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An analysis of the effect of supply chain and manufacturing parameters on inventory cost reduction for push type manufacturing systems

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AN ANALYSIS OF THE EFFECT OF SUPPLY CHAIN AND MANUFACTURING PARAMETERS ON INVENTORY COST REDUCTION FOR PUSH TYPE MANUFACTURING SYSTEMS

A Dissertation

Submitted

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Industrial Technology

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ABSTRACT

In the global network of businesses, supply chain and order fulfillment managements are the most critical functional departments to determine the winner of the global competition. In this research a network of companies that are flowing information, product and services between providers and a receiver is investigated in order to gain a better insight of the current situation. Analyses, explanations and solutions were developed through responding to the following research questions:

1. What are the most important variables that affect the quality and delivery performances of a supply chain?
2. What are the most important variables that affect the service rate or fill rate of a supply chain of a manufacturing company?
3. What levels of the selected variables could be used in order to minimize inventory on hand?

The research was based on the analysis of a supplier network of a midwestern manufacturing company. Initial study verified that there was no company policy established to prevent stock-outs resulting from late deliveries or quality nonconforming parts.

In order to investigate the effects of existing company policies and guidelines a discrete event simulation model was developed. During the model building phase historic data was utilized to create simulation parameters. Analysis of the historic data revealed

that neither the production lead time nor the schedule changes affect the quality or delivery performance of suppliers.

The results of the simulation confirm the importance of the number of suppliers in a supply chain. The number of suppliers negatively affects the efficiency of the order fulfillment process and high numbers of suppliers require higher inventory levels. The company's supplier classification guideline was also validated for delivery performance ratings by the simulation model. However, the supplier classification based on the quality performance was not found to be practically significant.

CHAPTER I

INTRODUCTION

Inventory control is the activity which organizes the availability of items to the customers. It coordinates the purchasing, manufacturing and distribution functions to meet marketing needs. This role includes the supply of current sales items, new products, consumables, and all other supplies. Inventory enables a company to support its customer service, logistic or manufacturing activities in situations where purchase or manufacture of the items is not able to satisfy customer demand. The aim of the inventory control is not to make all items available at all times as this may be detrimental to the finances of the company. Wild (1997) defines the normal function for stock control as meeting the required demand at a minimum cost possible.

The aim of long term profitability of an organization has to be translated into operational and financial targets which can be applied to daily operations of the organization. On the other hand, the purpose of the inventory control function is to support business activities to optimize three main functions: inventory cost, customer service, and operating costs. Inventory levels in a company are driven by the company's sales and marketing strategy for its product lines, an understanding of customer buying patterns, and the competitive and economic environment. These factors are all external to the inventory management department in a company. How they are translated into inventory levels and availability is the function of the inventory strategy as translated into internal planning and control processes and procedures.

The purpose of this research is to investigate internal and external factors and relevant parameters that affect inventory level, service rate and cost variations in final assembly lines. In order to do that, a model that captures all the cited parameters of interest is proposed by the researcher. Later, this model is tested by a discrete event simulation technique using ARENA ® simulation software. At the end of the study, the results will be analyzed for their sensitivity to explain the variations under real life conditions.

The vision behind the current production strategies in many production settings is to have the target inventory, at the target time, at the target place, in the target quality, in the target orientation with zero deviation from target. However, from an absolutely practical perspective, zero-deviation performance for all parts across all dimensions all the time is impossible to achieve. This vision is different than an "all inventory is waste" vision, which is supported by Just-in-Time (JIT) and Toyota Production Methods; Bernard (1999) suggests an integral strategy that is based on the recognition that a given level of inventory is necessary to the effective operation of the business. This level is a function of business conditions which existed at the time the inventory was ordered and which are forecasted to exist through the duration of the stocking horizon. Ensuring that the target level of inventory is available to support the needs of the business is the mission of inventory management.

Statement of the Problem

The problem of this research was to develop a simulation model to analyze the effects of lead time, order schedule changes, number of suppliers, and delivery and quality related problems on safety stock levels in order to minimize inventory amount and reduce cost.

Statement of the Purpose

Like all other activities in a manufacturing company, inventory management has to contribute to the welfare of the whole organization. Therefore, the expected results of this research will allow organizations to align their suppliers and their suppliers' resources and capabilities, thereby create a competitive advantage and provide value to their customers. In order to do that, the goal of this research is to identify key inventory control parameters, and develop a mathematical model based on the factors that are being employed at the company under study.

Importance of the Research

Inventory cost reduction should be one of the prime goals of all manufacturing companies. According to Kobert (1992) because inventory is a huge asset on the balance sheet accounting for as much as 50% of current assets, inventory management plays a major role in a company's cost reduction strategy. It is also noted that a better control over inventory level results in improvements in such areas as purchasing, warehousing, distribution, labor utilization, equipment scheduling, data presentation, quality assurance, vendor relations, packaging, materials handling, and even personnel administration.

The need for this research first came out at a meeting with the Order Fulfillment Management of a Midwestern Manufacturing Company. Currently, the company establishes operating parameters using rules of thumb and experiential knowledge. This leads to inconsistencies and variations from planner to planner and factory to factory. It is believed that current practices are not leading to optimum business results.

The company is on the journey to continuously improve operations execution and asset velocity. However, the company doesn't fully understand the mathematical relationship between operations execution parameters and the business outcome metrics. It is the administration's desire to discover and understand the relationships so that they may systematically establish the operating execution system parameters, to proactively drive future business results. More specifically, the company under study has asset reduction targets which will drive financial advantage to the company. However, there are no guiding principles or formulas for setting up optimal inventory levels.

The company is doing business with more than six thousands suppliers from all over the world. Correlating optimal inventory levels to supplier lead times and supplier performances as well as factory execution performance will help the suppliers and order fulfillment activities get aligned in order to achieve asset reduction objectives.

Research Questions

Modeling and formulating an efficient inventory planning and control policy to guarantee the product availability at a certain level with the lowest cost is not an easy task. There are many uncertainties inherent to the process itself, such as delivery or replenishment lead time, inaccurate demand forecasting, and variations between delivery and order quantities. These variations and uncertainties require the building up of safety stock.

Although overstocking involves more inventory holding costs than necessary, being short of safety stocks may cause sales losses and higher rate of postponed orders than desirable, which at the end results in the deterioration of service levels and customer service standards.

The current research addresses the following questions. The findings will be addressed in Chapter IV.

1. What are the most important variables that affect the quality and delivery performances of a supply chain?
2. What are the most important variables that affect the service rate or fill rate of a supply chain of a manufacturing company?
3. What levels of the selected variables could be used in order to minimize the inventory on hand?

The research questions were evaluated in an experimental design that analyzes the effects of parameters at different levels. Also multiple regression analysis and analysis of variance methods were employed along with the design of experiments method.

Assumptions

The following assumptions were made in pursuit of this study:

1. That the methods and the efficiencies of manufacturing, logistics, and supply management operations stayed the same during the data collection period at the suppliers' manufacturing facilities.
2. The data collected from the suppliers and from the company under study are considered to be valid and representative for simulation and statistical analysis purposes.
3. That the supply chain network and the inventory control operations can be simulated using ARENA® discrete-event simulation software.
4. That the parameters under consideration are measurable.

Limitations

This research study was conducted in view of the following limitations:

1. The simulation model will be developed in ARENA ® discrete event simulation program. The limitations of the program determine the model accuracy.
2. The detail and the representation quality of the simulation model depend on the needs and the system knowledge of the order fulfillment management team.

Definition of Terms

To provide a clearer understanding of the terms used in this study, the following definitions are provided.

1. Discrete-event Simulation: "A discrete-event simulation is one in which the state of a model changes at only a discrete, but possibly random, set of simulated time points." (Schriber & Brunner, 1997)
2. Model: "A model is defined as a representation of a system for the purpose of studying the system. A model is not only a substitute for a system, it is a simplification of a system." (Mihram & Mihram, 1974)
3. Supply Chain: "A supply chain is a group of organizations (including product design, procurement, manufacturing, and distribution) that are working together to profitably provide the right product or service to the right customer at the right time" (Geunes & Pardalos, 2005)
4. Supply Chain Management: "All the management tasks necessary to obtain, move, transport, process, and deliver goods from vendors, through manufacturing, to the final customer." (Schniederjans & Cao, 2002)
5. Electronic Data Interchange (EDI): "A technology for electronic business that allows the computer to computer exchange between the organizations of standard transaction documents. EDI systems lower transaction costs because they automate transactions between information systems through a network. EDI systems can reduce the inventory costs by minimizing the amount of time that components are in the inventory." (Laudon & Laudon, 2004)

CHAPTER II

LITERATURE REVIEW

It is the goal of all manufacturing industries to produce high-quality products in the most economical and timely manner. In his study Altiok (1996) pointed out three parameters; quality, economics, and time as being the most important indicators of the customer-satisfaction. Thus, these parameters can also measure the manufacturing performance of a company. Companies invest into the information technologies such as computers, communication networks, sensors, actuators, and other equipment that give them an abundance of information about their materials and resources. In today's global competition, a manufacturing company's survival is becoming more dependent on how best this influx of information is utilized. Consequently, there evolves a great need for sophisticated tools of performance analysis that use this information to help decision makers in choosing the right course of action. These tools will have the capability of data analysis, modeling, computer simulation, and optimization for use in designing products and processes.

According to Meyers and Stewart (2001), Frederic Taylor's "Scientific Management," which is a management approach for improving labor productivity, made the modern discipline of operations management possible. Not only did scientific management establish management as a discipline worthy of study, but also it placed a premium on quantitative precision that made mathematics a management tool for the first time. Meyers and Stewart (2001) claim that Taylor's primitive work formulas were the precursors to a host of mathematical models designed to assist decision making at all levels of plant design and control. Later, these models became standard subjects in business and engineering curricula. Entire academic research disciplines sprang up around various operations management problem areas, including inventory control, scheduling, capacity planning, forecasting, quality control, and equipment maintenance. In this chapter the history of the mathematical modeling approach to inventory control, supply chain management, discrete-event system simulation, and simulation of inventory control and supply chains are reviewed.

Inventory Control

The Economic Order Quantity (EOQ) Model

One of the earliest applications of mathematics to factory management was the work of Ford W. Harris (1913). In his pioneering study, Harris characterized the problem in a factory setting and dealt with the issue of setting manufacturing lot sizes. According to his problem design, he researched a factory producing various products. Depending on the orders, the production was switching between these products. However, these production changes were requiring costly setup changes. As an example, he described a metalworking shop that produced copper connectors. Each time the production changed from one type of connector to requiring another, the production and machines had to be stopped and adjusted for a different setup, clerical work to be done, and material might be wasted. Harris defined the sum of the labor and material cost to ready the shop to produce a product to be the setup cost.

Harris (1913) was consistent with the scientific management emphasis of his day on precise mathematical approaches to factory management. To derive a lot size formula, he made the following assumptions about the manufacturing system:

1. *Production is immediate*. There is no limit on the production capacity; the total number of orders can be produced instantly.
2. *Delivery is instantaneous*. There is no time interval between the production, shipment and delivery of the orders.
3. *Certain demands*. Time and the size of the order are known with certainty.
4. *Constant demand size over time*. If the minimum time interval is one day, the total yearly demand can be divided by the number of work days so that the daily demand can be calculated.
5. *Setup cost is fixed*. The size of the order or lot doesn't affect the setup cost.
6. *Products can be analyzed individually*. Either there is only a single product or there are no interactions between products.

With these assumptions, the optimal production lot sizes can be computed for EOQ model. The notation will be as follows:

D = annual demand

c = cost of producing one unit in dollars without setup and inventory costs added

A = setup related cost for the production of one lot in dollars

h = the dollar cost of holding one unit per year. If the interest rate is the only factor considered in the calculation of holding cost, and if the interest = i, then $h = ic$.

Q = the number of units in one lot; this is the variable we're trying to optimize

Harris (1913) treated time and product as continuous variables; this assumption was required for the modeling purposes. Because the demand size and time are known and fixed, we can order Q units of products when the inventory level drops down to zero. The result of this assumption is represented graphically in Figure 1.

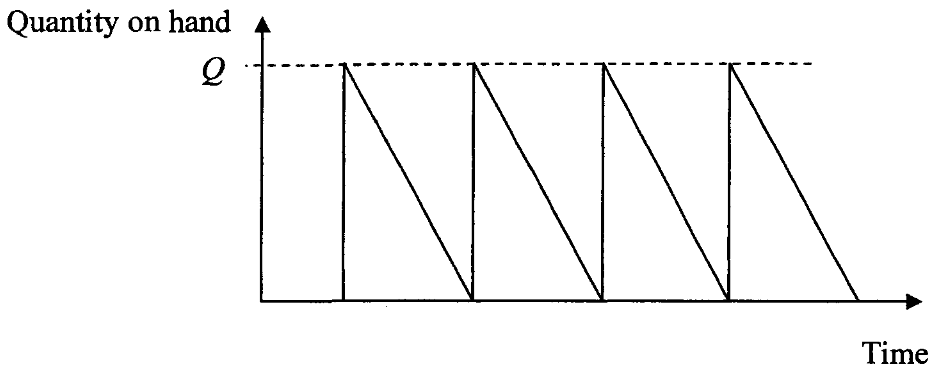

Figure 1. EOQ Inventory model

For every setup the cost is A, and the number of orders is D/Q per year. Thus, the setup cost per year is AD/Q. Since this cost of producing one unit is c, then for one year production, the production cost is cD. Thus, the total cost, which includes inventory, setup and production costs per year can be calculated as

$$Y(Q) = \frac{hQ}{2} + \frac{AD}{Q} + cD$$

So, for the cost function above, the lot size that minimizes the $Y(Q)$ can be expressed as

$$Q = \sqrt{\frac{2AD}{h}}$$

The formula above is the most basic form of economic order quantity (EOQ). This formula is also known as economic lot size. From this formula we can conclude that the optimal order quantity varies in direct relationship to the square root of the setup cost and the demand. However, optimal order quantity decreases with the square root of the holding cost. According to Harris, the most important implication of his study is that there is a tradeoff between lot size and inventory.

In summary, when the lot size is increased, the average amount of inventory also increases; on the other hand the frequency of ordering is reduced. By inserting setup cost into the formula, Harris was able to panelize frequent orders and prove this relationship in economic terms.

Dynamic Lot Sizing

Although the EOQ model successfully proves the existence of a relationship between setup cost, holding cost and optimal order quantity, it is not precise enough to apply to real life situations. One of the main concerns about the EOQ model is in the unrealistic assumptions it makes. Among these unrealistic assumptions is that the constant demand assumption is relaxed by the Wagner-Whitin model (Wagner & Whitin, 1958). The Wagner-Whitin model was established on the same problem of determining production lot sizes. The model accepts all the EOQ assumptions as valid except the constant demand. Demand is considered to be varying overtime in the Wagner-Whitin model. The dynamic lot sizing model has the most important effect on the modern production control which is the origin of the materials requirement planning (MRP).

The dynamic lot sizing approach also has implications on the modeling of time. Because the demand occurs at specific times, the time must be divided into discrete periods like hours, days, weeks, or months. The length of the periods depends on the characteristics of the system. If the system has a very high volume production or if the demand is changing rapidly, short periods like days might be more appropriate. On the other hand if the production volume is low or the demand is changing slowly a larger time period such as monthly schedule might serve better.

The News Vendor Model

One of the earliest applications of statistical modeling in inventory control and production planning dates back to Wilson's work (1934). In order to analyze the problem, Wilson (1934) broke it into two parts:

1. The first part of the problem is to determine the order quantity, in other words, the quantity that will be purchased or produced for each order.
2. The second part consists of the determination of the reorder point. This is the level of inventory on hand at which the replenishment must be triggered.

The news vendor model considers a single replenishment situation. Thus, the only problem is to find the appropriate quantity while the demand is uncertain. The model's name comes from the resemblance to the problem of a person who purchases newspapers in the morning without any prior information on demand. She sells a random amount of newspapers and discards the leftovers.

In this situation, in order to find the appropriate production levels, two pieces of information are required. The first piece of information is the anticipated demand and the second piece is the cost of producing more or less than the required amount. For this model Wilson's (1934) suggested assumptions can be summarized as follows:

1. Products are separable. Products can be considered one at a time since there are no interactions.
2. Planning is done for a single period. Future periods can be neglected since the effect of the current decision on them is negligible.
3. Demand is random. Demand can be characterized with a known probability distribution.
4. Deliveries are made in advance of demand. All stock ordered or produced is available to meet demand.
5. Costs of overage or underage are linear. The charge for having too much or too little inventory is proportional to the amount of the overage or underage.

In order to develop the statistical model, the following notion is used with the assumptions above:

X = demand (in units), a random variable

$G(x) = P(X \leq x)$ = G is a continuous cumulative distribution function of demand:

$g(x) = \frac{d}{dx}G(x)$ = density function of demand

μ = mean demand (in units)

σ = standard deviation of demand (in units)

c_o = unit cost of overage in dollars

c_u = unit cost of underage in dollars

Q = Decision variable, which is the number of units to produce

Using the notation above the expected cost function can be defined as follows:

$$Y(Q) = c_o \int_0^Q (Q-x)g(x)dx + c_u \int_Q^\infty (x-Q)g(x)dx$$

The value of Q to minimize expected overage plus underage cost is obtained by differentiating $Y(Q)$.

$$G(Q^*) = \frac{c_u}{c_o + c_u}$$

If the demand is assumed to be normal, the above expression can be expressed as:

$$G(Q^*) = \phi\left(\frac{Q^* - \mu}{\sigma}\right) = \frac{c_u}{c_o + c_u}$$

where ϕ is the cumulative distribution function of the standard normal distribution. This means that

$$\frac{Q^* - \mu}{\sigma} = z$$

Then the Q can be found using normal tables to obtain standardized values of z in the following expression $\phi(z) = c_u/(c_o+c_u)$, and hence

$$Q^* = \mu + z\sigma$$

From the above expression it can be concluded that the Q (order quantity) increases with the increase in mean demand. It also implies that Q increases with the increase in the standard deviation if z is positive. In other words, if $c_u/(c_o+c_u)$ is greater than 0.5 (since $\phi(0) = 0.5$) or $c_o<c_u$ then Q will increase with the increase in standard

deviation. On the other hand if $c_o > c_u$ then z will be negative and the Q (optimal order quantity) will decrease while σ increases.

In summary, the model considers the situation where the demand is uncertain and can be expressed as a statistical distribution. In this case the optimal production quantity depends on the distribution of demand and the relative cost of overproducing and underproducing.

The Base Stock Model

In the base stock model, the demands happen randomly and the inventory is replenished unit at a time. Thus, the only question that needs to be answered is what the reorder point should be. The reorder point is known as a base stock level, and that is why the model is named as base stock model. Hopp and Spearman (2000) stated that the following modeling assumptions should be made:

1. Products can be analyzed individually. There are no product interactions.
2. Demands occur one at a time. There are no batch orders.
3. Unfilled demand is backordered. There are no lost sales.
4. Replenishment lead times are fixed and known. There is no randomness in delivery lead times.
5. Replenishments are ordered one at a time. There is no setup cost or constraint on the number of orders that can be placed per year, which would motivate batch replenishment.

The following notation is used for the model:

l = replenishment lead time (in days), assumed constant

X = demand during replenishment lead time (in units), a random variable

$P(x) = P(X = x)$ = probability demand during replenishment lead time equals x (probability mass function). It is assumed that the demand is discrete.

$G(x) = P(X \le x) = \sum_{i=0}^{x} p(i)$ = probability demand during replenishment lead time is less than or equal to x (cumulative distribution function)

$\theta = E[X]$, mean demand (in units) during lead time l

σ = standard deviation of demand (in units) during lead time l

h = cost to carry one unit of inventory for one year (in dollars per unit per year)

b = cost to carry one unit of backorder for one year (in dollars per unit per year)

r = reorder point (in units), which represents inventory level that triggers a replenishment order; this is the decision variable

$R = r+1$, base stock level (in units)

$S = r-\theta$, safety stock level (in units)

$S(R)$ = fill rate (fraction of orders filled from stock) as a function of R

$B(R)$ = average number of outstanding backorders as a function of R

$I(R)$ = average on hand inventory level (in units) as a function of R

$Y(R)$ = holding cost + backorder cost

The performance measures can be expressed as follows:

Service level: $S(R) = G(R-1) = G(r)$

Backorder level: $B(R) = \theta - \sum_{x=0}^{R}[1 - G(x)]$

Inventory level: $I(R) = R - \theta + B(R)$

The base stock level that minimizes holding plus backorder cost ($Y(R)$) is given by

$$G(R^*) = \frac{b}{b+h}$$

If G is normal, the above expression can be simplified to

$$R^* = \theta + z\sigma$$

where z is the value from the standard normal table for which $\Phi(z) = b/(b + h)$, μ and σ are the mean and standard deviation, respectively, of lead time demand.

Hopp and Spearman (2000) summarize the implications of base stock level as:

1. Reorder point controls the probability of stockouts by establishing a safety stock.
2. The required base stock level (and hence safety stock) that achieves a given fill rate is an increasing function of the mean and (provided that unit backorder cost exceeds unit holding cost) the standard deviation of the demand during replenishment lead time.
3. The optimal fill rate is an increasing function of the backorder cost and a decreasing function of the holding cost. Hence, if the holding cost is fixed, either a service constraint or a backorder cost can be used to determine the appropriate base stock level.
4. Base stock levels in multistage production systems are very similar to kanban systems, and therefore the above insights apply to those systems as well.

The (Q,r) Model

The (Q, r) model is an improved version of the "Base stock" model. This model is more appropriate for production or manufacturing environments with faster production lines or for sales departments with high sales rates. In the (Q, r) model the inventory levels are continuously under control and the demands are taking place randomly as in Base Stock model. Moreover, when the inventory level goes down to a certain level r, a Q amount of order is placed. The order is received after a lead time l, and there is a possibility that a stockout might occur during this period of time. The (Q, r) model seeks optimal levels for Q and r; that is why the model is called the (Q, r) model.

The fundamental principles and assumptions establishing the model are exactly the same as those underlying the base stock model. However, the (Q, r) model assumes that either for each order there is a fixed order cost or that the number of orders per year is limited. The first research on the (Q, r) problem was conducted by Wilson in 1934. In his study he mentioned that Q and r perform different roles in the model.

As in the EOQ model, the replenishment quantity Q affects the tradeoff between production or order frequency and inventory. Larger values of Q will result in few replenishments per year but high average inventory levels. Smaller values will produce low average inventory and many replenishments per year. In contrast, the reorder point "r" affects the likelihood of a stockout. A high reorder point will result in high inventory but a low probability of a stockout. On the other hand a low reorder point will reduce inventory at the expense of a greater likelihood of stockouts.

To develop the mathematical expressions for the model, the following notation is used:

D = expected demand per year (in units)

l = replenishment lead time (in days)

X = demand during replenishment lead time (in units), a random variable

$\theta = E[X] = Dl/365$ = expected demand during replenishment lead time (in units)

σ = standard deviation of demand during replenishment lead time (in units)

$P(x) = P(X = x)$ = probability demand during replenishment lead time equals x (probability mass function)

$G(x) = P(X \leq x) = \sum_{i=0}^{x} p(i)$ = probability demand during replenishment lead time is less than or equal to x (cumulative distribution function)

A = setup or purchase order cost per replenishment (in dollars)

c = unit production cost (in dollars per unit)

h = annual unit holding cost (in dollars per unit per year)

k = cost per stockout (in dollars)

b = annual unit backorder cost (in dollars per unit of backorder per year)

Q = replenishment quantity (in units)

r = reorder point (in units)

$s = r\text{-}\theta$ = safety stock implied by r (in units)

$F(Q, r)$ = order frequency (replenishment orders per year)

$S(Q, r)$ = fill rate (fraction of orders filled from stock)

$B(Q, r)$ = average number of outstanding backorders

$I(Q, r)$ = average on hand inventory level (in units)

Annual fixed order cost = $F(Q, r)A = (D/Q)A$

Stockout cost = $D[1 - S(Q, r)]$ where $S(Q, r) = 1 - \frac{1}{Q}[B(r) - B(r + Q)]$

Backorder cost = $B(Q, r) = \frac{1}{Q}\sum_{x=r+1}^{r+Q} B(x) = \frac{1}{Q}[B(r+1) + ... + B(r+Q)]$

Holding cost = $hI(Q, r)$ where $I(Q, r) \approx \frac{(Q+s)+(s+1)}{2} = \frac{(Q+1)}{2} + r - \theta$

The sum of setup and purchase order cost, backorder cost, and inventory carrying cost can be written as

$$Y(Q, r) = \frac{D}{Q}A + bB(Q, r) + hI(Q, r)$$

The Q and r values that minimize $Y(Q, r)$ are

$$Q^* = \sqrt{\frac{2AD}{h}} \text{ and } G(r^*) = \frac{b}{b+h}$$

If G is normally distributed with mean θ and standard deviation σ, then the above expression is simplified to

$$r = \theta + z\sigma$$

where z is the value in the standard normal table such that $\Phi = b/(b + h)$

Although some of these models require different kinds of data, or provide improvements on different parameters, they do offer some common basic insights:

1- There is a tradeoff between setups and inventory. The more frequently the inventory is replenished, the less cycle stock will be carried.

