# A Situated Decision Support System for Agile Supply Chain Management

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# Abstract


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Today's volatile business environment imposes a high level of uncertainly in decision making activities in supply chain management. Although high level of coordination and integration between organizations is necessary to achieve efficiency in supply chain, this level of integration might have adverse effects on organization's agility. Agility is the capability to adapt to unpredicted market changes and new customer requirements. This necessitate the development of effective decision support tools in the area of the supply chain that can provide a higher level of integration with business environment and help organizations to cope with unpredictable changes in order to conduct their business activities with more agility.

This work proposes a model and architecture for a situated decision support system for supply chain management and develops a prototype system in order to examine the feasibility of the model. The results of the empirical tests are presented and discussed. This study will be of interest to both academics in the field of supply chain and IS managers who want to make their supply chain more flexible and agile.

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# 1. Introduction

Today's business environment is characterized by a high level of volatility and uncertainty. In this turbulent market, organizations are facing globalization, technological shifts, shorter product life cycles and more knowledgeable and well-informed customers with unique and rapidly changing needs. These changing market conditions forces organizations to alter the way their supply chains are structured and managed in order to be more responsive to these changes. In response to the challenges and demands of today's business environment, companies have been undergoing a revolution in terms of implementing new operations strategies and technologies (Gunasekaran et al. 2008).

The focus of supply chain has shifted from production efficiency to customer-driven and partnership synchronization approaches which require a high degree of collaboration among all supply chain partners (Lou et al., 2005). Accordingly, the research on supply chain management has been mostly focused on integrating key business processes and information of supply chain components and creating bonds between them in order to achieve transactional efficiency (Gosian et al., 2005). Stable technologies such as Electronic Data Interchange (EDI) are widely used to enable this process-integration task among corporations. However, such an approach requires a stable and predictable business environment to be effective (Nissen, 2001). In a predictable environment, an enterprise might create highly specific process linkages with select partners; in a dynamic and competitive environment, highly partner-specific or offering-specific IT infrastructure investments might create lock-in among partners and therefore can have adverse effects on supply chain agility (Gosain et al., 2005).

Recent literature in supply chain has addressed this issue and suggests that the key to survival in these changing conditions is through agility by creation of responsive supply chains (Christopher, 2000).

In a constantly changing global competitive environment, an organization's supply chain agility directly impacts its ability to produce, and deliver innovative products to its customers in a timely and cost effective manner (Swafford et al, 2006). In such a volatile environment, enterprises need to develop more flexible and robust linkage with partners in order to respond to market conditions in a timely manner. Therefore, being agile and capable of rapid adaptation to unexpected changes, market opportunities, and new customer requirements undoubtedly becomes a critical success factor for organizations.

Recently there has been an increasing interest among information system researchers in investigating innovative solutions for supply chain that applies advanced decision support and intelligent software agents to address different supply chain decision making problems. Undoubtedly, supply chain can significantly benefit from decision making processes that constantly monitor changing conditions and dynamically evaluate available options in response to these conditions (Arunachalam, 2005). Researchers argue that software agents can provide new perspective to the discipline of supply chain management due to their dynamic nature and ability to deal with complex and changing environmental factors.

The purpose of this research is to explore the promise of advanced decision support systems and agent-based technologies in supply chain management. We propose a model of situated decision support system to enable supply chain agility and increase supply chain performance. We illustrate the usefulness of our model by simulating a supply chain and measuring supply chain performance under different market conditions.

In Summary, the analysis of the results shows that we can expect a significant increase in supply chain performance in volatile markets when situated decision support system is used.

The impact of using a situated decision support system on the supply chain performance in a stable market is still noticeable but it is less than the impact observed for volatile markets.

The central argument of this work is that the development of an effective decision support tool can help organizations cope with unpredictable changes and conduct their business activities in a flexible and agile manner.

# 2. Background and Related Work

The conceptual foundation of this study stems from two different disciplines: supply chain agility and decision support systems. In this section, the relevant aspects of these disciplines are discussed.

## 2.1. Supply Chain Agility

Supply chain agility has been receiving a lot of attention recently as a way for organizations to respond in a speedy manner to changing business environment and improve their customer service levels. In order to understand this concept, it is important to first establish the definition of supply chain management and organizational agility in the context of this work.

### 2.1.1. Supply Chain Management (SCM)

In 1990s as the markets became global and competition increased, the phrase "Supply Chain Management" came into use (Chang and Markatsoris, 2001). Organizations began to realize that it is not enough to improve efficiencies within an organization, but their whole supply chain has to be made competitive. Therefore SCM practices have become vital for competing in the global market (Li et al. 2006, Christopher and Peck, 2004).

Supply chain is defined as "a worldwide network of suppliers, factories, warehouses, distribution centers, and retailers through which raw materials are acquired, transformed, and delivered to customers"(Fox et al., 2000). Supply chain can include the focal firm and its immediate suppliers and customers or can have multiple levels to include the raw materials in one end and finished good at the other end (Premkumar, 2000). A supply chain typically includes suppliers, manufacturers, distributors and customers.

A supply chain network supports tree types of component flows: Goods and Services, Information, and Payment (Premkumar, 2000; Akkermans et al., 2003). According to Akkermans et al., all these three types of components flow in both direction:

- Goods and Services flow: includes the movement of raw material, work in progress material and finished goods and services in one direction as well as returned products and recycled products in other direction.
- Information flow: includes the flow of information associated with transformation, tracking and the coordination of the flow of goods and services.
- Financial flow: generally represents credit terms and payments.

Supply chains are subject to different sources of uncertainty which include (Arunachalam, 2005):

- Market fluctuations, such as changes in customer demand or in supply availability and prices
- Operational contingencies, such as delays in supply delivery, losses of capacity, or quality problems; and
- Changes in strategies employed by competitors, customers or suppliers

According to van der Vorst and Beulens (2002) the problem in managing and controlling complex networks is the presence of uncertainty which leads to "inefficient processing and non-value adding activities". In essence, there are three sources of uncertainty in a supply chain: demand, process, and supply (Jeffery, 2005). Supply Chain Management provides the opportunity to reduce decision-making uncertainties within the system (van der Vorst and Beulens, 2002).

Several authors have defined Supply Chain Management. According to Premkumar (2000), Supply chain management is a strategy to effectively link all entities in the supply chain and enable cost-effective and timely movement of materials from raw material supplier to the final consumer of the finished product. Chang and Markatsoris (2001), define supply chain management as "a process of integrating/utilizing suppliers, manufacturers, warehouses, and retailers, so that goods are produced and delivered at the right quantities, and at the right time, while minimizing costs as well as satisfying customer requirements". According to The Council of Supply Chain Management professionals (CSCMP), a leading association of Supply Chain Management professionals promoting SCM by developing, advancing, and disseminating supply chain knowledge and research, " Supply Chain Management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies".

Supply Chain Management practices, defined as the set of activities undertaken by an organization to promote effective management of its supply chain, can offer great potential for organizations to secure competitive advantage and improve organizational performance (Li et al., 2006). This concept offer great potential for organizations to reduce costs and improve customer service performance. According to Chang and Markatsoris (2001), expected benefits of Supply Chain Management can be summarized as follows:

- Throughput improvements through better coordination of material and capacity
- Cycle time reduction by considering constraints as well as its alternatives in the supply chain
- Inventory cost reductions through demand and supply visibility

- Optimized transportation by optimizing logistics and vehicles loads
- Increase order fill rate through real-time visibility across the supply chain
- Increase customer responsiveness by understanding the capability to deliver based on availability of materials capacity and logistics

According to Supply Chain Consultant (http://www.supplychain.com, 2002), cost reduction and customer service improvements are the main reasons for adopting supply chain planning. Figure 1 shows the benefits derived from a supply chain planning.

| | |
|---|---|
| 10% | reduction in total supply chain cost |
| 15% | improvement in on-time delivery performance |
| 25%-35% | reduction in order fulfillment lead times |
| 15%-20% | improvement in asset utilization |
| 40%-65% | advantage in cash-to-cash cycle time over average companies |
| 20%-30% | reduction in inventory |

Source: PRTM 2000 Supply Chain Benchmarking Study

Figure 1: Supply chain planning benefits (cited by: SC Consultant, 2002)

### 2.1.1.1. Supply Chain Performance Metrics

A supply chain performance measure is a multi-criteria decision problem affected by a large number of factors, yet it is critical to the success of the firms in the current global market (Bhagwat et al., 2007).

Supply chain performance measures are categorized into the following groups of metrics (Gunasekaran et al., 2001, 2004; Bhagwat et al., 2007):

- Order planning metrics
- Supply link metrics

- Production level metrics
- Delivery link metrics
- Service and satisfaction metrics
- Logistics cost metrics

In this section, we are going to discuss some of the most important performance metrics in a supply chain that are relevant to our research.

