follows:

1. The whole model is initially fixed at the y zero vector, which is a feasible solution,

   $y = [y_1, y_2, y_3 .... y_{ns}] = [0,0,0,...,0]$, where ns is the number of suppliers

   $yp = [yp_1, yp_2, yp_3,..., yp_{np}] = [0,0,0,...,0]$, where np is the number of plants

   With y fixed, the model becomes linear and is solved using simplex method and y vector becomes the initial y increment, y^k.

2. A step size, α , is calculated to minimize

$$f(y^k + \alpha^k d^k) \tag{3.12}$$

3. The y is incremented

$$y^{k+1} = y^k + \alpha^k \nabla f(y^k) \tag{3.13}$$

4. The model is fixed at y^{k+1} and in-turns the model becomes linear and is solved by the simplex method with respect to y^{k+1} to obtain $f(y^{k+1})$ and compute $f(y^k + \alpha^k d^k)$ correspondingly.

5. If

$$abs(f(y^k) - f(y^k + \alpha^k d^k)) < tolerance, \tag{3.14}$$

then the solution is reached (i.e. solution is obtained), otherwise y^{k+1} becomes y^k and procedure is pursued at step 2 again.

3.2.3 Experimental Results and Benefits of Integrating COQ

The solution methodology was experimented on SCND problems consisting of x suppliers, y plants and z clients (see Table 3.1). Various supply chain network configurations are experimented. Table 3.1 illustrates the procedures of the experimentations of varying the number of suppliers, plants, and customers. The number of suppliers, plants, and clients vary between 5 and 100 and different combinations of the number of suppliers, plants, and customers are evaluated. The corresponding mathematical models vary in the number of variables and constraints depending on the number of supplier, plants, and customers; among these different models, a model encompassing more than 15,000 variables and 1000 constraints was solved successfully. Different supply chain models were solved and their solutions are presented in Table 3.1.

Table 3.1 : Benefits of integrating COQ.

Supply Chain	(1) No. of Suppliers	(2) No. of Plants	(3) No of Clients	(4) No of Variables	(5) Objective Value: COQ not integrated (V2)	(6) Objective Value: COQ Integrated (V1)	(7) V2/V1 Ratio
1	20	20	100	2480	\$50,290,000	\$55,010,000	0.91
2	10	10	100	1140	\$50,211,000	\$55,064,000	0.91
3	10	30	100	3380	\$50,096,000	\$54,993,000	0.91
4	100	20	30	2840	\$14,974,000	\$16,295,000	0.92
5	100	10	20	1420	\$10,011,000	\$10,980,000	0.91
6	100	30	20	3860	\$9,991,700	\$10,862,000	0.92
7	30	100	20	5260	\$10,000,000	\$10,925,000	0.92
8	20	100	20	4240	\$9,895,300	\$10,834,000	0.91
9	20	100	30	5240	\$14,968,000	\$16,300,000	0.92
10	50	5	15	435	\$7,514,100	\$8,084,800	0.93
11	50	10	10	720	\$4,999,200	\$5,478,400	0.91
12	50	15	5	955	\$2,525,700	\$2,749,700	0.92
13	5	50	10	860	\$5,021,700	\$5,454,000	0.92
14	15	50	5	1130	\$2,531,400	\$2,743,700	0.92
15	10	50	15	1370	\$7,532,400	\$8,319,400	0.91
16	20	10	50	760	\$25,143,000	\$27,446,000	0.92
17	5	15	50	865	\$25,319,000	\$28,082,000	0.90
18	15	20	50	1370	\$25,133,000	\$27,413,000	0.92

All the input data are randomly generated, using a uniform distribution, and the results are obtained using a program written to perform the functionalities discussed in section 3.2.2. The tolerance (3.14) is very small and negligibly analogous to one dollar operational cost for a supply chain that has over a million dollars worth of operational costs. The gradient search procedure was developed on a MATLAB platform using a Pentium IV CPU, 3.00 GHZ with 2.99 GHz of 1.0 GB of Ram system.

The Cost of Quality functions are approximated as quadratic functions of the form: $fcoq = ay^2 - by + c$. Then, for the suppliers we have,

$$fcoq = (ae)(ys)^2 - (be)(ys) + ce \tag{3.15}$$

and for the plants,

$$fcoq = (ap)(ys)^2 - (bp)(ys) + cp \tag{3.16}$$

The constants *ae, be, ce, ap, bp*, and *cp* are input into the model and are randomly generated using uniform distribution. Instances of the input and output data are presented in Appendix A (Tables A1, A2, A3, A4, and A5). The *y*'s, percent of defectives, are fairly low and this is understandable as the system is minimizing the cost of rework (i.e. cost of replacing defective products). Various supply chain configuration network systems were solved to insure fair presentation of the real life situations as shown in Table 3.1. To illustrate the significance of integrating COQ further, different network configurations were solved with and without including the COQ. At each supply chain configuration, two instances are solved. In the first instance, COQ is integrated and the model is solved using the gradient search method approach, as discussed before. In the second instance, the COQ is disintegrated from the model and the model is then solved. Both instances are contrasted by comparing the values of their corresponding objective functions. The comparison is done through the use of a ratio that relates both instances.

$$V_2 / V_1 \ Ratio = \frac{V_2}{V_1} \tag{3.17}$$

V_1 = Objective value of the model with COQ integrated,

V_2 = Objective value of the model without COQ

V_1 is simply the objective value of the model with COQ integrated. V_2 is the objective value of the same model as V_1 with the exclusion of COQ. Table 3.1 illustrates the V_2/V_1 *Ratio* value in column (7). Column (5) depicts the value of V_2 and column (6) depicts the value of V_1. Eighteen different supply chain configurations are solved to ensure representative results. Each configuration yields different number of suppliers, plant, and/or customers. The different supply chain echelon configurations are found in column 1, 2, and 3 of Table 3.1.

Column (7) of Table 3.1 presents the V_2/V_1 *Ratio* values. The ratio varies between 0.90 and 0.93; hence there is a hidden quality cost of about 7% to 10% not explored when COQ is not integrated. For illustration purposes, if the overall operational cost of the supply chain is around 1 billion dollars, this would mean a hidden COQ of almost 80 million dollars. To illustrate this further, figure 3.4 shows the optimal supply chain network configuration with COQ integrated and figure 3.5 shows the optimal configuration when COQ is not integrated. The input data for both models are presented in Appendix A (Tables A1, A2, A3, A4, and A5). The COQ model chooses the fifth supplier which has a considerably low total quality cost compare to the other suppliers, while the model without COQ abandons this supplier and chooses the first supplier instead. The first supplier is not chosen by the COQ model as it has a disadvantageous quality function. In elaboration, the acceptable proportion of defectives (AD) (refer to section 3.1 for definition) for the network is 5.7%. At this level, one can calculate the corresponding COQ (i.e. Acceptable Cost of Quality, ACOQ). Thus, for a given supply chain node, the quality function value (i.e., COQ for that given supplier chain node) is presented as follows:

$fcoq = ay^2 - by + c$, where y is the ratio of defectives.

The acceptable proportion of defectives (AD) is 5.7% and hence the minimum acceptable cost of quality (ACOQ) is the COQ for a percent of defectives of 5.7%. Then,

$$ACOQ = a * AD^2 - b * AD + c \tag{3.18}$$

The ACOQ for the first supplier, as depicted in figure 3.4 and figure 3.5, is 1.63 which is the highest among suppliers. The COQ model avoids this supplier due to its high COQ, but the non-COQ model chooses this supplier regardless of its poor quality performance. Hence, integrating COQ assists managers in choosing partners that are running operations at good quality levels.

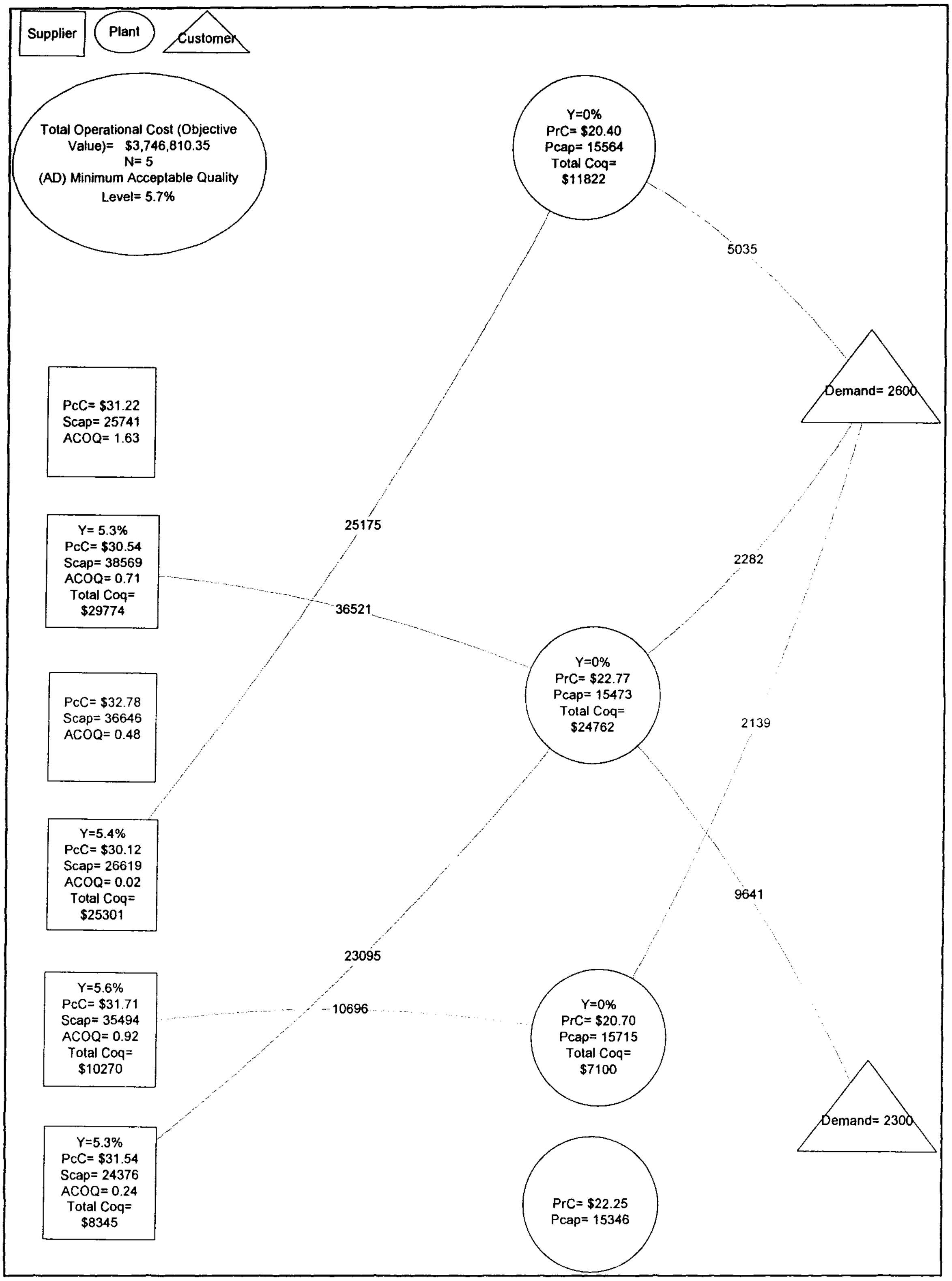


Figure 3.4 : Optimal supply chain network with COQ integrated.

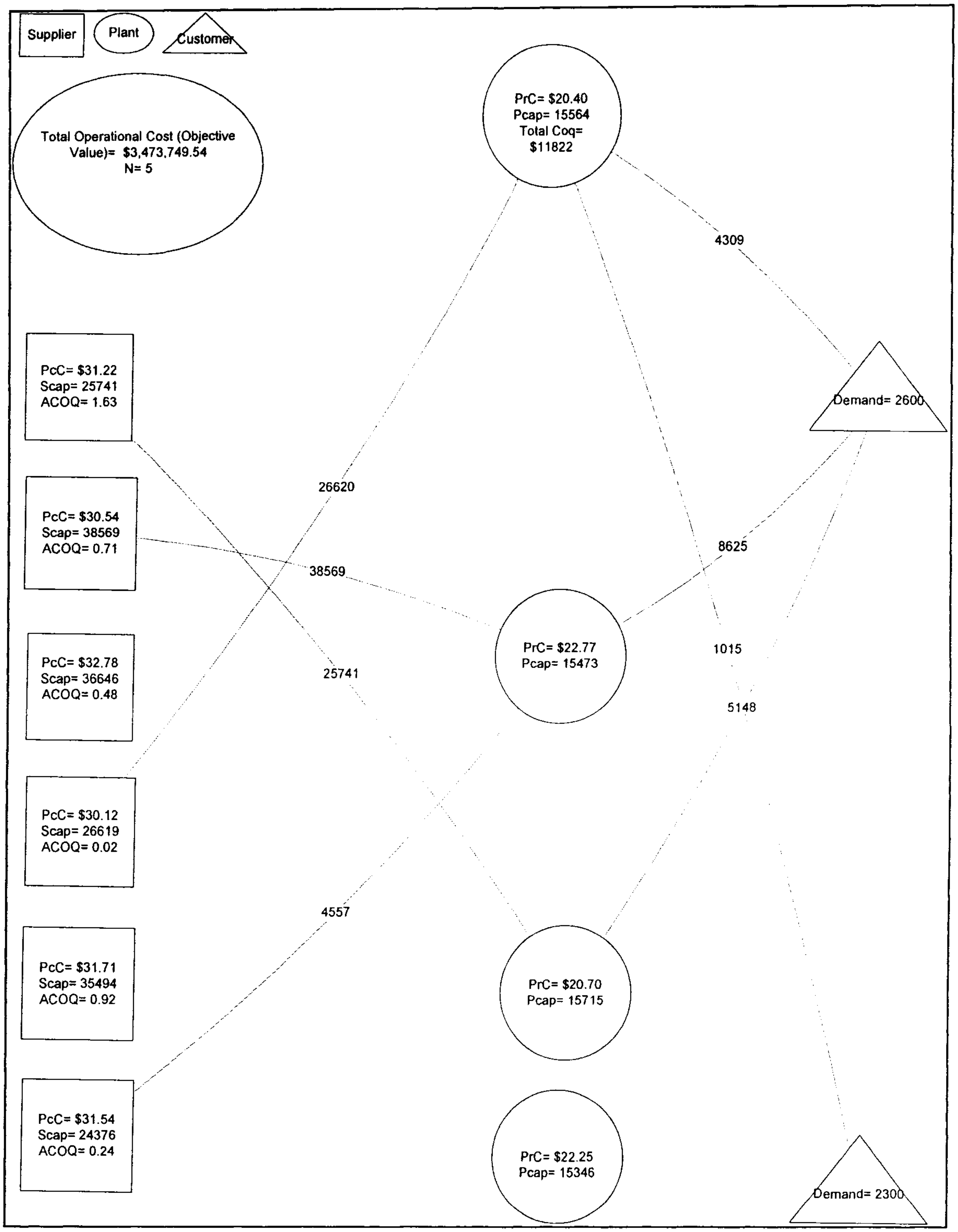


Figure 3.5 : Optimal supply chain network without the integration of COQ.

3.2.4 Insight into Results

In this section the production cost at both the suppliers and plants are varied and the responding changes in the results are analyzed. A supply chain network of nine suppliers, four plants and three customers is solved repeatedly under different production cost scenarios. For this analysis, constraints 3.10 and 3.11 are relaxed removing the bound on the ratio of defectives, *y*, in order to study the behavior of the model. The production costs at all the operational supply chain nodes are decreased and the percent of defectives, *y's*, are reported in Table 3.2 and Table 3.3. The input supply chain's parameters are presented in Appendix A (Tables A6, A7, and A8).

Table 3.2 : Suppliers' results corresponding to reduction in production cost.

Suppliers							
Supplier	Production Cost Fixed	30% reduction in Production Cost	40% reduction in Production Cost	50% reduction in Production Cost	70% reduction in Production Cost	80% reduction in Production Cost	90% reduction in Production Cost
	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives
1	0.00%	7.13%	8.89%	10.41%	11.73%	13.85%	13.85%
2	NA	NA	NA	NA	NA	NA	NA
3	5.55%	7.69%	9.49%	11.01%	12.30%	14.29%	14.29%
4	7.00%	9.74%	12.07%	14.06%	15.76%	18.43%	18.43%
5	7.28%	10.16%	12.63%	14.75%	16.56%	19.45%	19.45%
6	NA	NA	NA	NA	NA	NA	NA
7	NA	NA	NA	NA	NA	NA	12.55%
8	3.87%	5.37%	0.00%	7.71%	0.00%	10.01%	0.00%
9	7.98%	11.02%	13.57%	15.71%	17.50%	20.25%	20.25%

The percent of defectives are shown for all the supply chain nodes; for the nodes of which no production is perceived, the percent of defectives is not applicable and hence is denoted by *NA*. Insightfully, the percent of defectives, *y*, tend to increase when the production cost decreases; the reason for this is that as the production cost decreases, the cost of replacing defective parts with good ones declines and becomes a more viable option. In illustration, the suppliers' data, presented in Table 3.2, show drastic increases in the percent of defectives as the production cost decreases further.

Table 3.3 : Plants' results corresponding to reduction in production cost.