2- There is a tradeoff between customer service and inventory. Under conditions of random demand, higher customer service levels require higher levels of safety stock.

3- There is a tradeoff between variability and inventory. For a given replenishment frequency, if customer service remains fixed, then the higher the variability the more inventory must be carried.

Supply Chain Management

Although "supply chain" is a very common term used in business and industry today, there is no common definition of it for all types of businesses and industries. Moreover, the term has different meanings and applications changing from company to company, depending on the organizational structure and functional departments of the company. For the purpose of this study, the definition suggested by La Londe and Masters (1994) is adopted. According to the authors, "supply chain is an organized group of firms that pass materials forward." In this organized group, there are dependent and independent firms like wholesalers, material suppliers, and retailers who help to manufacture a product and finally deliver it to the user.

In his attempt to define supply chain, Christopher (1992) emphasizes two things; the importance of an "organized linkage" between the companies and the "value added" by these companies. Therefore, according to this definition, there must be some form of value added to the product by these organizations. Christopher (1992) also claims that the competition is not between the companies anymore, but between the supply chains.

In light of the above mentioned definitions, a supply chain can be defined as an organized network of companies that are flowing information, product and services between downstream and upstream providers and receivers in the network and finally to an end user.

Monczka, Trent and Handfield (1998) suggest that to get an upper hand in the business world, a supply chain management approach with a proactive strategy needs to be adopted. They also mention that a supply chain management depends on the control of functional units that deal with separate materials. A responsible unit in the management receives reports from the functional units and organizes all the materials and information processes with the suppliers at different levels.

La Londe and Masters (1994) analyzed the supply chain strategy with respect to business alliance and partnering strategies. They found that they have similarities in many ways. For example, any supply chain trust between the companies and commitment to the business relationship is vital. The trust and commitment is usually maintained with a long term agreement. The exchange and sharing of logistics information for a better alignment and orientation of the business is also a key element in the success of a supply chain.

Customer service level, inventory level and unit cost are always seen as the most important managerial parameters that affect the business strategy and business goals. Although many think that achieving optimum levels of these parameters causes goals and strategies to conflict, Stevens (1989) stated that it is supply chain's responsibility to reach optimum levels through synchronization of the customer requirements with the material flow between suppliers and receivers without any conflicting applications.

According to Monczka et al. (1998) sourcing, flow and control of materials constitute the main goals of any supply chain management. These three activities need to be integrated and managed with a total system perspective between many functions and levels of suppliers.

Cooper and Ellram (1993) view supply chain management as an extension of the concept, of partnership. In this new concept partners organize and control the flow of materials, parts and products between the suppliers and customers. By this definition, Cooper and Ellram (1993) implied that each member of the supply chain affects the performance of other members and hence, the overall performance of the supply chain.

Supply Chain Management (SCM) Practices

In order to run a successful and efficient supply chain, SCM philosophy must be adopted and understood by all functions of the company at all levels. Cooper and Ellram (1993) created the following list of practices that need to be implemented and performed to achieve a successful adoption of supply chain management philosophy.

1. Integrated behavior: As integrated behavior being a common business practice, in current highly competitive global market conditions, integrated behavior needs to reach to a broader range of participants including customers and suppliers. Without this external integration, supply chain management wouldn't be fully utilized.

2. Mutually sharing information: In any everyday business application, tons of data are created, collected, and processed. The data created are used mainly for two reasons, namely: monitoring processes and planning future activities. Organizing and aligning the activities of chain members depend on the frequency of updating information and mutually sharing it among the members of the channel.
3. Mutually sharing channel risks and rewards: Mutually sharing risks and rewards is the result of integrated behavior and mutual sharing information. With the help of integration and information sharing, risks and rewards will be apparent to all members of the supply chain. It is assumed that sharing, the risks and rewards create competitive advantage in the long run.
4. Cooperation: Another result of "integrated behavior" and "mutual sharing information" is cooperation. Cooperation helps to organize and manage similar or complementary activities performed by different partners or members in the channel around a mutual goal to attain better results.
5. The same goal and the same focus of serving customers: Since World War II the strategy of any business shifted from being financially oriented to customer oriented. In order to create a successful supply chain, all of the supply chain partners must adopt the same strategy and same goal of serving the customer.
6. Integration of processes: In any supply chain, all value adding activities can be grouped under three major operations; sourcing, manufacturing, and

distribution. Traditionally, these operations are coordinated separately. However, successful implementation of supply chain management requires the integration of these traditionally separate functions with the help of cross-functional teams.

7. Partners to build and maintain long term relationship: So far, we have seen that in a supply chain all business relations take place at the partnership level. Effectiveness of supply chains depends on the partnership which continues even after the end of the contract. On the other hand, it is suggested that the strength of partnership will be higher if the number of partners is small.

Performance Measurement of Supply Chains

A supply chain consists of three or more firms directly linked by one or more of upstream and downstream flow of products namely: services, finances, and information from a source to a customer. "Channels of distribution" and "vertical marketing systems" are other terms used to describe supply chains. Channels of distribution are characterized as loose collections of independent companies showing little concern for the overall channel performance. Vertical marketing systems are characterizing as having channel members acting in a unified manner (Armstrong & Kotler, 1999). The marketing and logistics functions of channel members are largely responsible for supply chain activities. Although logistics include both supply sourcing and demand fulfillment activities, the concept of the supply chain had its roots in transportation and warehousing, which together were known as distribution.

The most popular subjects of articles written on measurement in logistics include the three major topics of activity-based costing, quality, and customer service.

Pohlen and La Londe (1994) traced the evolution of costing approaches beginning from direct product profitability through Activity Based Costing (ABC) to supply chain costing. Such efforts of creating accurate and integrated cost measures were undertaken to increase the visibility of logistics costs within the supply chain so that cost reduction opportunities could be identified and pursued. By making use of standard and engineered times and existing rate information, the supply chain costing approach considers activities across the firms in the supply chain. However, Pohlen and La Londe (1994) list two significant constraints. First, those firms that have not implemented ABC cannot provide logistics or supply chain related costs at the activity level. Second, the detailed level of information about process steps and costs of activities that must be shared by the enterprises require a highly coordinated or integrated partner relationship between them.

Quality measures in logistics are a second major area covered by the literature. Topics covered in quality measures include continuous improvement measures, quality control systems, process controls, and quality programs in logistics (Read & Miller, 1991). Related topics of research in this area include logistics measurement for strategic planning, strategic performance, outsourcing, and flow analysis.

A related area of interest is customer service which has become a crucial measure of competitiveness in markets throughout the world. As La Londe and Cooper (1988) pointed out in their study, the competition has become more intense and service quality has become a primary determinant of overall customer satisfaction. The necessity to achieve service excellence in markets characterized by shrinking margins and tight budgets has created a powerful challenge for supply chain management. The challenge is to balance these operational realities with the need for quality customer service. Quality service can be managed effectively, even when market conditions are difficult and resources are limited, if the organization can focus on a limited number of high priority logistics service features. In a study by La Londe & Cooper (1988) they presented some previous studies that used a technique for the evaluation and management of customer service quality, and in another study a customer's perspective on product and information flow. They concluded that the customer satisfaction depends directly on measurement of effective order fulfillment.

Discrete-event System Simulation

In their reference book for discrete-event simulations studies, Banks and Carson (1984) describe the concepts of simulation and its components for a simulation practitioner. In this text, the simulation is defined as "the imitation of the operation of a real-world process or system over time."

The history of simulation dates back to 1970's; since then simulation has been extensively utilized to solve our problems in science, engineering and business (Seila, Ceric & Tadikamalla, 2003). Most of the simulation studies are not reported and documented in academic literature, because they're conducted for private businesses and reports are confidential to company usage only.

Early simulations were done manually; however after the introduction of computers, their power and speed made them essential tools for simulation studies.

Simulations can be done on computer or performed manually, yet the common characteristic all simulation studies is artificially generating the history of a system and drawing inferences from the observations on the operation of the system.

The artificial history developed for the analysis purposes is known as the simulation model. The model is created in a way that it represents the real world system. In order to capture the characteristics of the real world system assumptions are incorporated into the simulation. Actually, it is the "assumptions" that tell the model how to react to certain conditions in a simulation. Depending on the type of the simulation model being created, the assumptions can be in the form logical, mathematical or symbolic expressions. These assumptions also help to define the relations between the entities and objects of the model. After the model is fully developed the simulation can create answers to different scenarios. Creating the artificial history of the real system is not the sole usage of simulation. According to Banks and Carson (1984) the main advantage of simulation is its power to predict the effects of changes on an existing system to predict the performance of a nonexistent future system.

When to Use Simulation?

With the new advancements in electronics and computer science the processing capabilities of computers are higher than ever before. The developments on the computer hardware have made it possible to use more advanced and complex simulation software and languages for virtually any area in science, engineering and business. The areas which the simulation is considered to be the most appropriate tool to use are almost limitless. Naylor, Balintify, Burdick and Chu (1966) discussed many possible situations where simulation would be helpful:

1- A complex system can be simplified with a simulation model and internal interactions of this system can be analyzed or a segment of a complex system can be studied.
2- All organizational identities have specific characteristics that affect the way that they conduct their business. Whether, organizational, environmental or informational the characteristics of the organizations can be altered in a simulated environment and the effects of these changes can be observed.
3- Modeling efforts help to better understand the system under study. Recommendations can be made based on the knowledge gained by modeling practices as well.
4- Most importantly, simulations serve us to understand relationships between input and output values of the systems through controlled experiments. Controlled experiments can be conducted by changing the input values and observing for the output values. Controlled experiments identifies the most affecting variables and the correlation between the input and output values.
5- Simulation can be used in any engineering, science and business curricula to reinforce the students' understanding of theoretical concepts via applications of simulation as an analytical solution tool.

6- Simulation can be used as an experimentation tool to test a new system, product or a strategy before putting them into service. This way it prevents to invest in faulty designs or projects.

7- Solutions to complex analytical problems can be validated by simulations.

Advantages and Disadvantages of Simulation

Simulation is one of the most efficient tools in system analysis. However, there are always advantages and disadvantages specific to the system under consideration. In order to evaluate the usage of other possible tools and techniques, these advantages and disadvantages must be assessed by the analyst. Schmidt and Taylor (1970) created a list to guide the users of simulation on the advantages and disadvantages of simulation.

1. Model creation is the most critical and time consuming step in a simulation study. However, once it is created, the model can be used over and over again with different sets of variables values.
2. Even if there is no precise input data, simulation can still be used to analyze a system.
3. Output data creation and collection is almost costless compared to obtaining the same data from real system.
4. Compared to the analytical tools, learning and applying simulation methods is easier and faster.
5. In many cases analytical methods can be employed to perform system analysis, on the other hand, in most of these instances it requires the simplification of the actual system to make the mathematical equations

solvable. Simulation doesn't require any model simplification, yet sometimes it can be desirable in order to save time. Another problem with the analytical models is their limitedness in creating system performance measures. Analytical methods are usually used for predefined set of performance measures, whereas simulation tools can create any output value that can be imagined.

6. There are cases that simulation is the only technique to solve a problem.

Simulation may not be the best tool for all applications; nonetheless it is superior over most of the analysis tools. Schmidt and Taylor (1970) described some of the instances where analysts may experience disadvantages of using simulation:

1. Complex simulation software for computers requires expensive hardware to run these products.
2. If the model under consideration is relatively big, model creation, data collection and simulation runs of a study can consume excessive amounts of time and energy.

System in Simulation

If simulation is considered to be a virtual laboratory for controlled experiments, the model is the test subject that represents the system in real world. To be able to create an appropriate model, an understanding of "system" is vital. Banks and Carson (1984) defined the system as "a group of objects that are joined together in some regular interaction or interdependence toward the accomplishment of some purpose." A production system manufacturing automobiles is given as an example: "The machines, component parts, and workers operate jointly along an assembly line to produce a high quality vehicle."

A system can be affected by either inside or outside changes. If the change takes place on the outside of the system but still affecting the system, the change can be said to take place in the "system environment." To be able to fully incorporate the characteristics of the real world, it is essential to define the system, its boundary and the environment outside the boundary. Gordon (1978) clarifies these terms with two examples:

> In the case of factory system, for example, the factors controlling the arrival of orders may be considered to be outside the influence of the factory and therefore part of the environment. However, if the effect of supply on demand is to be considered, there will be a relationship between factory output and arrival of orders, and this relationship must be considered an activity of the system. Similarly, in the case of a bank system, there may be a limit on the maximum interest rate that can be paid. For the study of a single bank, this would be regarded as a constraint imposed by the environment. In a study of the effects of monetary laws on the banking industry, however, the setting of the limit would be an activity of the system. (p.4)

Discrete and Continuous Systems

Depending on the type of the state variables there are either discrete or continuous systems. Law and Kelton (1982) argue that there is no fully discrete or continuous system in practice. However, one type of variable is usually more dominant than the other. In such cases it is possible to identify the system as continuous or dominant. Banks and Carson (1984) define the discrete system as "one in which the state variables change only at a discrete set of points in time." The bank is the most common example used to characterize discrete systems in literature. If the number of customers in the bank is assumed to be the state variable, it changes only when a customer comes to the bank or leaves the bank.

A continuous system is described in the same text (Banks & Carson, 1984) as "one in which the state variables change continuously over time." Most of the physical phenomena happening around us are considered to be continuous. Foe example, the level of sea depends on the distance of the moon from earth. When moon gets closer to earth sea level rises, when it moves away from earth the sea level goes down. From these definitions it can be concluded that a discrete system simulation deals with systems where the system variables change at a discrete set of points in time.

The main difference between an analytical and simulation approach is that simulation uses numerical methods to analyze a system. On the other hand, analytical methods solve the model using mathematical deductive reasoning. In a simulation study, numerical methods or numerical analysis uses computational procedures to compute system variables rather than solving the model mathematically. The system dependent variables are computed as the simulation runs or as the system's independent variables change and iterate. The simulation runs according to the historical data collected and the assumptions made to model the real system. As the model runs and data are generated the observations are recorded and processed to analyze the system performance. The type of the simulation tool is selected according to the size of the model. Real systems, like manufacturing systems, require a large number of transactions and calculations to be processed. In these cases, computers are the most suitable tools to use. For smaller size simulations, manual simulations or spreadsheet programs can be considered.

Steps in a Simulation Study

Figure 2 from Banks and Carson (1984) shows a flow chart that depicts the steps of a simulation study. According to the representation discrete event simulation is a 12 step process. These steps are briefly summarized here:

1. Problem formulation. Either it is a simulation or a different type of study, every study starts with a statement of the problem. Most of the time, people are aware of the existence of a problem, but the nature, origin or size of the problem is unknown to them. It's the analyst's responsibility to find and explain or formulate the problem in cases where the problem is unknown or unclear to the policymakers. In those situations, analyst should make certain that the problem understood and agreed by both parties.
2. Setting of objectives and overall project plan. Problems reveal the existence of a situation that requires a solution. However, solution is acquired by answering the right questions. In an analysis study, these questions are known as the objectives. At this step, it should be determined whether the simulation is the most appropriate tool to solve or analyze the problem with the objectives defined. If the simulation is proven to be the most appropriate device for the purpose of the study, the alternative systems and the way these alternative systems will be evaluated must be included in to the project.
3. Model building. The aim of any study is to find the best answer to the problem; however, there is usually more than one model that can provide that answer. The model creation efficiency depends on the expertise of the analyst

on the simulation software or simulation tool and on the experts understanding of the real system. Morris (1967) expresses this situation as "although it is not possible to provide a set of instructions that will lead to building successful and appropriate models in every instance, there are some general guidelines that can be followed." Modeling is a progressive process that needs to start with a simple model. The model will resemble to the real system as the understanding of the system increases and the objectives become clearer. However, it shouldn't be the intention of the model builder to create a one-to-one copy of the original system. Only the characteristics of the real system need to be captured. Otherwise, increasing the level of unnecessary details will cause waste of time and effort.

4. Data collection. Model building and data collection are two concurrent processes. The type of the data needs to be collected depends on the model structure and model elements. Data collection is the most time consuming and labor intensive step of the simulation. Thus, data collection must be started at the very early stages of model building.

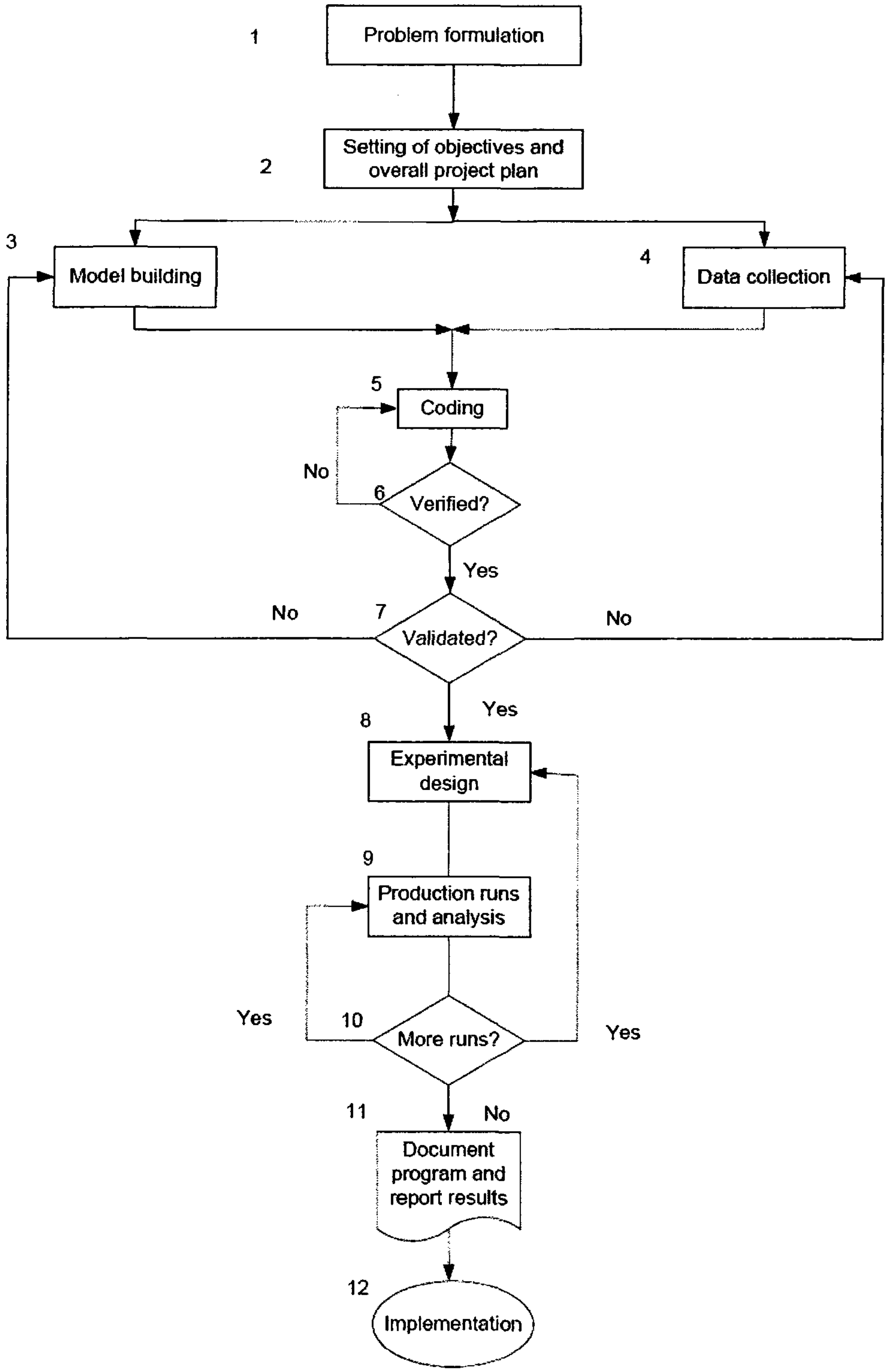

Figure 2. Flow diagram of steps in a simulation study

5. Coding or software modeling. At this step, the model is converted into a computer program that can read, process and store information in an electronic environment. Today's modeler has many alternatives to select from. The cheapest, most flexible but most time consuming way is to use a general-purpose language such as C++, VisualBasic or FORTRAN. There are also special-purpose simulation languages developed for certain type of systems such as GPSS, SIMSCRIPT and SLAM. The most advanced tools are the visually animated simulation programs with built-in objects and libraries for simulating specific processes such as ARENA, Simul8 and ProModel.
6. Verify. Verification is related to the testing of modeling logic. Either created by a simulation language or a simulation program all simulation models require a logic test to ensure that the model is behaving, reacting or running in an expected way. This step can be performed by test runs and observing the change of the system parameters with different sets of input parameters. Instead of using statistical or mathematical techniques common sense is enough to complete this step.
7. Validate. A verified model is ready for further analysis and refinements to maintain the accuracy of the model. The best way to increase the accuracy is performed by comparing the simulation output variables with actual data. Until the desired accuracy is reached the process is repeated. Trial and error is one of the methods that can be applied for model validation. This step is also an opportunity to better understand the model and its logic.

8. Experimental design. In this phase the design alternatives are developed and evaluated. Before the alternatives are modeled and run some of the simulation parameters must be set. The most common parameters to concern are the initialization period, total simulation length, and number of replications.
9. Production runs and analysis. Finally the simulation is run for analyzing the performance measures for the system under study. Typical performance measures are efficiency, utilization and service rate for any manufacturing or business model.
10. More runs. Based on the results of the initial runs and analysis, more runs with alternative designs would be required.
11. Document program and report results. Without proper documentation of the program and the results, the study wouldn't have the expected effect and influence on the decision makers. Documentation helps other people to understand the model, logic and the system of the simulation model. If the simulation needs to be run in the future by different users the documentation makes it easier to understand, modify and reuse. The documentation and the report are strong decision making tools. Both of them together give confidence to the managers and decision makers so that the decision can be made based on the results of the simulation.
12. Implementation. The final step is the implementation of the simulation to the real life. The successful implementation depends on the successful execution of the previous steps. If the previous steps are completed successfully with the

full involvement of the model user, the chances of a robust implementation is high. On the other hand, if the model has not been discussed with the final model users, the implementation will fail even with a completed validity step.

Inventory Control and Supply Chain Simulation

Analysis, planning, and control of supply chains and inventory problems occur frequently in practice and discrete event system simulation is often used as the solution methodology (Banks & Carson, 1984). However, faced with such a problem, the analyst should initially determine if a mathematical analysis can accomplish the result with much less expenditure and resources. There is an important difference between mathematical analysis and simulation. Mathematical analysis yields formulas or a computational procedure to produce an exact value of the model's performance measures. A simulation, however, will yield a sample of observations that can be used to compute a confidence interval for the performance measures, therefore to estimate the value of the performance measure from data. Thus, simulation cannot be used to compute the exact value of the performance measures. The probability theory is the mathematical tool which is used to derive and compute output parameters for stochastic models. According to Seila et al. (2003) the majority of realistic stochastic models are too complex for analysis using probability theory. This leaves simulation as the only other available method for obtaining information about the performance measures of interest.

There is a very rich literature of simulation on inventory control and supply chain management. Most of the literature is originated from the business case studies and real life applications.

Bier and Tjelle (1994) conducted a spare parts control and inventory planning study at Boeing. At Boeing they control the inventory through a set of control parameters. These parameters are programmed to generate inventory plans for significant percentage of the spare parts. However, because of the number and nature of the control parameters, it is hard to predict the effect of the parameters. In their paper, they presented a simulation prototype to determine how control parameters affect inventory and customer service performance.

Garcia, Silva and Saliby (2002) developed an analytical expression for proper safety stock sizing. Their model refers to periodic review system and lot for lot replenishment policy with randomness in forecast errors and in order fulfillment. They validated and tested the adequacy of the model using simulation techniques with Microsoft Excel and Risk software.

Another simulation study was performed by Bhaskaran (1998) on supply chain instability and inventory. In his paper, he presented how supply chains can be analyzed for continuous improvement opportunities. The study was conducted at General Motors supply chain, based on the operating data.

Bertolini and Rizzi (2002) also studied inventory replenishment points. They studied a simulation model to find the optimum finished goods inventory levels to minimize costs deriving from holding inventory. They figured that there is a trade off between holding cost and preventing stock outs according to master schedule plan.