Gunasekaran et al. (2001, 2004) provide a framework to promote a better understanding of the importance of SCM performance measurement and metrics. According to them supply chain performance metrics should focus on the way that order-related activities are performed. One of the most important order-planning metrics according to them is order lead-time which refers to "the time that elapses between the receipt of the customer's order and the delivery of the goods". Shorter order cycle time results in shorter response time, improves delivery performance and consequently ends in higher customer satisfaction level.

Another group of supply chain performance metrics include supply chain partnership metrics. Supply chain literature has recently paid a lot of attention to supply chain partnership or extended enterprise view of supply chain (Bhagwat et al., 2007). The aim of the supply chain is to create value for the whole supply chain network as a result supply chain metrics also should focus on the whole supply network.

Another important supply chain production level metric according to Gunasekaran et al. (2001, 2004) is Capacity Utilization which is an evidence for effectiveness of scheduling techniques or the way all different operation are planned. More efficient scheduling results in higher supply chain performance.

Gunasekaran et al. (2001, 2004) also refer to the percentage of goods in transit which indicates rate of inventory turn over as another measure of delivery performance metric in supply chain. Higher percentage of goods in transit means lower inventory turns and higher carrying charges. This will consequently result in lower supply chain performance.

Among service and satisfaction metrics, flexibility is referred to as a very important factor by which suppliers compete. Gunasekaran et al. (2001, 2004) define flexibility as "having the capability to provide products/services that meet the individual demands of customers". Another concept similar to flexibility which has recently been discussed a lot in supply chain literature is the concept of agility. In fact, both supply chain flexibility and supply chain agility positively impact business performance (Swafford et al., 2008). Next sections of this document provide more detailed explanation of this concept and its metrics.

Finally, financial performance of a supply chain can be determined by the total logistical cost. Logistics covers the flow and storage of materials from point of origin to point of consumption. Therefore the efficiency of a supply chain can be assessed through these costs (Gunasekaran et al., 2001, 2004).

### 2.1.2. From Organizational Agility to Supply Chain Agility

Agility is one of the latest concepts in business strategy and has attracted both academics and practitioners. Many studies have provided a conceptual definition of organizational agility. Christopher (2000) identifies agility as "a business-wide capability that embraces organizational structures, information systems, logistics processes and, in particular, mindsets". Van Hoek et al. (2001) conceptualize agility as "an emerging concept focused on responsiveness to dynamic markets and customer demand". According to the authors, agility is about creating customer responsiveness and mastering the uncertainty. Alternatively, Naylor et al. (1999) define agility as "using market knowledge and a virtual corporation to exploit profitable opportunities in a volatile market place". Sharp et al. (1999) describe agility as "being lean, flexible and capable of responding to rapidly changing situations".

Although most of these definitions focus on the uncertainty of the environment and the effective responsiveness to the changes in the environment as key elements of agility, the concept of agility remains a broad concept and there are several factors that determine and influence an organization's agility

Mathiyalakan et al. (2005, cited by Ashrafi et al., 2005) provide a more comprehensive definition that includes many different aspects of the agility and its drivers. According to them, agility is defined as "the ability of an (inter-connected) organization to detect changes, opportunities, and threats in business environment and to provide speedy and focused responses to customers, as well as other stakeholders, by reconfiguring resources and processes, and through strategic partnership and alliances".

Originally, the concept of agility was derived from the concept of flexible manufacturing systems (FMS) and later on evolved into an organizational orientation (Christopher and Towill, 2000). Today, the concept of agility has moved further from a single organization level to the domain of Supply Chain Management (White et al., 2005). This change is due to the fact that in today's market, competition is no longer among stand-alone businesses but among supply chains (van Hoek et al., 2001; Christopher and Towill, 2000).

In today's rapidly changing environment, it is extremely important for an organization's supply chain to be able to quickly recognize and react to change effectively. Consequently, companies must achieve a level of agility beyond the reach of individual companies to achieve a competitive edge in the global market (Lin et al. 2006). For that reason, a supply chain wide focus of agility is more relevant and provides a more practical setting in assessing agile capabilities (van Hoek et al., 2001; Naylor et al., 1999).

The definition of agility in the context of supply chain is also based on responsiveness (Christopher et al. 2004). Swafford et al (2006) define supply chain agility as "the supply chain's capability to adapt or respond in a speedy manner to a changing marketplace environment". An agile supply chain has been distinguished with having certain characteristics (Christopher, 2000) which include being:

- Market sensitive: capable of reading and responding to real demand
- Virtual: being information-based rather than inventory based
- Process-Aligned: having high degree of process interconnectivity
- Network-based: gaining agility by structuring, managing, and coordinating relationships with partners in a network

In fact, in a constantly changing global competitive environment, an organization's supply chain agility directly impacts its ability to produce, and deliver innovative products to its customers in a timely and cost effective manner (Swafford et al., 2006). Therefore, agility receives a great deal of attention in supply chain literature as a way for organizations to become more responsive to changes in the business environment (Jeffery, 2005).

### 2.1.3. Agility and Flexibility

A similar concept to agility which has also been discussed a lot in the supply chain literature is flexibility. This section tries to elaborate on the differences between these two concepts. According to Dove (1995), "Flexibility is the planned response to anticipated contingencies. Agility, on the other hand, postures the fundamental approach in order to minimize the inhibitions to change in any direction". In another word, if the latitude of change that we can completely accommodate is too little, the supply chain is flexible and not agile.

Supply chain flexibility is a consequence of both internal enterprise flexibility and flexibility of its linkage with other entities in the supply network (Gosain et al., 2004). Gosain et al. (2004) focus on the second type of flexibility and categorize it into Offering Flexibility and Partnering Flexibility. Offering Flexibility refers to the ability of a supply chain linkage to support changes in product and service offering. Partnering Flexibility on the other hand refers to the ability of changing the linkage to partner with different supply chain players.

Swafford et al. (2006) present a framework of an organization's supply chain process flexibilities as an important antecedent of supply chain agility. In a broader sense, Swafford's classification of flexibility fits aptly into Gosain et al (2004) typology of flexibility. Swafford et al. (2006) view Supply Chain Agility "as an externally focused capability that is derived from flexibilities in the supply chain processes". Based on these arguments, they posit that "the key antecedents of a firm's supply chain agility are the inherent flexibility dimensions within each of the three supply chain processes". These processes include: procurement/sourcing, manufacturing, and distribution/logistics.

Although investigating the agility of every process in an organization's extended supply chain is desirable, from a practical viewpoint it would be difficult if not impossible (Swafford et al., 2006). In order to keep this study manageable, we focus on the focal firm and its immediate suppliers and customers, trying to gain an understanding of the antecedents of a firm's supply chain agility.

#### 2.1.3.1. Agility Metrics

Although it is easy to consent on the importance of agility, it is difficult to agree on how to measure agility. Among different ways to measure agility, metrics proposed by Dove (1995) and Hofman and Cecere (2005) are very much similar.

Dove focus is on organizational agility defined as the degree of change proficiency of an organization. He breaks down the concept of agility into four change proficiency metrics: cost of change, time of change, robustness of change and scope of change. Hofman and Cecere's portfolio of supply chain agility metrics include speed, predictability, ease, and quality.

Time of change or speed concerns the speed at which a change or an unpredictable demand can be sensed and effectively responded to. According to Dove (1995), Speed can be measured in terms of the end-to-end cycle time or time to completion of a product or time-to-market in case of a new product. Hofman and Cecere also mention ease or flexibility as a metric in conjunction with speed as it is important to measure how easy it is to sense the change and respond to it. Of course the speed of response should not be achieved through a massive cost increase therefore cost should be taken into consideration while assessing agility. Cost can be considered as the cost of change and is measured in terms of the cost to completion or cost-to-market of a new product (Dove, 1995).

Apparently, rapidness and the cost efficiency are not sufficient factors to measure agility if the outcome is not robust. Robustness is about post-change functional quality and can be measured in terms of the amount of time that it takes for an organization to reach their quality target (Dove, 1995).

Finally, despite being fast, cost-effective and robust, an organization is not still agile if the scope of change that it can accommodate is very limited or in other words, it can not thrive on unpredictable change. Scope is the principal difference between flexibility and agility. Predictability or the ability of an organization to predict the completion of a change activity can be indicators of the scope. In addition, another good indicator of scope can be to the number of lost opportunities as it indicates those occasions that a change had fall out of our scope as well as the number of self initiated changes or innovations (Dove, 1995).

## 2.2. Decision Support System (DSS)

Decision support system is the second conceptual foundation of this study. In this section, the relevant aspects of this realm are discussed.