Plants							
Plant	Production Cost Fixed	30% reduction in Production Cost	40% reduction in Production Cost	50% reduction in Production Cost	70% reduction in Production Cost	80% reduction in Production Cost	90% reduction in Production Cost
	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives	y, percent of defectives
1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	16.57%
2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	15.90%
3	0.00%	0.00%	NA	NA	NA	NA	15.11%
4	NA	NA	0.00%	0.00%	0.00%	0.00%	16.29%

Alternatively, the plants' data, presented in Table 3.3, show consistency until the 90% decrease of production cost is reached; at that point, the percent of defectives show a significant increase. The original production cost at the plants, shown in Appendix A (Table A7), is quite higher than that of the suppliers and in-turn replacements are more cost intensive; for this reason, the percent of defectives remain unchanged until drastic production cost reductions (i.e. 90% reduction) is reached. Another factor that would see the percent of defectives increase is an amplification of the quality functions. When the quality functions are advantageous (i.e. COQ is low for low ratio of defective values), the optimal percent of defectives would be quite low and high for the vice versa. To maintain a good quality level, managers using this modeling approach could place a minimum acceptable quality level, which the model allows for by the use of constraints 3.10 and 3.11, to ensure an acceptable quality level.

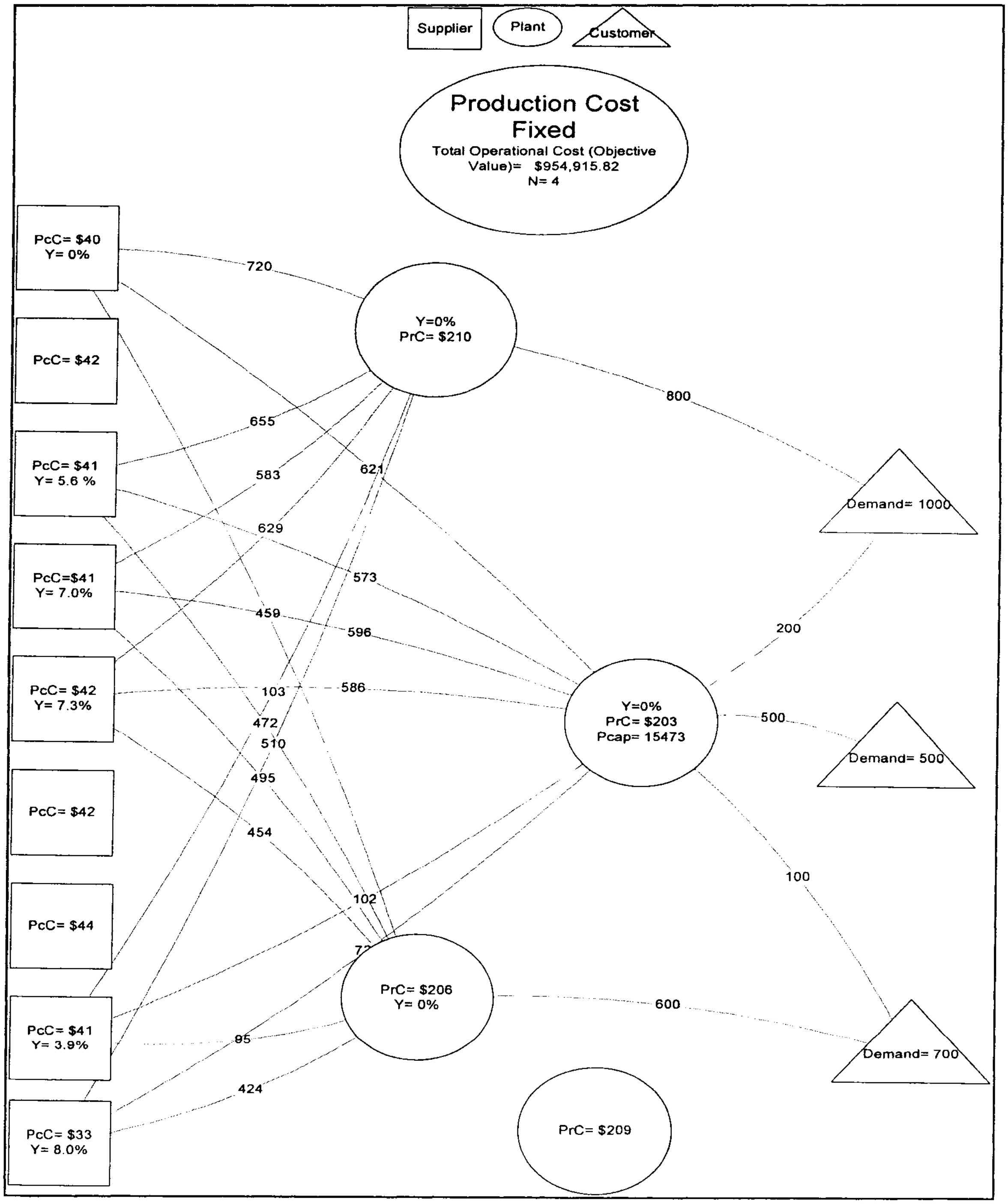


Figure 3.6: Optimal supply chain network at the original production costs.

A graphical illustration is presented in figures 3.6, 3.7, and 3.8. Each of the figures captures a sketch of the optimal operational supply chain at a given production cost reduction scheme. The figures annotated on the links express the number of products transferred between respective supply chain nodes. Also all the details of product sourcing within the supply chain nodes is presented and the overall objective value is also presented within the figures. Information pertaining to production cost and ratio of defectives are noted on the nodes. Nodes annotating no information are non producing nodes. Figure 3.6, presents the optimal supply chain with the production costs fixed at their originally values given in Appendix A (Table A6 and Table A7). This figure illustrates the optimal network if the production cost is not tempered with. Six suppliers are chosen to source products and each of the suppliers is running at a different percent of defectives in accordance to its respective quality function (refer to Table A6 and A7 for the quality function parameters' values). The 9th supplier possesses the lowest production cost and is in-turns the one with the highest percent of defective in conformance to the insight discussed before.

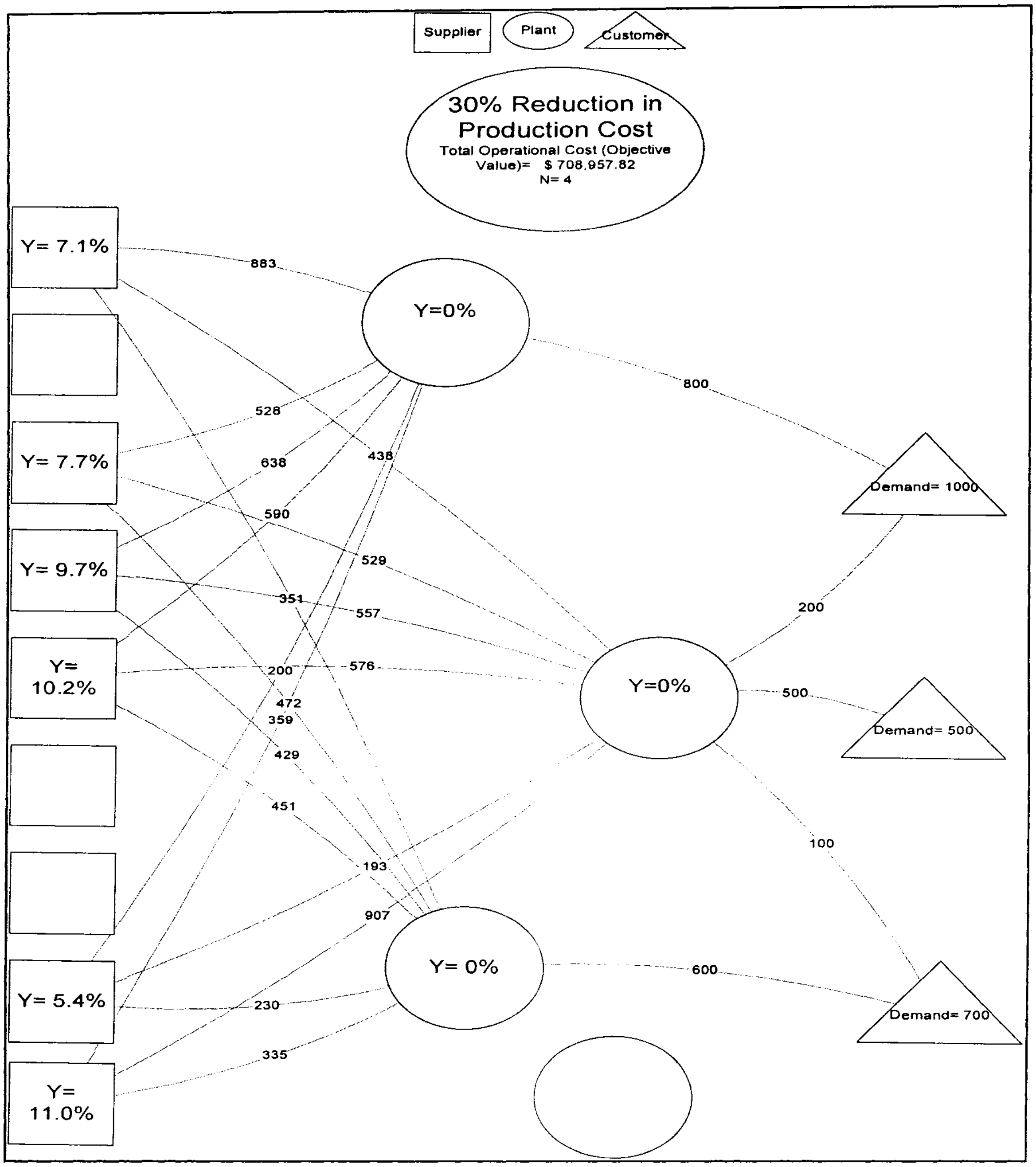


Figure 3.7: Optimal supply chain network at 30% reduction in production cost.

This insight is also evident as the production cost is reduced. With the reduction in production cost taking place at all the supply chain nodes, the supply chain overall percent of defectives increase at the first reduction in production cost (i.e. 30% reduction), as illustrated in figure 3.7.

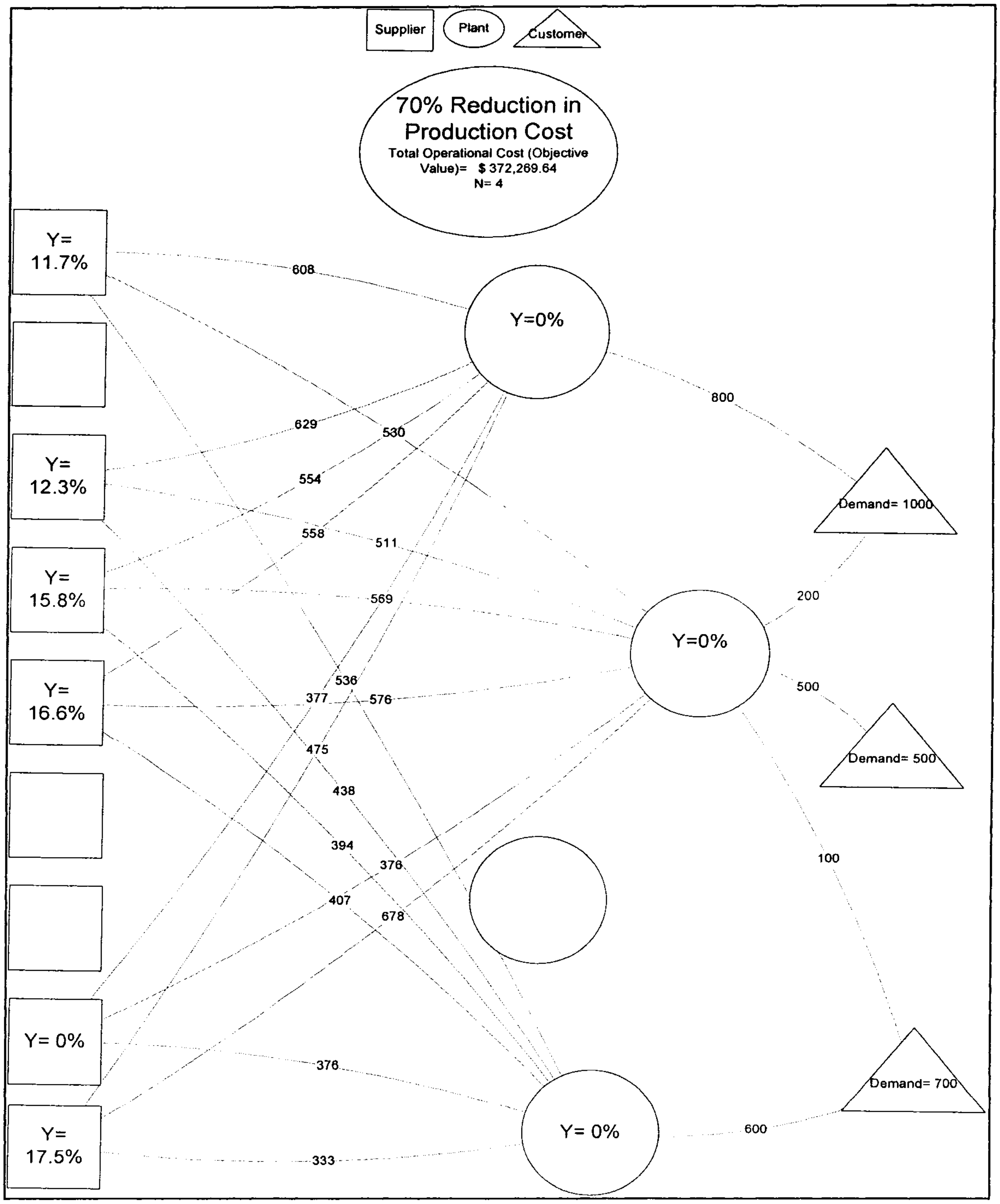


Figure 3.8: Optimal supply chain network at 70% reduction in Production Cost .

Further a decrease of 70% in production cost increases the percent of defectives further as illustrated in figure 3.8. As a note, the 9th supplier, one with the lowest production cost, still has the highest percent of defectives among the suppliers.

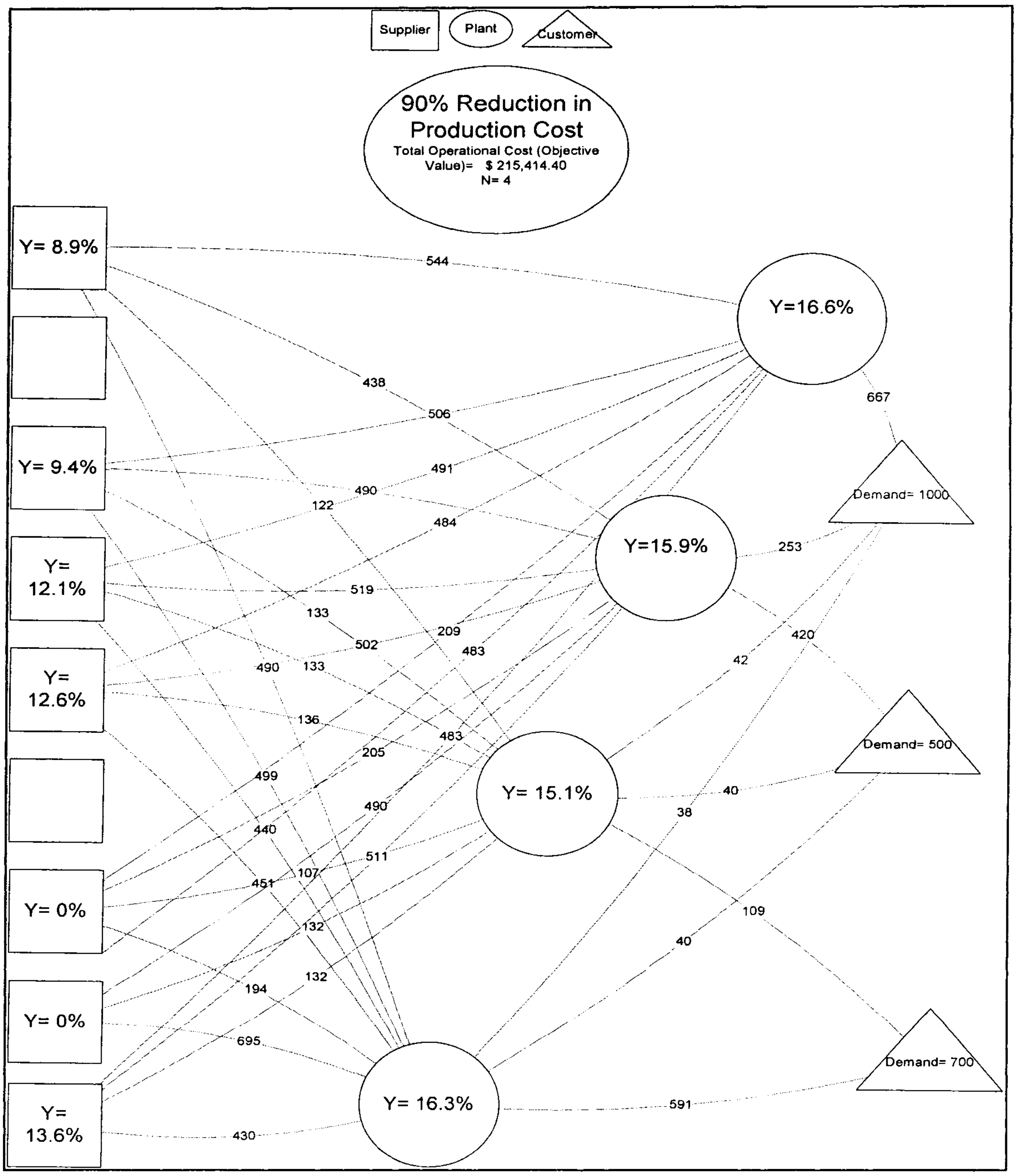


Figure 3.9 : Optimal supply chain network at 90% decrease in Production Cost.