Kang and Gershwin (2005) studied the effects of information inaccuracy in inventory systems. In their research, they made use of both the analytical and simulation tools. They proved that even a small amount of undetected stock loss creates severe out of stock situations. They also found out that revenue losses due to the inaccurate information are greater than the stock losses themselves.

Cao, Patterson and Melkonian (1996) suggest a three stage simulation approach to inventory control problem. In the first stage the actual demand is fitted in theoretical distribution. In the second stage, target inventory levels are set according to the desired customer service levels. In the last step final target inventory levels are searched depending on the independent variables. In their case study, they managed to find opportunities for inventory reduction.

CHAPTER III

RESEARCH DESIGN AND METHODOLOGY

Research Design

This experimental research was designed to identify the most influential supplier and factory based parameters and to develop a simulation model to analyze the relations between these parameters. The three research questions stated in Chapter I were used for this study.

1. What are the most important variables that affect the delivery performance of a supply chain?
2. What are the most important variables that affect the service rate or fill rate of a supply chain of a manufacturing company?
3. What levels of the selected variables could be used in order to minimize inventory on hand?

Answers to the first and third questions were investigated through a discrete event system simulation and design of experiments techniques. Analysis of variance approach was utilized in order to evaluate the simulation results. The second question was handled by a multiple regression analysis approach using historical data.

Initial Information

This research was designed around the necessities and desires of the Order Fulfillment Integration Management (OFIM) of the Manufacturing Company. The company at hand is doing business with more than six thousand suppliers. The long term success of the company depends on the performance of the supply chain management and the strength of partnership between the company and its suppliers.

As mentioned in the literature section, there are many reasons for the inventory build-up in the manufacturing environment. Among these reasons, the OFIM is focused on the ones that could be identified and eliminated in their work area. The main goal of the OFIM is to improve the performance of the supply chain management activities. In order to do that, OFIM's first responsibility is to coordinate and improve the suppliers according to the company's Order Fulfillment Process (OFP). The expected outcome of the OFIM operations is leaner and more flexible business operations. In this context, becoming lean means holding fewer inventories and being able to respond quickly to the demand changes. The overall picture of OFP and suppliers' role in this process can be seen in Figure 3.

As seen in Figure 3 the company is working under a push system. A yearly forecast and production plan is prepared and shared within the company through an Enterprise Resource Planning (ERP) software called "Systems, Applications and Products in Data Processing" (SAP). These data are shared with the suppliers through the Electronic Data Interchange (EDI) channels between suppliers and supply chain specialists. However, Materials Requirement Planning (MRP) is directly connected with the customer orders and triggered by dealers. If there is an available inventory on hand to manufacture the order, the order is put into the production schedule to be produced on time. Otherwise, a rescheduling takes place and the order is delayed until the parts arrive to the factory. In this flow of information and parts, there are supplier and factory based parameters that have roles in determining the order fulfillment rate of the overall system. As mentioned in Chapter I, this study is focused on the Quality and Delivery Performances and Manufacturing Time of the suppliers. On the factory side, the factors that are under investigation are Inventory Levels, Service Rate and Order Changes.

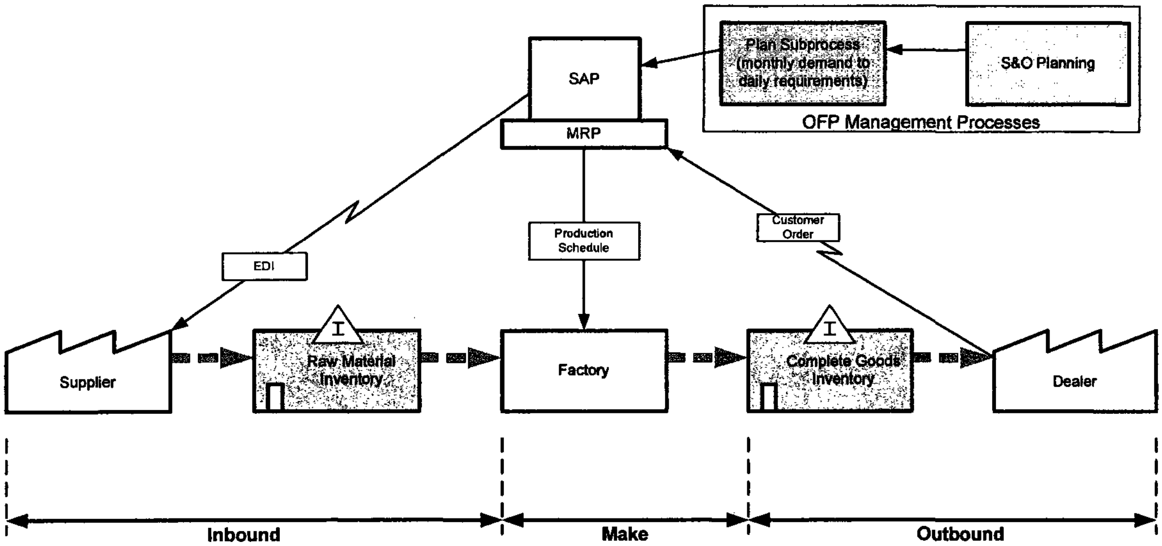

Figure 3. Data and material flow

Field Study

The company has a supplier development group under OFIM. The entire supplier related improvement, support and alignment projects are performed by supplier development engineers. The company has been restructuring and organizing its approach to supply chain management and order fulfillment process since 1994. Among many strategies and approaches the company adopted Quick Response Manufacturing (QRM). Suri (1998), who is the founder of QRM Center at the University of Wisconsin Madison, defines the main difference of QRM from the other production strategies as "relentless emphasis on lead time reduction." According to Suri (1998) QRM has a long term impact on every aspect of a company. The single principle of minimizing lead time has implications for organizational structure, manufacturing systems, purchasing policies, office operation structures, capacity planning and lot sizing.

The initial section of the study depends on the projects conducted by the supplier development group in order to implement QRM strategies. In October 2005, the company has launched a new organizational campaign for asset reduction. The main role of this large project is to organize and improve suppliers utilizing QRM tactics. The success of the QRM approach results in the Manufacturing Critical-path Time (MCT) reduction throughout the enterprise. Initially 35 suppliers in the US were selected as a "supplier focus group" to implement the QRM approach. Selection was based on the size of the business between the company and the supplier. From these 35 suppliers, 224 parts with the highest financial impact were selected. Value stream mapping studies were conducted with each supplier for the selected parts in order to define and document the true supply chain lead times. These studies helped to create MCT database for the research.

Regression Analysis

In this part of the study, it is intended to investigate the effects of some of the factors that would help to explain the supplier performance under certain conditions with limited capacity.

One of the most important factors affecting the performance of supply chains is the delivery performance of the suppliers. Delivery performance is a representation of the supplier capacity. Bollapragada, Rao, and Zhang (2004) reported that uncertainties regarding the supplier capacity have negative effect on the planning of safety stock levels. Besides, it is hard to determine the supply capacity of suppliers. On the other hand, when the demand is stable and there is minimum demand forecast variation, one expects to have high on-time-delivery performance.

Quality of the purchased parts is another metric that represents the suppliers' performance. For an uninterrupted, smooth production and flow of products, conformance to the quality standards is crucial. It is also anticipated by the management that poor quality is also a result of schedule and order changes. It is hypothesized that with limited production capacity suppliers become overloaded as a result of order changes, and overload causes the production or delivery of defective parts.

The independent factors chosen for this investigation are: scheduled order changes, manufacturing critical path time, and electronic data interchange firm zone. The dependent variables are the percentages of delivery and quality non-conformances.

Independent Variables

One of the key parameters regarding the supplier performance is the Manufacturing Critical-path Time (MCT). MCT is the typical amount of calendar time from when a manufacturing order is created through the critical-path until the first, single piece of that order is delivered to the customer.

The company has an MCT mapping tool to help suppliers in determining and logging in the MCT data. Every MCT analysis starts with a chart that shows symbolic representations of the activities as shown in Figure 4. The main inputs to this tool are times that have been gathered through observation or specific tracking of activities used to produce a product. A sample process and activities with their values can be seen in Figure 5.

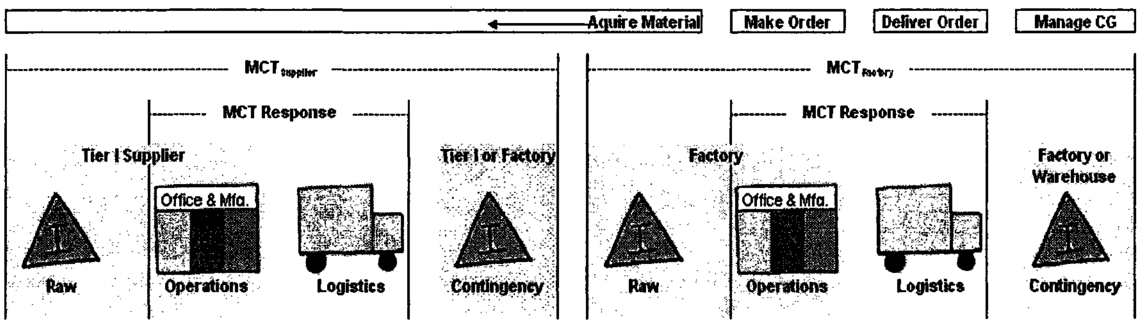

Figure 4. Sample MCT analysis

These activities are then grouped and defined as processes. These processes are then sequenced so that a flow from the original cut of a part through the complete build of a product can be defined to produce an MCT Map as in Figure 6.

Another factor that affects the OFIM processes is the number of order changes. The marketing department has annual forecast of orders for each production and service parts. The forecasted data is shared with the suppliers, so that the suppliers could have an idea about the future production requirements. However, the forecast doesn't mean any commitment on the company side. Instead, the company under investigation developed a parameter called "Electronic Data Interchange (EDI) Firm Zone." EDI firm zone represents the time zone that a forecast order becomes firm. For example, if EDI firm zone is 20 days, it means that all the forecasted orders within 20 days starting from today is firm and the company is committed to buy it.

Step	Description	Activity	Time-Value Total	Total (Days)	Value
1	Receive EDI ORder	Order Entry	0 days 3 hrs. 0 mins.	0.1250	Non-Value Add Necessary
2	Master Schedule	Schedule	1 days 0 hrs. 0 mins.	1.0000	Non-Value Add Necessary
3	Receive Material	Receive	1 days 0 hrs. 0 mins.	1.0000	Non-Value Add Necessary
4	Raw Material Kanban/VMI/Min-Max	Wait	5 days 12 hrs. 0 mins.	5.5000	Non-Value Add Unnecessary
5	Material Presentation/Staging	Setup	0 days 0 hrs. 15 mins.	0.0104	Non-Value Add Necessary
6	Cable Cut & Strip	Operation	0 days 0 hrs. 36 mins.	0.0250	Value Add
7	Super Market/Kanban	Wait	5 days 0 hrs. 0 mins.	5.0000	Non-Value Add Unnecessary
8	Hook Connectors	Operation	0 days 0 hrs. 39 mins.	0.0271	Value Add
9	Super Market/Kanban	Wait	5 days 0 hrs. 0 mins.	5.0000	Non-Value Add Unnecessary
10	Load Rack for Welder	Setup	0 days 0 hrs. 6 mins.	0.0041	Non-Value Add Necessary
11	Super Market/Kanban	Wait	5 days 0 hrs. 0 mins.	5.0000	Non-Value Add Unnecessary
12	Weld-Conduit	Operation	0 days 1 hrs. 8 mins.	0.0472	Value Add
13	Coil	Other - NVA-N	0 days 0 hrs. 6 mins.	0.0041	Non-Value Add Necessary
14	Test	Inspection	0 days 0 hrs. 8 mins.	0.0055	Non-Value Add Necessary
15	Coil	Other - NVA-N	0 days 0 hrs. 6 mins.	0.0041	Non-Value Add Necessary
16	Packaging	Pack	0 days 0 hrs. 3 mins.	0.0020	Non-Value Add Necessary
17	Storage	Other - NVA-N	5 days 0 hrs. 0 mins.	5.0000	Non-Value Add Necessary

Figure 5. MCT mapping tool

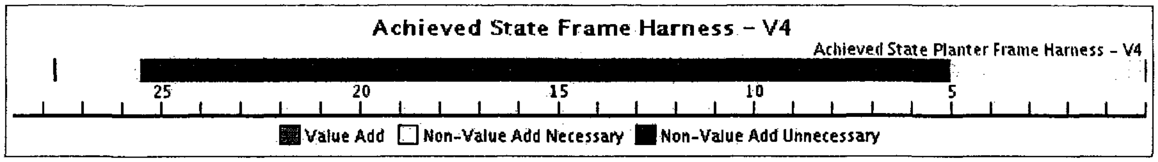

Figure 6. MCT map

However, in reality it is not unusual that in the firm zone, order quantities are changed or new orders are added. These changes in the firm zone affect the performance of the supplier in a negative way. OFIM believes that late deliveries, low quality and inventory add-ups on the suppliers' side are some of the consequences of these short time order changes. If a new order is added within ten business days of firm zone, it is called "A10." If the quantity ordered is changed within ten business days, it is called "B10." A10 and B10 data are stored in the company's data base for 12 months for every purchased part in production.

It is the anticipation of the OFIM managers that the length of the EDI firm zone and MCT might represent the flexibility, responsiveness or capacity of the suppliers. On the other hand, order changes (A10 and B10) are expected to have negative effects on the delivery performance at different supplier capacity or responsiveness levels.

Dependent Variable

The regression study is focused on the delivery and quality performances. The delivery performance is characterized by the percentage of delivery non-conformances and quality performance is characterized by the percentage of quality non-conformances. The same database, which contains part per-million information, is utilized in order to attain the percentages of non-conforming orders.

Simulation Study

The Simulation Model

In order to create and develop the simulation model, the information gained from the OFIM engineers and supplier development engineers has been used. The model is illustrated in Figure 7. Factors such as, DPPM, QPPM, service rate and DOH were investigated in the simulation study in order to address the relationship between these variables. To simulate the system, a discrete-event system approach is adopted. The model is created using ARENA® discrete-event system simulation program. ARENA® is one of the most general, flexible, and powerful discrete-event system simulation programs suitable for manufacturing and supply chain simulations (Kelton, Sadowski, & Sturrock, 2007).

In the model, the flow of materials is shown with solid lines, and the flow of information is shown by dotted lines. The model represents the system at the level of detail that enables us to capture the relationship between DPPM, QPPM, stock level and service rate. The circulation of material and information starts with the forecast of demand.

Independent Variables

The company under consideration has a very well established supplier performance analysis method and a database of supplier information to keep track of supplier performance on critical metrics. These performance metrics are crucial to the alignment of the suppliers with the company goals.

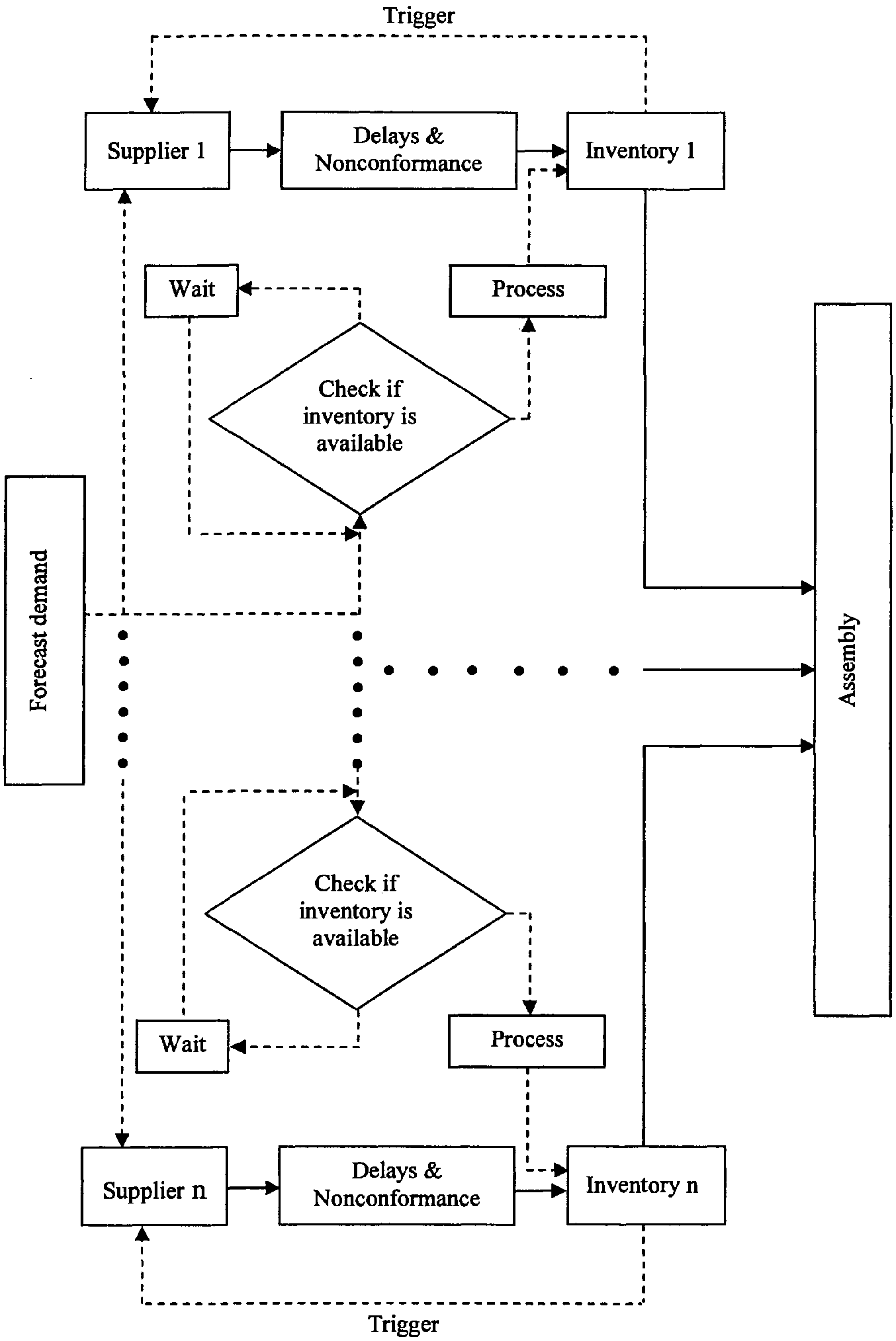

Figure 7. Simulation model

The suppliers are classified into four categories according to their quality and delivery ratings; partner, key, approved and conditional. A partner is a supplier who exceeds the highest performance criteria in quality and delivery. This supplier maintains ongoing activities to insure continuous improvement and has world class performance. The supplier who exceeds the minimum performance criteria in quality and delivery measurements and is working towards best in class and world class performance levels is called a "Key" supplier. If the supplier meets the minimum performance criteria, it is called an "Approved" supplier. Improvement plans are to be completed and reviewed each year for Approved suppliers. A conditional supplier is the one that does not meet the minimum performance criteria and is a candidate reduction. A supplier with this classification must create a plan to improve. First year suppliers are automatically assigned a conditional classification by the company.

Quality performance is measured with a parameter called Quality Part Per Million (QPPM). The quality rating provides a supplier with statistical evidence of their product quality. The rating is expressed as follows:

$$\frac{\text{Total \# of Quality Nonconformances}}{\text{Supplied pieces}} \times 1{,}000{,}000 = \text{QPPM}$$

The delivery performance is measured with a parameter called Delivery Part Per Million (DPPM) in a similar way to the quality performance. A delivery rating is derived from early, late, over or short deliveries. The delivery rating is expressed as follows:

$$\frac{\text{Total \# of Delivery Nonconformances}}{\text{Supplied pieces}} \times 1{,}000{,}000 = \text{DPPM}$$

The classification guideline is given in Table 1.

Table 1. *Supplier classification guideline*

Classification	Quality PPM	Delivery PPM
Partner	≤ 200	≤5,000
Key	≤700	≤15,000
Approved	≤1,300	≤30,000
Conditional	>1,300	>30,000

Although these are not the only factors that affect the performance of a supply chain or the asset levels, they are considered as the primary factors that must be tackled first by the OFIM.

Dependent Variables

The simulation study is focused on two key metrics: inventory level and service rate. Even though the aim is to decrease the inventory levels, an acceptable level of service rate should be maintained as well. The inventory level is measured as monthly

Days on Hand (DOH) average inventory. It is calculated by taking the average monthly inventory on hand divided by the average daily spend. Service rate is the percentage of on time fulfilled orders. The OFIM aims to achieve a significant reduction in DOH while keeping a 99% service rate. The study will help managers to see which of these parameters has considerable effect on decision variables. Thus, the supplier development group and the order fulfillment group can concentrate their effort on certain factors.

Model Parameters

The simulation model is designed in a way to capture the characteristics of a supply chain under certain conditions. The model is not the representation of any specific real system. The information gathered from the suppliers will be used to create the model and the logic of the system. However, the quantitative data will not be used for parameter input. Instead of using the actual parameters, a reference set of parameters will be used.

The aim of this study is not to improve the performance of a specific assembly line or a supply chain. It is intended to observe the generic behavior of the part of the supply chain with certain order fulfillment processes. Thus, using actual quantitative values from real systems is not relevant to the aim of the study.

There is not much available literature on creating the reference set of parameters. Kritchanchai and MacCarthy (2002) have organized an iterative procedure to find a suitable reference set. As they mentioned in their study, this approach is appropriate for qualitative simulation studies where comparative performance is being investigated and where precise numerical estimation is not required. The procedure can also be utilized for studies where data is not available. Kritchanchai and MacCarthy (2002) pointed out two major factors in their approach as being the steady state behavior of the simulation and the validity. As it is noted, different sets of input data can generate the desired levels of the reference output indicators. However, only the ones that satisfy the steady state behavior of the system which are sufficiently valid can be considered as appropriate for the model.

Kritchanchai and MacCarthy (2002) suggest starting with the fixed input parameters that control the core functions of the model. These are typically the system resources in the model. Then, it is advised to set the variable input parameters, which are then considered the experiment parameters. Next, the steady state criteria must be satisfied by appropriate capacity allocations. Lastly, they presented a nine-step procedure to attain the desired level of output indicators as follows:

1- List all fixed value and variable value parameter in all stages in the model.
2- Set the values of the fixed parameters. There is no specific guidance for setting the values at this step, as it is likely to be model and application dependent. Insights on appropriate levels and relative magnitudes will sometimes be guided by known likely values in real systems or by data that has been used in existing studies.
3- Set the steady state criteria and the desired level of output indicators of interest.
4- Set the initial values of the variable parameters.
5- Run the simulation with the values for variable input parameters to try to reach steady state with the desired level of output indicators.
6- If steady state conditions are reached with the desired level of out put indicators go to step (9).
7- If the desired level of output indicators or system steady state cannot be achieved, change the values of variable input parameters slightly and then go to step (5).
8-If the desired level of output indicators or system steady state cannot be achieved, adjust the values of fixed input parameters slightly and then go to step (5).

9- Once a reference state has been identified, conduct experiments to validate the model under these conditions. (Kritchanchai & MacCarthy, 2002, p.335)

CHAPTER IV

RESULTS AND DISCUSSION

The purpose of this research was to find the optimum levels for inventory on hand and analyze the effects of such parameters as: manufacturing critical path-time (MCT), electronic data interchange firm zone (EDI firm), quality defective parts per million (QPPM), and parts with delivery problems per million (DPPM). The study was also designed in a way to help analyze the management's supplier classification criteria and to validate the actions of the supplier development group with respect to the classification guidelines.

Initial Research

The adopted study was based on the assumption that there must be a relation between the quality and delivery problems, and the inventory levels. In a manufacturing environment with certain demand levels, if there is no quality or delivery problem associated with the suppliers, it is expected to see the same levels of inventory for every part provided by the suppliers. If quality or delivery problems are experienced with suppliers, the inventory levels of the parts with quality or delivery problems are expected to be higher to absorb the problems. The flow of materials and the continuation of the production depend on the availability of the inventory. In order to compensate for the non-conforming parts or late receipts, the company needs to hold more inventories. It is the responsibility of the manufacturing or production engineer to prevent the assembly line from stopping by keeping the stockroom full with raw materials or purchased parts. However, the pressure to run an assembly line without any stoppage could force the engineers to fill the stocks with excessive amount of inventory. According to the supply chain development manager, one yelling of the supervisor or manager is enough to overstock the inventory (B. El-Jawhari, personal communication, December 6, 2006).

In the direction of these expectations and assumptions initial analysis was conducted on the year 2006 production parameters. Two hundred and two (202) purchased parts were selected for analyses from different suppliers. The parts were selected from the top 20% suppliers, in terms of the size of the business between the company and the supplier. For each part, QPPM, DPPM and average number of inventory on hand or days on hand (DOH) information was collected.