The development of DSS started in the 1970s, but these systems have evolved a significantly since then (Shim, et al., 2002). Broadly defined, Decision Support Systems (DSS) are a category of tools that an organization utilizes to support and improve its decision-making activities (Bhatt and Zaveri, 2002). The original concept of DSS is partly evolved from Simon's description of decision Types (Shim, et al., 2002). Simon (1960) suggests that decision problems can be arranged on a continuum from programmed (well structured, easily solved) to non-programmed (ill-structured, difficult to solve). A DSS is defined as a computer system that deals with a problem where at least some stage is semi-structured or unstructured (Shim, et al., 2002).

Recently, the field of decision support systems has become more sophisticated and includes paradigms such as active DSS, adaptive DSS, connected DSS, Real-time DSS and situated DSS. Moreover, artificial intelligence based techniques are being combined with many DSS tools to improve the decision capabilities of these systems (Bhatt and Zaveri, 2002). Traditionally DSS used to take a passive approach to decision making, meaning that the process of decision making was initiated through explicit user commands (Rao, et al., 1994). As DSS evolved, an alternate approach emerged that stressed active involvement of computer systems in decision making (Rao, et al., 1994).

Today, the increasingly changing and complex business environment requires decision support systems to provide higher levels of connectivity and tighter integration with the environment. Vahidov and Kersten (2004) argue for a type of decision support system which is referred to as a situated DSS that is situated in the environment and designed to sense the problem environment and offer decision support. Connective-ness and proactive-ness are two key characteristics that distinguish this type of DSS. The framework for situated DSS stems from two disciplines: DSS and intelligent software agents. The following section discusses the second discipline, intelligent software agents.

## 2.2.1. Agent Technology

Despite being a widely used term, no universal definition exists for agent technology. Definition of agents can be better illustrated based on the important properties defined by Wooldridge and Jennings (1995). They use the term agent to denote a software-based system that possesses the properties of autonomy, social ability, reactivity and pro-activeness. Autonomy refers to the ability of agents to "operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state". Social ability means that agents are able to interact and cooperate with other agents and possibly humans. Reactivity is the capability of agents to perceive their environment, and respond to changes in a timely fashion. And finally, pro-activeness is referred to the ability of agents to take initiatives in order to achieve defined goals.

In another definition, Jennings (2001) refers to an agent as, "an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives". The key factors of this definition are that agents are embedded in the environment; they receive inputs through sensors, and act accordingly through their effectors.

Although the agents are defined as being autonomous, the system can not be able to automate all levels of intelligent activities and human intervention is require specially in performing higher level intelligent tasks (Yoon et al., 2005). In a taxonomy provided by Nissen (2001), existing agent applications are grouped into four classes: (1) information filtering agents, (2) information retrieval, (3) advisory agents and (4) performative agents. Information filtering perform tasks such as filtering network news groups, frequently asked questions and arbitrary text; Information retrieval agents perform tasks such as collecting information about products and services ; advisory agents provide intelligent advice such as purchase recommendation; and performative agents are focused on tasks such as business transactions and work performance.

In general, the agent technology provides a new powerful and flexible mean for decomposing, abstracting and generally conceptualizing complex problems. Specially, the flexible interaction among agents enables the effective handling the problems that are characterized by dynamic knowledge. In addition, agents offer mechanisms for facilitating interpretability between heterogeneous data sources (Yoon et al., 2005).

Recently, the use of software agents in enterprise supply chain has gained a lot of attention among researchers as this kind of technology integrates the capability of several classes of information technologies and enables more powerful decision making for supply chain problems (Nissen, 2006).

## 2.2.2. DSS and Agents Technology in SCM

Advanced decision support and agent technology offers tremendous potential to overcome different limitations of current supply chain technologies and to integrate supply chain processes in a flexible and agile manner.

Intelligent agents can be set up throughout the supply chain to look for different information such as the most competitive prices or the cheapest supplier for a given product and they can be deployed to compare characteristics and functionality (Rodriguez et al., 2007).

In this section we review the studies that focus on applying these technologies for supply chain management.

Supply chain decision making involves several problems such as customer demand management, procurement, inventory management, logistic planning, etc. While some studies incorporate agent technology into specific areas of supply chain managements, others use agent technology to improve supply chain process integration as a whole.

In recent years, a new software architecture which utilizes software agents has emerged for managing the tactical and operational problems of supply chain. The main focus of this work is to increase communication between partners and improve coordination. In this architecture, supply chain is regarded as a set of agents interacting with each other and each responsible for one or more activities in supply chain (Fox et al., 2000).

Research by Nissen (2001) explores the role of agent technologies in supply chain integration and presents an agent-based supply chain process design in which the agents represent and autonomously conduct business on behalf of users, buyers, and vendors. All in all, these works exemplify that agent-based supply chain integration is feasible and offers potential for supply chain performance improvement. The work by Fox et al. (2000) also attempted to increase coordination between supply chain partners in a simulation of computer system manufacturing industry. Their approach used a multi-agent based methodology. Their architecture included 40 agents throughout the supply chain to implement a messaging system to improve notification and collaboration between partners. Through use of these early indications improvements in costs and also inventory quantities show differences depending on the type of optimization attempted by the system, whether the system tries to optimize one node in the chain or over the whole chain itself. Upstream improvements have been shown to be lesser than those of downstream improvements when individual nodes are optimized.

Lou et al. (2005) focus on supply chain agility and the need for customer responsiveness and close collaboration between partners. They explore agent technologies' potential in supporting collaboration in supply chain management and apply it to support the modeling and coordinating of supply chain management.

Agent based technology and situated decision support is also used to improve company efficiency by addressing costs within the company. Activities such as inventory control are among the critical business activity that substantially effect company's bottom line profits. IT research has responded to this accordingly. For example, Achabal et al. (2000) incorporate an inventory decision support system to derive optimal inventory and turnover levels. Specifically, the authors develop a vendor managed inventory (VMI) DSS and tests the system at a major apparel manufacturer and the 30 retail partners that work with the manufacturer. The system was designed to address three specific user activities: Identifying a forecasting model for the company's historical data, sales forecasting, and performance analysis. By providing revised sales forecasts on a weekly basis, the system constantly adjusted parameter values and forecasted inventory performance targets. Using service level changes and inventory turnover levels as indicators, the authors demonstrate how the DSS brings value to both the manufacturer and the retail outlets involved. For manufacturers, the system was able to increase the breadth of product line offered to retailers and service levels achieved. For retailers, the system improved sales forecasts and inventory management, which lead to higher financial performance.

Research by Kimbrough et al. (2002) further demonstrates this concept by investigating the use of agents in a virtual enterprise with multi-agent system architecture. Each part of the supply chain – retailer, wholesaler, distributor, and manufacturer- is equipped with an agent aiming to minimize long-term inventory costs when ordering from their immediate supplier. Using genetic algorithms to learn rules, the agents attempt to optimize inventory levels in a classic beer game, which represents the trends of the typical beer industry. In this game, each agent attempts to optimize reorder levels. In both cases, the agents converged into Nash Equilibrium optimal ordering points.

Petrovic et al. (1997) also address this issue by developing a DSS to determine the stock levels and order quantities for each inventory in a supply chain during a finite time horizon to obtain an acceptable delivery performance at a reasonable total cost for the whole supply chain. They used fuzzy sets to represent two sources of uncertainty inherent in the external environment: customer demand and external supply of raw material. In addition, they developed a supply chain simulator to provide a dynamic view of the supply chain and assess the impact of decisions recommended by the models on the performance.

Liang and Huang (2006) develop a multi-agent system to simulate a supply chain in which agents are coordinated to control inventory and minimize the total cost by sharing information and forecasting. Their study proposes an inventory system formulation which incorporates with agent technology to coordinate the supply chain and is capable of adapting to environmental changes dynamically and modeling different management behaviors and systems. The results show that total cost decreases and the ordering variation curve becomes smooth.

Among supply chain problems, procurement represents a problem area which contains significant level of ambiguity and therefore makes a good potential for agent based technology innovation (Nissen, 2006). For example, the work by Cheung et al. (2004) focuses on procurement problems and presents an agent-oriented and knowledge-based system for strategic e-procurement. In their study, agents are used to collect updated market information such as material price and exchange indexes from the Internet continuously and store the information in the knowledge repository for the subsequent analysis.

Vendaktari et al. (2006) also address this issue within the ecommerce industry. The study focuses on order promising to customers (Available to promise or ATP). In this case, decision support is applied to address how the supplier should negotiate and quote price, products, and due dates. Using optimization based decision support mechanisms, the author present a solution to optimize supplier benefit in such scenarios. Using cost and lead time as parameters, the model presented demonstrates the capabilities of decision support to maximize benefit within this context.

Another study by Jiang (2005) evaluates the use of intelligent decision support within the steel industry. The authors focus on an industry where inconsistencies and fluctuations are common within the supply of materials. Addressing this weakness, an intelligent decision support model is developed for the selection of supplier and subcontractors for projects.