A 90% decrease in production cost sparks a significant increase in percent of defectives at the plants, figure 3.9. At this point, the production cost is low enough to offset the COQ that had prevented the plants from producing at a high percent of defectives. Remarkably, as the percent of defectives at the plants start increasing, the percent of defectives at the suppliers decrease; the reason for this is that when the plants are running at higher percent of defectives, they would require more total parts supplied from the suppliers as they have to replace more defective products. So, the total demanded parts sourced from the suppliers to the plants increases correspondingly. The suppliers react to the increase of demand by running at lower percent of defectives to conserve (i.e., better manage) resources. Also, the increase in production at the suppliers approaches the suppliers' capacities, and hence, the model favors producing at lower percent of defectives as not to exceed the capacity limitations. Overall, a variety of supply chain configurations were contested. Some of the supply chain nodes possessed quality functions that favored lower ratio of defectives and other possessed functions that favored higher ratios. The model was adequate in handling the sensitivity and variability of extreme and broad spectrum of supply chain quality attributes.

3.2.5 Performance of the Solution Methodology

To assess the performance of the solution methodology, a lowerbound is constructed on the objective function. As discussed before, the quality functions are modeled as quadratic functions in the form, $fcoq = ay^2 - by + c$, with y being the ratio of defectives and a, b, and c being constants. Now, the tangent to the $fcoq$ curve, that is linear, serves as a lower bound as it underestimates the objective function. The tangent line to the quality function can be expressed as:

$$tcoq = \left.\frac{dfcoq}{dy}\right|_{y_1} * (y_2 - y_1) + fcoq(y_1) \qquad (3.19)$$

where y_1 and y_2 are two points on the tangent line and $\left.\frac{dfcoq}{dy}\right|_{y_1}$ is the gradient of the quality function at y_1. A graphical illustration of different tangent lines to the *fcoq* curve is present in figure 3.10.

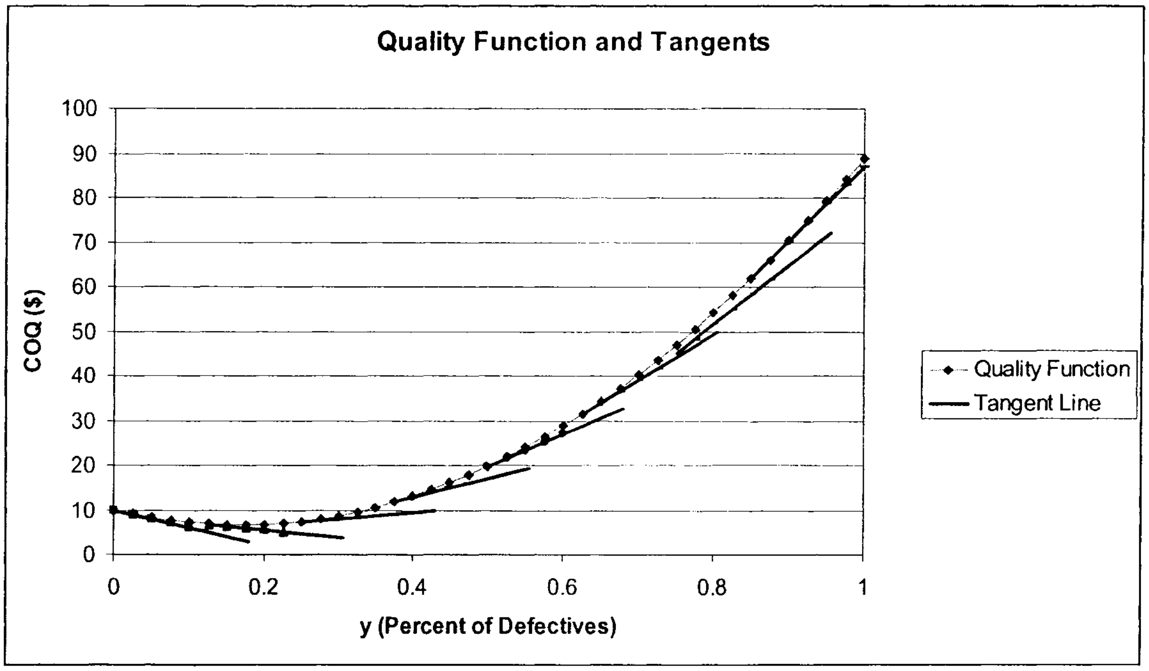


Figure 3.10 : Examples of tangent lines, lower bounds, of a quality function.

The *tcoq* functions replace the *fcoq* functions to give a lowerbound on the objective function. In Table 3.4 (Note: the different supply chains configuration are the same as for the supply chain configurations in Table 3.1 respectively), the value of the lower bound for each supply chain is presented in column (1), hence $f'(b)$. And then in column (2) the percent difference between the model and its lower bound, *Soln-Gap*, is fetched. The *Soln-Gap* is presented mathematically as follows:

$$So\ln - Gap = \frac{f(x) - f'(b)}{f'(b)} * 100 \tag{3.20}$$

$f(x)$ = The objective value of the model obtained by the subgradient search method.

$f'(b)$ = The objective value of the lower bound.

The solution gap, *Soln-gap,* between the solution obtained by the gradient-based search and the lower bound is less than 1% (i.e., varies from 0.09% to 0.57%) which illustrates good quality solutions for the gradient-based search.

Table 3.4: Lower bound and Upper Bounds on solutions.

Supply Chain	*(1)* *f'(b)* Lower Bound Value ($)	(2) Objective Value-Lowerbound gap (%)	*(3)* *f(b)* Upper Bound ($)	*(4)* *Ub-Gap* *f(x) - f(b)* gap (%)
1	5.4491E+07	0.25	5.4650E+07	0.04
2	5.6224E+07	0.09	5.6325E+07	0.09
3	5.4489E+07	0.50	5.4838E+07	0.14
4	1.6099E+07	0.40	1.6166E+07	0.01
5	1.0853E+07	0.31	1.0890E+07	0.03
6	1.0884E+07	0.38	1.0926E+07	0.01
7	1.0784E+07	0.57	1.0859E+07	0.13
8	1.0877E+07	0.25	1.0908E+07	0.04
9	1.6263E+07	0.34	1.6319E+07	0.00
10	8.3222E+06	0.30	8.3485E+06	0.02
11	5.4784E+06	0.30	5.5011E+06	0.11
12	2.7280E+06	0.21	2.7347E+06	0.04
13	5.4771E+06	0.34	5.4975E+06	0.04
14	2.7598E+06	0.26	2.7677E+06	0.03
15	8.1388E+06	0.33	8.1687E+06	0.04
16	2.6872E+07	0.19	2.6936E+07	0.04
17	2.7405E+07	0.52	2.7582E+07	0.12
18	2.7535E+07	0.17	2.7599E+07	0.06

In column (3), the solutions, y^*_{lb} (i.e. the vector y^* corresponds to the lower bound) are substituted into the original model, giving a value of *f(b)*. The latter is an upper bound on the optimal solution. Column (4) in Table 3.4 gives, upper bound gap, *Ub-Gap*, between *f(b)* and *f(x)* . It is calculated as follows:

$$Ub - Gap = \frac{f(b) - f(x)}{f(x)} * 100 \qquad (3.21)$$

f(x) = The objective value of the model

f (b) = The objective value of the model for the y solutions of the lower bound.

As can be deduced from the results in Table 3.4, *f'(b), f(b)* and *f(x) do conform to the following inequality:*

$$f'(b) \leq f(x) \leq f(b) \qquad (3.22)$$

From the experimentations (Table 3.4), *f (b),* the upper bound, varies between 0.04% and 0.14% from the solution which demonstrates the tightness of the solution found by the gradient-based search. And this upper bound, which can be obtained by successive linearization of the quality functions, could be a good approximation of the model.

Chapter 4

Binary Variables and Genetic-Based Solution Procedure

4.1 Binary Variables for the Opening and Closing of Plants

The effectiveness of a supply chain is a product of many factors. The location of the facilities within a supply chain is an important factor that has a major impact on the overall performance of a supply chain. In illustration, given a network of existing facilities in a supply chain, the changing economies might require the closing of some of these facilities. The opening and/or closing of plants for example can reduce the cost of the final product delivered to the customer and hence could be favorable. In Chapter 3, a nonlinear model that incorporated quality functions was solved. The nonlinear model did not account for the possibility of opening and closing of plants. In improving the preliminary model presented in Chapter 3, binary variables that govern the opening and closing of plants are integrated into the model.

The original model would need to be revised for the binary variables to be incorporated at the plants. A new term, $\sum_{j\in J}\sum_{p\in P} Fix_{j,p} z_{j,p}$, will be added to the objective function (3.1), where the following parameters are defined for the same sets defined in section (3.1),

$Fix_{j,p}$ = Fixed cost of producing product p at plant j; $j \in J, p \in P$

and $z_{j,p}$ is a binary decision variable that dictates the opening and closing of a plant and is defined as the following:

$z_{j,p}$ = Binary variable which is one if node j is opened for production for product p and zeros if otherwise $j \in J, p \in P$

The new objective function is denoted $(3.1')$ and constraint (3.3) would be adjusted to account for the possibility of opening and closing of plants, $(3.3')$, as follows:

$$XT_{j,p} \leq z_{j,p} Cap_{j,p} \qquad \forall j, \forall p$$

The revised model will be solved by a gradient based-search procedure which will be discussed in the following section.

4.2 Genetic Algorithm Methodology

Recently, there has been an increasing interest in using various evolutionary computation methods to solve hard optimization problems (Gen and Cheng 1997). Among them, Genetic Algorithm (GA) is one of the most well known classes of evolutionary algorithms. GA deals with a coding of the problem instead of decision variables and it requires no domain knowledge-only the payoff or objectives for evaluating fitness after operating genetic operations (Goldberg 1989). A difference between traditional methods and genetic algorithm is the latter searches from a set of points, while the former from a single point. These characteristics make GA more robust than traditional methods regarding their potential as optimization techniques to solve many real world problems (Gen and Cheng 1997). Michalewicz (1994) is the first researcher, who used GA for solving linear and non-linear transportation/distribution problems. In his method, he represents each chromosome of the problem by using $m \times n$ matrix (Syarif et al. 2002).

In Chapter 3, the model was proven to be convex. Later, the model was solved using a gradient-based search based method. Now that binary variables are asserted into the model, important considerations need to be addressed in order to solve the model and hence modifications need to be made. Tailoring the gradient search method to accommodate binary variables is implausible; the gradient search method caters to continuous variables while binary variables are discrete. Advantageously, GA is a great tool as it is a problem-independent approach. Since the GA is a problem independent approach, GA would complement the gradient-based solution search method to solve the overall model.

Genetic Algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. GA incites a population composed of many individuals to evolve under specified selection rules to a state that maximizes the "fitness" (i.e. minimizes the cost function). The method was originally developed by John Holland (1975) over the course of the 1960s and 1970s. In 1975, the work of De Jong (1975) illustrates the usefulness of the GA for function optimization and makes the first concerted effort to find optimized GA parameters. Haupt R. and Haupt S. (2004) note that Goldberg in his 1989 work contributed the most fuel to the GA fire with his successful applications and book.

Haupt R. and Haupt S. (2004) explore and explain the important steps of GA. The GA begins, like any other optimization algorithm, by defining the optimization variables, the cost function, and the cost. It ends like other optimization algorithms too, by testing for convergence. The GA defines a chromosome or an array of variables values to be optimized. If the chromosome has N variables (an N-dimensional optimization problem) given by $v_1, v_2, v_3, \ldots, v_N$, then the chromosome can be perceived as following:

$$chromosome = [v_1, v_2, v_3, \ldots, v_{N_v}] \tag{4.1}$$

It is necessary to define the cost function which generates an output from a set of input variables. Hence, the cost function is a function of the chromosomes and is as follows:

$$\cos t\ function = f(chromosome) = f(v_1, v_2, \ldots, v_N) \tag{4.2}$$

An important terminology that should be introduced is the term 'population'. The GA starts with a group of chromosomes known as the 'population'; a matrix, $N_{pop} \times N_{bits}$, will result with N_{pop} chromosomes population and N_{bits} number of bits. The $N_{pop} \times N_{bits}$ matrix will be filled with random ones and zeros. The chromosomes will correspond to the number of solutions contested. A chromosome is a member of the population and is a random solution. The number of *bits*, N_{bits}, is analogous to the number of variables and the number of *population*, N_{pop}, is analogous to the population of solutions.

Natural Selection plays a major role in improving the fitness of the population of solution and in achieving best result. In a minimization problem as the current, survival of the fittest translates into discarding the chromosomes with the highest cost. Chromosomes are ranked in accordance to their corresponding cost value, from lowest cost to highest cost. Then, only the best are selected to continue, while the rest are discarded. The selection rate, X_{rate}, is the fraction of N_{pop} that survives for the next step of mating, next generation. Thus, the number of chromosomes that are kept each generation is

$$N_{Keep} = X_{rate} N_{pop} \tag{4.3}$$

Now, natural selection occurs each generation or iteration of the algorithm. Of the N_{pop} chromosomes in a generation, only the top N_{Keep} survive for mating, and the bottom $N_{pop} - N_{keep}$ are discarded to make room for the new offsprings. Selection is the next step in GA. Two chromosomes are selected from the mating pool of N_{Keep} chromosomes to produce two new offsprings. Pairing takes place in the mating population until $N_{pop} - N_{keep}$ offsprings are born to replace the discarded chromosomes.

Mating is the creation of one or more offspring from the parents selected in the pairing process. The genetic makeup of the population is limited by the current members of the population. The most common form of mating involves two parents that produce two offsprings. A crossover point is randomly selected between the first and last bits of the parents' chromosomes. First, $parent_1$ passes its binary code to the left of the crossover point to $offspring_1$. In a like manner, $parent_2$ passes its binary code to the left of the same crossover point to $offspring_2$. Next, the binary code to the right of the crossover point of $parent_1$ goes to $offspring_2$ and $parent_2$ passes its code, to the right of the crossover point, to $offspring_1$ as clearly illustrated in Figure 4.1. Consequently the offspring contain portion of the binary codes of both parents. The parents have produced a total of $N_{pop} - N_{keep}$ offspring, so the chromosome population is now back to N_{pop}.

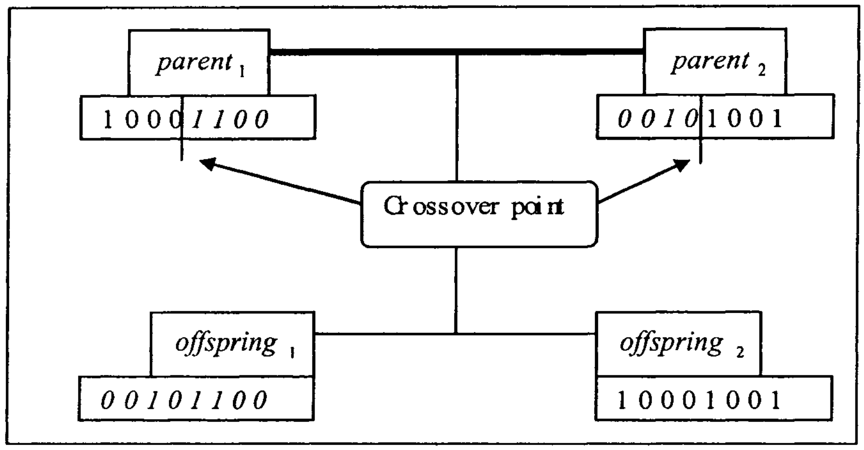


Figure 4.1: Depiction of the mating in GA.

Mutations in GA insure that the algorithm is not trapped in a local minimum. Random mutations alter a certain percentage of the bits in the list of chromosomes. Mutation is the second way a GA explores a cost surface. It can introduce traits not in the original population and keep the GA from converging too fast before sampling the entire cost surface. A single point mutation changes a 1 to a 0, and vice versa. Mutation points are randomly selected from the $N_{pop} \times N_{bits}$ total number of bits in the population matrix. The number of mutations is expressed in terms of the mutation rate and the size of the solution population matrix as follows:

$$no.\ of\ mutations = mutation\ rate * N_{pop} * N_{bits} \tag{4.4}$$

The number of generations that evolve depends on whether an acceptable solution is reached or a set number of iterations is exceeded. After a while all the chromosomes and associated costs would become the same if it were not for mutations. At this point the algorithm should be stopped (Haupt R. and Haupt S. 2004).

4.3 Combining Gradient Search and Genetic Algorithm

In this section binary variables are associated with the opening and closing of plants. The overall model is a mixed binary problem of continuous and binary variables. The binary variable will be optimized using the genetic-based search method, outlined in the previous section and the continuous variables will be optimized using a gradient-based search method; this is done through the coupling of both methods.

In implementing GA to solve the model, the starting point would be in defining the optimization variables. As mentioned already, the only binary variables into the model are the variables associated with the opening and closing of plants. The binary variables are denoted by the $\vec{z}$ vector ($\vec{z} = [z_1, z_2, \ldots\ldots, z_{np}]$) and *np* is the total number of plants. *z* is a binary variable that alternates the opening or closing of plants as follows:

$$z = \begin{cases} 1 & \textit{if plant is open} \\ 0 & \textit{if plant is closed} \end{cases}$$

The population for the problem will be that of the feasible solutions for the *z* variables. The population is a $N_{pop} \times N_{bits}$ matrix with a N_{pop} feasible chromosomes and N_{bits} number of bits. The number bits will be simply the number of binary variables and in turns is the number of plants in the model. The $N_{pop} \times N_{bits}$ matrix will be filled with random ones and/or zeros. To insure the feasibility of the $N_{pop} \times N_{bits}$ matrix, the feasibility of each chromosome within the population is evaluated.