The data were analyzed to search for any evidence that would relate QPPM and DPPM to DOH. More specifically, it was expected to see a positive relationship between QPPM, DPPM and DOH. Delivery or quality related problems should have led to increased inventory levels. Statistically, there wasn't enough evidence to claim a positive relationship between these parameters. ($p > 0.05$) The data table, scatter plot diagrams are constructed as in Figure 8 and Figure 9 and SAS analysis outputs are provided in Appendix A.

The analysis suggested that for some purchased parts unnecessarily excessive amount of inventory has been held, on the other hand, for some purchased parts, the inventory levels might be too low to risk the continuity of the production. Both cases are equally harmful for the future competitiveness and success of the company. Inventory is accepted as one of the eight sources of waste in modern production philosophies (Meyers

& Stewart, 2001). Lack of inventory could lead to production stoppage, which, in turn, causes late productions, late deliveries, and unsatisfied customers.

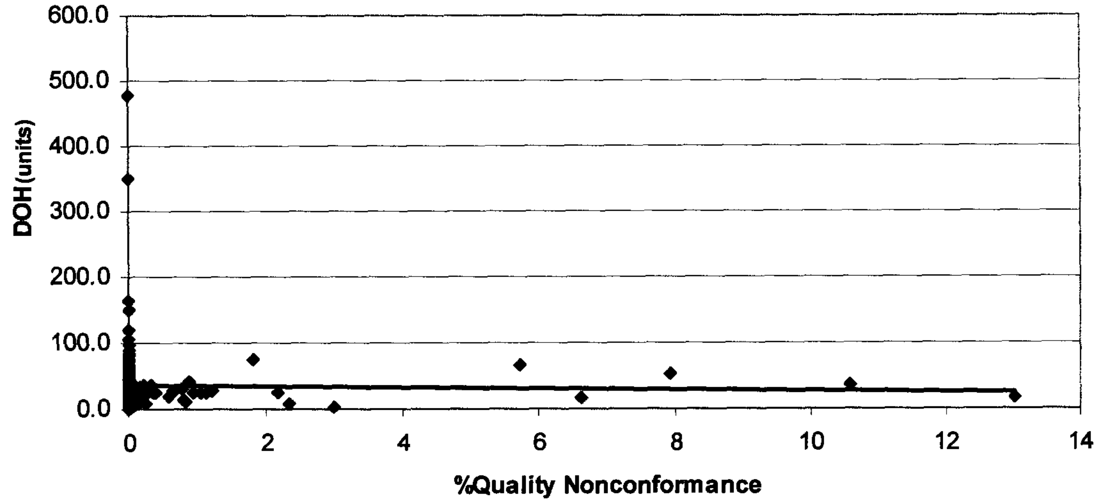

Figure 8. Plot for average inventory on hand vs. % of quality nonconformance

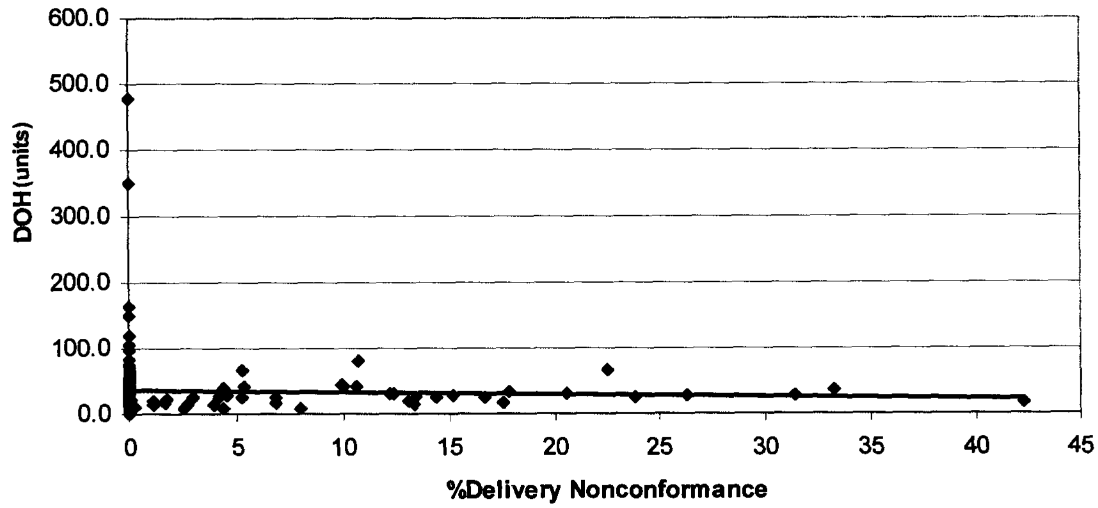

Figure 9. Plot for average inventory on hand vs. % of delivery nonconformance

Simulation

Preliminary Analysis

Before the research began it was known that there was no local or company wide policy or procedure established to determine the stock level. However, order fulfillment integration management was hoping to see a correlation between the quality and delivery non-conformances and average inventory on hand. The findings of the initial study proved that the average on hand inventory wasn't affected by the quality or delivery non-conformances.

The results of the initial study led the research to the second step. At this phase, the aim was to find the appropriate levels of inventory with respect to certain values of controlling variables. Manufacturing critical path time (MCT), electronic data interchange firm zone (EDI firm), number of changes made on scheduled orders, number of quality non-conforming parts received, and number of delivery non-conforming parts received were the parameters that the management was trying to relate to the average days on hand inventory levels (DOH).

In order to relate the previously mentioned parameters to DOH, or to find appropriate levels of DOH for a given set of controlling parameters a simulation model was developed. However, MCT, EDI firm and changed scheduled orders were the parameters that couldn't be represented in the model separately. The only way to create a link between these parameters and the model is by analyzing the effects of these parameters on other model parameters. The parameters "number of quality non-conforming parts received" and "the number of delivery non-conforming parts received" were selected to be the model parameters to relate to MCT, EDI firm, and changed scheduled orders. The simplified system and parameters are shown in Figure 10.

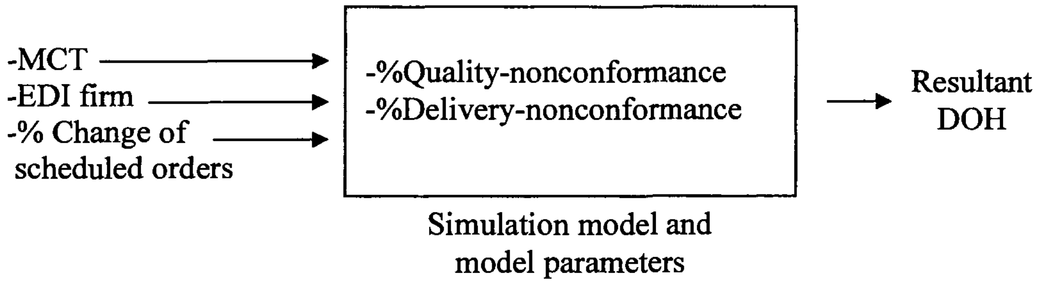

Figure 10. Representation of the simplified simulation model

The selection of such parameters was based on the idea that the root cause of the delivery and quality problems was the changes made on the scheduled and committed orders. If a new order is created with a short notice, or an already scheduled order is changed, the supplier would either deliver the order later than the scheduled time or deliver the order with defective parts as a result of increased production speed.

The idea adopted in this model has two practical benefits. First of all, two of the variables, “EDI firm” and “changed scheduled orders” are parameters controlled by the company. Second, although MCT is a supplier dependent parameter it could be measured and improved by the company. So, the idea is also proposing that it is possible to control and estimate the quality and delivery problems with the parameters generated or controlled by the company.

All of the data, except MCT, are generated and recorded by the company. To be able to measure MCT, thirty five suppliers were selected. The selection was based on the size of the business with the supplier. In 2006 a group of engineers from the supplier development group was assigned to conduct MCT analyses on selected suppliers. Among these thirty five sets of data, thirty three were used in the study because of missing "delivery" and "quality" information. The supplier development engineers visited the suppliers on site to calculate MCTs. MCTs were calculated through a "Value Stream Mapping" tool. In these studies, concurrent flow of information and material were observed and analyzed with the help of the supplier personnel. Supply chain engineers, manufacturing engineers and production line supervisors were the typical attendees of these meetings.

The anticipated results of the analysis were very important for the company. Linking the order changes which took place within a certain time period to quality and delivery problems would provide a very valuable information for assessing the overall efficiency of the supply chain operations.

In order to test the hypothesis two regression analyses were conducted. The first regression analysis was run for two independent variables of "percentage of changed scheduled orders" and "estimated delay" and the dependent variable of "percentage of quality non-conformances." The second regression was run with the same independent variables, and "percentage of delivery non-conformances." Percentage of changed scheduled orders is the percentage of all order changes that occurred in the EDI firm zone. To expect a negative effect of the order changes, it should take place in the committed time zone. It wouldn't be reasonable to expect a delivery or quality problem because of a change that takes place before the order becomes firm and the company is committed to purchase. Estimated delay is the difference between MCT and the time left for the delivery at the time of order change. So, if the MCT of a certain supplier is 15 days and if a new order is created with 10 days due date, the estimated delay would be 15-10 = 5 days.

The two regression models analyzed by the SAS® statistical analysis software were:

$$(1) \quad \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 = Y$$

$$(2) \quad \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_1 X_2 = Z$$

Model variables are:

X_1 Change of scheduled orders %

X_2 Estimated delay

X_3 Interaction term

Y Quality nonconformity %

Z Delivery nonconformity %

Initial analysis on the plot diagrams showed no apparent positive relation between the explanatory and dependent variables (Figure 11 through Figure 14). In order to find the statistically significant parameters, stepwise regression methods were utilized. However, the results didn't suggest any statistically significant parameter. The SAS code, SAS output and the data sets for regression models (1) and (2) can be found in Appendix B and Appendix C respectively.

Both models (1) and (2) have very low R^2 values (0.08 and 0.06 respectively) with statistically insignificant model and parameter estimates. Although the plots show very slight positive relationship between the dependent variable and estimated delay (Figure 12 and Figure 14), the relationship between the dependent variable and schedule changes looks negative (Figure 11 and Figure 13). Thus, the findings are not supporting the aim of this part of the study. According to supply chain development engineers, the main reason for the unexpected results could be the safety stocks of the suppliers. By holding high amounts of finished products the suppliers are able to respond to schedule changes even though they have high lead times. Thus, a supplier with a high lead time and high stock level can respond to schedule changes better than a supplier with low lead times and low safety stock levels. Although this practice comes with a cost covered by the suppliers, in order to maintain the smooth delivery of the purchased parts and production, the suppliers are willing to follow this method. Because of the insignificance and the inconsistent implications of the regression models the simulation is modeled without the schedule changes represented in the model.

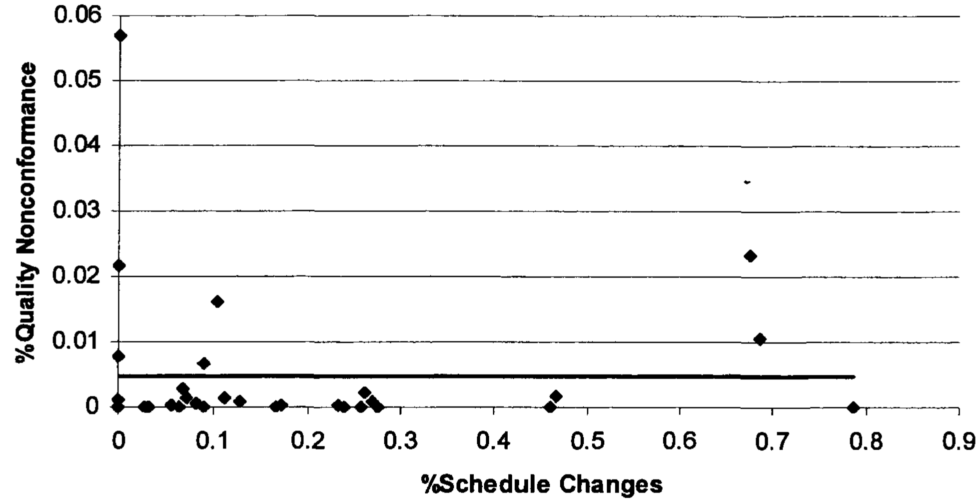

Figure 11. Plot of quality nonconformance percentages versus the percentage of schedule changes of each supplier

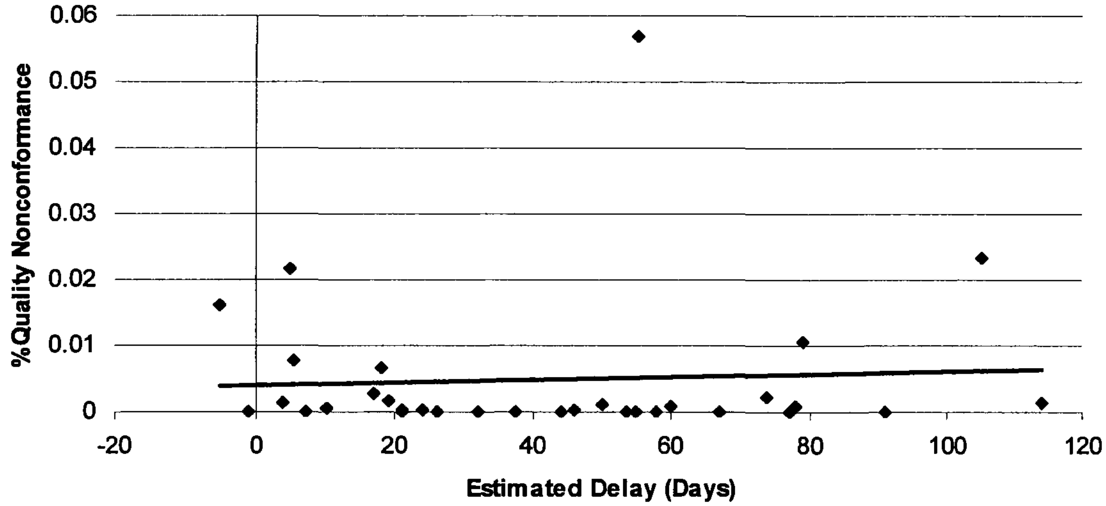

Figure 12. Plot of quality nonconformance percentage versus the estimated delays for each supplier

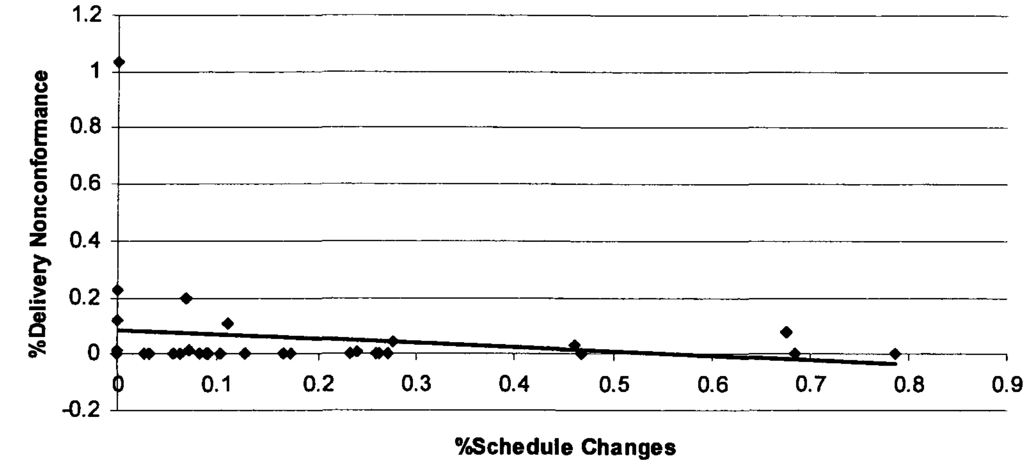

Figure 13. Plot of delivery nonconformance percentage versus the percentage of schedule changes of each supplier

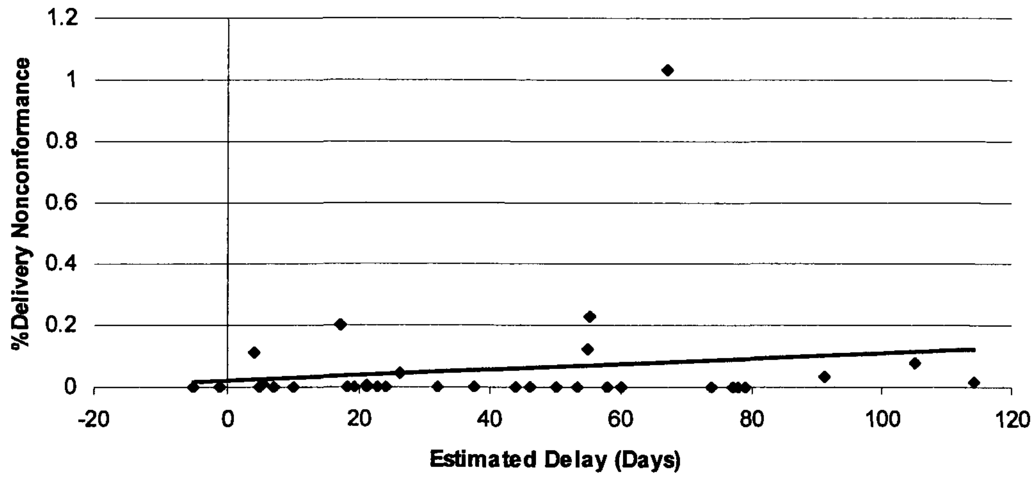

Figure 14. Plot of delivery nonconformance percentage versus the estimated delay for each supplier

Simulation Model

Currently, the supplier development team is working with the suppliers to improve their performance. The expected outcome of the improvement efforts is a stable production line with a target order fulfillment rate. The company's production goal is to maintain 95% order fulfillment. In order to sustain the targeted order fulfillment rate, the company has two options to do: either increase the supplier performance or increase the inventory safety stock levels. Increasing the safety stock levels which means increasing the assets on hand works against the company's Quick Response Manufacturing strategy. Increasing the supplier performance is more reliable and leaner method for order fulfillment development practice.

With the insight gained from the preliminary statistical studies conducted on the effects of the MCT and schedule changes, the simulation is modeled without linking the MCT and schedule changes to quality and delivery performance.

In the new design, quality performance, delivery performance and number of suppliers are the independent variables of the system. In the simulation model these parameters are defined in a way that allows the operator's manipulation.

For a better alliance the company is sharing the forecast data with the suppliers, so that the suppliers can deliver the orders right on time at the right quantity. However, there are two factors that cause divergence from this target namely: DPPM and QPPM. In the simulation model, the model parameters will be chosen to assure the 100% order fulfillment unless there is delivery or quality problem.

Following the nine-step reference set creation procedures (Kritchanchai & Mac Carthy, 2002) and considering the steady state behavior of the system, the variables and fixed input parameters are obtained as in Table 2.

Table 2. *Values of reference state input parameters*

Parameters	Values
Time between order arrivals	Erlang (0.022, 3636)
Service time	Erlang (0.02, 3600)
Order size	250
Replenishment point	125
Number of suppliers	10
Quality PPM	0%
Delivery PPM	0%

The selection of the probability distributions depends on the suggestions made by Law (2007), and Minner (2000) on service rate and demand distributions. Law (2007) recommends using Erlang distributions for any kind of service rate distributions. Minner (2000) also pointed out that Erlang distribution is widely used in inventory models and any probability distribution can be approximated closely by Erlang distribution.

The analysis of data suggested that for some purchased parts unnecessarily excessive amount of inventory had been held. On the other hand, for some purchased parts, the inventory levels might be too low to risk the continuity of the production. Both cases are equally harmful for the future competitiveness and success of the company. Inventory is accepted as one of the eight sources of waste in modern production philosophies (Meyers & Stephens, 2004). The lack of inventory could lead to production stoppage which in turn causes late productions, late deliveries, and unsatisfied customers.

There are mainly two inventory review policies: continuous and periodic. For inventory auditing purposes the simulation model utilizes continuous inventory review method. In case of continuous inventory reviews, Bertolini and Rizzi (2002) recommend using fixed size orders when the inventory drops below a certain replenishment point. Replenishment point and fixed order size (EOQ) are the two main system capacity controllers and their values are chosen to reach a steady state model behavior.

Using the given fixed and variable reference state input parameters the output indicator parameters are obtained as in Table 3.

Table 3. *Values of reference state output indicators*

Performance parameters	Values
Average inventory days on hand	23.3
Utilization	90%
Service rate	100%

Validation and Verification

Although the reference state values have been attained, Kritchanchai and MacCarthy (2002) suggested testing the model with the reference state values to validate the model and the reference state values. A pilot test was conducted in order to analyze whether the model outputs are consistent with the direction of the predicted values.

As mentioned in the literature review section, the most significant implication of the Economic Order Quantity model is that increasing the lot size increases the average amount of inventory on hand. In order to examine the existence of this relationship average inventory on hand is measured at different order quantity levels. The simulation is replicated with three different random number seeds at each level (three replications). With the purpose of minimizing the bias in the simulation, it is run for one year of warm up period without collecting any statistical data. After the warm up period the simulation is run for a period of three years. The average results are shown in Table 4.

Table 4. *Validation results for model behavior*

Order Size (units)	250	275	300	325
Average Days on Hand	23.3	25.3	27.5	29.7

Figure 15 shows that the model creates the average days on hand values as predicted. As shown, average days on hand levels are increasing as the order size increases. The pilot run confirms and validates that the system is consistent with the known or predictable results.

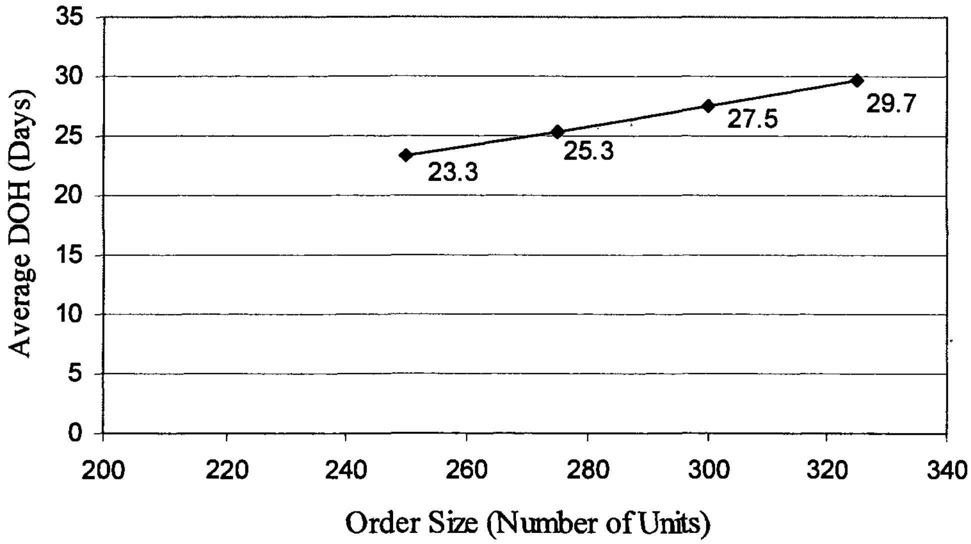

Figure 15. Average days on hand values for model validation

Design of Experiments

The factors that will be investigated by the simulation model are Quality Part per Million (QPPM), Delivery Part per Million (DPPM), and the number of suppliers. In order to fulfill the objectives of this study a full factorial design was employed and the effects of the controllable factors on two measures of performance: average stock level and service rate. The selected parameters (factors) with their corresponding levels are presented in Table 5.

Table 5. *The Levels of the Parameters*

Parameters	Levels				
QPPM	1 Partner	2 Key	3 Approved	4 Conditional	
DPPM	1 Partner	2 Key	3 Approved	4 Conditional	
Number of Suppliers	1 2 suppliers	2 4 suppliers	3 6 suppliers	4 8 suppliers	5 10 suppliers

QPPM and DPPM levels are selected in a way to represent each four categories of suppliers (partner, key approved, conditional). In order to do that, Bollapragada, Rao, and Zhang (2004) suggested using the same level of supplier performance for all suppliers in the model. In the same study it was recommended to choose from (2, 4, 6, 8, 10) suppliers. It was also mentioned that larger number of suppliers couldn't be effectively handled in simulation based optimization procedures.

A supplier with less than or equal to 200 QPPM is in the "partner" classification according to the quality metric. Similarly, for a "partner," maximum allowable DPPM is 5,000. On the other hand, a supplier with more than or equal to 1,300 QPPM is a "conditional" supplier. DPPM rating for a "conditional" supplier must be more than or equal to 30,000.