Rodriguez et al. (2007) introduce a conceptual framework for supporting electronic collaboration, operations, and relationships among trading partners across supply chain networks. This framework incorporates a form of intelligent agents (called e-sensors) that are designed to sense and respond in a real time fashion to changes occurring throughout the supply chain.

# 3. Situated DSS for Supply Chain Management

In this section we first introduce the generic model of the situated decision support system (SDSS) and then we propose a layered model of SDSS applied in supply chain context (figure 3).

## 3.1. Generic Model of Situated Decision Support System (SDSS)

The generic model of a SDSS (figure 2) proposed by Vahidov and Kersten (2004) consists of four major components: DSS kernel, Sensors, Effectors and Active User Interface.

DSS kernel contains traditional components of a DSS such as database, models, and knowledge base. In addition, it includes an active component called DSS manager which is capable of performing certain acts proactively and autonomously such as contacting the user or even acting on his behalf.

The main objective of sensors is to assess the Problem domain and capture the relevant data. In addition to that, these devices can incorporate more advanced functions such as searching the problem domain, generating alerts, filtering and pre-processing the data relevant to the problem domain from variety of sources.

Effectors on the other hand are devices used by the decision station that are capable of changing the state of the environment. These devices can also include more advanced functions in order to take on different activities to implement a decision.

The last component of the SDSS is the active UI which facilitates human machine dialogues. The structure of the decision station can be described as:

$$DS=\{S, E, N, KN\}$$

Where $S$ represents the sensors, $E$ represents the effectors, $N$ is the user interface, and $KN$ indicates the DSS kernel. In the figure below, the information exchanged between the decision station and the user is indicated with $D$. the information obtained from, and passed to the environment are respectively indicated by $X$ and $Z$ and the information flow between the DS components are represented by $Y$.

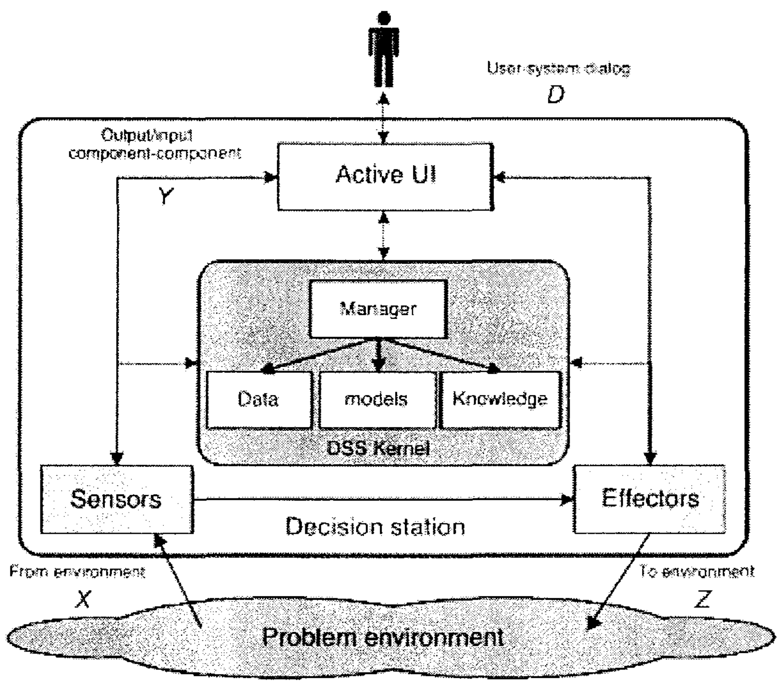


Figure 2: Generic Architecture of a decision station (Vahidov and Kersten, 2004)

# 3.2. A Layered Model of SDSS in Supply Chain Management

In this section we present a layered architecture of an agent-based SDSS applied in supply chain context (figure 3). Layered architecture of SDSS was introduced by He (2006) to make SDSS model more structured and organized. In this model the components of a SDSS are categorized into 3 layers: Reactive layer, Operational layer and Judgmental layer.

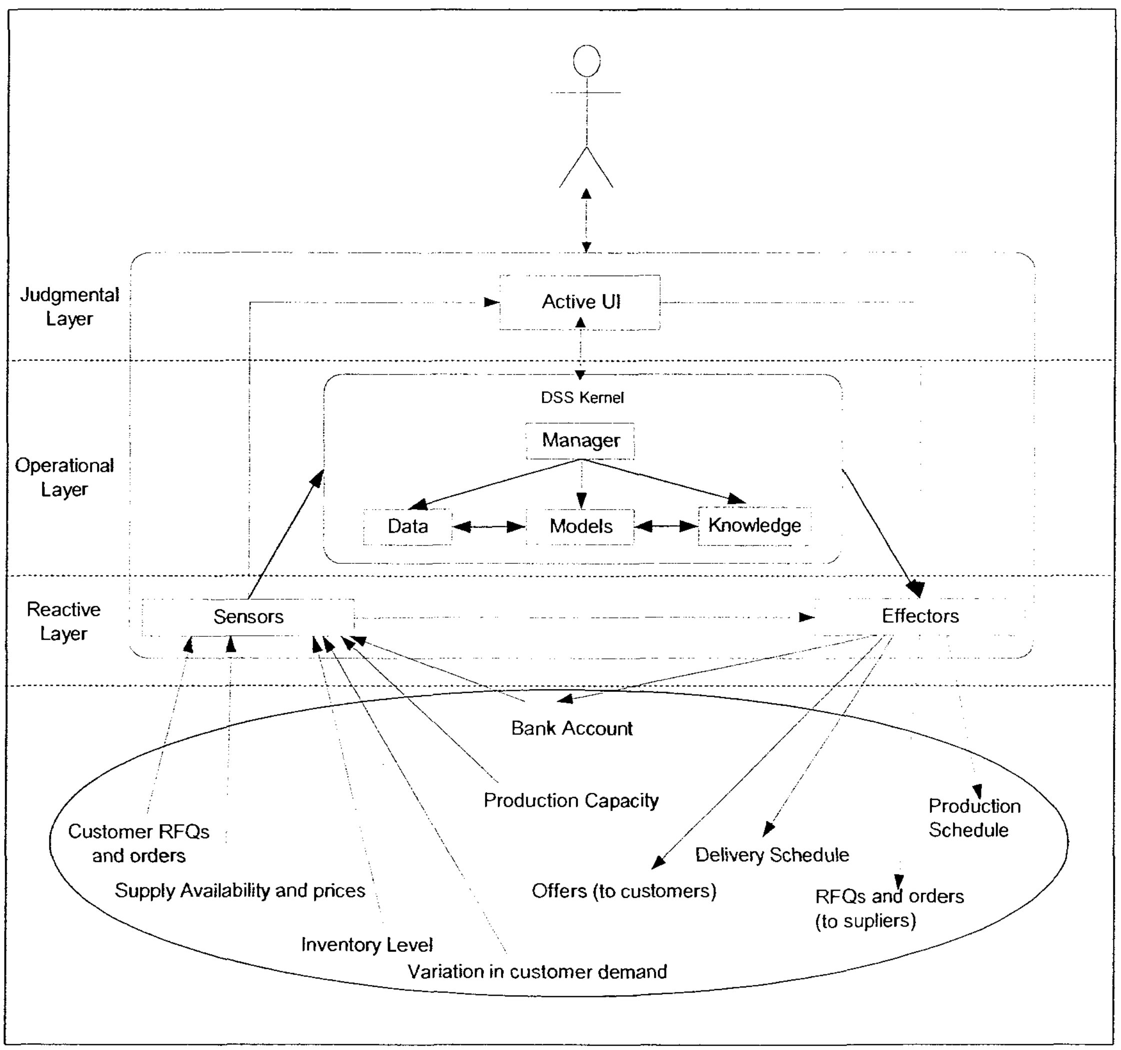


Figure 3: Decision station for an agile supply chain

### 3.2.1. Reactive Layer

The idea of reactive layer is derived from reactive agents. Reactive agent is referred to a type of agent that can react to an environmental stimulus or a request (Kendall et al., 1998). In this model Reactive layer contains the components that connect to the environment and can react to an environmental stimulus. These components include sensors and effectors.

Sensors incorporate multiple agents that monitor, collect and filter information from different sources. These sources can include general informational sources related to problem environment such as news, articles and trends regarding overall market as well as information related to demands and supply in the specific industry. Theses agents can search news from various news sources on the Internet or an intranet, filter important news items, spot the changing trends.

Rather than these general informational sources, the sensors also monitor the flow of new information into the supply chain. These include customer orders, shipments of raw material from suppliers, modifications to customer orders, resource unavailability and delivery delays from suppliers and machine breakdowns.

In the demand side, they are responsible for monitoring the receiving customer RFQs and Customer orders, observing the variations in demand from historical data and market information, and notifying user about the demand variations. In the supply side, sensors monitor availability of supply and variable supply prices and notify users about the trends and variation in supply market. Sensors also monitor the inventory level, remaining production capacity and the bank account and notify user if pre-specified targets are reached.