To evaluate feasibility, a population of random binary solutions is initiated; the population of random binary solutions is the matrix $N_{pop} \times N_{bits}$. Recalling the constraint $(3.3')$ in the model where the plant capacity is coupled with the binary $\vec{z}$ array.

$$XT_{j,p} \leq z_{j,p} Cap_{j,p} \qquad \forall j, \forall p$$

In order for feasibility to be satisfied, a sufficient number of plants needs to be open to meet overall customer demand. In other words, the total capacity of all the plants opened must exceed the total customers' demand.

$$\sum_{j \in J} Cap_{j,p} z_{j,p} \geq \sum_{k \in K} D_{k,p} \qquad \forall p \qquad (4.5)$$

For feasibility to be preserved, expression (4.5) needs to be satisfied, where all terms in (4.5) are all previously defined in Chapter 3. Then, to evaluate the feasibility of the random population, $N_{pop} \times N_{bits}$, all chromosomes should be checked for feasibility (i.e., satisfying expression 4.5) and all infeasible chromosomes should be discarded and replaced by feasible ones until all the chromosomes in the population, $N_{pop} \times N_{bits}$, are feasible. Figure 4.2 explores this further; chromosomes in each generation are checked if they abide to expression (4.5) or not. If a chromosome satisfies expression (4.5), the solution is kept, and if the contrary is true, the solution is discarded and new feasible solution (i.e., chromosome) is generated.

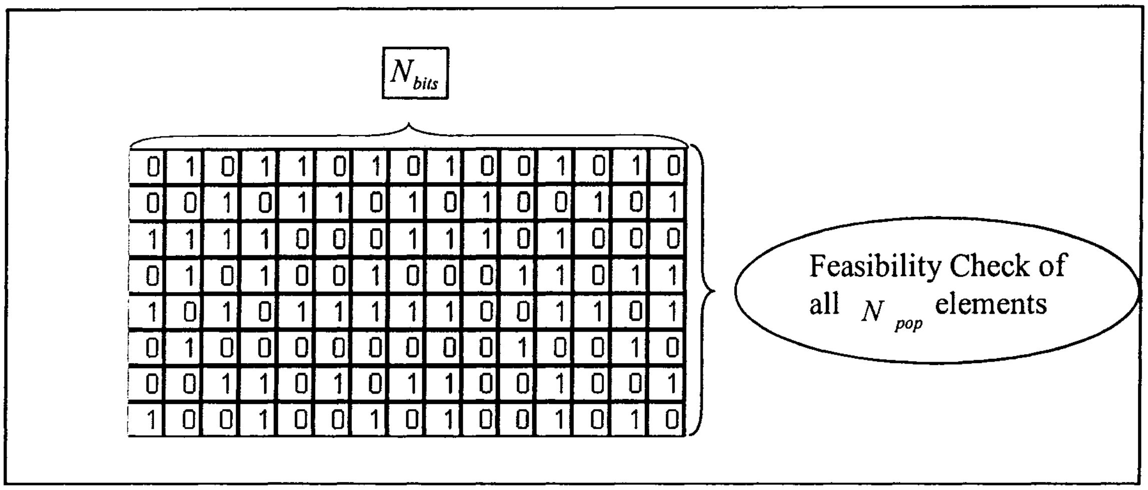


Figure 4.2: Feasibility check for chromosomes.

Once the verification of feasibility has been carried out, the cost function is evaluated. The cost function value is obtained by implementing the gradient-based search procedure discussed in Chapter 3. Thus, the gradient-based search fetches all the cost function values for all the chromosomes. Post to fetching the cost function values, the chromosomes are categorized in accordance to their cost function values. The chromosomes are sorted in an ascending order from lowest to highest cost since the objective of the model is a minimization one.

Once the chromosomes are sorted from most to least *fit*, the process of natural selection takes place. An X_{rate} equal to 0.5 is chosen so only half of the population is kept (see expression 4.3); the choice is made based on preliminary results. The rest of the population is replaced by the new offsprings. Figure 4.3 elaborates on the selection of the *fittest* half the population where the top half of the population is kept and the bottom half is discarded.

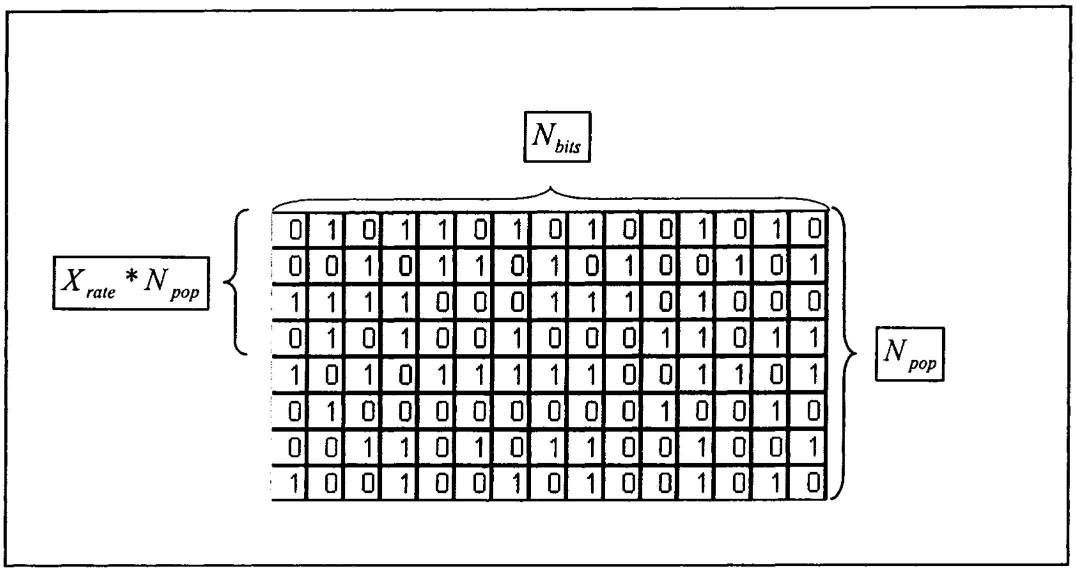


Figure 4.3: Natural selection of the fittest population.

Each pair of parents produces two offsprings. The new offsprings replace the discarded population. Mating then occurs where a single cross over point is used and the crossover point is randomly chosen each iterate. This process is maintained until no further improvement in the population is achieved. So the procedure will be as follows:

1. A random $N_{pop} \times N_{bits}$ matrix of chromosomes is initiated
2. The $N_{pop} \times N_{bits}$ matrix is checked for feasibility and a feasible $N_{pop} \times N_{bits}$ matrix is produced.
3. The set of $N_{pop} \times N_{bits}$ chromosomes are inputted into the model
4. A gradient search methodology is used to solve the nonlinear system for each N_{pop} solution.
5. N_{pop} cost values are produced

6. N_{pop} chromosomes are ranked from lowest to highest in correspondence to their cost values.

7. Top half of N_{pop} are mated and $X_{rate} * N_{pop}$ offsprings are produced

8. Lower half of N_{pop} is replaced by top half of old N_{pop}

9. Three mutations are performed

10. A new $N_{pop} \times N_{bits}$ matrix is obtained

11. A solution is obtained if there is no change in the fitness of chromosomes; otherwise, step two is pursued again.

4.4 Results and Discussion

As previously discussed, having nonlinearities in the objective function and in the constraint was a challenge. Also adding binary variables to the model resulted in more complications. These results show the effectiveness of GA combined with a gradient-based search method in solving a nonlinear mixed binary programming model. The methodology discussed in section 4.2.2 is encoded (figure 4.4) using C language in a Matlab platform.

Procedure of GA
1. Initialization
   1.1 Initiate random N_{pop} of zeros and ones;
   1.2 Initiate selection rate, *sel = 0.5 in this case*
   1.3 Initiate mutation rate, *mutrate = 0.1 in this case*
   1.4 Create population $N_{pop} \times N_{bits}$
   1.5 Insure feasibility of N_{pop} chromosomes
      If chromosome is infeasible, then
      Replace by a new feasible chromosome
2. Do
   2.1 Sort Chromosomes from most to least *fit*
   2.2 Mate the $N_{pop} \times N_{bits}$ population
   2.3 Perform a mutation to $N_{pop} \times N_{bits}$
   2.4 Check and insure feasibility of $N_{pop} \times N_{bits}$
   2.6 Insure feasibility of the new N_{pop} chromosomes
      If chromosome is infeasible, then
      Replace by a new feasible chromosome
   2.7 Sort $N_{pop} \times N_{bits}$ from fittest to worst
3. If non-improvement persists n_{ni} consecutive times, return x

Figure 4.4: Schematic of the gradient-based search procedure.

The methodology was tested with a supply chain network of moderate size; the supply chain network contains 6 suppliers, 15 plants and 3 customers. The input parameters' data for the network are recorded in Appendix B (Table B1, B2, and B3). For the purpose of illustrating the results and also investigation the soundness of the methodology, the capacity is varied and results are noted in Appendix B. In Appendix B (Tables B4, B5, B6, B7, and B8), the capacity of all the supply chain nodes is increased and the percent of defectives and the number of opened plants are reported. As the capacity increases the number of opened plants decreases as the model becomes less scarce and fewer plants are needed for operations. An important insight that should be noted is the behavior of the percent of defectives, the percent of defectives tends to increase as the capacity increases. When the model is constricted and capacity is limited, waste and repair are not tolerated by the model and hence the corresponding percent of defectives, y, is small. As the capacity is expanded there is more free capacity for replacing parts and hence a higher percent of defectives (y) becomes more tolerable.

With a more dynamic presentation of the optimal results, figure 4.5, 4.6, 4.7, and 4.8 visually present the results in an ordered fashion. The figures depict the corresponding behavior of the supply chain in accordance to the increases in capacity.

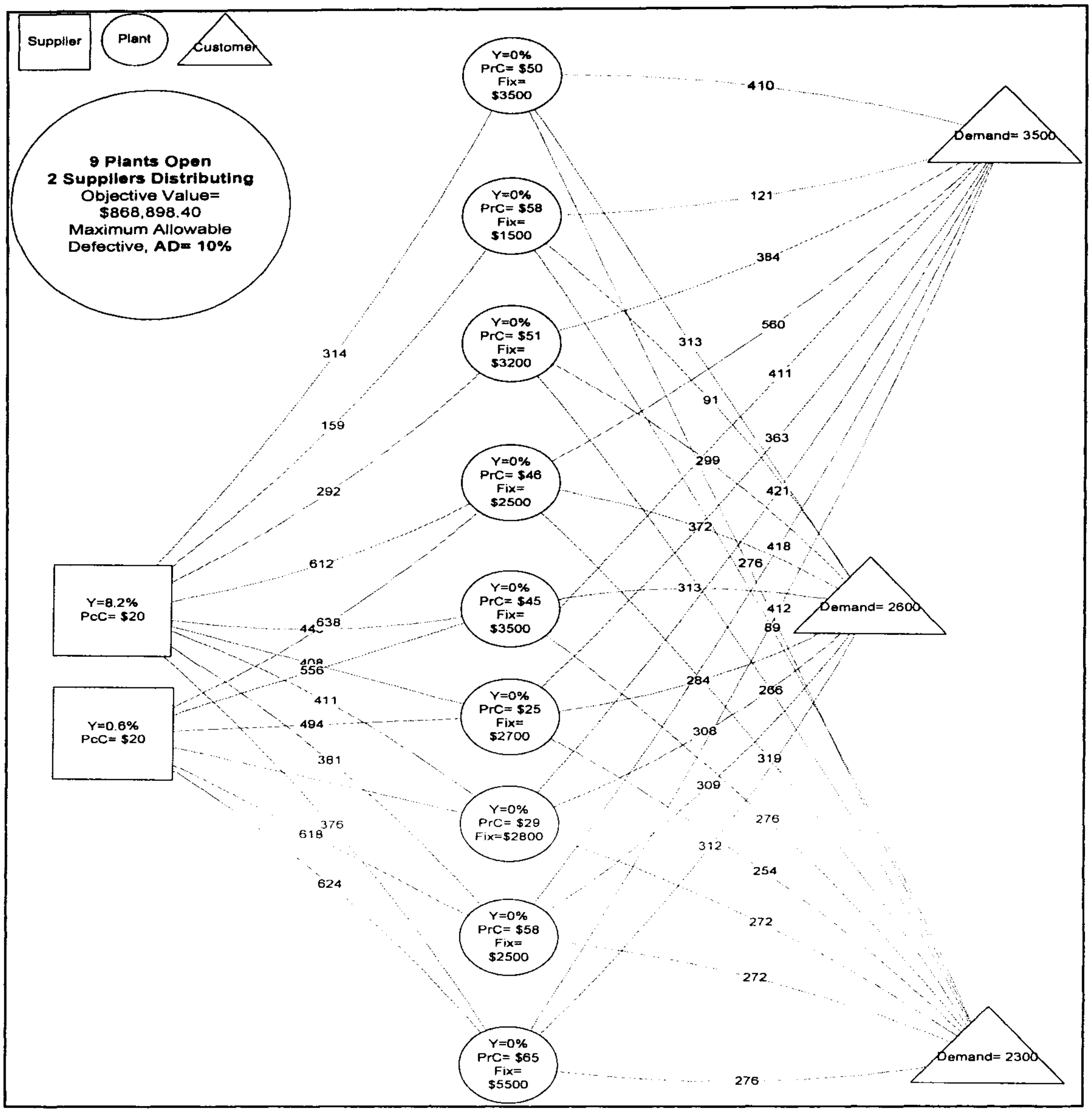


Figure 4.5: GA-based optimal network for original capacity figures.

Figure 4.5 depicts the optimal supply chain network for the input data in Appendix B (Table B1, B2, and B3). Also in the figure, the objective value of the optimal network and the allowable percent of defectives is illustrated; keeping in mind, at this point, there are no changes in capacity. Moreover, the exact input data is used for figure 4.6, 4.7, and 4.8 with the only variation in capacity.

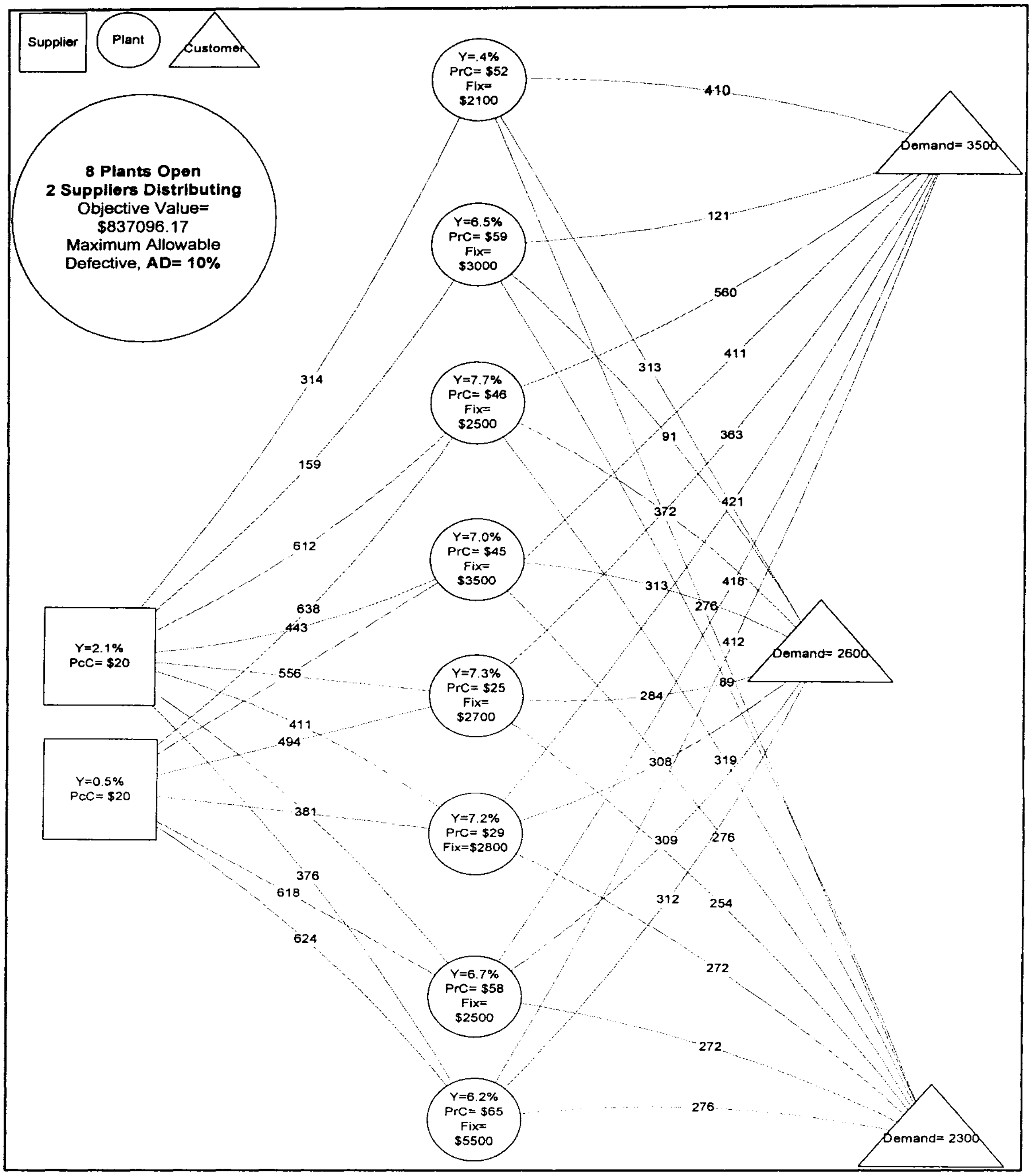


Figure 4.6: GA-based optimal network with a capacity increase of 50%.