Choosing QPPM and DPPM levels based on different supplier categories will support supplier development group decisions on development projects. Helping suppliers to develop their business and manufacturing operations would construct a reliable supply chain for the long run. However, it is also important to measure the effects of supplier development projects in terms of cost and performance. In fact, most of the cost and performance considerations are captured through QPPM and DPPM metrics.

Four “QPPM” levels, four “DPPM” levels and five “number of suppliers” levels produce a total of eighty (4 X 4 X 5) combinations of factor levels. With three replications for each factor level combination the simulation was run for 240 times. The simulation generated average inventory, average utilization, and order fulfillment rate for each run. As stated before the company’s target order fulfillment rate is 95%. Thus, holding the order fulfillment rate fixed at 95%, the resultant average inventory amounts are recorded for each replication. At the next step, the analyses are performed on the average inventory levels.

Statistical Analysis of the Simulation

The factorial experimental design made it possible to use the analysis of variance technique (ANOVA) to investigate the significance of level differences for each factor. A three-way ANOVA was performed with two-way and three-way interactions included in the model. Thus, the general linear model is structured as follows:

$$Yijkl = \mu + \alpha j + \beta k + \gamma l + (\alpha\beta)jk + (\alpha\gamma)jl + (\beta\gamma)kl + (\alpha\beta\gamma)jkl + \varepsilon ijkl$$

Mean model components:

μ The overall mean of the scores (average inventory)

Main effect model components:

αj The effect of being in level j of QPPM

βk The effect of being in level *k* of DPPM

γl The effect of being in level *l* of "number of suppliers"

Two-way interaction model components:

$(\alpha\beta)jk$ The effect of being in level *j* of QPPM and level *k* of DPPM

$(\alpha\gamma)jl$ The effect of being in level *j* of QPPM and level *l* of number of suppliers

$(\beta\gamma)kl$ The effect of being in level *k* of DPPM and level *l* of number of suppliers

Three-way Interaction Model Components:

$(\alpha\beta\gamma)jkl$ The effect of being in level *j* of QPPM, level *k* of DPPM, and level *l* of number of suppliers

Error components:

$\varepsilon ijkl$ The unexplained part of the score

The SAS code, data set, and the SAS report for assumptions and ANOVA table are presented in Appendix D. The residual plots and normality test confirms that there is no violation of assumptions. The ANOVA table, main effects plot, and the interaction effects plots imply significant three-way interaction of the factors ($p < 0.0001$). Although the main effects are also significant three way interaction of factors does not allow performing a pair wise comparison of the factor levels. Three way interaction implies that the level of two way interaction varies at different levels of the third factor. At this point, no more conclusions could be made on the main effect levels.

In order to investigate the nature of the two way interactions, two way ANOVA was performed at each level of factor "number of suppliers." From the two-way ANOVA table (Appendix E) when there are two suppliers, interaction effect is not statistically significant ($p = 0.332$). However, for other levels (4, 6, 8, 10) interactions are still statistically significant for $\alpha = 0.05$. To determine the factor differences, one-way ANOVA was performed at all factor level combinations.

Initially, DPPM level differences are analyzed at all factor level combinations of the "number of suppliers" and QPPM. Five "number of suppliers" levels and four QPPM levels resulted in twenty (5 x 4) factor level combinations. Thus, twenty one-way ANOVA analyses were executed. The results of Tukey's pair wise comparison tests for the levels of DPPM at each factor level combinations of "number of suppliers" and QPPM are summarized in Table 6. For each row of factor level combinations, the levels with the same color of underline are found not significantly different from each other for $\alpha = 0.05$.

The table portrays that as the "number of suppliers," QPPM and DPPM increase the average inventory level also increases. Statistical pair wise comparison tests are run for the levels of DPPM at each factor level combinations. From the summary table it can be concluded that DPPM levels become significantly different as the "number of suppliers" and QPPM increases. Especially for more than four suppliers all DPPM levels except three of them are significantly different. The table suggests that for the number of suppliers higher than four, the classification of suppliers is reasonable. The company's efforts to improve the delivery performances of the suppliers would have significant effect on the inventory stock levels.

Table 6. *Summary of Tukey's pairwise comparison test. (For each row, levels with the same color are not significantly different.)*

Factor Level Combinations		Levels of DPPM			
# of Suppliers	QPPM				
1	1	1	2	3	4
	2	1	3	2	4
	3	1	2	3	4
	4	1	2	3	4
2	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4
3	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4
4	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4
5	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4

Secondly, QPPM level differences are analyzed at all factor level combinations of "number of suppliers" and DPPM. Five "number of suppliers" levels and four DPPM levels resulted in twenty (5 x 4) factor level combinations. Thus, twenty one-way ANOVA analyses were conducted. The results of Tukey's pair wise comparison tests for the levels of QPPM at each factor level combinations of "number of suppliers" and DPPM are summarized in Table 7. For each row of factor level combinations, the levels with the same color of underline are found not significantly different from each other for $\alpha = 0.05$.

Table 7 shows the effects of QPPM levels on inventory stock levels at all factor level combinations of DPPM and "number of suppliers." It is clear that QPPM has an effect on the amounts of average inventory held by the company. However, the significance of each level at all factor level combinations is not very clear. Moreover, when there are two, six or eight suppliers in the system, there is no difference observed between QPPM levels except one where there are eight suppliers and DPPM is at level two. As summarized in Table 7, it is not possible to claim that each QPPM levels has significant effect on the average inventory on hand. As the number of suppliers increases, the effect of QPPM becomes visible, but not strong enough to differentiate each QPPM levels. Even in cases, where the QPPM levels have significant effects, there appear two or three groups indistinctive and with overlapping regions. In this case, it is hard to justify the company's efforts to improve the suppliers' quality performances. It could

Table 7. *Summary of Tukey's pairwise comparison test. (For each row, levels with the same color are not significantly different.)*

Factor Level Combinations: # of Suppliers	DPPM	Levels of QPPM			
1	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4
2	1	1	2	3	4
	2	1	2	3	4
	3	1	4	2	3
	4	1	2	3	4
3	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4
4	1	1	2	3	4
	2	1	2	3	4
	3	1	2	3	4
	4	1	2	3	4
5	1	1	2	4	3
	2	1	4	2	3
	3	1	2	3	4
	4	1	2	3	4

make more sense to either classify the suppliers into two or three categories instead of four categories, or change the classification criteria to widen the limits of each category.

Lastly, "number of suppliers" level differences are analyzed at all factor level combinations of QPPM and DPPM. Four QPPM levels and four DPPM levels resulted in sixteen (4 x 4) factor level combinations. Thus, sixteen one-way ANOVA analyses were conducted. The results of Tukey's pair wise comparison tests for the levels of "number of suppliers" at each factor level combinations of QPPM and DPPM are summarized in Table 8. For each row of factor level combinations, the levels with the same color of underline are found not significantly different from each other for $\alpha = 0.05$.

The results of sixteen one-way ANOVA and the Table 8 of pair wise comparisons clearly show that the "number of suppliers" has a significant effect at all factor level combinations of QPPM and DPPM for $\alpha = 0.05$. Although, not all of the "number of suppliers" levels are significantly different at all factor level combinations, it proves that increasing the number of suppliers would negatively effect the overall supply chain performance. In other words, reducing the number of suppliers would help to improve the order fulfillment rate or to reduce the amount of inventory on hand.

Table 8. *Summary of Tukey's pairwise comparison test. (For each row, levels with the same color are not significantly different.)*

Factor Level Combinations		Levels of "Number of Suppliers"				
DPPM	QPPM					
1	1	3	1	4	2	5
	2	1	2	3	4	5
	3	1	2	3	4	5
	4	1	2	3	4	5
2	1	1	2	4	3	5
	2	1	2	4	3	5
	3	1	2	4	3	5
	4	1	2	4	3	5
3	1	1	2	3	5	4
	2	1	2	3	4	5
	3	1	2	3	4	5
	4	1	2	3	4	5
4	1	1	2	3	4	5
	2	1	2	3	4	5
	3	1	2	3	4	5
	4	1	2	3	4	5

Regression Analysis

The last statistical study is conducted to analyze how the average inventory on hand is related to DPPM, QPPM and "number of suppliers." It was also intended to construct a formula that would help to predict the required amount of inventory on hand for a given set of independent variables (DPPM, QPPM and number of suppliers).

The regression model is based on the results attained from the one-way ANOVA analysis. The one-way ANOVA suggests that all main factor effects are significant and the average inventory on hand increases as the main factors increase. Two-way and three-way interaction effects are also found to be significant and interactions contribute to the increase of the average inventory on hand. Thus, the following regression model is analyzed for significant factors to include in the final model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 + \beta_6 X_2 X_3 + \beta_7 X_1 X_2 X_3 + \varepsilon$$

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$ are the regression coefficients that need to be estimated.

X_1	independent variable QPPM
X_2	independent variable DPPM
X_3	independent variable "number of suppliers"
X_1X_2	interaction term for QPPM and DPPM
X_1X_3	interaction term for QPPM and "number of suppliers"
X_2X_3	interaction term for DPPM and "number of suppliers"
$X_1X_2X_3$	interaction term for QPPM, DPPM and "number of suppliers"

The full model is fitted with SAS "proc reg" procedure. Assumptions for normality and constant variance hold for the model with three data point having large residuals. These three data points with large residuals are left in the model. The SAS program code, data set and the diagnostic results for assumptions are given in Appendix F. Initial study points out two interactions (QPPM*DPPM and QPPM*number of suppliers) to be statistically insignificant ($p = 0.3635$ and $p = 0.1050$ respectively). The estimated coefficients for these two interaction effects are also inconsistent with the insight gained from the one-way ANOVA and pair wise comparison tests (-19503 and -158.77 respectively). Interaction term coefficients suggest that as QPPM, DPPM and the number of suppliers increase, the required amount of inventory reduces. Step-wise procedures also found interaction terms of (QPPM*DPPM) and (QPPM*number of suppliers) to be statistically insignificant for $\alpha = 0.15$. In addition, plots of R^2 and MSE versus the number of terms to be included in the model are also created to evaluate the effect of adding interaction terms to the model. Plots don't suggest any strong effect of adding excluded interaction terms to the model. Thus, the final model is constructed with all independent variables and interaction terms except (QPPM*DPPM) and (QPPM*number of suppliers). Final regression model and estimated coefficients are as follows:

Average inventory on hand = 152.91 + 374.98(QPPM) + 64.99(DPPM) +
0.25(number of suppliers) +
33.14(DPPM*number of suppliers) +
3605.5(QPPM*DPPM*number of suppliers)

The final model has three main effect terms, one two-way interaction term and one three-way interaction term. All of the coefficients are positive. Thus, the dependent variable (average inventory on hand) increases with the increase of any of the independent variables. However, the interaction terms imply that the increase rate will also increase at the higher levels of other variables.

CHAPTER V

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Summary

Manufacturing cost reduction through inventory elimination is a common goal for all manufacturing companies. It is a very complicated problem with many uncertainties included in it. However, it is known that a better control over inventory level results in improvements in such areas as purchasing, warehousing, distribution, labor utilization, equipment scheduling, data presentation, quality assurance, vendor relations, packaging, materials handling, and even personnel administration.

The importance of this research became more apparent during the collaboration with a Midwestern Manufacturing Company. Working with the company helped to identify the inventory related problems and establish the goals for the research.

The problem that has been studies in this research is to develop a simulation model to analyze the effects of lead time, order schedule changes, and delivery and quality related problems on safety stock levels in order to minimize inventory amount and reduce cost.

The results of this research would allow businesses to organize their resources and efforts to align their suppliers and their suppliers' resources and capabilities to create a competitive advantage and provide value to their customers. As a result of this research, key inventory control parameters were identified, and a mathematical model was developed based on these factors.

The current research addressed the following questions.

1. What are the most important variables that affect the delivery and quality performances of a supply chain?
2. What are the most important variables that affect the service rate or fill rate of a supply chain of a manufacturing company?
3. What levels of the selected variables could be used in order to minimize inventory on hand?

Answers to the research questions were sought through regression analysis, design of experiments, discrete-event simulation and ANOVA analysis techniques.

Conclusion

The first analysis was conducted on the parts from 202 suppliers. The suppliers were selected randomly from the company's supplier focus group in order to gather the most reliable data possible. For 202 parts quality and delivery performances of the suppliers were collected. Average inventory levels of these parts were also created by the company. Analysis of the data showed that there is no relationship between the performances of the suppliers and the inventory being held by the company. The company is holding high quantities of inventory for the purchased parts with low quality or delivery problems, and lower amounts for the parts with high quality and delivery problems. The finding is against the basic manufacturing and inventory holding practices. The delivery and quality problems are usually balanced with holding more material in stock. The research questions and methods are designed to address this finding.

At the next step, a discrete-event simulation was modeled to answer the research questions. At the start, it was intended to simulate the quality and delivery problems as a result of other factors. Meetings with the supplier development management and order fulfillment integration management led the research to concentrate on the order schedule changes and manufacturing critical-path time (MCT, lead time). It was suggested that the quality and delivery problems of the suppliers could be the result of order changes with very short notices. Because of the sudden changes on the quantity or the delivery date of the orders, the suppliers could have hard time delivering the parts on time with the desired quality. To be able to investigate the relationship between scheduled order changes, estimated delay time (based on the MCT), and suppliers' performances (quality and delivery) supplier development teams performed Value Stream Mapping studies and provided information of 33 suppliers in 2006. However, the regression analysis showed no significant relationship between the variables under study. One of the explanations of this unexpected result is believed to be supplier's holding too much safety stock regardless of the forecast and order schedules.

As a result, the simulation is built by using the quality and delivery performances as major factors in the model. The simulation model is created in a way that allowed constructing a full factorial design of experiments. Quality performance, delivery performance and number of suppliers were selected to be the main factors to be investigated through the simulation and ANOVA studies. Four quality and four delivery performance factor levels were determined according to the company's supplier classification guideline. By using the company's supplier classification guideline, we also got the chance to test the reasonableness of the classification. Five levels of "number of suppliers" resulted in eighty (5 X 4 X 4) factor level combinations. The simulation was replicated three times at each factor level combination. The results of the simulation were analyzed by ANOVA. The three-way ANOVA suggested a significant three-way interaction. Thus, one-way ANOVA was also run to further investigate the way of interaction and effects of major factor. Pair-wise comparison was also utilized to identify the significantly different levels of one factor at the factor level combinations of other two variables. The ANOVA and pair-wise comparison studies revealed that as the number of suppliers and delivery related problems increase their levels become significantly different. However, quality levels were not found to be significantly different. The findings suggest that the number of suppliers, in other words the number of parts, strongly affects the performance of a production line and causes carrying on higher amounts of stocks. This finding is consistent with the Just-in-Time practice of reducing the number of parts. It could also be concluded that the delivery classification guideline is reasonable. However, categorization of quality performance is not consistent with the company's goals.

Finally, a regression model was developed based on the simulation data. The model creation is intended to show how to construct such a mathematical expression starting with a given set of reference parameters.

Recommendations

The primary goal of the research was to find answers to the research questions utilizing, valid, scientific methods and tools. However, being scientifically correct does not always guarantee practical or useful results. It is an important aspect of any research to evaluate the practicality and the deficiencies which pertain to the study.

One of the most important steps in this research was the MCT studies through Value Stream Mapping tool. The suppliers included in the study were selected according to their sizes of businesses with the company under the study. It was intended to gain the maximum effect possible with the minimum effort. However, a better way of conducting the research would be by narrowing down the diversity of the businesses, and classifying them according to their production technique. Among tens of manufacturing techniques, such as metal casting, forging, injection molding, and sheet metal working, the most common one or two categories could be selected to concentrate on a specific manufacturing industry.

In order to gain a better understanding of suppliers' response to scheduled order changes a more detailed investigation is required. A detailed supplier capacity analysis could help to identify the factors affecting the responsiveness of the suppliers. A more precise analysis could be performed by breaking the manufacturing critical-path time into two segments as MCT raw and MCT response. Utilizing the two MCT parameters, MCT raw (the time that it takes to deliver an order starting from raw material), and MCT response (the time to deliver a finished part waiting in the warehouse), could result in a better understanding of the supplier MCT.

Delivery performance should include early deliveries as a delivery nonconformance measure as well. Although an early delivery doesn't cause material shortage directly, it damages the stock level accuracy, and causes problems in the long run. The chances of damage also increases as the early delivered parts stay in the stock room for a long period of time. Material handling and storage cost is another negative effect of early delivery of purchased parts.

A stronger supply chain partnership is necessary for the success of the supply chain. A partnership based on mutual-trust should be established. A trust-based partnership could help to better evaluate the capacity of the partners, and more accurate performance measures could be identified. Currently, the capacity of the suppliers is measured by only quality and delivery performance, but the factors that are influencing the delivery performance should be studied in depth.

Supplier development teams and order fulfillment integration teams should get more attention in the company. Currently, these teams are small so as to deal with problems that they're confronting. The teams need more resources and more personnel to do research and to implement their solutions on more than 6000 suppliers.

REFERENCES

Armstrong, G., & Kotler, P. (1999). *Marketing: An introduction.* Upper Saddle River, NJ: Prentice Hall.

Altiok, T. (1996). *Performance analysis of manufacturing systems.* New York, NY: Springer-Verlag New York Inc.

Banks, J., & Carson, J. (1984). *Discrete-event system simulation.* Englewood Cliffs, NJ: Prentice Hall.

Bernard, P. (1999). *Integrated inventory management.* New York, NY: John Wiley & Sons, Inc.

Bertolini, M., & Rizzi, A. (2002). A simulation approach to manage finished goods. inventory replenishment economically in a mixed push/pull environment. *Logistics Information Management, 15*(4).

Bhaskaran, S. (1998). Simulation analysis of a manufacturing supply chain. *Decision Sciences, 29*(3).

Bier, I. J., & Tjelle, J. P. (1994). The importance of interoperability in a simulation prototype for spares inventory planning. *Proceedings of the 1994 Winter Simulation Conference, Orlando, FL.*

Bollapragada, R., Rao, U. S., & Zhang, J. (2004). Managing inventory and supply performance in assembly systems with random supply capacity and demand. *Management Science, 50*(12).

Cao, Q., Patterson, J. W., & Melkonian, J. (1996). A three stage simulation based approach to inventory management with discrete demand. *International Journal of Production Research, 34*(9).

Christopher, M. L. (1992). *Logistics and supply chain management.* London:Pitman.

Cooper, M. C., & Ellram, L. M. (1993). Characteristics of supply chain management and the implications for purchasing and logistics strategy. *The International Journal of Logistics Management, 4*(2).

Garcia, E. S., Silva, C. F., & Saliby, E. (2002). A simulation model to validate and evaluate the adequacy of an analytical expression for proper safety stock sizing. *Proceedings of the 2002 Winter Simulation Conference, San Diego, CA.*

Geunes, J., & Pardalos, P. M. (2005). *Supply chain optimization.* New York: Springer.

Gordon, G. (1978). *System simulation.* Englewood Cliffs, NJ: Prentice Hall.

Harris, F. W. (1913). How many parts to make at once. *Factory: The Magazine of Management, 10*(2).

Hopp, W. J., & Spearman, M. L. (2000). *Factory physics*. New York, NY: McGraw-Hill.

Kang, Y., & Gershwin, S. B. (2005). Information inaccuracy in inventory systems: stock loss and stockout. *IIE Transactions, 37*(9).

Kelton, W. D., Sadowski, R. P., & Sturrock, D. T. (2007). *Simulation with Arena.* New York, NY: McGraw-Hill.

Kobert, N. (1992). *Managing inventory for cost reduction*. Englewood Cliffs, NJ: Prentice Hall.

Kritchanchai, D., & MacCarthy, B. (2002). A procedure for establishing a reference state in qualitative simulation of operational systems. *Industrial Management and Data Systems, 102*(6).

La Londe, B. J., & Cooper, M. C. (1988). *Customer service: A management perspective.* Oak Brook, IL: Council of Logistics Management.

La Londe, B. J., & Masters, J. M. (1994). Emerging logistics strategies: Blueprints for the next century. *International Journal of Physical Distribution and Logistics Management, 24*(7).

Laudon, K. C., & Laudon, J. P. (2004). *Management information systems: managing the digital firm*. Englewood Cliffs, NJ: Prentice Hall.

Law, A. M. (2007). *Simulation modeling and analysis*. New York: McGraw-Hill.

Law, A. M., & Kelton, W. D. (1982). *Simulation modeling and analysis*. New York: McGraw-Hill.

Meyers, F. E., & Stephens, M. P. (2004). *Manufacturing facilities design and material handling*. Englewood Cliffs, NJ: Prentice Hall.

Meyers, F. E., & Stewart, J. R. (2001). *Motion and time study for lean manufacturing.* Upper Saddle River, NJ: Prentice Hall.

Mihram, D., & Mihram, G. A. (1974). Human knowledge, the role of models, metaphors, and analogy. *International Journal of General Systems, 1*(1).

Minner, S. (2000). *Strategic safety stocks in supply chains*. Germany, Magdeburg: Springer.

Monczka, R. M., Trent, R., & Handfield, R. (1998). *Purchasing and supply chain management*. Cincinnati, OH: South Western College Publishing.

Morris, W. T. (1967). On the art of modeling. *Management Science, 13*(12).

Naylor, T. H., Balintify, J. L., Burdick, D.S., & Chu, K. (1966). *Computer simulation techniques*. New York: Wiley.

Pohlen, T. L., & La Londe, B. J. (1994). Implementing activity based costing in logistics. *Journal of Business Logistics, 15*(2).

Read, W. F., & Miller, M. S. (1991). The state of quality in logistics. *International Journal of Physical Distribution and Logistics Management, 21*(6).

Schmidt, J. W., & Taylor, R. E. (1970). *Simulation and analysis of industrial systems*. Homewodd, Ill: Irwin.

Schniederjans, M. J., & Cao, Q. (2002). *E-Commerce operations management*. City of Singapore, Singapore: World Scientific Publishing. Co. Pte. Ltd.

Schriber, T. J., & Brunner, D.T. (1997). Inside discrete event simulation software: how it works and why it matters. *Proceedings of the 1997 Winter Simulation Conference, Atlanta, GA.*

Seila, A. F., Ceric, V., & Tadikamalla, P. (2003). *Applied simulation modeling*. Belmont, CA: Thomson Learning Inc.

Stevens, G. C. (1989). Integrating the supply chain. *International Journal of Physical Distribution and Materials Management, 19*(8).

Suri, R. (1998). *Quick Response Manufacturing: A companywide approach to reducing lead times*. Portland, Oregon: Productivity Press.

Wagner, H. M., & Whitin, T. M. (1958). Dynamic version of the economic lot size model. *Management Science, 5*(1).

Wild, T. (1997). *Best practice in inventory management*. New York, NY: John Wiley & Sons, Inc.

Wilson, R. H. (1934). A scientific routine for stock control. *Harvard Business Review, 13*(1).