Effectors on the other hand are responsible for executing user's decisions. Effectors corporate agents who are capable of negotiating with customers about prices, due dates, or other items of their orders, handling customer requests for modifying or canceling their orders. Effectors can generate offers to be sent to customers interactively with the user, based on received customer RFQ, availability of supply, required profit margin and other factors. In supply side, effectors send RFQs and orders to suppliers based on predicted future demand, supply inventory level and supplier reputation. The actions that are related to manufacturing is creating production plans based on supply inventory levels and delivery schedules based on finished products availability and due date information.

## 3.2.2. Operational Layer

Operational layer is the middle layer in the model and includes the DSS kernel. The kernel includes traditional DSS components such as data, models, and knowledge base plus an active component - the DSS manager- which makes the situated DSS active and capable of performing certain tasks autonomously (Vahidov and Kersten, 2004).

### 3.2.2.1. Data, Models, and Knowledge Base

- Data includes historic data related to customer demand and supplies' prices and availability, observed delays, supplier reputation, etc.
- Models include:
    - ✓ Forecasting models: used in order to predict future orders and prices, supplies delivery dates
    - ✓ Procurement models: used in order to handle requesting and purchasing of components according to changing market conditions
    - ✓ Scheduling models: used in order to determine daily production schedule
    - ✓ Bidding models: used in order to respond to customers' RFQ

Different OR (Operations Research), heuristic and statistical modeling techniques can be used to create these models.

- Knowledge Base provides the means for organization, and retrieval of knowledge

## 3.2.3. Judgmental Layer

Judgmental layer is the highest layer in the model and includes the active user interface and the user. This layer establishes the communication between people and machines and incorporates user judgments in the decision making. Vahidov and Kersten (2004) stress the involvement of user intervention as an important capability of an active DSS.

The active interface is an intermediary between the user and the system. It passes information received from other components to the user, transforms messages from the user to the system and back to the user, queries other components if additional information is necessary in order to formulate the output directed to the user

# 4. Supply Chain Simulation Model

In this section we will introduce a supply chain management scenario and discuss the details of simulating that scenario. Then we will present the architecture of a situated DSS in supply chain. At the end we will discuss the implementation of the simulation system and situated DSS.

## 4.1. A Supply Chain Management Scenario

The scenario for this study is adopted from the specification for the Trading Agent Competition Supply Chain Management Game or TAC SCM (http://www.sics.se/tac). This scenario is designed to be representative of a broad range of supply chain situations and to capture the major sources of uncertainty, complexity and many of the challenges involved in supporting dynamic supply chain practices. It is challenging as it requires the firms to compete in two markets at the same time, markets for different components on the supply side and markets for different products on the customer side in presence of interdependencies and incomplete information.

The scenario (figure 4) consists of a number of days or rounds during which a PC assembly manufacturing firm manages customer orders and procurement of a variety of components as well as its daily assembly and delivery activities.

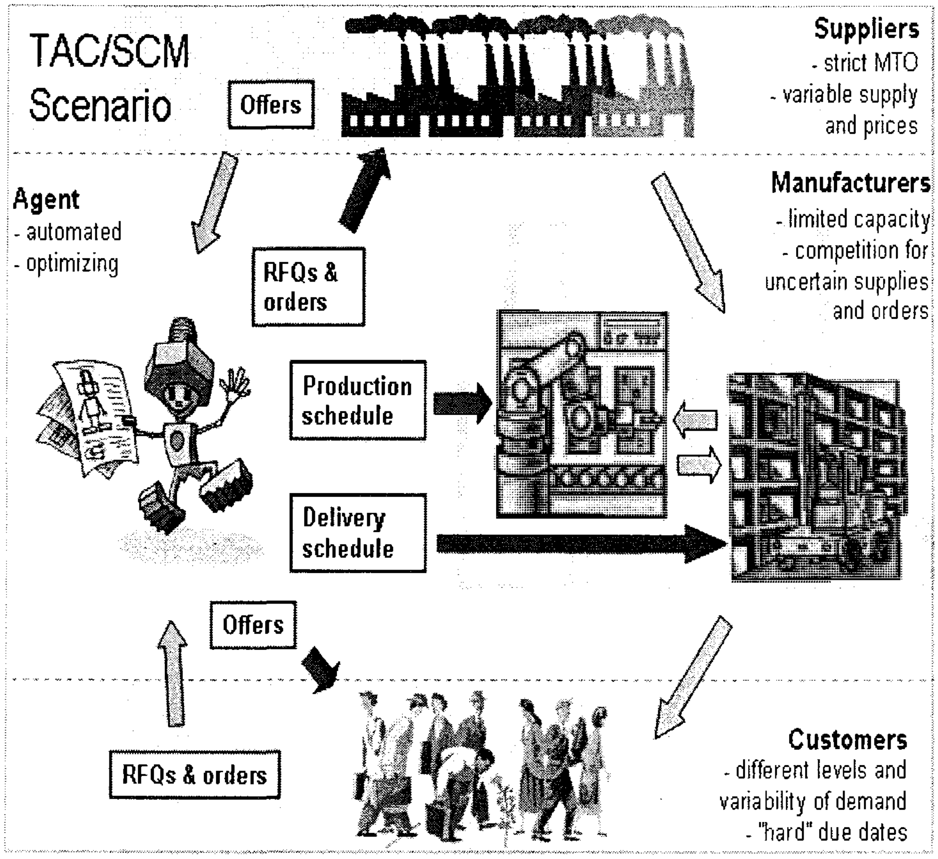


**Figure 4: TAC SCM Scenario (source: http://www.sics.se/tac)**

In this scenario the manufacturing firm is responsible for the following tasks:

1. Negotiate supply contracts

2. Bid for customer orders

3. Manage daily assembly activities

4. Ship completed orders to customers

Customer demand comes in the form of requests for quotes (RFQ) for different types of PCs, to be delivered by a certain Due Date. The firm receives each of the customers' RFQs that are generated each day. If the agent wishes to respond to a particular RFQ, it returns a bid to the customer containing a price, a quantity, and a due date. The customers select the bids with the lowest price as the winning bid by issuing orders back to the firm. Orders are fulfilled when agents ship products to customers.

From the supplier side, the firm receives offers to deliver particular quantities and types of components at particular prices in response to the RFQs that are sent in the previous day. The supplier collects all RFQs received during the day, and processes them together at the end of the day to send a combination of offers that approximately maximizes its revenue. On the following day, the supplier sends back an offer for each RFQ, containing the price adjusted quantity, and due date.

Four types of components are required to build a PC: CPUs, Motherboards, Memory, and Disk drives. Each component type is available in multiple versions. The firm has to procure components from a set of eight suppliers. The components catalogue is shown in table 1.

Components in TAC-SCM

| Components | Suppliers | Component specification |
|---|---|---|
| CPU | Pintel | 2 GHz |
| | | 5 GHz |
| | IMD | 2 GHz |
| | | 5 GHz |
| Motherboard | Basus | For Pintel CPUs |
| | | For IMD CPUs |
| | Macrostar | For Pintel CPUs |
| | | For IMD CPUs |
| Memory | MEC | 1 GB |
| | | 2 GB |
| | Queenmax | 1 GB |
| | | 2 GB |
| Hard drive | Watergate | 300 GB |
| | | 500 GB |
| | Mintor | 300 GB |
| | | 500 GB |

Table 1: Component Catalogue (source: http://www.sics.se/tac)

Each PC type is identified by an integer identifier called a Stock Keeping Unit (SKU). The bill of materials (table 2) specifies, for each PC type, the constituent components, the number of assembly cycles required.

| SKU | Components | Cycles |
|---|---|---|
| 1 | 100, 200, 300, 400 | 4 |
| 2 | 100, 200, 300, 401 | 5 |
| 3 | 100, 200, 301, 400 | 5 |
| 4 | 100, 200, 301, 401 | 6 |
| 5 | 101, 200, 300, 400 | 5 |
| 6 | 101, 200, 300, 401 | 6 |
| 7 | 101, 200, 301, 400 | 6 |
| 8 | 101, 200, 301, 401 | 7 |
| 9 | 110, 210, 300, 400 | 4 |
| 10 | 110, 210, 300, 401 | 5 |
| 11 | 110, 210, 301, 400 | 5 |
| 12 | 110, 210, 301, 401 | 6 |
| 13 | 111, 210, 300, 400 | 5 |
| 14 | 111, 210, 300, 401 | 6 |
| 15 | 111, 210, 301, 400 | 6 |
| 16 | 111, 210, 301, 401 | 7 |

Table 2: Bill of Materials (source: http://www.sics.se/tac)

The production process is taking place in a simplistic PC factory containing an assembly cell capable of assembling any type of PC, and a warehouse that stores both components and finished PCs. Each PC type requires a specified number of processing cycles and the assembly cell has a fixed daily capacity. Each day the firm sends to its factory a production schedule for its assembly cell. Shipping is controlled by a delivery schedule, which the agent sends to its factory on a daily basis.