Figure 4.6 shows the optimal supply chain network with capacity being increased by 50%. The percent of defectives at the supply chain nodes show a surge with the overall objective value lessening. The objective value is less due to the availability of more capacity at the more cost-effective suppliers. Hence lower-cost producing suppliers are producing more and hence bringing down the overall all cost values.

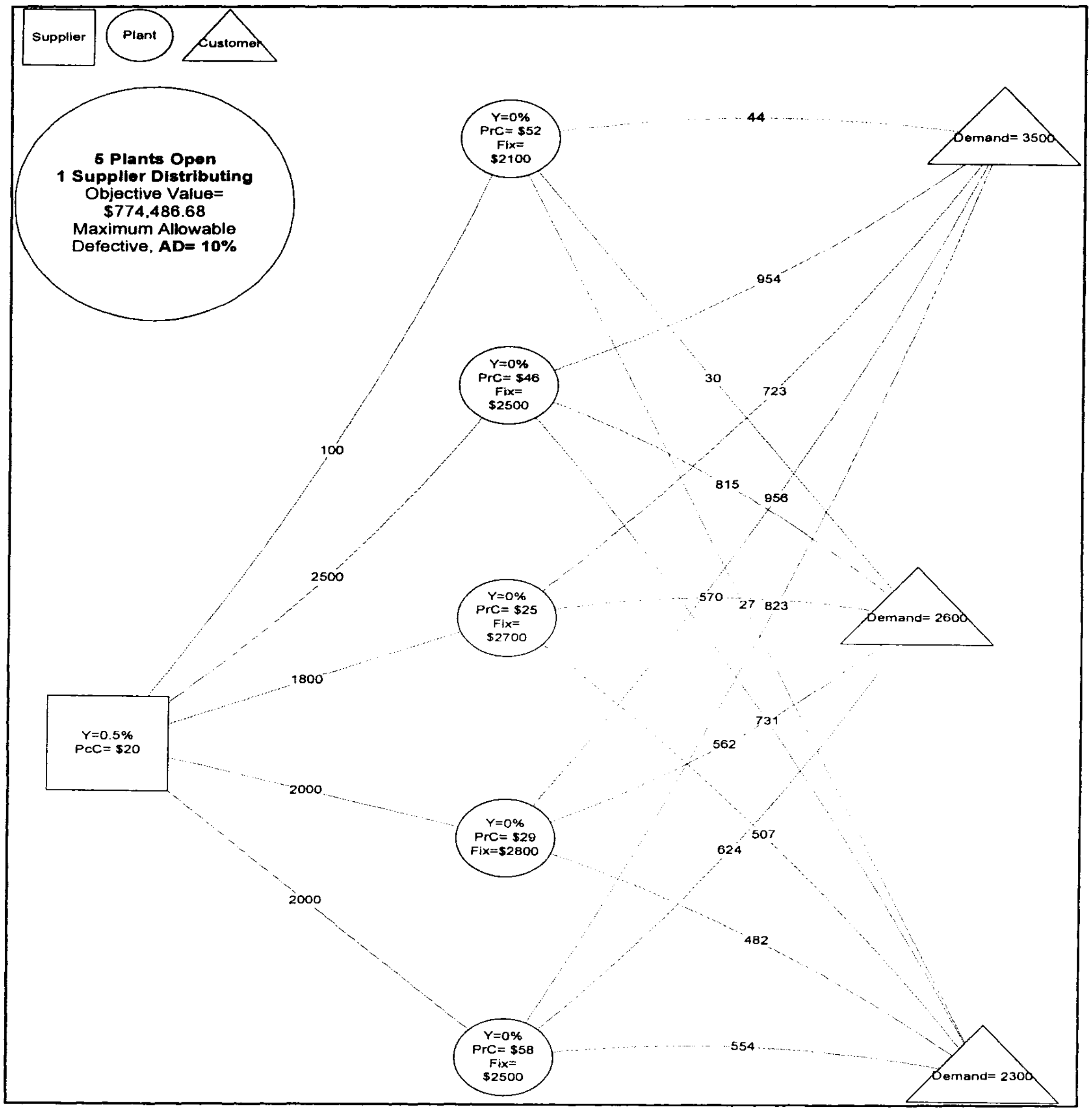


Figure 4.7: GA-based optimal network with a capacity increase of 100%.

Figure 4.7 captures the optimal supply chain network with 100% increase in capacity. The number of opened plants shows a significant reduction to five due to the availability of more capacity for production. The percent of defectives decreases as the model favors closing the plants that are running at higher percent of defectives.

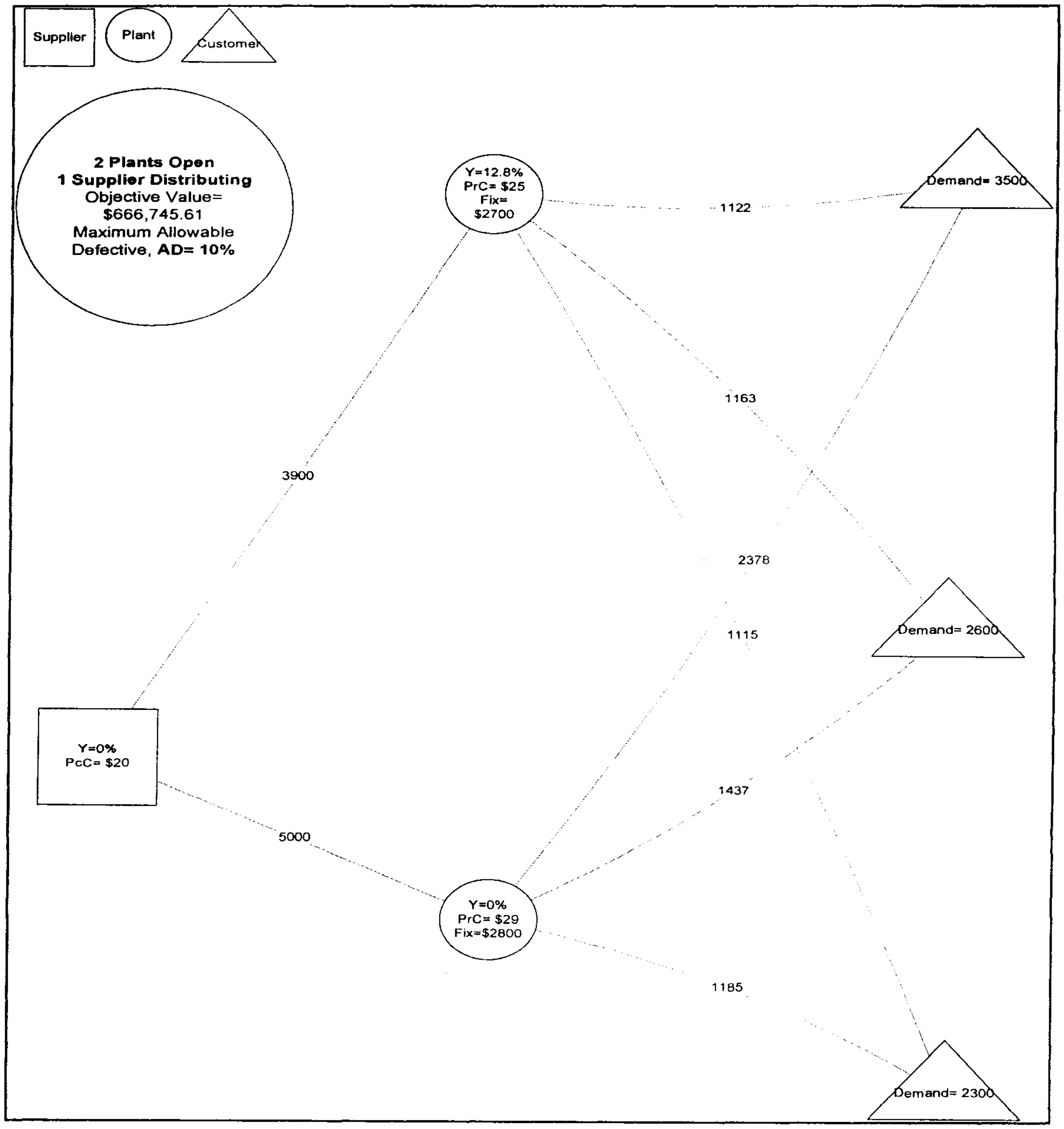


Figure 4.8 : GA-based optimal network with a capacity increase of 200%.

Figure 4.8 shows the optimal supply chain network with 200% increase in capacity. In the figure, the percent of defectives increase drastically reaching the allowable percent of defectives limit (AD defined in section 3.1). The increase takes place at the plant with a lower production cost due to its corresponding low cost of reproduction for compensating defectives.

Chapter 5

Real Life Case Study and the Expanded Model

With the assistance of a leading company in the aerospace industry, real supply chain data was attained. The supply chain data encompass supply chain nodes that incorporate assignment costs; further, the BOM for the supply chain activities is an n level BOM. The assignable costs are the setup costs for initiating production for a given product at a given supply chain node and is represented by a binary decision variable in the context of mathematical programming. Previously in Chapter 4, binary variables were introduced, but the model didn't handle an n level BOM. In this section, the model is revised to account for an n level BOM and assignable costs. Further, the supply chain case study is solved using different solution procedures as will be explained later.

5.1 The Supply Chain in the Aerospace Industry

Many industries today utilize optimization techniques to improve the design and cost structure of their supply chains. The aerospace industry is no different as the need to choose and coordinate sourcing options is important; one of the major options is quality. Suppliers in the aerospace industry are scrutinized for their quality programs and quality is a prominent criterion for choosing in between them. Traditionally, supply chains were dominated by original equipment manufacturers (OEMs). This has changed significantly as new organizational structures are needed to cope with shifting marketing demands to secure strategic supply and sourcing of key parts (Williams et al. 2002). The aerospace industry is one industry where these changes are particularly relevant. Aircraft prime contractors, platform assemblers and systems integrators have traditionally played the dominant role in co-coordinating the value chain top-down. Up to 70% of the final value of a typical aerospace platform is outsourced and the prime contractor traditionally played the lead role handling most of the risk associated with innovation, development funding and production (SBAC 1998). Firms in the aerospace industry now face considerable pressure to improve the co-ordination of their supply chains (Tabibzadeh and Wireman 2003).

The supply chain network studied is that of a highly reputable major Canadian firm in the aerospace industry. The supply chain consists of vendors, subcontractors, and clients. Specific information about the vendors and the subcontractors was gathered; costs and Bill of Materials (BOM) were also retrieved from the company's database. Full and exact data were modified to preserve business privacy. The original model does not account for assignable costs and also does not simulate the special characteristics of the company's supply chain. As mentioned before, the company's supply chain requires the possibility of assignable costs (i.e., binary assignment for nodes of production) and also requires an n level BOM. The n level BOM can be illustrated in the schematic shown in figure 5.1.

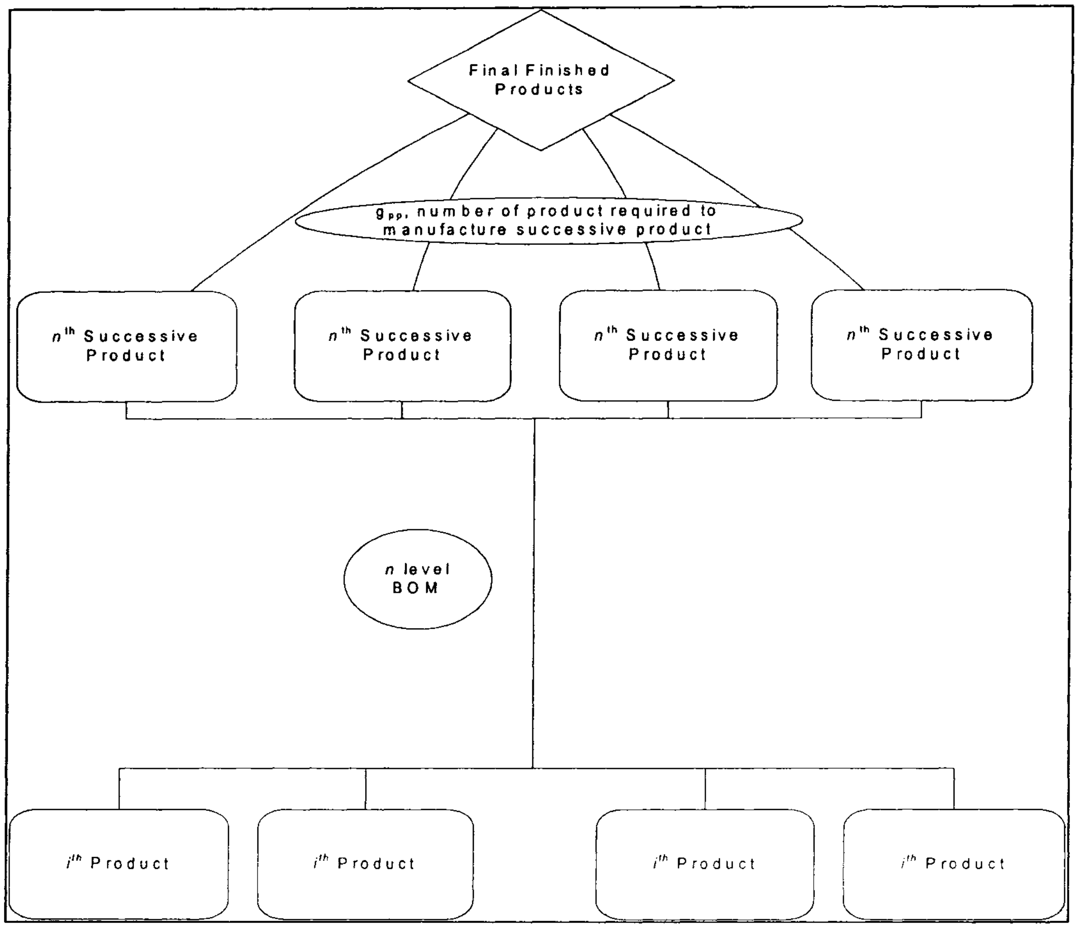


Figure 5.1: Schematic of an n level BOM.

5.2 Binary Nonlinear Supply Chain Model with n Level BOM

Two primary additions are needed to simulate the real life supply chain. First, binary variables need to be integrated into the model. Second, the model has to be revised to cater for the *n* level Bill of Materials (BOM). The work of Ramudhin and Pronovost (2006) model a capacitated supply chain network. Their work tailors to the aerospace industry and models the overall supply chain with the incorporation of their modeling approach, integration of COQ, and the special requirements of the company's supply chain, the model is presented in the following two sections.

5.2.1 Nomenclature

Sets:

V = Group of Vendors.

S = Group of Subcontractors.

R = Set of raw material types.

M = Set of semi-finished product types

C = Set of finished products

P = Set of all product types

D = Set of Clients

Parameters:

$SucV$ = Function that returns all vendors for the set of immediate successors of raw material type $p \in R$.

$SucS$ = Function that returns all subcontractors for the set of immediate successors of product type $p \in M$.

Suc = Set of immediate successors of product type $p \in P$

$fix_{i,p}$ = Fixed cost associated to the assignment of product $p \in P$ to node $i \in V \cup S$.

$\Pr C_{i,p}$ = Unit production cost of product $p \in P$ manufactured at node $i \in V \cup S$.

$t_{i,j,p}$ = Unit transportation cost of product $p \in P$ from node $i \in V \cup S$ to node $j \in SucV \cup SucS \cup D$.

$fcoq_{i,p}$ = Function that returns the cost of quality for product $p \in P$ manufactured at node $i \in V \cup S$ at a percent of defective (i.e. ratio of defective) of $y_{i,p}$ at supply chain node $i \in V \cup S$ for product $p \in P$.

$Cap_{i,p}$ = Allowable capacity of product $p \in P$ that can be manufactured at supply chain node $i \in V \cup S$.

$Dem_{j,p}$ = Demand of product $p \in C$ manufactured at client $j \in D$.

$g_{pp'}$ = Number of product $p \in P|C$ required to manufacture one unit of product $p' \in Suc$

$X_{i,p}$ = Number of product $p \in P$ manufactured at facility $i \in V \cup S$

$XT_{i,j,p}$ = Number of product $p \in P$ transported from node $i \in V \cup S$ to node $j \in SucV \cup SucS \cup D$.

$XG_{i,p}$ = Number of good product $p \in P$ manufactured at facility $i \in V \cup S$

$Z_{i,p}$ = Binary variable which equals 1 if product $p \in P$ is assigned to node $i \in V \cup S$, or zero otherwise.

$y_{i,p}$ = Percent of defectives (i.e. ratio of defectives) for product $p \in P$ manufactured at link $i \in V \cup S$.