APPENDIX A

STATISTICAL PROGRAM AND OUTPUTS FOR REGRESSION ANALYSIS (INDEPENDENT VARIABLES: QUALITY AND DELIVERY NONCONFORMANCES DEPENDENT VARIABLE: INVENTORY ON HAND)

```
options ls=72;
data production2006;
input index QNonconformance DNonconformance DOH;
interaction=QNonconformance*DNonconformance;
cards;
1 0 13.33 14.42
2 0 0 19.25
3 0.2 17.82 32
.
.
.
.
.
200 0.78 1.17 14.25
201 0 0 96
202 0 0 63.33
;
proc reg data=production2006;
model DOH=Qnonconformance DNonconformance interaction;
plot DOH*Dnonconformance;
plot DOH*Qnonconformance;
plot residual.*predicted.;
plot r.*nqq.;
var index;
plot cookd.*index;
proc reg data=production2006;
model DOH=Qnonconformance DNonconformance interaction/ r p influence;
proc reg data=production2006;
model DOH=Qnonconformance DNonconformance interaction /
selection=forward slentry=0.15;
proc reg data=production2006;
model DOH=Qnonconformance DNonconformance interaction /
selection=backward slstay=0.15;
proc reg data=production2006;
model DOH=Qnonconformance DNonconformance interaction /
selection=stepwise;
proc reg data=production2006;
model DOH=Qnonconformance DNonconformance interaction /
selection=rsquare rmse;
run;
```

Table A1. *SAS Regression output for initial analysis. Independent variables: Quality and Delivery nonconformances Dependent variable: inventory on hand*

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	983.57386	327.85795	0.16	0.9199
Error	198	393585	1987.80391		
Corrected Total	201	394569			

Root MSE	44.58479	R-Square	0.0025
Dependent Mean	35.80193	Adj R-Sq	-0.0126
Coeff Var	124.53182		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	35.53827	3.34952	10.61	<.0001
QNonconformance	1	-0.52657	2.94895	-0.18	0.8585
DNonconformance	1	0.20047	0.35249	0.57	0.5702
interaction	1	-0.03210	0.11213	-0.29	0.7749

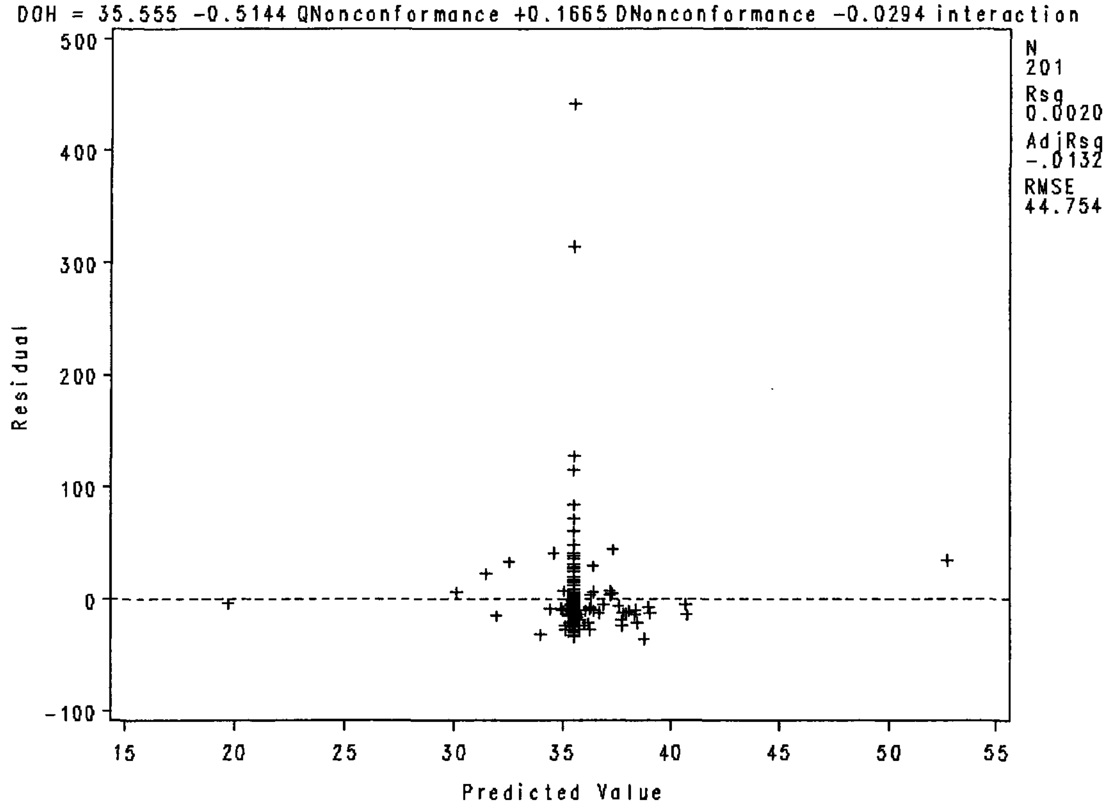

Figure A1. Residuals vs. Predicted value plot for the regression model.

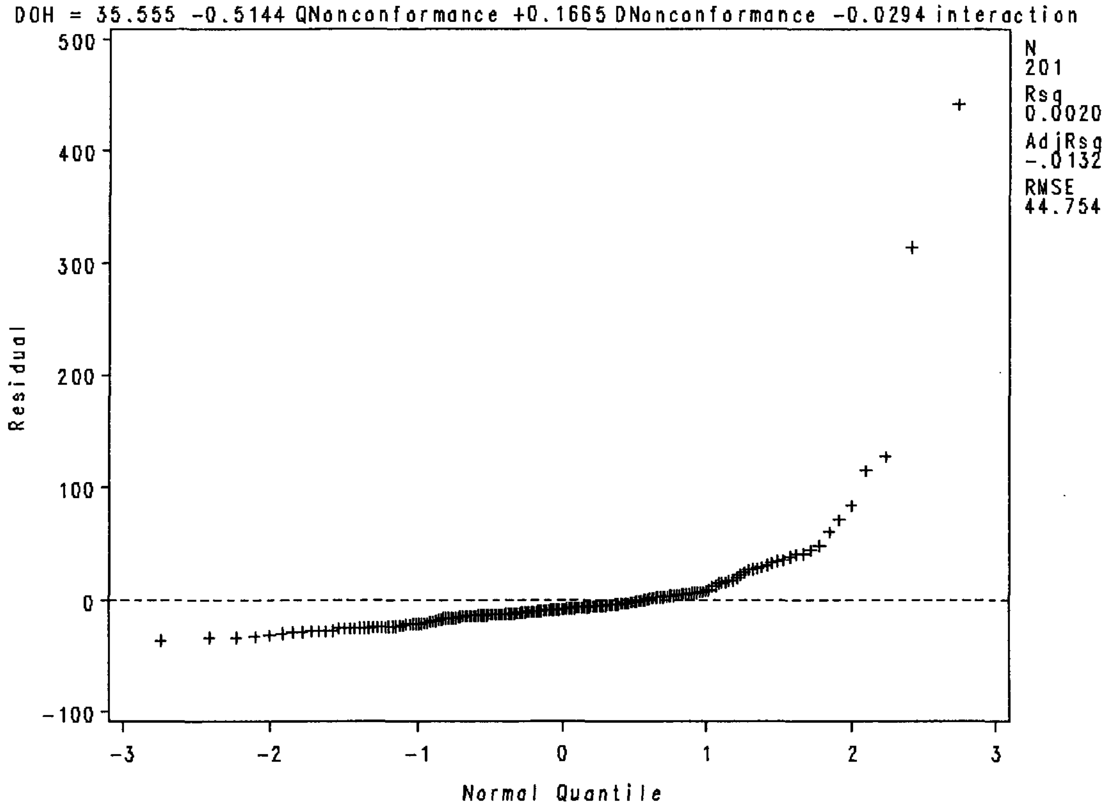

Figure A2. Normal probability plot of residuals for the regression model.

APPENDIX B

STATISTICAL PROGRAM AND OUTPUTS FOR REGRESSION ANALYSIS (INDEPENDENT VARIABLES: % OF SCHEDULE CHANGES AND ESTIMATED DELAY DEPENDENT VARIABLE: % OF QUALITY NONCONFORMANCES)

```
options ls=72;
data MCT2006;
input index ScheduleChanges EstimatedDelay QNonconformance;
interaction=ScheduleChanges*EstimatedDelay;
cards;
1 0.1115 4 0.0015
2 0.069 17 0.0029
3 0.0897 18 0.0066
.
.
.
.
.
31 0 5.5 0.0078
32 0 44 0
33 0 22.5 0
;
proc reg data=MCT2006;
model QNonconformance=ScheduleChanges EstimatedDelay interaction;
plot QNonconformance*ScheduleChanges;
plot QNonconformance*EstimatedDelay;
plot residual.*predicted.;
plot r.*nqq.;
var index;
plot cookd.*index;
proc reg data=MCT2006;
model QNonconformance=ScheduleChanges EstimatedDelay interaction/ r p
influence;
proc reg data=MCT2006;
model QNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=forward slentry=0.15;
proc reg data=MCT2006;
model QNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=backward slstay=0.15;
proc reg data=MCT2006;
model QNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=stepwise;
proc reg data=MCT2006;
model QNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=rsquare rmse;
run;
```

Table B1. *SAS Regression output. Independent variables: % of schedule changes and estimated delay, Dependent variable: % of quality nonconformances.*

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	0.00032457	0.00010819	0.85	0.4781
Error	29	0.00369	0.00012732		
Corrected Total	32	0.00402			

Root MSE	0.01128	R-Square	0.0808
Dependent Mean	0.00477	Adj R-Sq	-0.0143
Coeff Var	236.42310		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.00778	0.00423	1.84	0.0760
ScheduleChanges	1	-0.02011	0.01557	-1.29	0.2069
EstimatedDelay	1	-0.00006917	0.00008777	-0.79	0.4370
interaction	1	0.00038892	0.00025036	1.55	0.1312

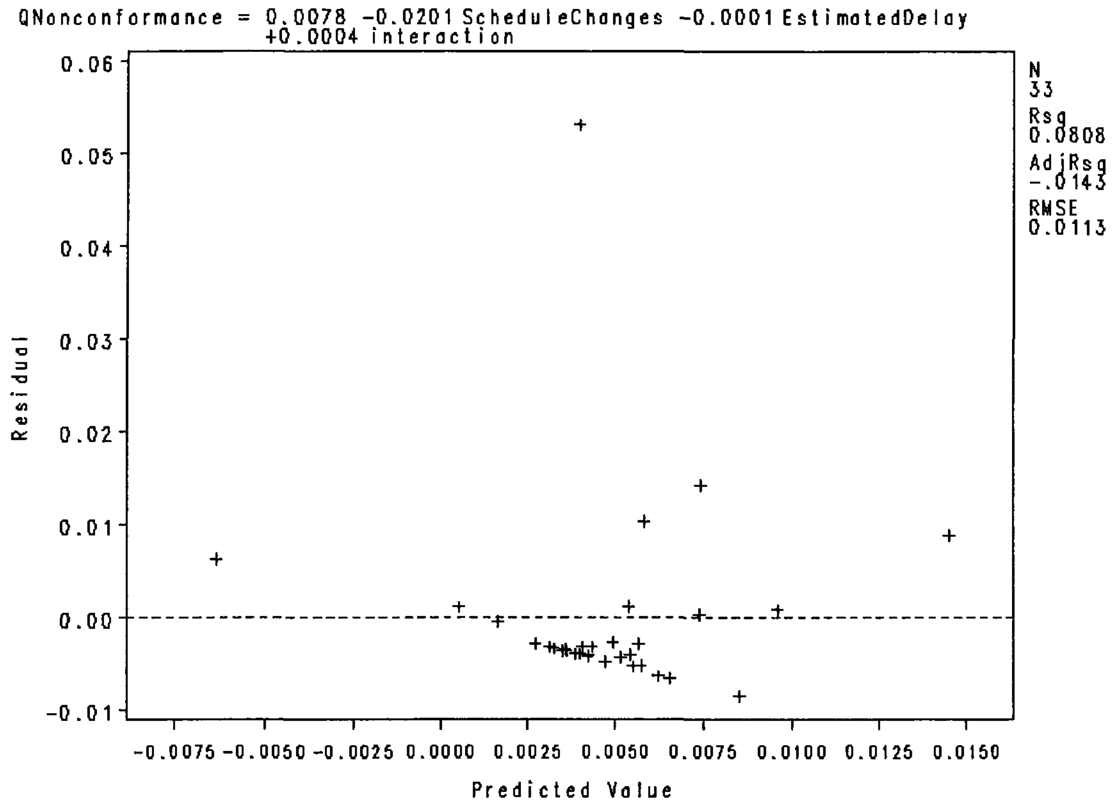

Figure B1. Residuals vs Predicted value plot for the regression model.

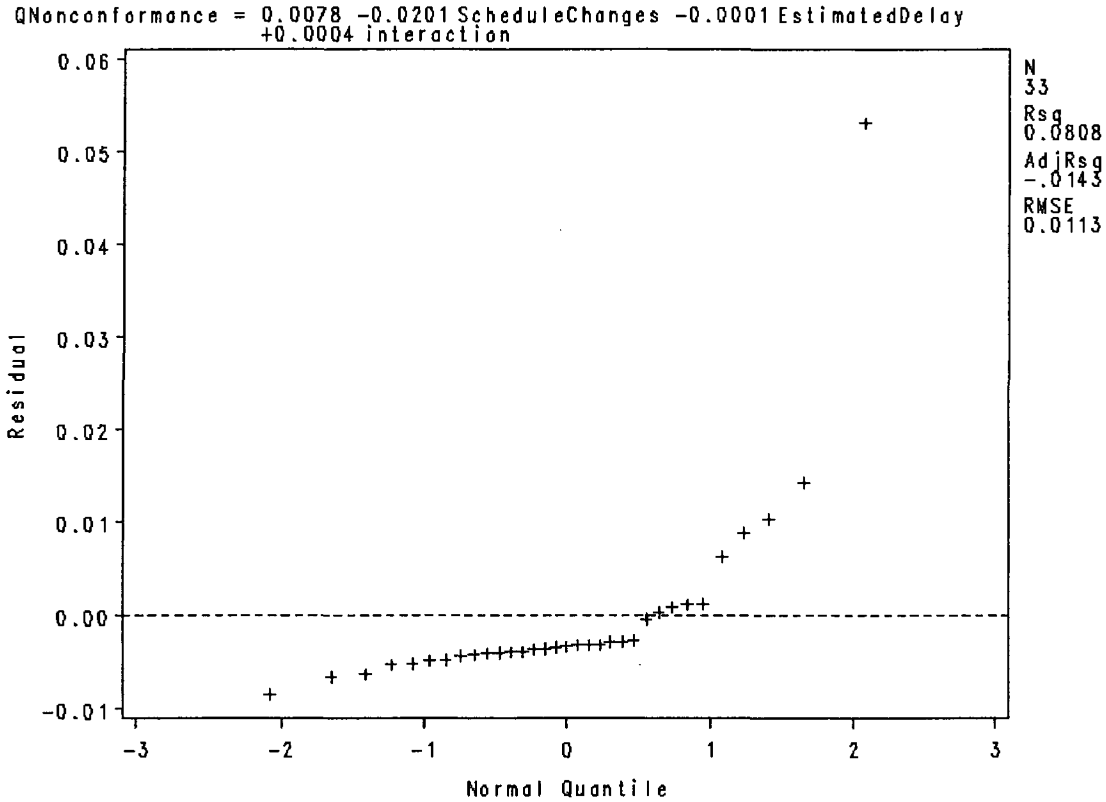

Figure B2. Normal probability plot of residuals for the regression model.

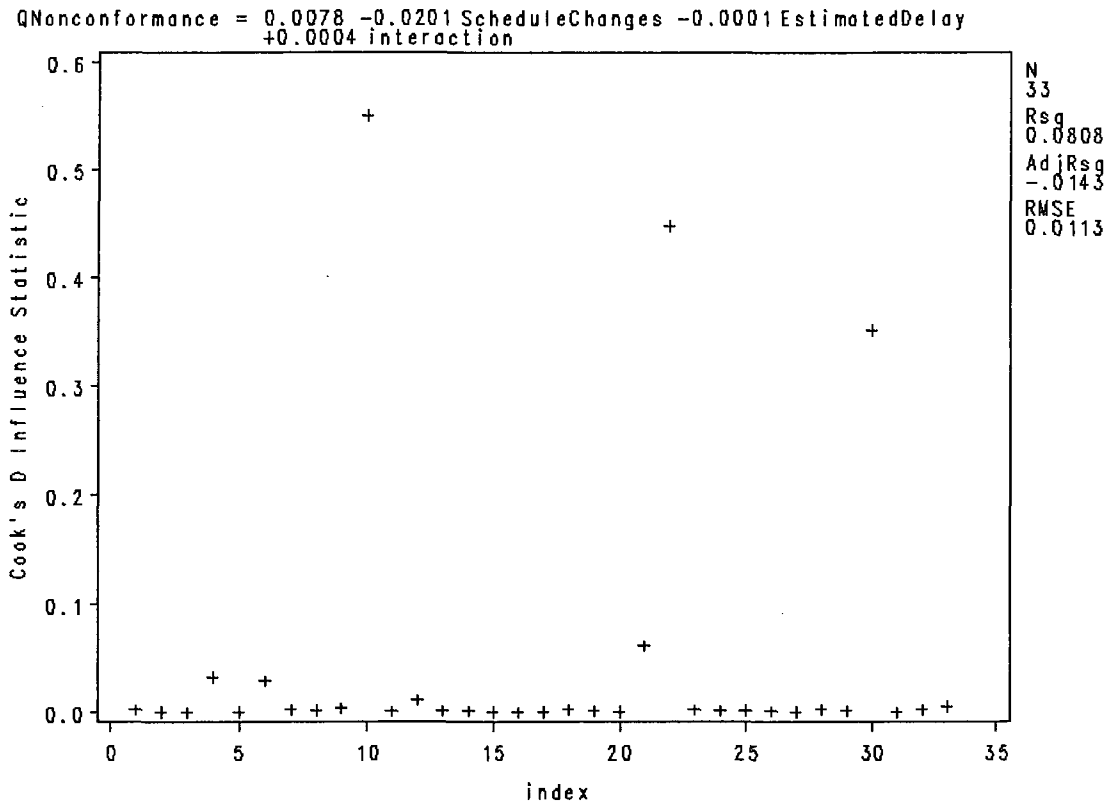

Figure B3. Cook's distance plot showing the most influential data points.

APPENDIX C

STATISTICAL PROGRAM AND OUTPUTS FOR REGRESSION ANALYSIS (INDEPENDENT VARIABLES: % OF SCHEDULE CHANGES AND ESTIMATED DELAY DEPENDENT VARIABLE: % OF DELIVERY NONCONFORMANCES)

```
options ls=72;
data MCT2006;
input index ScheduleChanges EstimatedDelay DNonconformance;
interaction=ScheduleChanges*EstimatedDelay;
cards;
1 0.1115 4 0.1097
2 0.069 17 0.1985
3 0.0897 18 0
.
.
.
.
31 0 5.5 0.0117
32 0 44 0
33 0 22.5 0
;
proc reg data=MCT2006;
model DNonconformance=ScheduleChanges EstimatedDelay interaction;
plot DNonconformance*ScheduleChanges;
plot DNonconformance*EstimatedDelay;
plot residual.*predicted.;
plot r.*nqq.;
var index;
plot cookd.*index;
proc reg data=MCT2006;
model DNonconformance=ScheduleChanges EstimatedDelay interaction/ r p
influence;
proc reg data=MCT2006;
model DNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=forward slentry=0.15;
proc reg data=MCT2006;
model DNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=backward slstay=0.15;
proc reg data=MCT2006;
model DNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=stepwise;
proc reg data=MCT2006;
model DNonconformance=ScheduleChanges EstimatedDelay interaction /
selection=rsquare rmse;
run;
```

Table C1. *% Schedule changes, estimated delays, and % delivery nonconformances for 33 companies.*

%Schedule Changes	Estimated Delay (Days)	%Delivery Nonconformance
0.1115	4	0.1097
0.069	17	0.1985
0.0897	18	0
0.4604	91	0.0332
0.6842	79	0
0.104	-5	0
0.0565	24	0.0019
0	55	0.1209
0.0833	10	0
0.7857	7	0
0	50	0
0.0635	-1	0
0.2327	21	0
0.2578	32	0
0.4667	19	0.0023
0.0726	114	0.0156
0.1724	46	0
0.2692	78	0.0004
0.2383	21	0.0062
0.128	60	0
0	5	0
0	55.25	0.2254
0	67	1.0313
0.2752	26.1	0.0437
0.0323	58	0
0.1667	53.4	0
0.2615	73.9	0.0009
0.0278	77.2	0
0.0909	37.5	0
0.6748	105	0.0801
0	5.5	0.0117
0	44	0
0	22.5	0

Table C2. *SAS Regression output. (Independent variables: % of schedule changes and estimated delay, Dependent variable: % of delivery nonconformances.)*

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	0.06479	0.02160	0.62	0.6108
Error	29	1.01820	0.03511		
Corrected Total	32	1.08299			

Root MSE	0.18738	R-Square	0.0598
Dependent Mean	0.05702	Adj R-Sq	-0.0374
Coeff Var	328.59233		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.04161	0.06650	0.63	0.5364
ScheduleChanges	1	-0.12523	0.25348	-0.49	0.6250
EstimatedDelay	1	0.00124	0.00143	0.87	0.3930
interaction	1	-0.00134	0.00410	-0.33	0.7459

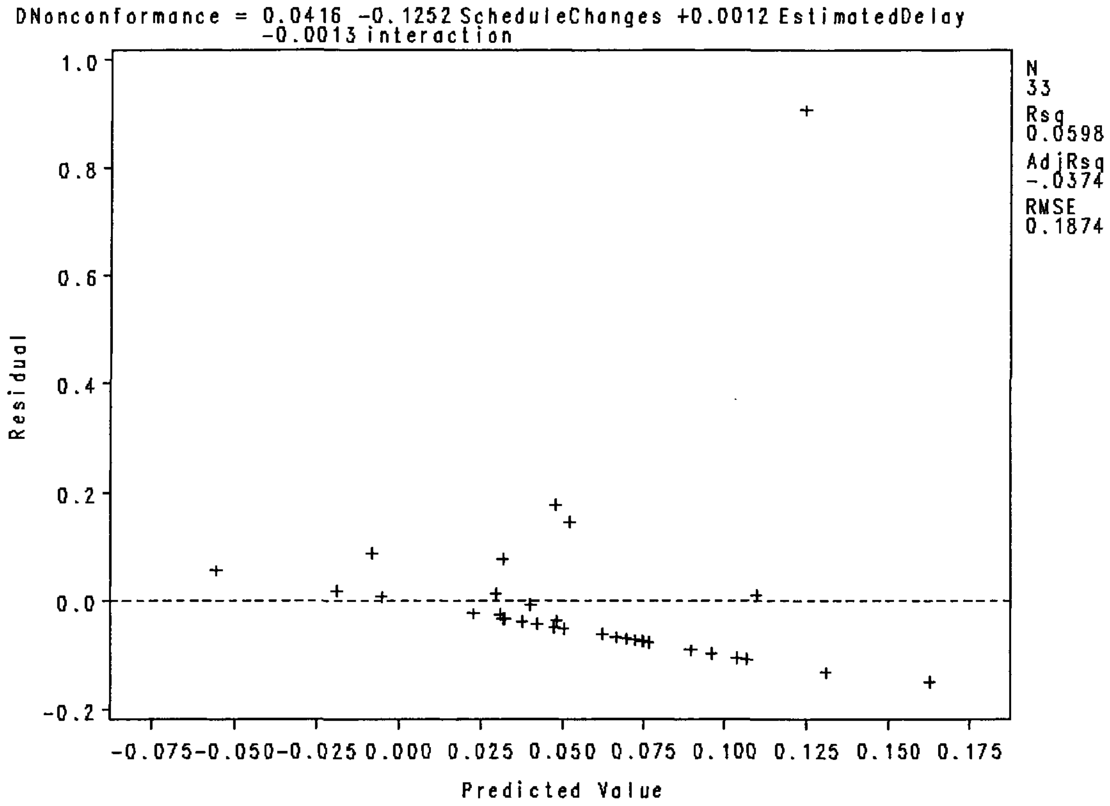

Figure C1. Residuals vs Predicted value plot for the regression model.

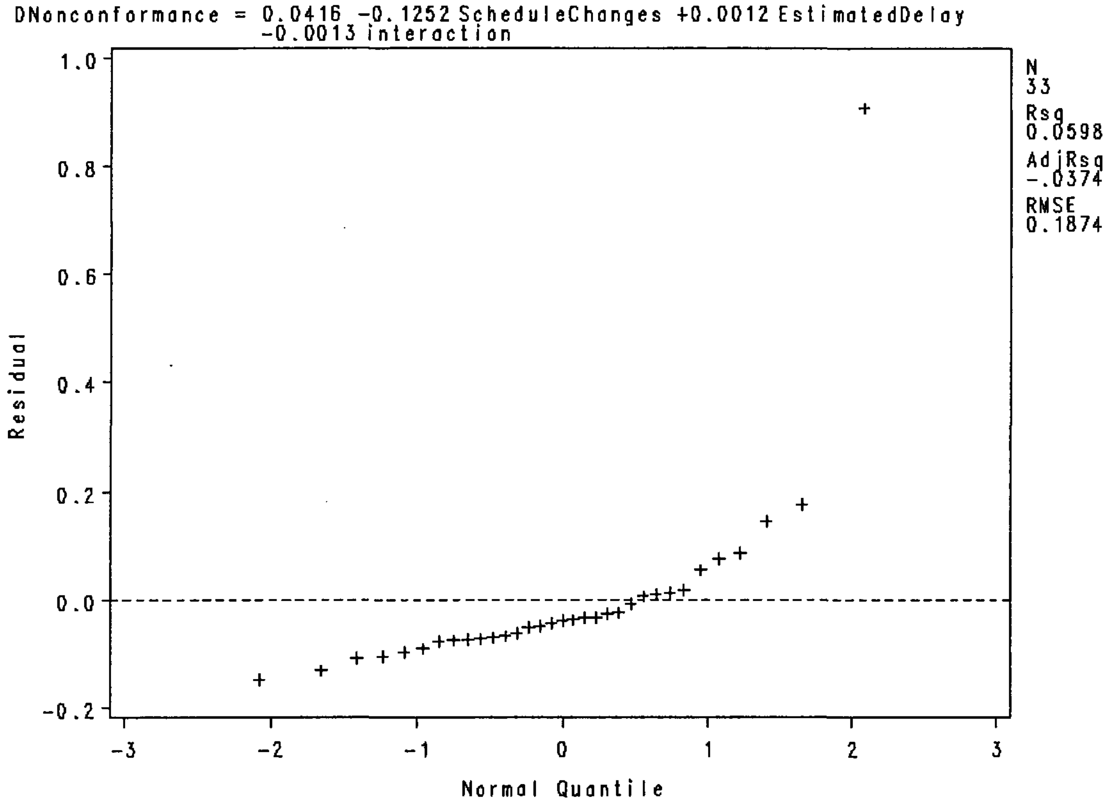

Figure C2. Normal probability plot of residuals for the regression model.