The firm has a bank account with starting balance of zero. Money is added to the account when a customer pays for a product shipment and money is deducted from the account when components are received from suppliers, or when penalties are incurred for late deliveries to customers.

## 4.2. Simulating the Supply Chain Management Environment

Using simulation as a mean for understanding issue of organizational decision-making has received attention in recent years. Simulation modeling can be a useful tool for supply chain performance. Using this method, a complex supply chain can be modeled and analyzed. Simulation models can be used to validate different scheduling techniques, to test optimization patterns, or testing different strategies and operational tactics (Bandinelli, 2006). Supply chain simulation is useful as it helps to understand the overall supply chain processes and characteristics, enables the user to capture system dynamics by modeling unexpected events in certain areas and understand the impact of these events on the supply chain and permit the user to try various alternatives and different what-if simulation (Chang and Markatsoris, 2001).

The objective of simulation in this study is to model the dynamic behavior of the supply chain and to evaluate the consequences of different configurations on supply chain performance. The simulation model takes into account the uncertain and changing elements of the supply chain such as customer demand and production fluctuations.

In this context, a computer program is designed and developed to simulate the supply chain environment. In this computer program, the behavior of the decision maker is also simulated so that s/he passively accepts the recommendations of the situated decision support system. The simulation system works as if the system is on auto pilot which means the intervention of a human user is not needed.

The simulation is performed essentially based on the supply chain scenario mentioned in section 5.1 with a few added functionalities and some alterations in line with the goals of this study.

The figure below is a UML activity diagram for our simulation system. This diagram represents a general overview of business and operational step-by-step workflows, divided by four major components of the system. Both the upstream and downstream processes are documented in the below figure. The upstream process is initiated when a sensor receives a Request for Quote (RFQ) from a potential customer. The downstream process is also initiated by sending RFQs to suppliers.

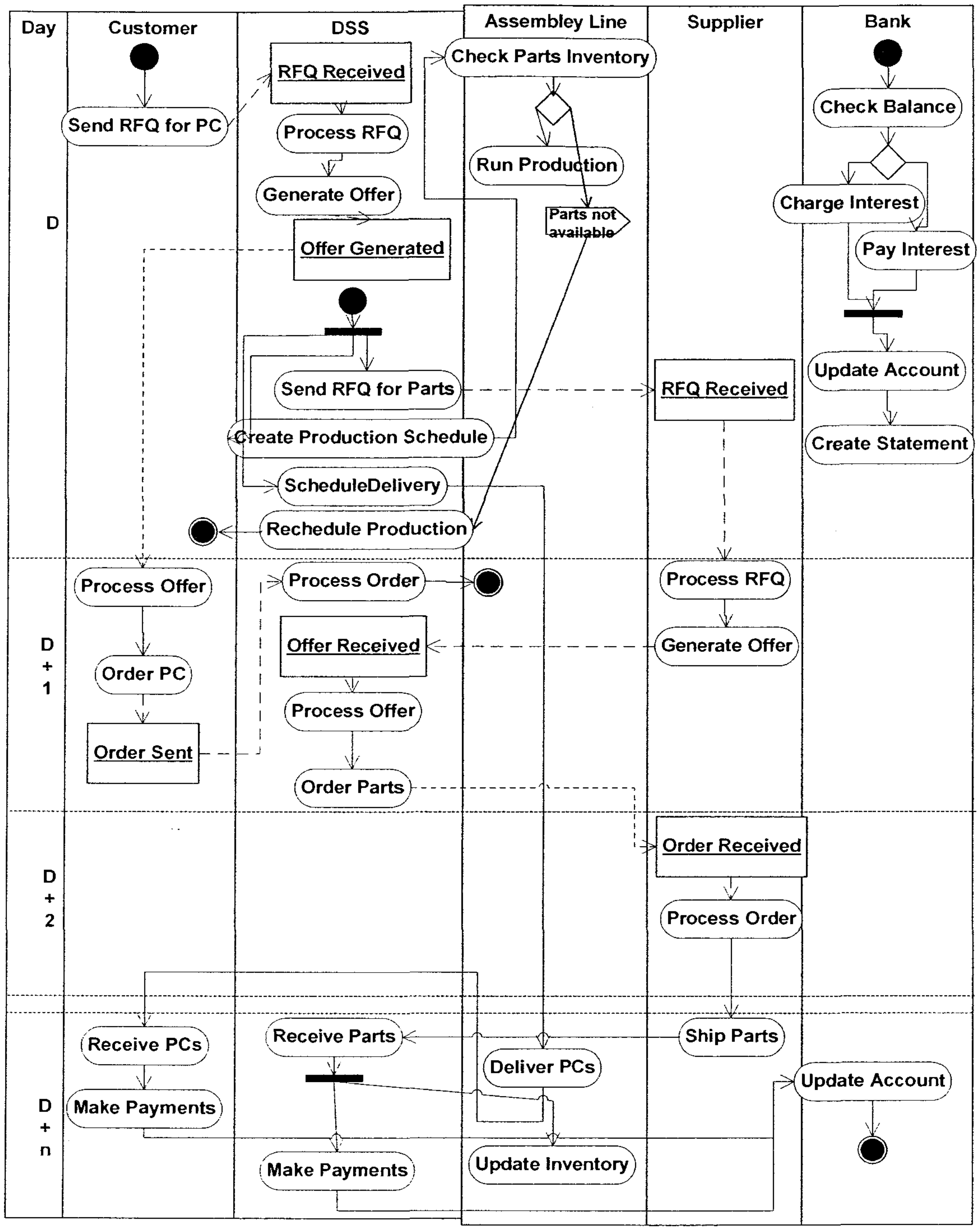


Figure 5: UML activity diagram for simulation system.

There are various elements or players in a supply chain environment. Each one of these players is represented in the simulation system. In this section, we will describe each player and its related properties and functions.

### 4.2.1. Customer

Customer is the player who initiates the order process by sending a "Request for Quote" (RFQ) specifying the number and type of products s/he needs and the date s/he needs them. In each RFQ, customer specifies a reserve price and a penalty amount.

Reserve price is the maximum price customer is willing to pay to purchase a unit of the product. Penalty is the amount customer will receive each day the order is late. Customer is also responsible for reviewing the offers that are generated in response to RFQs in order to accept or reject them. Customers in real world can select their own set of criteria for accepting or rejecting offers. In our simulations, customer uses one criterion for this purpose. That criterion is price that has been offered to the customer. We made an assumption in our simulation system to simplify customer offer selection process to make sure we do not introduce another random factor in the system. We have to make sure we eliminate as many external factors as possible that might affect the results in our simulations. The algorithm, which the customers use to select offers, is a good example. The initial definition for the selection criterion was:

*The lower the offered price compared to the reserve price, the customer is more likely to accept the offer.*

If we had implemented customer offer selection algorithm based on the above definition, this would have introduced a non deterministic factor in the selection process for simulations. This non deterministic factor had nothing to do with the decision support system used in the supply chain and its presence could have complicated the comparison of the results since each simulation would have demonstrated different customer offer selection behaviour. This complication was not in line with our research goals and would not have helped in the analysis of the results. To avoid this complication, we had to eliminate this non deterministic factor. At the end we used this definition for the selection criterion:

*If the delta of reserve price and offered price divided by delta of reserve price and actual price of product (based on prices of components on that day) is greater than 0.4, the offer is accepted.*

The above criterion will behave the same for all simulations regardless of the type of decision support system that is used in the supply chain. This selection process depends on the simulation data set characteristics that are the same for any simulations running on the same data set. This implementation does not introduce a non deterministic factor and would make comparing results from various simulations that use the same simulation data set much easier.

### 4.2.2. Product

Product is the entity that customer requests and should be produced by the plant. Each product has an id and a name, and is composed of four components. To begin production of a product, plant needs all required components be available in the inventory. When this condition is satisfied, plant will consume a certain number of cycles to turn components into the product. Each product needs a certain number of cycles to be produced. The number of cycles and the components that are required to produce a product determine the profit margin of the product. The profit margin for a product is not constant. In fact it fluctuates as prices of components change.

When a product is produced, that product is moved to inventory until the time it is shipped as part of an order. When products of an order are shipped, bank will receive an amount equal to the price that was offered to the customer multiplied by the number of products shipped for that order.

### 4.2.3. Product Demand Data

The data of customer product demand is generated at the first stage of simulation and recorded in the database. This data is the first element of what we call a simulation data set. To generate the product demand data, we start from an initial demand quantity for each product which is a value between one and 20. For each day we generate a normal [Gaussian] random deviate from a normal [Gaussian] distribution with a mean of zero and standard deviation of two. This value is the "change indicator" of the demand of a product for that day. To produce the actual quantity demanded for a product in a day, the change indicator is added to the initial demand quantity of a product. The sum of the two values is considered the demand for the day and for the specific product.