5.2.2 Model

Minimize $Z = \sum_{i \in S \cup V} \sum_{p \in P} fix_{i,p} * Z_{i,p} + \sum_{i \in S \cup V} \sum_{p \in P} \Pr C_{i,p} * X_{i,p} +$

$$\sum_{i\in V}\sum_{j\in SucV\cup SucS}\sum_{p\in R}t_{i,j,p}*XT_{i,j,p} + \sum_{i\in S}\sum_{j\in SucS}\sum_{p\in M}t_{i,j,p}*XT_{i,j,p} +$$

$$\sum_{i\in S}\sum_{j\in D}\sum_{p\in C}t_{i,j,p}*XT_{i,j,p} + \sum_{i\in S\cup V}\sum_{p\in P}fcoq_{i,p}*XG_{i,p} \tag{5.1}$$

The objective function (5.1) minimizes a series of terms starting at the first term of assignable costs at all supply chain nodes for all products group. Next, the production cost at all supply chain nodes for all products group is minimized. Three transportation related terms are included. The first term annotates the transportation of raw materials from a vendor to its successive vendor and from a vendor to its successive subcontractor. The second term notes the transportation of semi-finished products from a subcontractor to its successive subcontractor. The third term denotes the transportation of a finished product from a subcontractor to a client. The last term annotates the cost of quality at all supply chain nodes for all products group.

Subject to

$$X_{i,p} \le Cap_{i,p} * Z_{i,p} \qquad \forall i \in S\cup V, \forall p \in R\cup M \tag{5.2}$$

Constraint (5.2) insures that production at each vendor and subcontractor does not exceed the capacity for that given product.

$$\sum_{i\in S}XT_{i,j,p} = Dem_{j,p} \qquad \forall j \in D, \forall p \in C \tag{5.3}$$

Constraint (5.3) insures that the demand for a given product at a given client is met.

$$XG_{i,p} = (1-y_{i,p})*X_{i,p} \qquad \forall i \in S\cup V, \forall p \in R\cup M \tag{5.4}$$

Constraint (5.4) insures that sufficient number of products is made to meet demand and also possible replacements of defective parts for a given supply chain node $i \in S \cup V$ for a specific product type $p \in P$, subject to the BOM.

$$XG_{i,p} - \sum_{j \in SucV \cup SucS} XT_{i,j,p} = 0 \qquad \forall i \in V, p \in R \qquad (5.5)$$

Constraint (5.5) insures that sufficient raw material types are shipped out to meet the demand at the successive subcontractor or successive vendor, subject to the BOM.

$$\sum_{j \in SucV \cup SucS} XT_{i,j,p} - \sum_{p' \in Suc} g_{pp'} * XG_{i,p'} = 0 \qquad p \in R \cup C, i \in V \cup S \qquad (5.6)$$

Constraint (5.6) facilitates the flow-in of raw material types from a given vendor to a successive subcontractor or successive vendor and the flow-in from a subcontractor to a successive subcontractor, subject to the BOM.

$$XG_{i,p} - \sum_{j \in SucS \cup D} XT_{i,j,p} = 0 \qquad \forall i \in S, p \in M \qquad (5.7)$$

Constraint (5.7) facilitates the flow-out of products from a subcontractor to a successive subcontractor and to a client, subject to the BOM.

$$XT_{i,j,p} \geq 0, X_{i,p} \geq 0, XG_{i,p} \geq 0, y_{i,p} \geq 0, Z_{i,p} \in [0,1] \qquad (5.8)$$

Constraint (5.8) insures non-negativity and binary representation.

5.3 Solution Procedures

The model is tested using the obtained supply chain data and the solution procedures' results and discussion are presented and critiqued in this section. Heuristics have been introduced to solve Binary Quadratic Programming (BQP) problems before. A majority of these heuristics are geared towards unconstrained problems where feasibility might not be a concern. The model introduced in this work is a constrained one making feasibility and constraints a criterion for optimality. In this section, solution procedures, which are used in BQP problems, are reviewed and modified to entertain feasibility concerns. Also a hybrid solution procedure is introduced to solve the model effectively. Seven different solution procedures are used to solve the model; one of which is the genetic solution procedure already discussed. The seven solution search procedures are as follows:

1. *1-opt* first move strategy search
2. *k-opt* first move strategy search
3. *1-opt* best move strategy search
4. *k-opt* best move strategy search
5. Simulated Annealing based on 1-opt best search strategy
6. A hybrid solution procedure combining an 1-opt and k-opt search strategies
7. Genetic based search

The first four search strategies are local search strategies and will be discussed in section 5.3.1 and the remaining strategies are discussed in 5.3.2 and 5.3.3.

5.3.1 Local Search Solution Procedures in BQP

The model presented in section (5.2.2) is a binary nonlinear model. Further, the quality functions, presented in Chapter 3, are quadratic and function of the decision variable y and are themselves multiplied by another decision variable. One could analyze the solution strategies available for the BQP problems to find an insight into possible solution strategies to solve the model.

To solve BQP problems, several exact methods have been developed. However, BQP problems belongs to the class of NP-hard problems (Garey and Johnson 1979), and due to the computational complexity of the problem, at the present time exact methods are only capable of solving the small size instances. For larger instances, such methods would become prohibitively expensive to apply, whereas high-performance solution procedure algorithms might find high-quality solutions with short times (Katayama and Narihisa 2001).

Katayama and Narihisa (2001) cited that in obtaining near-optimal solutions in reasonable times, several heuristic approaches such as tabu search (Beasley 1998; Glover et al. 1998), simulated annealing (Beasley 1998; Katayama and Narihisa 2001), genetic (local search) algorithms (Katayama et al. 2000; Lodi et al. 1999; Merz and Freisleben 1999), and scatter search (Amini et al. 1999) have been proposed for the BQP so far.

Local search (LS) algorithms are improvement heuristics that search in the neighborhood of the current solution for a better one until no further improvement can be made (i.e. there is no better solution in the neighborhood of the current solution). Local search algorithms can be categorized by the neighborhoods they consider. For example, the neighborhood of a solution represented by a binary vector can be defined by the solutions that can be obtained by flipping a single or multiple components in the binary vector simultaneously (Merz and Freisleben 2000).

The basic idea of LS is to start from a randomly generated solution and to repeatedly replace it with a better cost chosen from a set of neighbor solutions that can be reached by a slight modification of the current solution. If no better neighbor solution can be found, the LS immediately stops and finally returns the best solution found during the search (Katayama and Narihisa 2001).

The binary solution vector in the case of this work is designated as $Z_{i,p}$, defined in section (5.2.1). The four local search solution procedures used in this work are *1-opt-first*, *1-opt-best*, *k-opt-first*, and *k-opt-best*. In section (5.3.1.1) the first two strategies are discussed and in section (5.3.1.2) the latter two are also discussed.

5.3.1.1 1-opt local search

At each step in a *1-opt* local search, a new solution with a higher fitness in the neighborhood of the current solution is searched. The neighborhood of the current solution is defined by the set of solutions that can be reached by flipping a single bit. *1-opt* neighborhood is the neighborhood of all solutions with a hamming distance of 1 to the current solution. In the implementation, a search for the solution is initiated by a move. In the move, a single bit is flipped and the gain is calculated as the difference between the objective value prior to the move and post to the move, $g = f_{old} - f_{new}$. The gain of flipping a random bit m in the current solution can be calculated as follows (Merz and Freisleben 2000),

$$g = f(z) - f(z') \text{ , with} \tag{5.9}$$

z = binary solution z prior to move.
z' = binary solution z post to the move.

Two types of move strategies are sought in a *1-opt* based search; the first one is a best improvement move strategy, where solution z is chosen if it is the best cost in the entire candidate set of $N(z)$. In elaboration, the *1-opt-best* solution procedure contests a group of solution $N(z)$ and calculates a gain for each solution z, producing a group of gains *G(z)*. The move which is associated with the highest gain among *G(z)* becomes the incumbent move. The move strategy follows the best gain.

The second move strategy is a first improvement move strategy which scans solutions in $N(z)$ according to pre-specified order and z becomes incumbent if the solution z improves the objective value. The *1-opt-first* solution procedure contests a group of *N(z)* solutions but this time a move is made when the first positive, gain, improvement, is achieved (Kattayama and Narihisa 2001), opposed to the 1-opt-best procedure where the highest positive gain is pursued.

In this work, *1-opt-best* will refer to the best move strategy and the *1-opt-first* will refer to the first move strategy and both are utilized to solve the model. Generally, each of the seven solution procedures, with the exception of the genetic one, starts with an initial random seed z solution and then the solution, at a given improvement criterion, is updated at each iterance. Beginning with the *1-opt*-first solution procedure as detailed in figure 5.2, a random element is flipped and then a gain is calculated (5.9). If the gain is positive, and hence the objective value is minimized, the new solution z, is updated and the move is pursued. If the gain is negative, the move is disregarded and solution z remains unchanged. The local search continues until no improvement is perceived. In each iterance, the feasibility of the move is checked. If the move is infeasible then it is disregarded and the solution would remain un-improved; only in the case of feasibility, a move pursued and the solution becomes incumbent. The *counter* parameter (figure 5.2) is used to count the number of consecutive iterations where no improvement to the solution is perceived. Also in figure 5.2, n_{ni} is the maximum number of non-improvement moves before the search is opted out. n_{ni} is a blocked parameter and is the same for all the seven solution procedures (i.e. the convergence criterion is the same for all the solution procedures). If the *counter* exceeds n_{ni}, the solution procedure is terminated and the solution is reported.

```
Procedure of 1-opt-first
1. Initialize: counter = 0;
   initiate a random seed  x
2. Do following until counter > n_ni
   flip random element i
   calculate gain, g_i
    if gain_i>0 & x_i is feasible
      update x,
      counter = 0;
   otherwise
      counter = counter+1
3. Return x
```

Figure 5.2 : 1-opt-first search procedure.

Alternatively, figure 5.3 illustrate the 1-opt-best solution procedure. The 1-opt-best solution procedure flips a random element *i* and calculates a $gain_i$. This is repeated *s* times to create a group of solutions *N(z)* and a group of gains *G(z)*. Then the solution procedure locates the maximum $gain_i$ and its corresponding z_i solution and this solution becomes the updated solution. This process is repeated until the number of non-improvements exceeds n_{ni} and the solution hence converges. The remains of the procedure in figure 5.3, is analogous to that of the 1-opt-first search procedure.

```
Procedure of 1-opt-best
1. Initialize: counter = 0;
   initiate a random seed x
2. Do following until counter > n_ni
   flip random element i for all i in {1,...,s}
   calculate gain, g_i i for all i in {1,...,s}
   fetch maximum gain, gain_max
   if gain_max>0 & x_i is feasible
      update x,
      counter = 0;
   otherwise
      counter = counter+1
```

Figure 5.3 : 1-opt-best search procedure.

5.3.1.2 K-opt local search procedure

The k-opt local search solution procedure seeks a solution by flipping a variable number of k bits in the solution vector per iteration. Contrary to the *1-opt* search method, the *k-opt* method flips more than one bit at a time. The *k-opt* neighborhood (N_{k-opt}) of a binary vector of length n is defined by the binary vectors that can be reached by flipping up to k bits in the vector simultaneously. Analogous to the 1-opt search method, the *k-opt* search method is branched into two different methods distinguished by their move strategy. The two *k-opt* move strategies are *k-opt-first* and *k-opt-best* move strategies. The first method is based on the first improvement move strategy and the second method is based on the best improvement strategy. The contrast between a *k-opt* move strategy and *1-opt* move strategy are presented in figure 5.4.

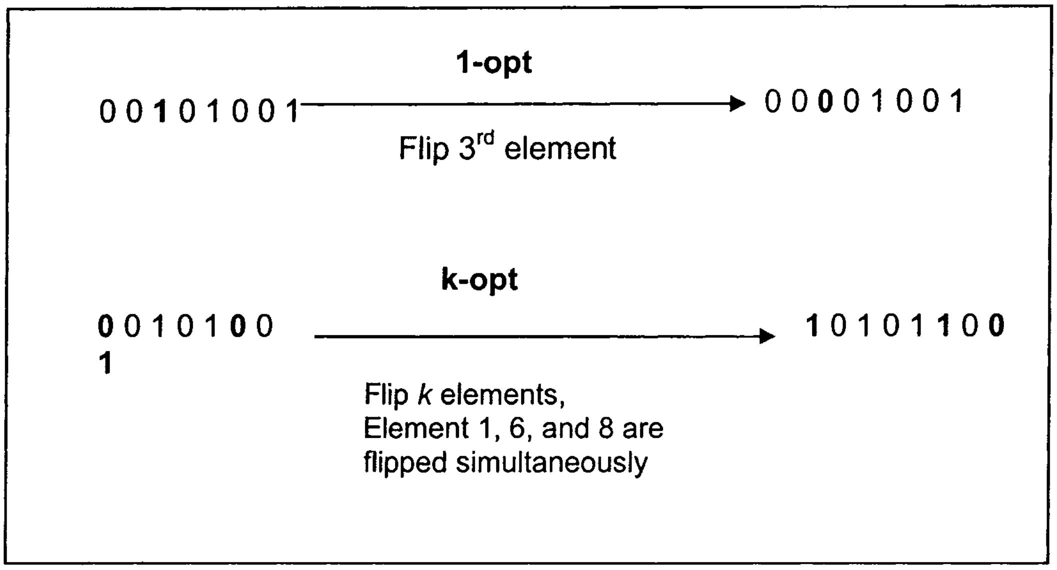


Figure 5.4 : 1-opt versus k-opt move strategy.

The two 1-opt solution procedures already presented would have to be modified to account for the k-opt criterion of flipping one upto k elements simultaneously.

```
Procedure of k-opt-first
1. Initialize: counter = 0
   initiate a random seed x
2. Do following until counter > n_ni
   flip random k number of element simultaneously
   calculate gain,
   if gain>0 & x is feasible
      update vector x,
      counter = 0;
   otherwise
      counter = counter + 1
3. Return x
```

Figure 5.5 : K-opt-first search procedure.

In figure 5.5, the steps in the *k-opt-first* solution procedure are presented and the overall procedure is analogous to the *1-opt-best* procedure except this time k bits are flipped simultaneously. Similarly, in figure 5.6, the procedure for the *k-opt-best* is presented.

```
Procedure of k-opt-best
1. Initialize: counter = 0
   initiate a random seed x
2. Do following until counter > n_ni
     Do for all i in {1,...,s}
       flip random k number of element simultaneously
       calculate gain_i,
       end
   fetch maximum gain, gain_max
   if gain_max>0 & x is feasible
      update vector x,
      counter = 0;
   otherwise
      counter = counter + 1
3. Return x
```

Figure 5.6 : K-opt-best search procedure.

5.3.2 Simulated Annealing-Based Solution Procedure

Simulated annealing (SA) is based on the analogy between simulation of the annealing solids and the problem of solving large combinatorial optimization problems (Kirkpatrick et al. 1983). SA has been applied to various deterministic optimization problems and its effectiveness of SA is attributed to the nature that it can explore the design space by means of neighborhood structure and escape from local minima by probabilistically allowing uphill moves controlled by the temperature parameter (Wang and Zhang 2006).

The Simulated Annealing methodology is based on multiple annealing processes from an initial annealing temperature. The first annealing temperature starts at a higher temperature and then gradually is lowered (Katayama 2001). Each iteration of the simulated annealing search process moves from the current trial solution to an immediate neighbor in the local neighborhood of this solution. The immediate neighbor is selected to be the next trial solution. Now among all immediate neighbors of the current trial solution, a solution is accepted if it improves the objective function. If the solution does not improve the objective function it will be compared to a probability criterion. A random number is compared to the probability, if the probability is greater than the random number, the solution will be accepted or rejected if otherwise (Hillier and Lieberman 2005).

The probability of acceptance is (Hillier and Lieberman 2005):

$$probability = e^{\frac{(obj_0 - obj)}{T}}, \text{ where} \tag{5.10}$$

obj = objective function value of new trial solution,

obj_o = objective function value of the current trial solution,

T = Parameter that measures the tendency to accept the current candidate to be the next trial solution if this candidate is not an improvement on the current trial solution.

The Simulated Annealing (SA) procedure, in figure 5.7, is based on the *1-opt-best* improvement procedure. The *1-opt-best* methodology is conducted, but at each iterance a new step is implemented: when a gain is negative an acceptance criterion is evaluated. As illustrated in figure 5.7, a random number between zero and one is compared to the acceptance probability (5.10); if the random number happens is less than the calculated probability and feasibility is maintained, the solution is preserved and the move is applied and the solution becomes incumbent. The temperature, for the SA, will start at an initial temperature and is then reduced thereafter. The reduction in temperature is referred-to as a cooling schedule. A constant factor cooling scenario is used to cool the temperature. The cooling scenario is as follows (Kirkpatrick et al. 1983):

$$T_n = T_o \left(\frac{T_f}{T_o} \right)^{\frac{i}{N}} \quad \text{, where} \tag{5.11}$$

T_n = the temperature for the later iterance and

T_o= the temperature at the current iterance.

T_f= the final temperature

i = cycle parameter that increases from 0 to 1

N= cooling parameter

```
Procedure of simulated annealing
1. Initialize: counter = 0
   initiate a random seed x
2. Do following until counter > n_ni
   flip random element i for all i in {1,...,s}
   calculate gain, g_i i for all i in {1,...,s}
   fetch maximum gain, gain_max
   if gain_max> 0 & x_i is feasible
      update x, x_i = 1 - x_i
      counter = 0;
   if gain_max<0 & x_i is feasible
      if rand number < probability & x_i is feasible
       update x,
       counter = 0;
     otherwise
      counter = counter+1
3. Return x
```

Figure 5.7 : Simulated annealing-based solution procedure.

The simulated annealing-based procedure is initiated by a 1-opt-best search criterion. Then the solution is accepted if it improves the solution or it meets criterion

(5.10). Like the other solution procedures, the search converges if n_{ni}, number of non-improving moves, is reached.