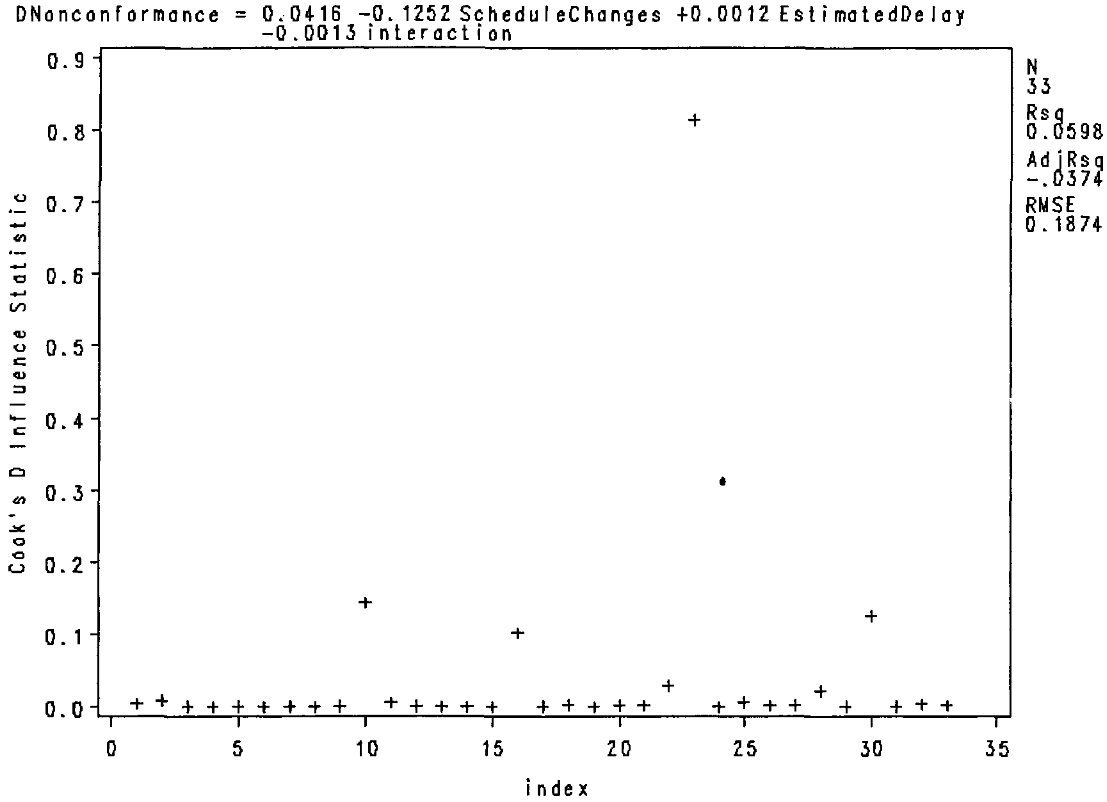

Figure C3. Cook's distance plot showing the most influential data points.

APPENDIX D

STATISTICAL PROGRAM AND OUTPUTS FOR 3-WAY ANOVA USING THE SIMULATION DATA

```
options ls=72;
data simulation;
input replication qppm dppm supplier doh;
cards;
1 1 1 1 154.4
1 2 1 1 154.1
1 3 1 1 155.2
.
.
.
.
.
.
3 1 4 5 175
3 2 4 5 175.7
3 3 4 5 179.5
3 4 4 5 178.3
;

proc glm data=simulation;
class replication qppm dppm supplier;
model doh=replication qppm dppm supplier qppm*dppm qppm*supplier
dppm*supplier qppm*dppm*supplier;
output out=next r=resid p=yhat;

proc print data=next;

proc rank normal=blom;
var resid;
ranks nscore;

proc plot;
plot resid*nscore;
plot resid*yhat;
run;
```

Table D1. *SAS 3-WAY ANOVA table for simulation data.*

Class Level Information		
Class	Levels	Values
replication	3	1 2 3
qppm	4	1 2 3 4
dppm	4	1 2 3 4
supplier	5	1 2 3 4 5

Number of Observations Read	240
Number of Observations Used	240

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	81	9644.818074	119.071828	137.13	<.0001
Error	158	137.196511	0.868332		
Corrected Total	239	9782.014585			

R-Square	Coeff Var	Root MSE	doh Mean
0.985975	0.575542	0.931844	161.9073

Source	DF	Type I SS	Mean Square	F Value	Pr > F
replication	2	3.158822	1.579411	1.82	0.1656
qppm	3	111.446602	37.148867	42.78	<.0001
dppm	3	5690.336295	1896.778765	2184.39	<.0001
supplier	4	2707.466031	676.866508	779.50	<.0001

(table continues)

Source	DF	Type I SS	Mean Square	F Value	Pr > F
qppm*dppm	9	23.889288	2.654365	3.06	0.0021
qppm*supplier	12	31.222652	2.601888	3.00	0.0008
dppm*supplier	12	965.987959	80.498997	92.71	<.0001
qppm*dppm*supplier	36	111.310424	3.091956	3.56	<.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
replication	2	3.158823	1.579411	1.82	0.1656
qppm	3	111.446602	37.148867	42.78	<.0001
dppm	3	5690.336295	1896.778765	2184.39	<.0001
supplier	4	2707.466031	676.866508	779.50	<.0001
qppm*dppm	9	23.889288	2.654365	3.06	0.0021
qppm*supplier	12	31.222652	2.601888	3.00	0.0008
dppm*supplier	12	965.987959	80.498997	92.71	<.0001
qppm*dppm*supplier	36	111.310424	3.091956	3.56	<.0001

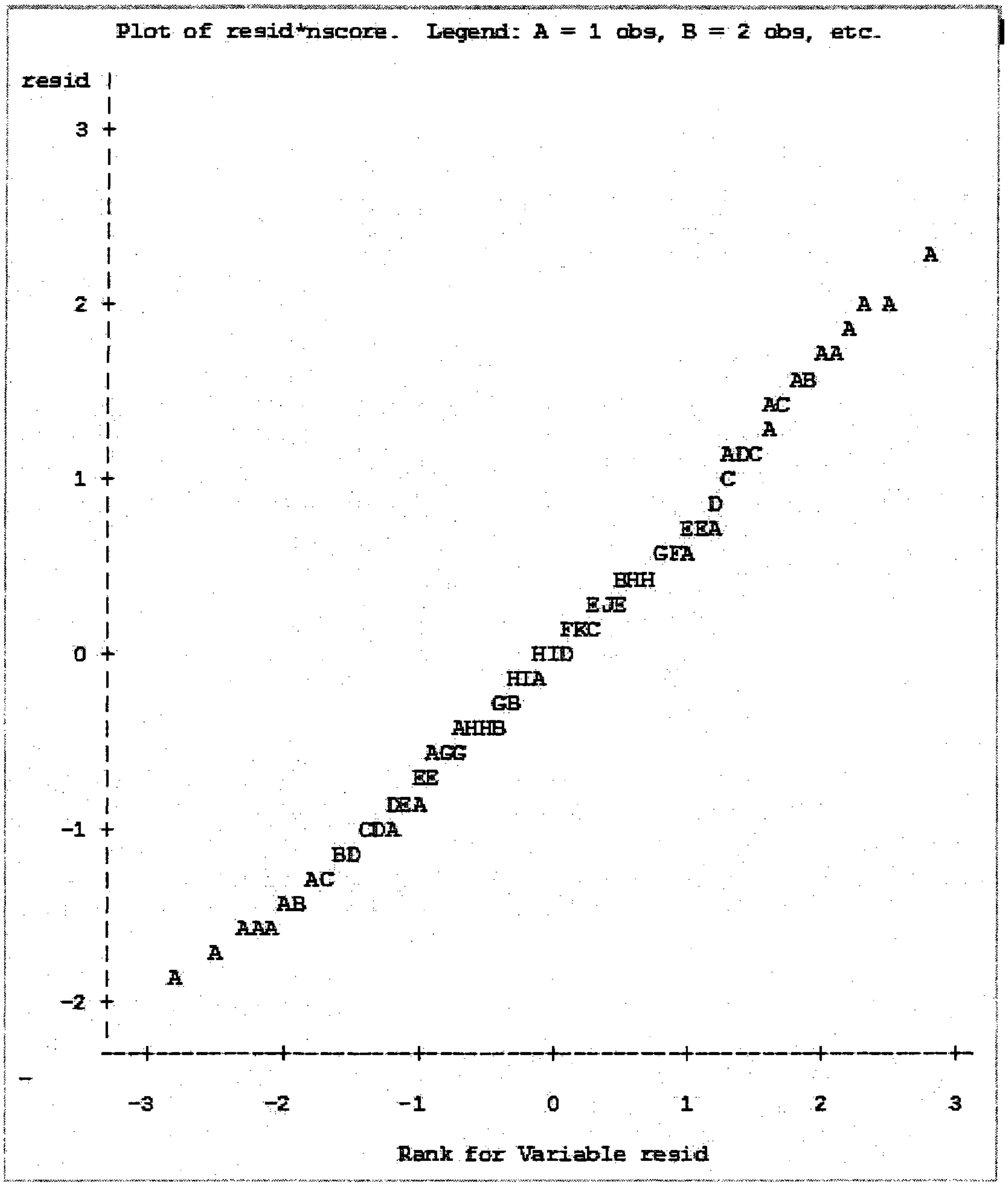

Figure D1. Normal probability plot of residuals for the 3-WAY ANOVA model.

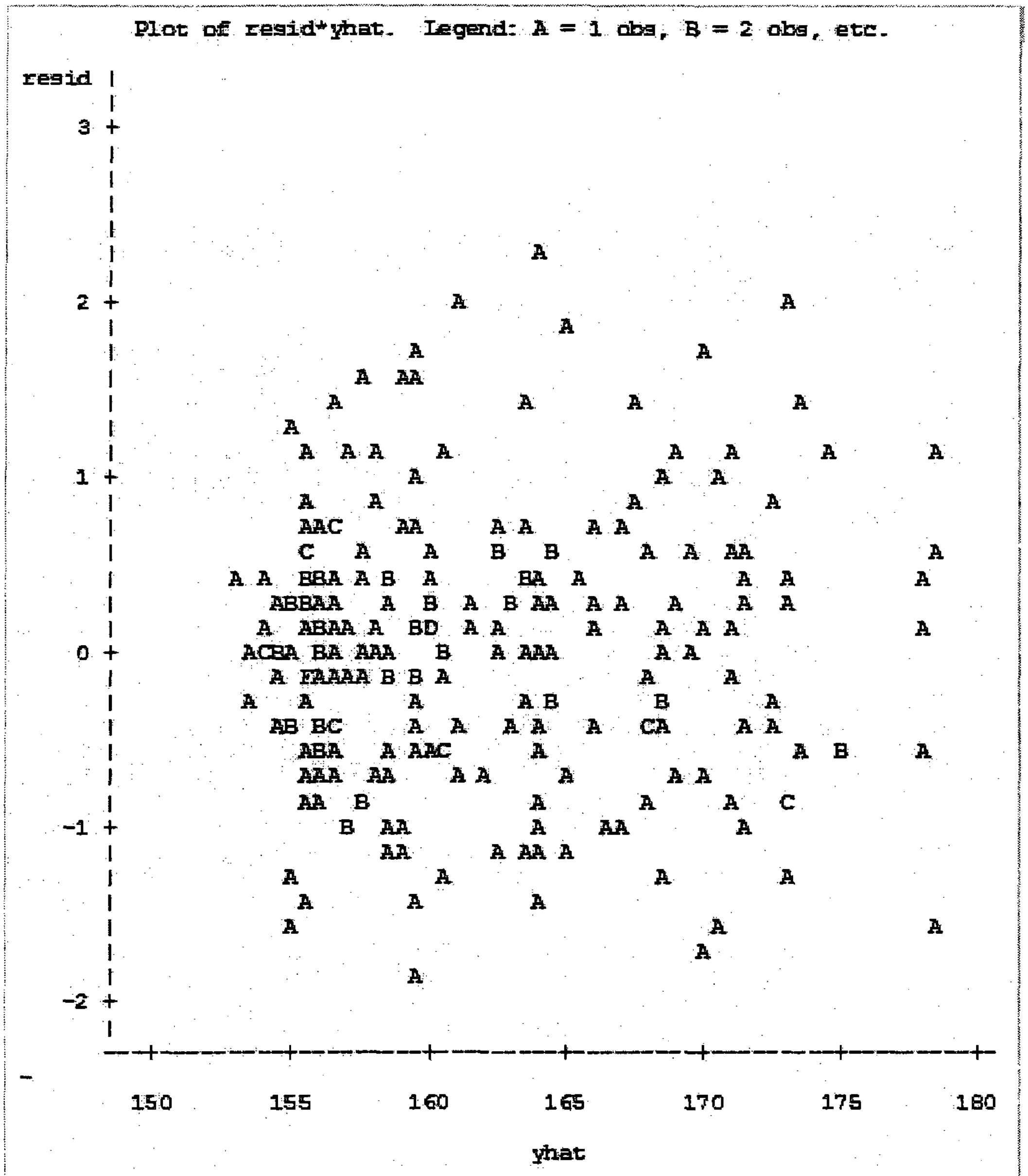

Figure D2. Residuals vs. predicted values for 3-WAY ANOVA model.

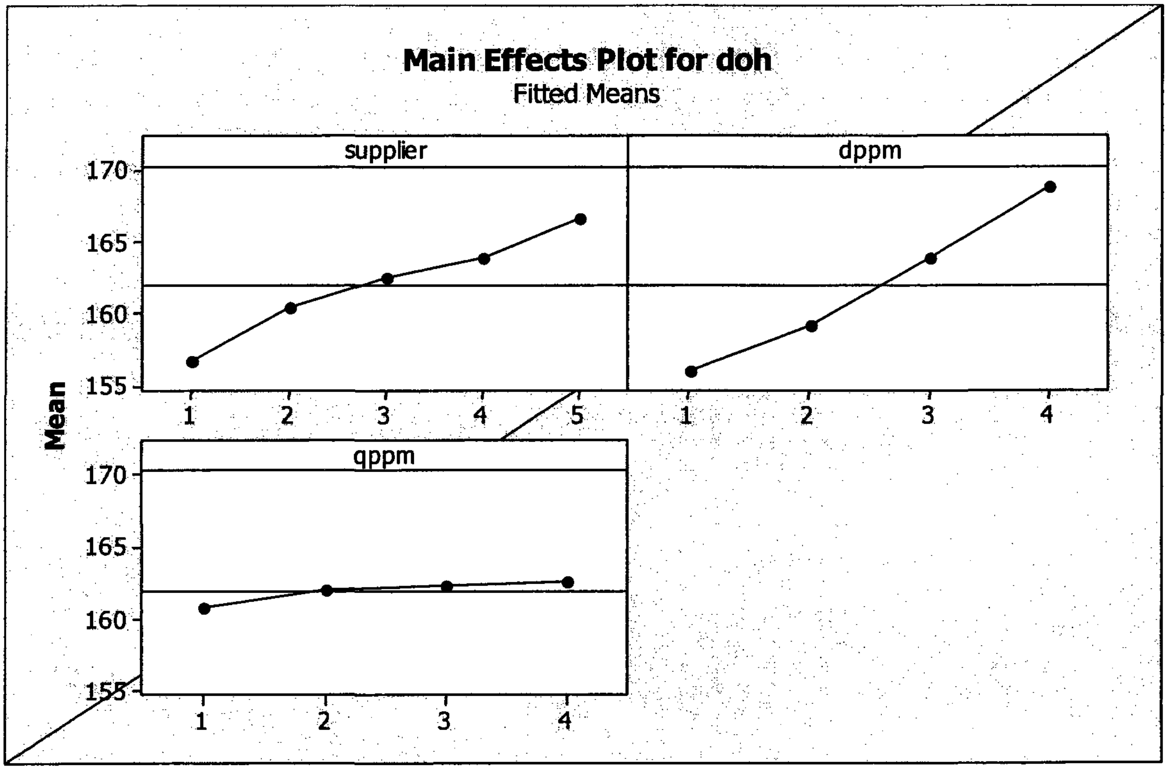

Figure D3. Main effects plot for average inventory on hand.

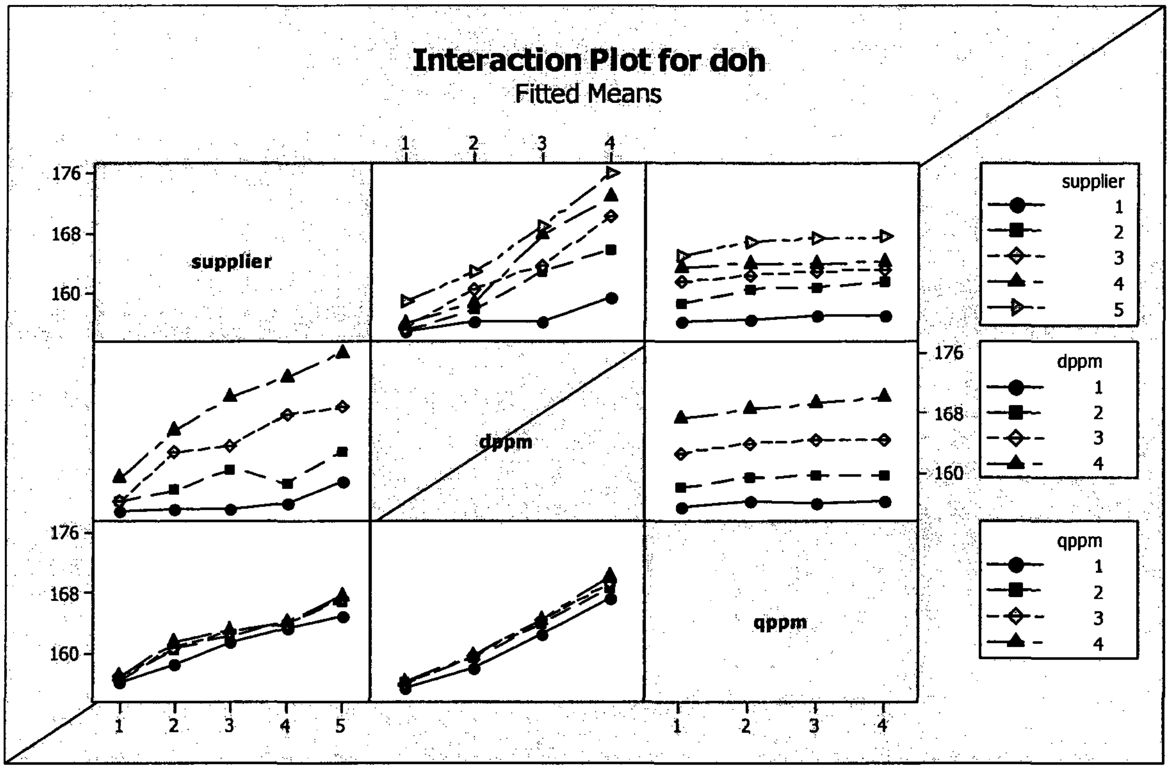

Figure D4. Interaction effects plot for average inventory on hand.

APPENDIX E

STATISTICAL PROGRAM AND OUTPUTS FOR 2-WAY ANOVA USING THE SIMULATION DATA

```
options ls=72;
data simulation;
input replication qppm dppm doh;
cards;
1 1 1 154.8
2 1 1 154.8
3 1 1 154.8
.
.
.
.
.
.
1 4 4 161.18
2 4 4 158.18
3 4 4 159.24
;
proc glm data=simulation;
class replication qppm dppm;
model doh=replication qppm dppm qppm*dppm;
means qppm / tukey;
means dppm / tukey;
output out=next r=resid p=yhat;

proc print data=next;

proc rank normal=blom;
var resid;

ranks nscore;

proc plot;
plot resid*nscore;
plot resid*yhat;
run;
```

Table E1. *SAS 2-WAY ANOVA table for simulation data. (number of suppliers level = 1)*

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	131.7450667	7.7497098	7.44	<.0001
Error	30	31.2514000	1.0417133		
Corrected Total	47	162.9964667			

R-Square	Coeff Var	Root MSE	doh Mean
0.808269	0.652725	1.020644	156.3667

Source	DF	Type I SS	Mean Square	F Value	Pr > F
replication	2	7.7940667	3.8970333	3.74	0.0354
qppm	3	6.2615000	2.0871667	2.00	0.1347
dppm	3	106.4525667	35.4841889	34.06	<.0001
qppm*dppm	9	11.2369333	1.2485481	1.20	0.3320

Source	DF	Type III SS	Mean Square	F Value	Pr > F
replication	2	7.7940667	3.8970333	3.74	0.0354
qppm	3	6.2615000	2.0871667	2.00	0.1347
dppm	3	106.4525667	35.4841889	34.06	<.0001
qppm*dppm	9	11.2369333	1.2485481	1.20	0.3320

Table E2. *Tukey's studentized range test for average inventory on hand. (number of suppliers level = 1)*

Means with the same letter are not significantly different.			
Tukey Grouping	Mean	N	qppm
A	156.8808	12	3
A			
A	156.4908	12	4
A			
A	156.1858	12	1
A			
A	155.9092	12	2

Means with the same letter are not significantly different.				
Tukey Grouping		Mean	N	dppm
	A	158.8042	12	4
	B	156.2025	12	2
	B			
C	B	155.6292	12	3
C				
C		154.8308	12	1

Table E3. *SAS 2-WAY ANOVA table for simulation data. (number of suppliers level = 2)*

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	933.3312500	54.9018382	76.30	<.0001
Error	30	21.5879167	0.7195972		
Corrected Total	47	954.9191667			

R-Square	Coeff Var	Root MSE	doh Mean
0.977393	0.529093	0.848291	160.3292

Source	DF	Type I SS	Mean Square	F Value	Pr > F
replication	2	2.3854167	1.1927083	1.66	0.2076
qppm	3	60.1158333	20.0386111	27.85	<.0001
dppm	3	851.5808333	283.8602778	394.47	<.0001
qppm*dppm	9	19.2491667	2.1387963	2.97	0.0119

Source	DF	Type III SS	Mean Square	F Value	Pr > F
replication	2	2.3854167	1.1927083	1.66	0.2076
qppm	3	60.1158333	20.0386111	27.85	<.0001
dppm	3	851.5808333	283.8602778	394.47	<.0001
qppm*dppm	9	19.2491667	2.1387963	2.97	0.0119

Table E4. *SAS 2-WAY ANOVA table for simulation data. (number of suppliers level = 3)*

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	1502.698125	88.394007	170.63	<.0001
Error	30	15.541667	0.518056		
Corrected Total	47	1518.239792			

R-Square	Coeff Var	Root MSE	doh Mean
0.989763	0.443789	0.719761	162.1854

Source	DF	Type I SS	Mean Square	F Value	Pr > F
replication	2	12.271667	6.135833	11.84	0.0002
qppm	3	8.908958	2.969653	5.73	0.0032
dppm	3	1463.418958	487.806319	941.61	<.0001
qppm*dppm	9	18.098542	2.010949	3.88	0.0024

Source	DF	Type III SS	Mean Square	F Value	Pr > F
replication	2	12.271667	6.135833	11.84	0.0002
qppm	3	8.908958	2.969653	5.73	0.0032
dppm	3	1463.418958	487.806319	941.61	<.0001
qppm*dppm	9	18.098542	2.010949	3.88	0.0024

Table E5. *SAS 2-WAY ANOVA table for simulation data. (number of suppliers level = 4)*

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	2248.878385	132.286964	255.75	<.0001
Error	30	15.517813	0.517260		
Corrected Total	47	2264.396198			

R-Square	Coeff Var	Root MSE	doh Mean
0.993147	0.438957	0.719208	163.8448

Source	DF	Type I SS	Mean Square	F Value	Pr > F
replication	2	0.293854	0.146927	0.28	0.7547
qppm	3	5.521406	1.840469	3.56	0.0258
dppm	3	2224.360573	741.453524	1433.42	<.0001
qppm*dppm	9	18.702552	2.078061	4.02	0.0019