For stable markets, the initial demand value is constant and does not change. For volatile markets, the initial demand value is updated each day with the calculated demand value for that day. This change in initial value introduces volatility to the demand values. Please see figure 6 which represents demand values for product 5 in a stable market and figure 7 that represents demand values for the same product in a volatile market.

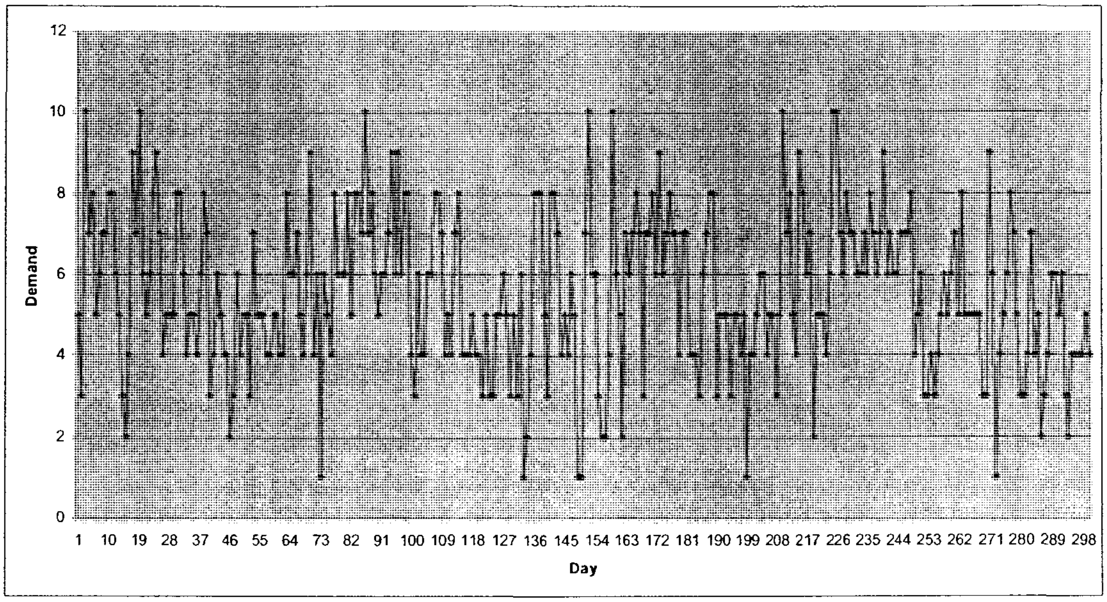


Figure 6: Demand Values for Product 5 in Stable Market

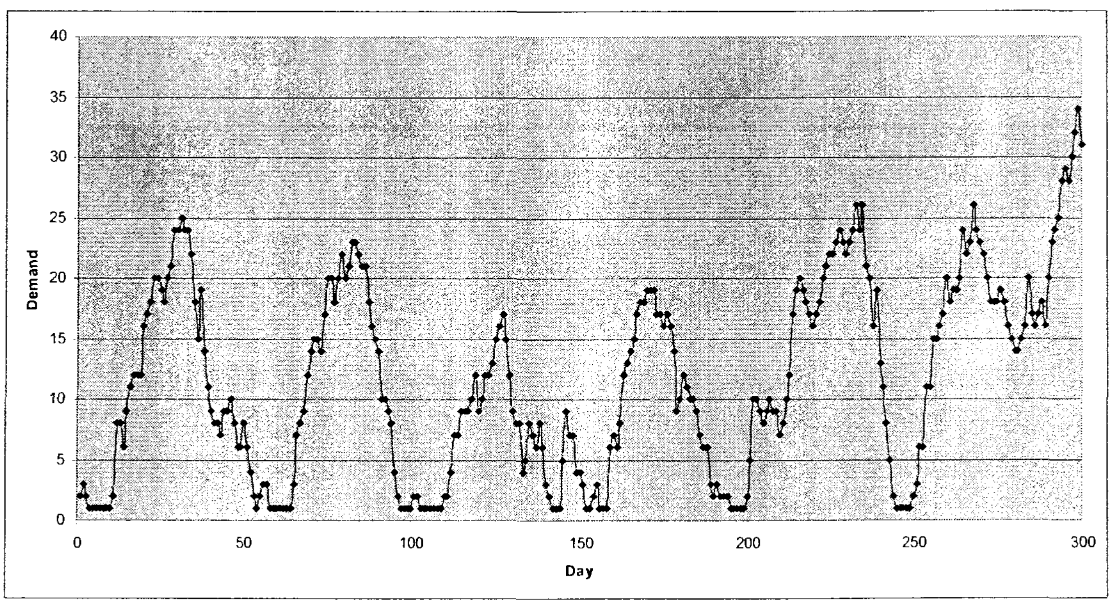


Figure 7: Demand Values for Product 5 in Volatile Market

Due date of each order is generated from the current date plus a uniformly generated order lead time in the interval between three and 12 days. Reserve price specifies the maximum price per unit of the product that a customer is willing to pay. This reserve price is randomly generated between the ranges of 95% to 115% of the nominal price of the product. For each customer order, a penalty for late delivery is generated uniformly between the ranges of 2% to %8 of the nominal price of the product.

The simulation system is designed and implemented in a way that none of these values are hard coded and all of them can be changed rather easily through the database.

### 4.2.4. Request for Quote

Request for Quote (RFQ) is the vehicle that captures all the information about the customer product demand and carries that information through the system. An RFQ in the context of a simulation has a unique identifier and carries the following data fields: Product Type, Quantity, Due Date, Reserve Price, and Penalty.

### 4.2.5. Offer

After an RFQ is received, an offer might be generated for the customer. The decision to generate an offer in response to an RFQ or ignore an RFQ is based on several factors such as profitability, available capacity, and production liability. When an RFQ is chosen to be processed, an offer will be generated for the customer. An offer is basically very similar to an RFQ. The only difference is that offers have an "Offered Price" value. The offered price value is the price that is offered to the customer to buy the product. Obviously the offered price should be less than the reserve price set by the customer so that the offer has a chance of being accepted and it should also be more than the cost of producing the product so that the offer that is presented to the customer generates revenue and not loss. The cost of producing a product is sum of components, labor, transportation, inventory, and etc costs.

Since we are focusing on different supply chain management scenarios, we have assumed that any cost other than components cost is generally the same for different scenarios and thus we have not included them in our calculations. This assumption will give more weight to the costs of components and the way customer demand is managed and met. This will eliminate the effects of other costs such as inventory that might be of interest in certain scenarios and environments. This could be considered a restriction of this simulation system and could be a candidate for future work.

### 4.2.6. Component

Component is the entity that is used to produce products. It has an id, a name and a base price. Each component is provided by at least one supplier. Each supplier can provide certain number of a component per day. Components can be ordered in excess of daily supplier capacity and supplier will fulfill the components order whenever all ordered components are ready.

A component might be used in production of more than one product, thus patterns of components demand are determined by products demand patterns and costumer offer selection behavior. Figure 8 demonstrates the demand pattern for one component in a stable market and figure 9 demonstrates the demand pattern for one component in a volatile market. These diagrams do not take into account the customer offer selection behavior.