5.3.3 Hybrid Solution Procedure

The hybrid solution procedure combines both the *1-opt-best* and *k-opt-best* methodologies. The hybrid solution procedure is inspired by the results obtained from the *1-opt-best* and *k-opt-best* preliminary results. For the *k-opt* solution procedure, when a large number of bits are flipped simultaneously, the chance of breaching feasibility becomes more eminent. While the *1-opt* methodology only flips one bit at a time and hence has a lesser chance of breaching feasibility, but at a cost of more computation, as flipping one bit at a time requires longer computational time. When the feasibility threshold (the point at which feasibility is breached) is distal to the initial z solution seed, flipping more than one bit at a time would fare better. But when the initial z seed is proximal to the feasibility breach threshold then flipping more than one bit at a time would be counterproductive as feasibility could be breached. Now if both methodologies (i.e. *1-opt* and *k-opt)* were to be combined, the solution would be sought in a clever manner. As shown in figure 5.8, the *k-opt* and *1-opt* moving strategies are altered and each respective gain is recorded. The best move that brings about the fittest solution, among a group of k-opt and 1-opt, is then chosen. In this way, the best move could be a *k-opt* or a *1-opt* move, depending on the solution topography and the proximity of the infeasibility threshold, and would correspond to the highest gain while meeting the feasibility criterion.

Procedure of hybrid algorithm
1. Initialize: counter = 0,
   initiate a random seed x
2. Do following until counter > n_{ni}
   2.1 if rand number < 0.5 (perform 1-opt)
         flip random element i for all i in $\{1,\ldots,s\}$
         calculate gain, g_i i for all i in $\{1,\ldots,s\}$
       otherwise (perform k-opt)
         flip random k number of element simultaneously
         calculate gain_i,
       fetch maximum gain, gain_{max}
   2.2 if $\text{gain}_{max}>0$ & x_i is feasible
         update x,
         counter = 0;
       otherwise
         counter = counter + 1
3. Return x

Figure 5.8 : A hybrid search procedure.

As illustrated in figure 5.8 a random number is compared where the *k-opt* move strategy has 50% probability of being carried and similarly does the *1-opt* move strategy. Only if the gain is positive, the solution is pursued. The procedure converges if the n_{ni} exceeds the number of non-improving moves allowed.

5.4 Lower bound and Results

Given the integration of binary variables into the model, possible techniques of relaxation would produce a lower bound. The binary variables, z, associated with the assignable costs, could be relaxed to continuous variables with a lower bound of zero and an upper bound of one: $0 \le z \le 1$. Hence, all $Z_{i,p}$ decision variables within the model become continuous with an upper bound of one. Once the variables are relaxed, the model is solved and the solution would become the lower bound to the objective function (5.1). The original model (5.1) is then solved using all seven solution procedures discussed and the solutions are then contrasted against the lowerbound. In all seven solution procedures, at each iterate, the model is solved using a gradient search procedure discussed previously.

Each solution procedure's solution is contrasted against the lower bound and a gap difference, *Df*, is calculated.

$$Df = \frac{Hv - Lv}{Lv} * 100 \qquad (5.12)$$

Hv = Objective value of respective solution procedure
Lv = Objective value of lower bound

The input data is for the supply chain activities (see figure 5.9) is for a leading Aerospace firm and the results are shown in the Table 5.1; the quality functions are simulated to model the cost of quality parameters.

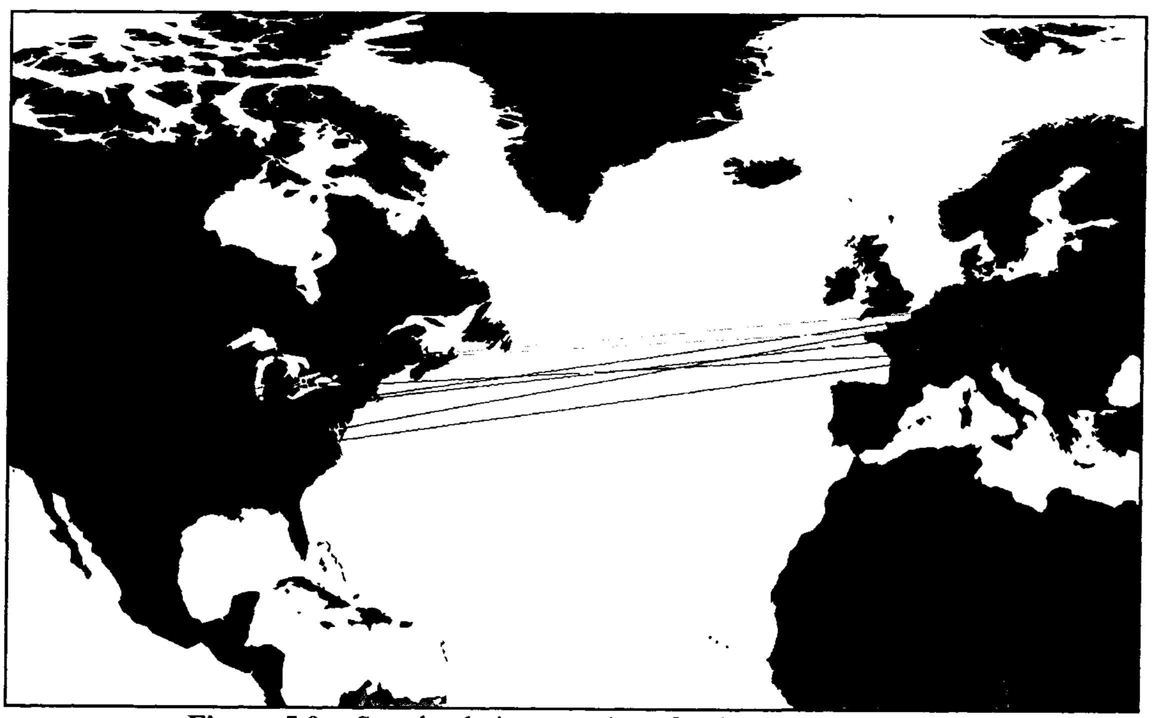


Figure 5.9 : Supply chain operations for the aerospace firm.

To better analyze and quantify the performance of the solution procedures, the supply chain network, in response to different finished product demands, is optimized. Each finished product has its respective demand and BOM. Hence for each finished product the supply chain network is solved (Table 5.1). The stopping criterion, n_{ni}, for all seven solution procedures is the same. n_{ni} is the maximum number of consecutive non-improvement moves allowed. An infeasible move is considered a non-improving move as it does not improve the solution. Therefore, the time duration till the stopping criterion is a measurement of how efficient and successful the solution procedure is in reaching the solution without breaching feasibility. In Table 5.1, the seven solution procedures are contested and the results of the, solution gaps, *Df* (see 5.12), between the solution procedure and the lower bound, are reported. In addition, the time duration of convergence is also noted for each of the seven solution procedures.

From Table 4.1, the *k-opt-first* and *k-opt-best* converge to the solution the fastest as they breach feasibility in the early iterations and in-turn converge prematurely. When a *k* number of bits are flipped, the resulting move is larger in magnitude than that for the *1-opt* move and hence it is more susceptibility to breaching feasibility. Consequently, the *Df* values for the k-opt searches are high as they deviate more significantly from the *lowerbound*. The SA and *1-opt-best* searches bear the closest results to the *lowerbound* but at a high cost of computations until convergence. Both solution procedures are based on a 1 bit move scenario and thus they approach the solution at a slower rate but are less likely to breach feasibility prematurely. The genetic based search procedure shows more consistency as it is not path dependent, although it does not fetch the solution in viable computational time. The *1-opt-first* procedure approaches the solution at a slow rate and does not out perform either of the simulated annealing-based search or the *1-opt-best* search. The hybrid search procedure is situated very well compare to the other procedures. It is not prematurely quick in approaching the solution and it is proximal to it once convergence takes place. Table 5.1 illustrates the resiliency of the hybrid search. It fetches solutions that are about 0.5% from the lowerbound and it outperforms the simulated annealing-based search and deviates by 0.08% from the 1-opt-best search; and it converges with less computation time than both procedures. Further it approaches the solution in about a minute which is considerably less than the timing for the *SA* and *1-opt-best* searches which is two minutes.

Table 5.1: Performance and computational time of the seven solution procedures.

Finished Product (FP)	SA		Genetic		1-opt-best		Hybrid		1-opt-first		k-opt-first		k-opt-best	
	Df (%)	Duration (sec)	Df (%)	Duration (sec)	Df (%)	Duration (sec)	Df (%)	Duration (sec)	Df (%)	Duration (sec)	Df (%)	Duration (sec)	Df (%)	Duration (sec)
FP1	0.33	135	1.00	104	0.30	125	0.51	48	2.44	77	1.59	8	2.44	9
FP2	0.30	198	0.24	236	0.29	129	0.28	70	1.93	128	1.93	2	1.93	4
FP3	0.32	122	0.48	138	0.37	143	0.59	60	2.32	33	1.84	3	2.32	4
FP4	1.21	56	0.58	276	0.72	71	0.52	50	1.98	53	1.98	2	1.98	5
FP5	0.59	153	1.05	101	0.40	128	0.66	59	2.86	249	2.86	8	2.86	4
FP6	0.26	122	0.96	81	0.23	109	0.51	61	1.91	54	1.71	6	1.91	2
FP7	0.49	117	0.51	125	0.75	72	0.61	51	1.96	231	1.96	3	1.96	3
FP8	0.47	146	0.73	129	0.43	98	0.43	63	2.97	24	2.97	9	2.97	5
FP9	0.53	103	1.35	152	0.50	212	0.89	68	2.61	231	2.61	2	2.61	7
FP10	0.60	102	0.88	110	0.31	162	0.46	72	2.02	69	1.67	8	2.02	4
FP11	0.43	140	0.71	170	0.43	353	0.85	54	2.59	345	2.59	7	2.59	4
FP12	0.48	109	1.53	153	0.90	131	0.48	75	3.27	89	1.59	12	3.27	3
FP13	0.83	140	0.69	145	0.46	127	0.52	63	3.10	67	3.10	5	3.10	4
FP14	0.81	178	1.83	55	0.47	155	0.42	66	2.79	49	2.56	12	2.79	4

Importantly, the platform for coding all the solution procedures was the same; a modulue for each solution procedures was programmed on a MATLAB platform using a Pentium IV CPU, 3.00 GHZ with 2.99 GHz of 1.0 GB of Ram system. All results were fetched using this common platform. The solution duration was calculated by a MATLAB built-in module and it closely measured the computational processing time.

In conclusive remarks, the hybrid solution procedure takes advantage of both solution procedures: the *1-opt-best* and *k-opt-best*. The k-opt solution procedure nears the solution at a faster rate because it flips more than one element per iterate. The *1-opt-best* is slower than the k-opt as it flips one element at a time. On the other hand, the *k-opt-best* solution procedure is more likely to miss the optimal than the *1-opt-best* solution procedure; to elaborate, the *1-opt-best* solution procedure only moves one element at a time, and hence it is finer tuned than the *k-opt-best*. The hybrid solution procedure brings the better of the two solution procedures. It chooses either of the *k-opt-best* or *1-opt-best* solution procedure when the move is most rewarding and hence it converges to the solution faster.

Chapter 6

Summary, Conclusion, and Recommendations for Future Research

6.1 Summary

The thesis began by introducing a comprehensive model that integrates Cost of Quality (COQ) into Supply Chain Network Design (SCND). The modeling of COQ into SCND resulted in a nonlinear programming model, which was solved using a combination of solution methodologies. Binary variables were later introduced to the model and the supply chain system was remodeled and a real life case study was used to test the solution methodologies and good quality results were fetched. Seven different solution procedures were used to solve the model with their performance were assessed explicitly.

6.1.1 Summary of COQ Integration into SCND

Supply Chain Network Design (SCND) is an important problem and attracts the attention of many researchers. However, there exists a gap in research for models that integrate COQ into the network design of the supply chain. This study illustrated a modeling approach that incorporates COQ in SCND using mathematical programming which resulted in a nonlinear model. The quality functions that were used are valuable as they represent mathematically the quality system of a given supply chain node (supply chain production facility). Although COQ costing differs among different companies, it is possible to analyze the behavior of COQ with respect to the ratio of defectives (y) and infer a mathematical function that represents it. Hence, using functions, the quality costs are expressed in terms of the ratio of defectives which in-turn is chosen to be a decision variable as it can be related to production activities. The model had not only sought the optimal quality level, but has realized a solution which takes into account day to day tradeoffs in supply chain operations. By minimizing the overall cost of the supply chain one fetches an optimal y that drives the overall operational costs down.

With COQ incorporated into SCND, managers can make decisions not only based on the operational costs, but also based on the quality nonconformance costs. A producer can be operating at a low production cost, but can be trading-off a high cost to remedy nonconformance, and hence, would not be a good choice for production allocation.

Integrating quality functions into the design of supply chain networks adds a challenge in solving the model. As seen, the quality functions are nonlinear and are also associated with other terms through multiplication. Effectively, this thesis first proved convexity of the objective model so the road to producing a methodology for solving the model can be paved. Then, a gradient-based search methodology was implemented successfully in solving the model. Further, this research studied how the model changes with the integration of COQ. The results show that the integration of COQ produces significant savings in supply chain operations. In the case when COQ is not accounted for, cost of replacement and failure is hidden within the operational costs and thus not clearly identified. The integration of COQ revealed these cost and their impacts on the optimal supply chain network.

To illustrate the significance of integrating COQ, two scenarios were tested: one with COQ integration and one without. Since the COQ is a function y in this study, optimizing y reduced the overall cost, and hence, the model with COQ integrated lowered the cost of rework and costs of remedying non-conformance. In addition, the integration of COQ insured that supply chain nodes with advantageous quality functions are chosen in the optimal network. Taking the case of one of the suppliers which had a high cost of quality, the advantage of integrating COQ could be highlighted. This supplier had an attractive low production cost but high COQ. In the model with the null-integration of COQ, this supplier was chosen for production in the optimal network. In the COQ-integrated model, the same supplier was abandoned and production was allocated to suppliers' with advantageous COQ structure.

Furthermore, an insight of how the percent of defectives (y) responds to changes in production cost was investigated. Reducing the production cost increased the ratio of defectives as excessive production is needed to compensate for the defectives. Further, a lower bound to the objective function was constructed and the gradient-based search solution was contrasted against it. The gradient search solution was in close range of the lower bound illustrating the good quality of the solution.

6.1.2 Summary of an Aerospace Case Study

The model was revised to handle a real life case study in the aerospace industry. Using data from a leading company in the aerospace industry, the model was reformed to adapt to the applicability of assignable costs at the supply chain nodes. Advantageously, operational costs at the vendors were also supplied making the model more apprehensive. The vendors and subcontractors are located all across the globe resembling a global supply chain network.

In the aerospace industry, COQ has a major bearing on the overall cost. In industries such as the aerospace industry where suppliers are scarce and the manufacturers of jet engines have to spend a lot of time and money in coaching and training the suppliers to develop their processes both in terms of production capabilities and quality, the cost of quality becomes pinnacle. Therefore, parts in the aerospace industry are scrutinized for quality and the reduction of the quality nonconformance cost is of importance, which makes the integrating of COQ attractive.

The modeling of the aerospace's supply chain brought forward some challenges. The organizations' BOM was quite complex and the sequencing of the sourcing nodes within the supply chain had to be assessed. Certain parts can be procured by exclusive vendors and their corresponding products had a subgroup of subcontractors to which the subsequent value adding operations can take place. A model was formulated to entertain the preceding and incorporated assignable costs to model the supply chain nodes' setup costs. Based on the configuration of the case study's supply chain, the integration of COQ was compatible. For the case study, the cost of transportation was quite high. Correspondingly, the cost of reverse flow, in the case of parts replacement or rework, is also high. Hence, it is critical that the parts are not flawed once they are shipped to the successive node of operations and in-turn minimizing the cost of quality would render a remarkable contribution.

6.1.3 Summary of Solution Procedures

Seven different solution procedures were successful in solving the overall model and were in proximal range of the lower bound. The solution procedures incorporated a feasibility check to insure solutions would be in the feasible region. A real life supply chain case was used to test the model with the supply chain being constrained by demand, capacity and other resource limitations; and the solution procedures were designed to handle the special characteristics of the model and ensure that feasibility is maintained.

In addition, a hybrid solution procedure was designed that integrated components from two other solution procedures to achieve good quality solutions with less computational efforts. The hybrid solution procedure proved to be effective and efficient in solving the case study. It was within close range of the lowerbound and it converged at the solution in superior timing in contrast to the other six solution procedures contested.

6.2 Conclusion

The results presented in this thesis affirm the importance and significance of integrating COQ into SCND. To sum the significance of integrating COQ, it is beneficial to integrate COQ as the quality non-conformance cost would otherwise be hidden. Managers cannot have an insight into how much cost supply chain entities are incurring due to poor quality if their analysis is only based on operational cost. The hidden cost of quality should be revealed, so managers can distinguish the value adding operational cost from the non-value adding one. Once COQ is integrated, managers could infer the difference between the cost of production and what the cost could have been if there were no nonconformities in production.

This thesis has demonstrated the impact of integrating COQ on the optimal supply chain network. For instance, suppliers that were incurring high non-conformance cost are no longer chosen for production. With the integration of COQ, the optimal design of the supply chain network does not reward supply chain entities only on the basis of operational costs, but also on the basis quality performance.

Binary nonlinear models are challenging to solve and they are computationally taxing. The solution procedures used in this thesis tailor to the topography of the model and bring about good quality solutions. Different solution procedures were used to solve the model; and interesting findings were noted and were the basis of implementing a hybrid solution procedure that encompasses different components of reviewed search procedures.