Source	DF	Type III SS	Mean Square	F Value	Pr > F
replication	2	0.293854	0.146927	0.28	0.7547
qppm	3	5.521406	1.840469	3.56	0.0258
dppm	3	2224.360573	741.453524	1433.42	<.0001
qppm*dppm	9	18.702552	2.078061	4.02	0.0019

Table E6. *SAS 2-WAY ANOVA table for simulation data. (number of suppliers level = 5)*

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	2189.457083	128.791593	178.75	<.0001
Error	30	21.615417	0.720514		
Corrected Total	47	2211.072500			

R-Square	Coeff Var	Root MSE	doh Mean
0.990224	0.509311	0.848831	166.6625

Source	DF	Type I SS	Mean Square	F Value	Pr > F
replication	2	0.511250	0.255625	0.35	0.7042
qppm	3	50.055833	16.685278	23.16	<.0001
dppm	3	2060.162500	686.720833	953.10	<.0001
qppm*dppm	9	78.727500	8.747500	12.14	<.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
replication	2	0.511250	0.255625	0.35	0.7042
qppm	3	50.055833	16.685278	23.16	<.0001
dppm	3	2060.162500	686.720833	953.10	<.0001
qppm*dppm	9	78.727500	8.747500	12.14	<.0001

APPENDIX F

STATISTICAL PROGRAM AND OUTPUTS FOR REGRESSION MODEL USING THE SIMULATION DATA

```
options ls=72;
data simulation;
input index qppm dppm supplier DOH;
interaction1=qppm*dppm;
interaction2=qppm*supplier;
interaction3=dppm*supplier;
interaction4=qppm*dppm*supplier;
cards;
1 0.0002 0.005 2 154.8
2 0.0007 0.005 2 154.2
.
.
.
.
237 0.0002 0.05 10 175
238 0.0007 0.05 10 175.7
239 0.0013 0.05 10 179.5
240 0.002 0.05 10 178.3
;

proc reg data=simulation;
model DOH=qppm dppm supplier interaction1 interaction2 interaction3
interaction4;
plot DOH*qppm;
plot DOH*dppm;
plot DOH*supplier;
plot residual.*predicted.;
plot r.*nqq.;
var index;
plot cookd.*index;
proc reg data=simulation;
model DOH=qppm dppm supplier interaction1 interaction2 interaction3
interaction4/ r p influence;
proc reg data=simulation;
model DOH=qppm dppm supplier interaction1 interaction2 interaction3
interaction4 / selection=forward slentry=0.15;
proc reg data=simulation;
model DOH=qppm dppm supplier interaction1 interaction2 interaction3
interaction4 / selection=backward slstay=0.15;
proc reg data=simulation;
model DOH=qppm dppm supplier interaction1 interaction2 interaction3
interaction4 / selection=stepwise;
proc reg data=simulation;
model DOH=qppm dppm supplier interaction1 interaction2 interaction3
interaction4 / selection=rsquare rmse;
run;
```

Table F1. *SAS Regression output. (Independent variables: QPPM, DPPM and number of suppliers, Dependent variable: average inventory on hand.)*

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	9201.03845	1314.43406	504.57	<.0001
Error	232	604.37424	2.60506		
Corrected Total	239	9805.41269			

Root MSE	1.61402	R-Square	0.9384
Dependent Mean	161.98767	Adj R-Sq	0.9365
Coeff Var	0.99638		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	151.97732	0.80693	188.34	<.0001
qppm	1	1259.38756	647.10227	1.95	0.0528
dppm	1	85.46553	26.71294	3.20	0.0016
supplier	1	0.42089	0.12165	3.46	0.0006
interaction1	1	-19503	21422	-0.91	0.3635
interaction2	1	-158.76807	97.55434	-1.63	0.1050
interaction3	1	29.24513	4.02713	7.26	<.0001
interaction4	1	7310.71343	3229.46178	2.26	0.0245

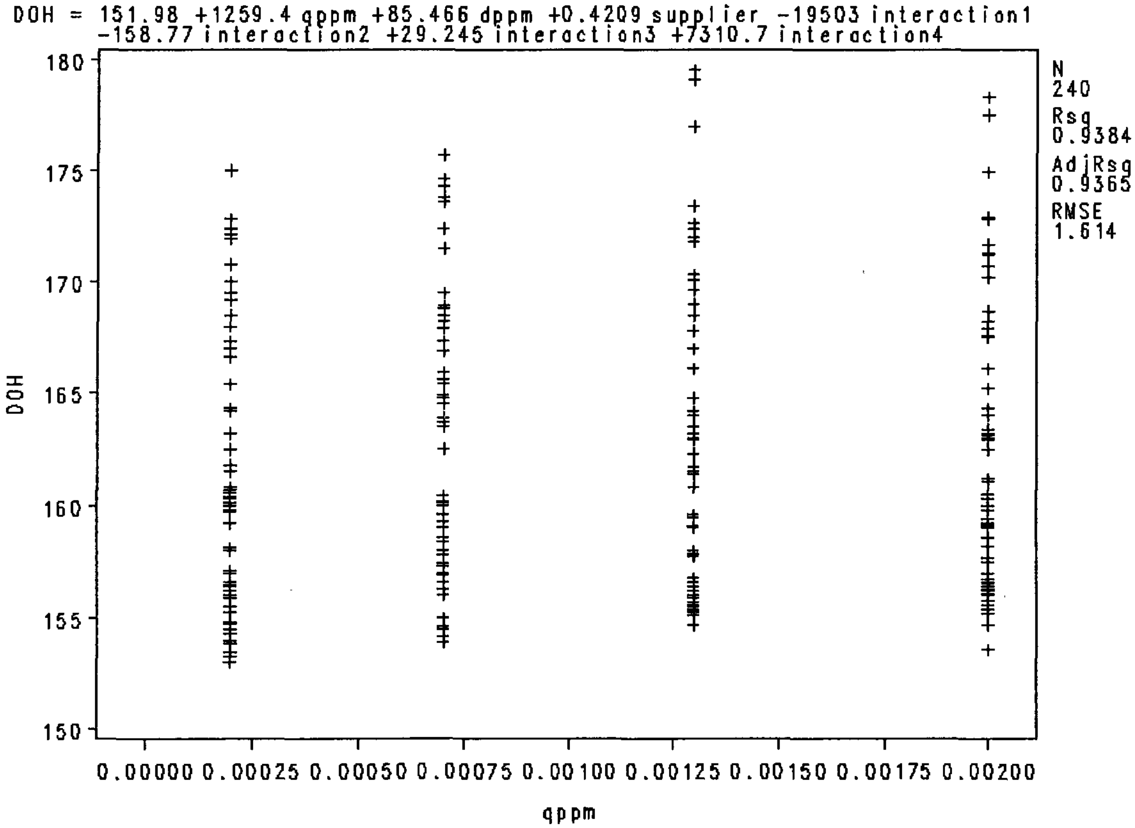

Figure F1. Plot for average inventory on hand vs. QPPM.

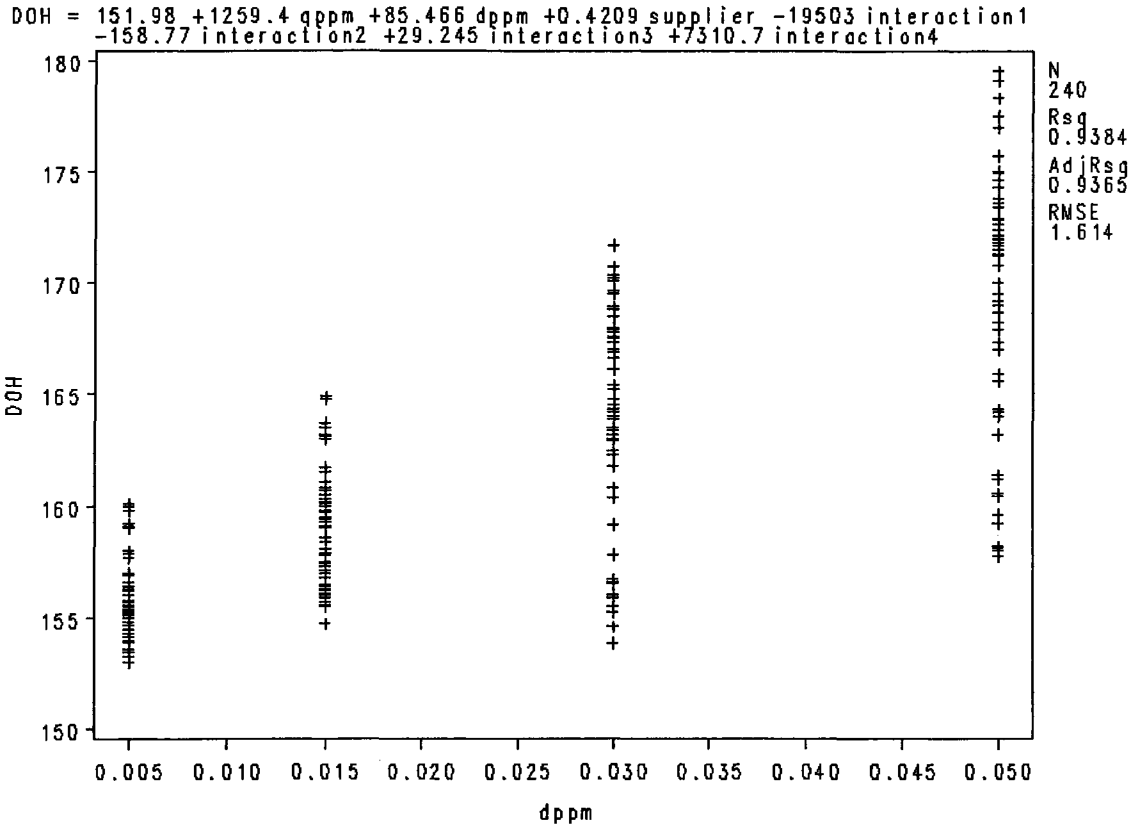

Figure F2. Plot for average inventory on hand vs. DPPM.

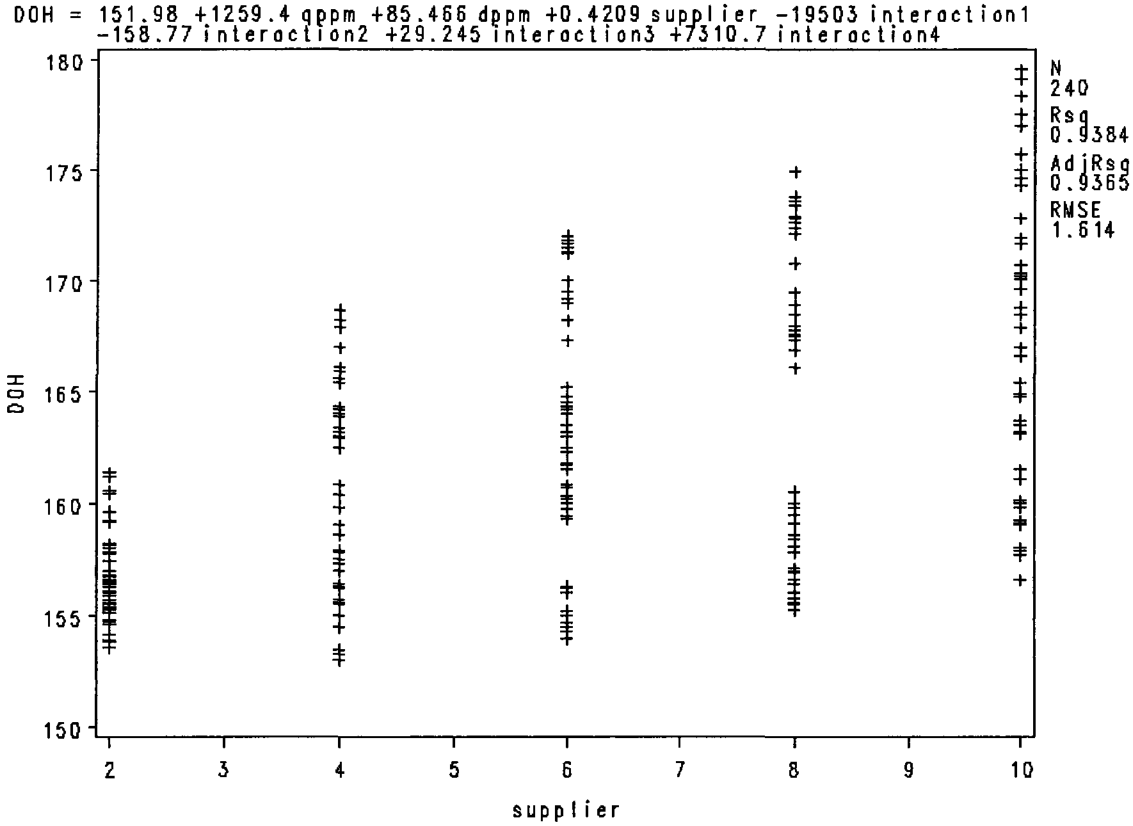

Figure F3. Plot for average inventory on hand vs. number of suppliers.

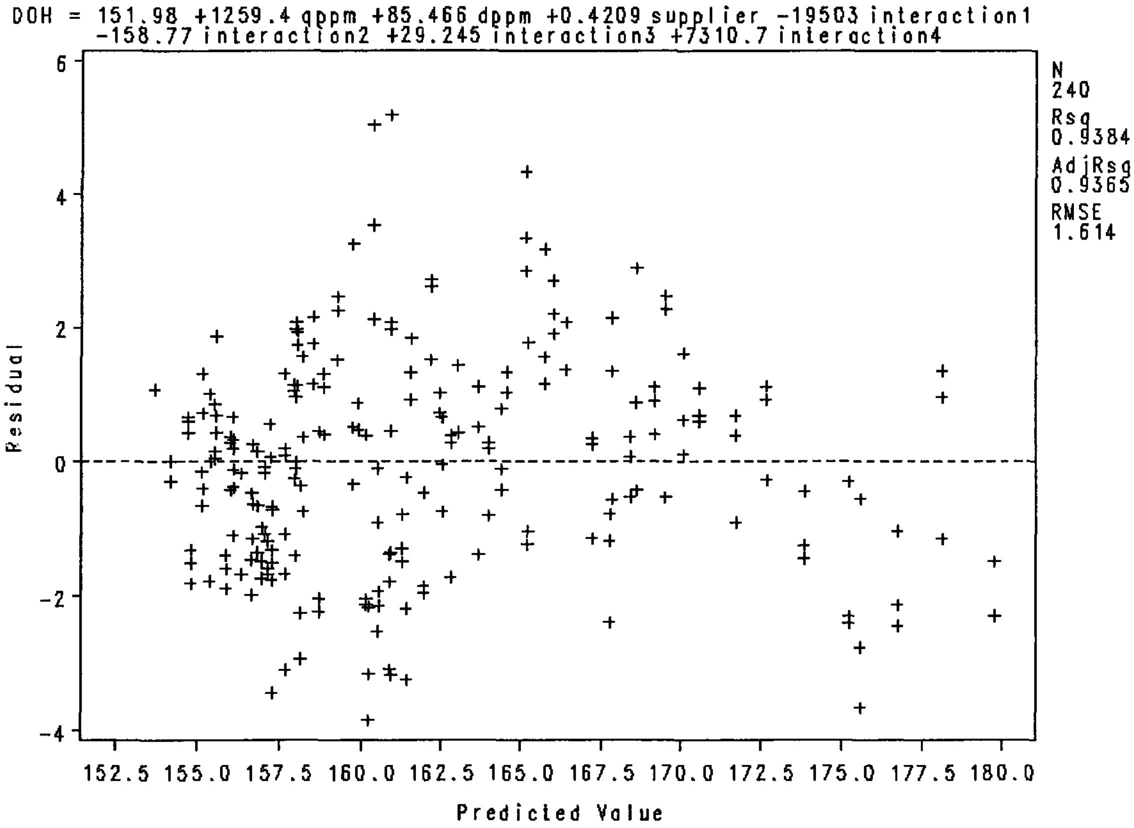

Figure F4. Resuduals vs the predicted values for the regression model.

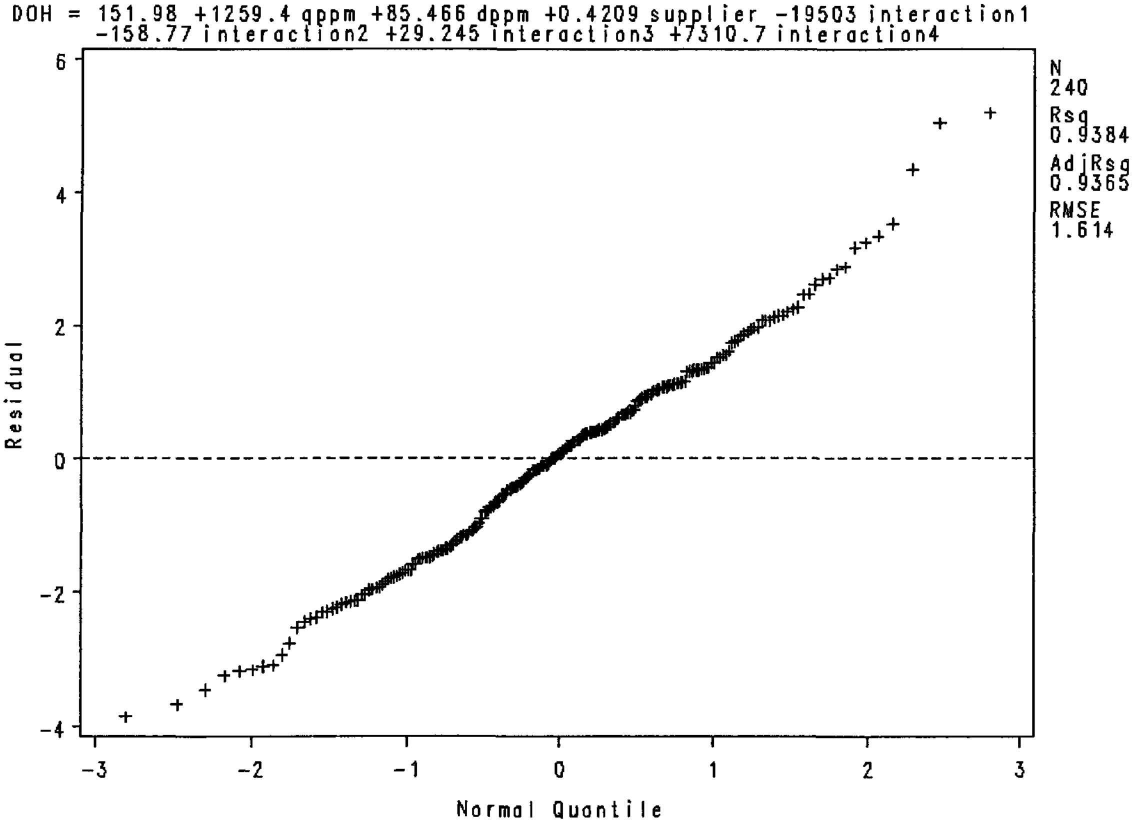

Figure F5. Normal probability plot of the residuals.

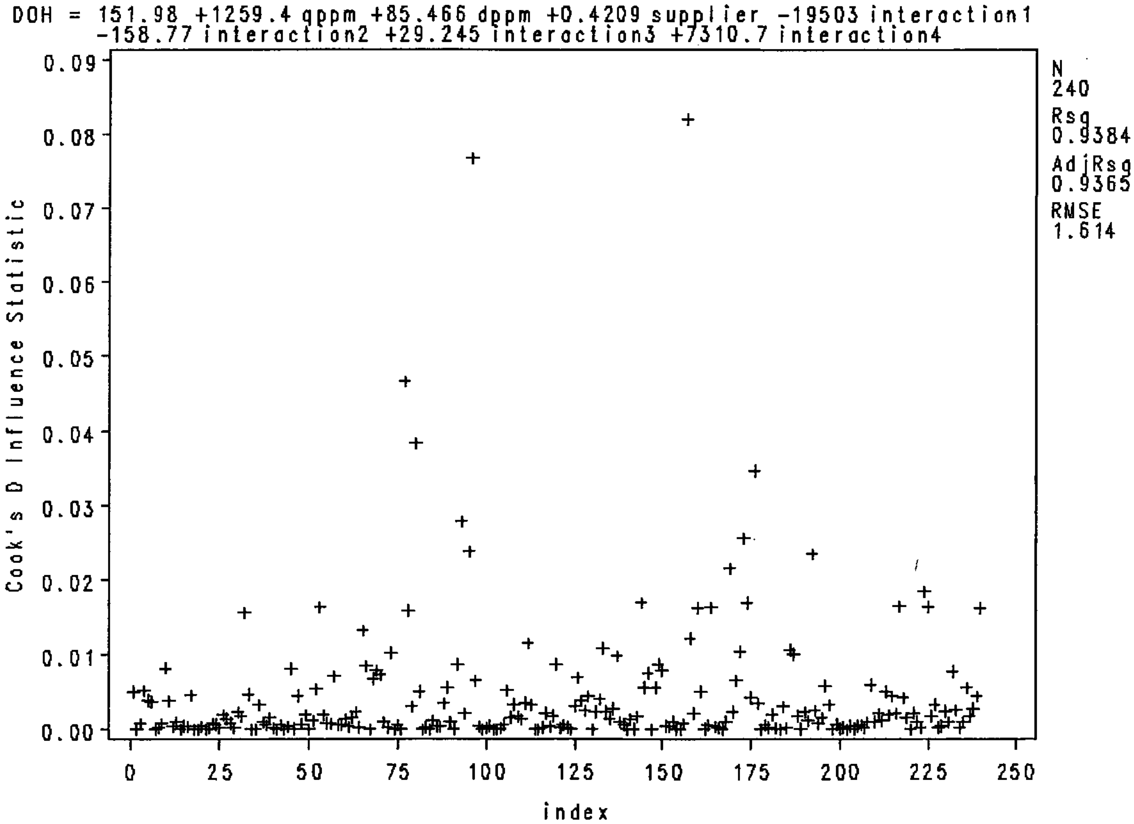

Figure F6. Cook's distance plot for most influential data points.

Table F2. *Forward selection method summary for the suggested regression model.*

Summary of Forward Selection							
Step	Variable Entered	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	interaction3	1	0.9202	0.9202	64.2941	2745.17	<.0001
2	interaction1	2	0.0121	0.9324	20.5993	42.54	<.0001
3	supplier	3	0.0032	0.9356	10.5054	11.77	0.0007
4	dppm	4	0.0011	0.9366	8.5528	3.89	0.0496
5	interaction4	5	0.0007	0.9373	7.8848	2.65	0.1051

Table F3.*Backward selection method summary for the suggested regression model.*

Summary of Backward Elimination							
Step	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	interaction1	6	0.0002	0.9381	6.8289	0.83	0.3635
2	interaction2	5	0.0005	0.9376	6.8643	2.04	0.1549

Table F4. *Stepwise selection method summary for the suggested regression model.*

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	interaction3		1	0.9202	0.9202	64.2941	2745.17	<.0001
2	interaction1		2	0.0121	0.9324	20.5993	42.54	<.0001
3	supplier		3	0.0032	0.9356	10.5054	11.77	0.0007
4	dppm		4	0.0011	0.9366	8.5528	3.89	0.0496
5	interaction4		5	0.0007	0.9373	7.8848	2.65	0.1051
6		interaction1	4	0.0004	0.9369	7.4411	1.54	0.2153
7	qppm		5	0.0007	0.9376	6.8643	2.57	0.1104

Table F5. *SAS Regression output with parameter estimates. (Independent variables: QPPM, DPPM and number of suppliers, Dependent variable: average inventory on hand.)*

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	9193.57668	1838.71534	703.23	<.0001
Error	234	611.83601	2.61468		
Corrected Total	239	9805.41269			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	152.90596	0.50056	243979	93311.0	<.0001
qppm	374.97582	234.02653	6.71267	2.57	0.1104
dppm	64.98696	14.43665	52.98327	20.26	<.0001
supplier	0.25418	0.06574	39.08443	14.95	0.0001
interaction3	33.13560	2.49813	460.02165	175.94	<.0001
interaction4	3605.50191	1167.94481	24.91759	9.53	0.0023

Table F6. *R Square and MSE values for selected variables.*

Number of Factors	R Square	MSE	Factors
1	0.9202	1.81298	dppm*supplier
2	0.9314	1.68513	dppm*supplier qppm*dppm*supplier
3	0.9329	1.66931	dppm dppm*supplier qppm*dppm*supplier
4	0.9369	1.62238	supplier dppm dppm*supplier qppm*dppm*supplier
5	0.9376	1.617	qppm supplier dppm dppm*supplier qppm*dppm*supplier
6	0.9381	1.61343	qppm supplier dppm dppm*supplier qppm*supplier qppm*dppm*supplier
7	0.9384	1.61402	qppm supplier dppm dppm*supplier qppm*supplier qppm* dppm qppm*dppm*supplier