Overall, this thesis gives a comprehensive study on quality cost in the context of supply chain modeling. It discusses initially the evolution of organization structuring beginning at vertically integrated organizations. Vertically integrated organizations possess the advantage of monitoring all operations within the supply chain closely. With recent trends, keeping all activities within the supply chain internalized or vertically integrated might not be advisable. Uncertainty and the need for flexibility might be a reason for this. If certain activities were vertically disintegrated while still being monitored, an integrated supply chain that resembles a vertically integrated organization would result. This has been the product of integrating the supply chain. In an integrated supply chain, operational information is available for analysis at different supply chain nodes as in the case of the aerospace case study. Therefore, the procurement of operational costs is attainable. A quality cost is an indicator of the inefficiency of a system and an example of that inefficiency is the cost of remedying production flaws. This inefficiency is hidden within the folds of operational costs and this work reveals the quality cost and integrates it into the tools at hand for choosing good supply chain partners.

Given a SCND with COQ integrated into it, managers could asses the corresponding weights of important operational parameters such as quality and production cost. In this case, production costs even at external suppliers are important because these costs explicate the component of value added activities to those which are non-value adding. Consequently managers can reward suppliers spending more money on value-adding activities and not on corrective action. COQ and production cost are complimentary as they reveal waste and other non-value added activities. Hence, the integration of both costs into the supply chain modeling can bring about a clearer picture of the supply chain operations.

6.3 Recommendations for Future Research

This work has modeled transportation, quality, and production cost. Future work could explore more possibilities such as including inventory related costs, tariffs, lot sizing discounts, and transportation discounts. Additionally, more solution procedures could be examined in future research. And on a different note, environmental issues can be discussed within the frame of supply chain network design and the costing and construction of COQ function could be further studied.

Inventory is an important parameter and is integrated in many of the supply chain models in the SCND literature. Inventory related costs are important, but fair analysis needs to be done before attempting to integrate them. It would be beneficial to formulate an empirical relationship between COQ and inventory related costs. The impact of reducing inventory on improving quality of products has been noted before. It would be constructive to further evaluate the impact of the inclusion of COQ on inventory cost and vice versa. Theoretically, reducing inventory has a positive impact on quality and hence the relationship between quality and inventory could be assessed quantitatively in the scope of integrating COQ into SCND in future research.

Tariffs and custom fees have been integrated in numerous models in the SCND literature. Given a global supply chain network, it is quite important to minimize the cost of tariffs through reducing the activities between trading zones especially those activities that incur high tariffs. In the assessment of the supply chain the allocation of production to nodes that belong to high-tariffs trading zones might prove to be unfavorable. Therefore, it would be beneficial to integrate a form of tariff costing into the SCND along with COQ.

Lot sizing discounts pertain more to some industries than to others. For a more generic supply chain model, it is favorable to incorporate discounts into SCND. A supplier could offer attractive discount for sourcing a bigger lot size and this might in-turn shift the configuration of the optimal supply chain network. In addition, transportation cost accounts for a considerable portion of the overall supply chain activities' costs especially with the rising cost of energy. It is advisable to ship bigger lot sizes and this might correspondingly affect the order quantity. Thus, this is an area where further research is recommended.

Seven different solution procedures were used to solve the model. Alternative solution procedures exist in literature and could be pursued. Tabu search is one of those procedures. Tabu search has gained a considerable amount of steam in the last few years as a robust meta-solution procedure in solving tough problems. Additionally, other solution procedures pertaining to artificial networks could be sought. Especially given the integration of more parameters into the SCND would result in different model characteristics. Advantageous solution procedures would prove useful and should be investigated further.

Environmental concerns are becoming important criteria for making decisions pertaining to operations. For instance in a manufacturing setting, harmful emissions are released-out to the atmosphere and the by-production of harmful omissions might result in penalties. With world nations setting ambitious targets on emission cuts, it would be quite interesting to integrate a form of an indicator, which models environmental levels of harmful emissions, into SCND. Integrating such a factor along with COQ could have a positive impact on quality and vice versa. Integrating COQ has resulted in better quality systems in the optimal supply chain network, one which favors reduction in rework, repairs, and replacements. Reduction in rework will reduce unnecessary production for rework or replacements and in-turns reduce unnecessary emissions as a result of excess production. Therefore, integrating an environmental indicator along with COQ into SCND should require more attention and further research.

In this work, COQ functions were represented by quadratic expressions as a function of the ratio of defectives. This is advantageous as it ties the ratio of defectives to the overall minimization of operational costs. However, other forms of COQ representation could be analyzed further. In addition, the costing of quality could be studied and the procedures for the procurement of COQ figures could be also studied further.

Appendix A

Table A1. Instances of Input Data for Suppliers

Supplier Number	Parameter (ae) in the Supplier Quality Function	Parameter (be) in the Supplier Quality Function	Parameter (ce) in the Supplier Quality Function	*(PcC)* Production Cost at Supplier	*(SC)* Supplier Capacity
1	117.5800	40.5440	7.9595	4.3567	18096.0000
2	117.9700	40.8160	7.4892	4.6553	18244.0000
3	118.7400	42.2890	7.0382	4.7010	18248.0000
4	115.7800	44.6570	7.9298	3.2503	18086.0000
5	114.9000	43.5190	7.6587	3.4532	18252.0000
6	116.2000	44.3510	7.1763	4.2844	18271.0000
7	110.4200	41.8140	7.6452	4.7698	18082.0000
8	114.5100	44.3540	7.4781	4.5579	18360.0000

Table A2. Instances of Output Data for Suppliers

Supplier Number	(S) Number of Good Products Produced at Supplier	(ST) Number of Total Products Produced at Supplier	Resulted (y) Percent of Defectives at Supplier
1	0	0	0.000
2	5338	5338	0.000
3	16311	18248	0.106
4	16055	18086	0.112
5	16236	18252	0.110
6	16794	18271	0.081
7	0	0	0.000
8	16289	18360	0.113
Number of supplier parts needed to make one product at the plant, *n*			1

Table A3. Instances of Input Data for Plants

Plant Number	Parameter (ae) in the Plant Quality Function	Parameter (bp) in the Plant Quality Function	Parameter (cp) in the Plant Quality Function	*(PrC)* Production Cost at Plant	*(Cap)* Plant Capacity
1	118.8300	43.0000	7.6489	8.2711	9003.2000
2	115.2500	40.2740	7.0886	9.9600	9005.5000
3	116.8000	42.4230	7.9384	9.3007	9002.8000
4	112.6300	44.8900	7.1754	9.5256	9001.8000
5	110.7800	42.1510	7.6974	9.6262	9008.2000
6	110.3900	41.1830	7.8320	9.8598	9002.7000
7	113.0900	43.7950	7.3366	10.2210	9006.4000
8	110.7500	41.9150	7.7994	10.8150	9001.0000

Table A4. Instances of Output Data for Plants

Plant Number	*(X)* Number of Good Products Produced at Plant	*(XT)* Number of Total Products Produced at Plant	Resulted *(yp)* Percent of Defectives at Plant
1	8010.5000	9003.2000	0.1103
2	5680.7000	6196.4000	0.0832
3	5963.2000	6661.4000	0.1048
4	1594.2000	1795.2000	0.1120
5	8014.0000	9008.2000	0.1104
6	8341.5000	9002.7000	0.0734
7	8656.9000	9006.4000	0.0388
8	0.0000	0.0000	0.0000

Table A5. Instances of Clients' Demands

Client Number	Demand at Client
1	9091.1
2	9013.6
3	9061.7
4	9026.9
5	9022.1
6	9071.3

Table A6. Suppliers' Input Data for production cost reduction models

Supplier Input Data					
Supplier	Capacity	Production Cost	Quality function a parameter	Quality function b parameter	Quality function c parameter
1	1800	40	97	39	7
2	1800	42	118	60	9
3	1800	41	112	43	6
4	1800	41	106	54	5
5	1800	42	102	56	6
6	1800	42	115	41	9
7	1800	44	131	41	8
8	1800	41	111	30	7
9	1800	33	116	62	7

Table A7. Plants' Input Data for production cost reduction models

Plant Input Data					
Plant	Plant Capacity	Production Cost at the plant	Quality function a parameter	Quality function b parameter	Quality function c parameter
1	800	210	130	78	39
2	800	203	131	75	38
3	800	206	142	73	44
4	800	209	132	77	42

Table A8. Demand Information

Customer	Demand at Customer	*n*, number of supplier parts to make one final product for customer
1	1000	
2	500	4
3	700	

Appendix B

Table B1: Suppliers' Input Data for Genetic Algorithm analysis

Supplier Input Data					
Supplier	Capacity	Production Cost	Quality function *a* parameter	Quality function *b* parameter	Quality function *c* parameter
1	5000	20	119	39	7
2	6000	20	45	60	12
3	4000	20	2	23	6
4	5000	20	49	6	5
5	4500	20	68	2	6
6	5500	20	88	30	11

Table B2: Plants' Input Data for Genetic Algorithm analysis

Plant Input Data					
Plant	**Plant Capacity**	**Production Cost at the plant**	**Quality function *a* parameter**	**Quality function *b* parameter**	**Quality function *c* parameter**
1	1000	54	119	69	65
2	1100	53	6	5.8	72
3	1000	52	4	4.2	71
4	1150	54	121	85	56
5	1000	50	134	77	54
6	1200	58	123	76	53
7	1000	59	122	72	51
8	950	51	124	82	43
9	1250	46	111	85	42
10	1000	45	142	78	47
11	900	25	133	81	35
12	1000	29	152	80	2
13	1000	58	141	74	8
14	800	67	101	65	65
15	1000	65	109	69	23

Table B3: Customers' Input Data for Genetic Algorithm analysis

Customer	**Demand at Customer**	***n*, number of supplier parts to make one final product for customer**
1	3500	
2	2600	1
3	2300	

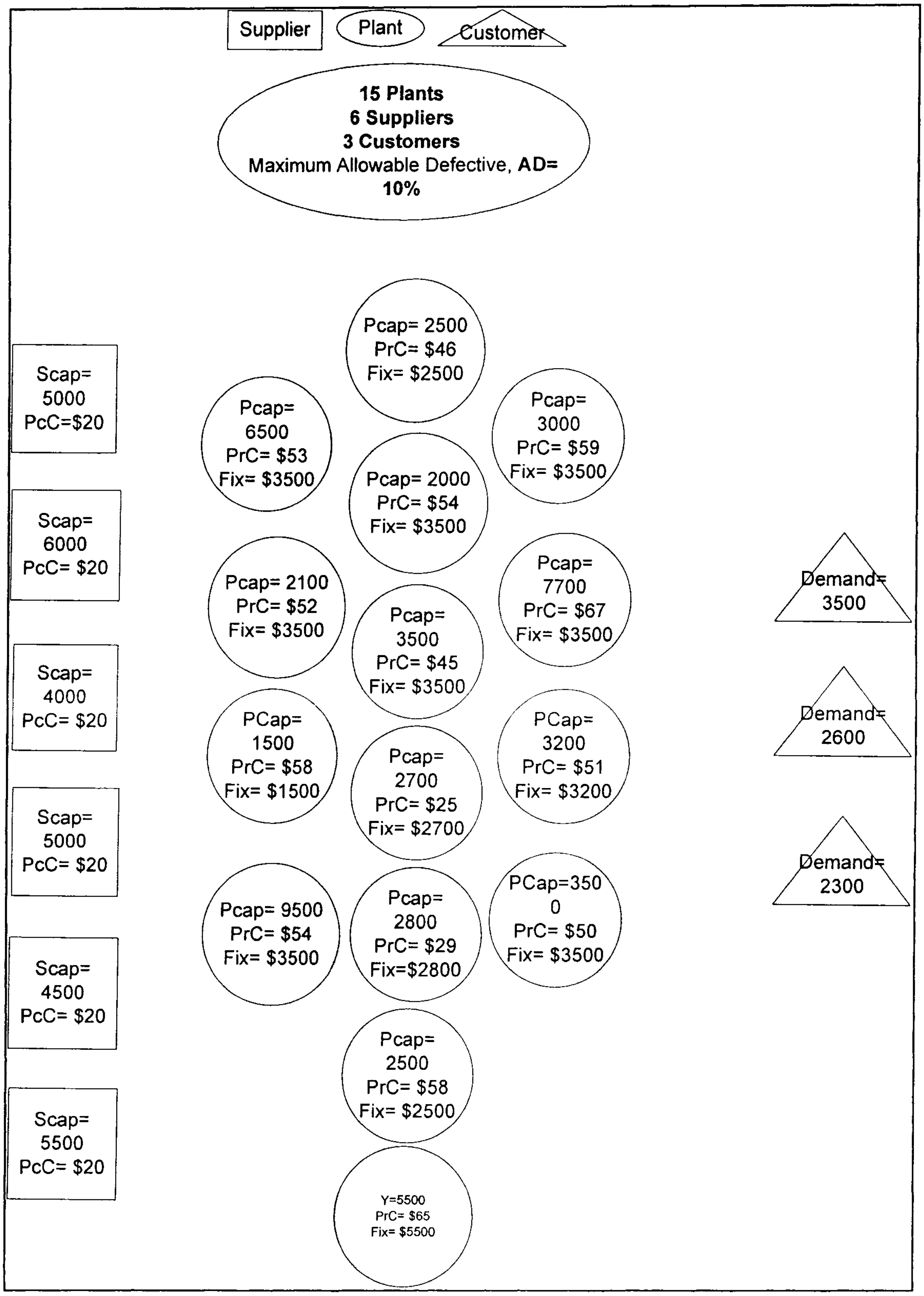


Figure B1: Supply chain network for genetic based search algorithm

Table B4: Results for Genetic based procedure at all the capacities fixed

Suppliers		Plants			Binary variable values
Supplier	**Supplier y**	**Plant**	**Plant y**	**Plant Fixed Cost**	
1	0.0%	1	0.0%	9500	0
2	0.0%	2	0.0%	6500	0
3	8.2%	3	0.0%	2100	0
4	0.0%	4	0.0%	2000	0
5	0.6%	5	0.0%	3500	1
6	0.0%	6	0.0%	1500	1
		7	0.0%	3000	0
		8	0.0%	3200	1
		9	0.0%	2500	1
		10	0.0%	3500	1
		11	0.0%	2700	1
		12	0.0%	2800	1
		13	0.0%	2500	1
		14	0.0%	7700	0
		15	0.0%	5500	1
		Total Number of Opened Plants			9

Table B5: Results for Genetic based procedure for 50% capacity increase

Suppliers		Plants			Binary variable values
Supplier	**Supplier y**	**Plant**	**Plant y**	**Plant Fixed Cost**	
1	0.0%	1	0.0%	9500	0
2	0.0%	2	0.0%	6500	0
3	2.1%	3	0.4%	2100	1
4	0.0%	4	0.0%	2000	0
5	0.0%	5	0.0%	3500	0
6	0.0%	6	0.0%	1500	0
		7	6.5%	3000	1
		8	0.0%	3200	0
		9	7.7%	2500	1
		10	7.0%	3500	1
		11	0.0%	2700	1
		12	0.0%	2800	1
		13	0.0%	2500	1
		14	0.0%	7700	0
		15	0.0%	5500	1
		Total Number of Opened Plants			8

Table B6: Results for Genetic based procedure for 100% capacity increase

Suppliers		Plants			Binary variable values
Supplier	Supplier *y*	Plant	Plant *y*	Plant Fixed Cost	
1	0.0%	1	0.0%	9500	0
2	0.0%	2	0.0%	6500	0
3	2.1%	3	0.0%	2100	1
4	0.0%	4	0.0%	2000	0
5	0.0%	5	0.0%	3500	0
6	0.0%	6	0.0%	1500	0
		7	6.5%	3000	0
		8	0.0%	3200	0
		9	7.7%	2500	1
		10	7.0%	3500	0
		11	0.0%	2700	1
		12	0.0%	2800	1
		13	0.0%	2500	1
		14	0.0%	7700	0
		15	0.0%	5500	0
		Total Number of Opened Plants			5

Table B7: Results for Genetic based procedure for 150% capacity increase

Suppliers		Plants			Binary variable values
Supplier	Supplier *y*	Plant	Plant *y*	Plant Fixed Cost	
1	0.0%	1	0.0%	9500	0
2	0.0%	2	0.0%	6500	0
3	0.0%	3	0.0%	2100	0
4	0.0%	4	0.0%	2000	0
5	0.0%	5	0.0%	3500	0
6	0.0%	6	0.0%	1500	0
		7	0.0%	3000	0
		8	0.0%	3200	0
		9	7.7%	2500	1
		10	0.0%	3500	0
		11	7.3%	2700	1
		12	0.0%	2800	1
		13	0.0%	2500	1
		14	0.0%	7700	0
		15	0.0%	5500	0
		Total Number of Opened Plants			4

Table B8: Results for Genetic based procedure for 200% capacity increase

Suppliers		Plants			Binary variable values
Supplier	**Supplier** *y*	**Plant**	**Plant** *y*	**Plant Fixed Cost**	
1	0.0%	1	0.0%	9500	0
2	0.0%	2	0.0%	6500	0
3	0.0%	3	0.0%	2100	0
4	0.0%	4	0.0%	2000	0
5	0.0%	5	0.0%	3500	0
6	0.0%	6	0.0%	1500	0
		7	0.0%	3000	0
		8	0.0%	3200	0
		9	0.0%	2500	0
		10	0.0%	3500	0
		11	10.0%	2700	1
		12	0.0%	2800	1
		13	0.0%	2500	0
		14	0.0%	7700	0
		15	0.0%	5500	0
		Total Number of Opened Plants			2

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