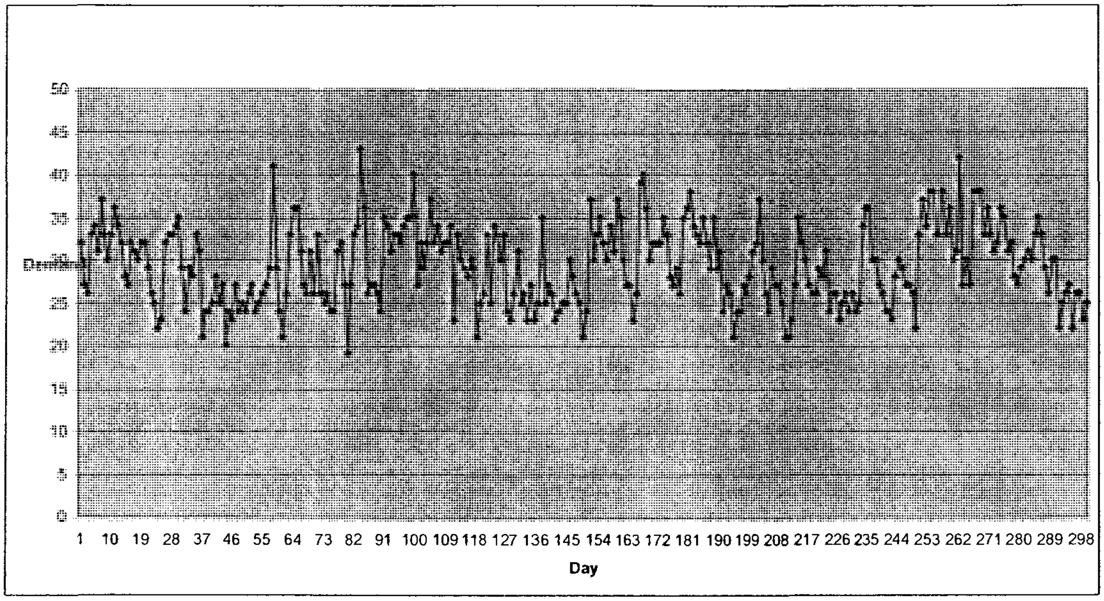


Figure 8: Component Demand Pattern, Stable Market

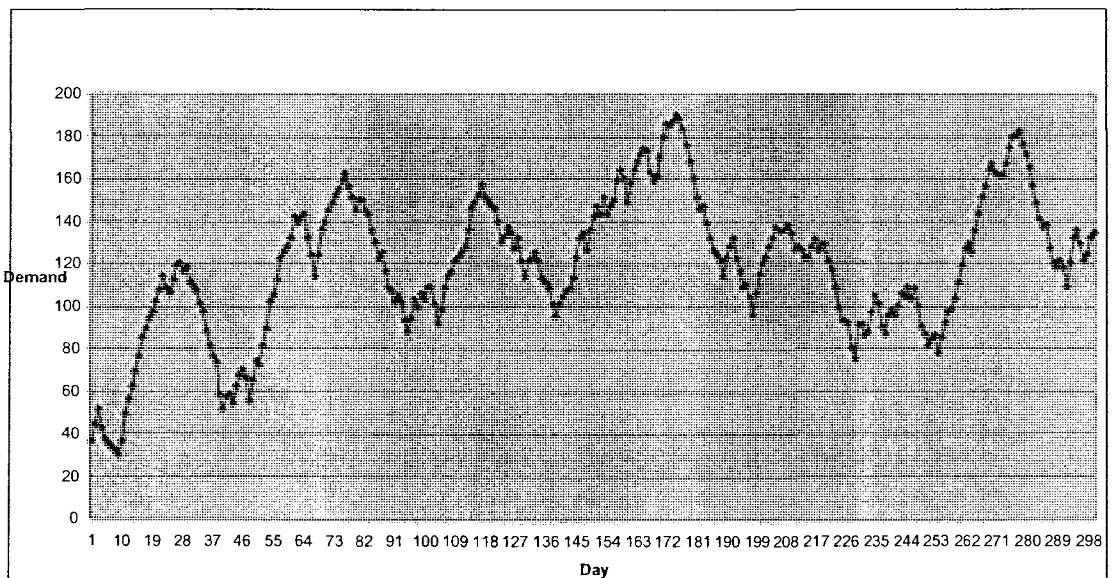


Figure 9: Component Demand Pattern, Volatile Market

As mentioned before in section 4.2.1., the customer offer selection behavior is the same for all simulations that process the same simulation data set. Therefore the above diagrams should be a good indication of the component demand in stable and volatile markets.

## 4.2.7. Component Price Data

As mentioned in section 4.2.3., the data of customer product demand is generated at the first stage of simulation and recorded in the database. This data is the first element of a simulation data set. Component price data is the second element of a simulation data set. It contains daily price information for components that are required to fulfill customer products demand. To generate component price data, first we calculate component demand using product demand data in a simulation data set. To determine the price of component for each day, we calculate the average demand and average price for a specified number of days before that day. The price for the day will be calculated as average price of previous x days multiplied by today demand divided by average demand of previous x days. Figure 10 demonstrates the component price calculated based on the product demand data for a stable market and figure 11 demonstrates the component price calculated based on the product demand data for a volatile market.

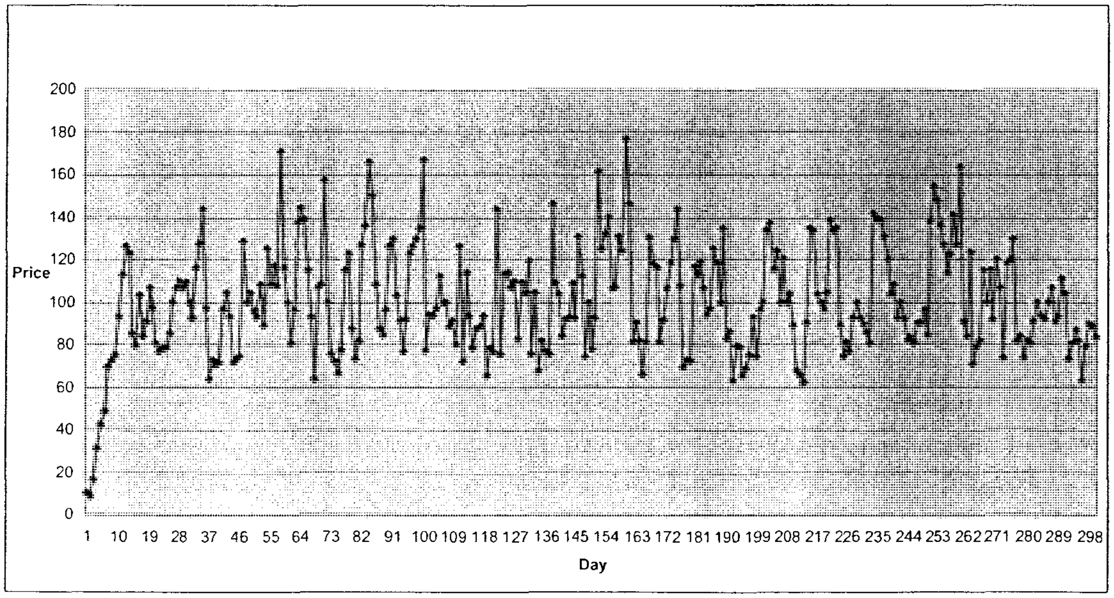


Figure 10: Component Price Pattern, Stable Market

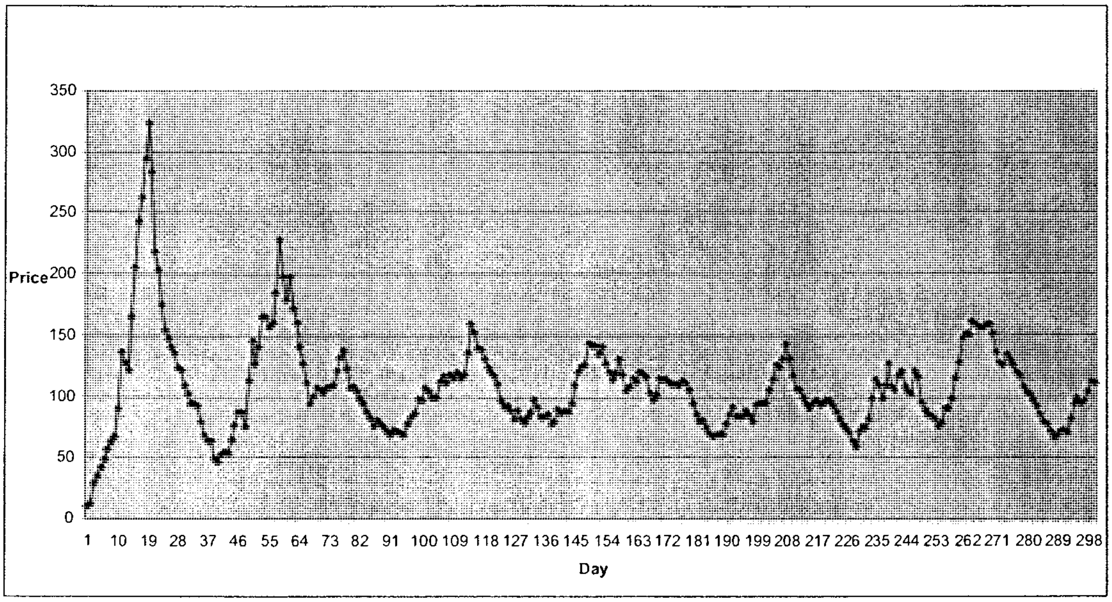


Figure 11: Component Price Pattern, Volatile Market

## 4.2.8. Inventory

Inventory is the entity in charge of storing components that arrive in a plant before they are consumed to produce products and also storing products after they are produced and before they are shipped to customers. In our simulation system, inventory is a repository which performs all book keeping tasks to keep track of what exists in the storage. Inventory in this context does not engage in financial transactions, therefore it does not have a positive or a negative impact on financial performance of the system.

## 4.2.9. Supplier

Supplier is the entity that provides components for plants. A supplier may provide one or more components. Supplier has a predefined daily capacity for each component it provides.

Suppliers provide components in response to orders received from plants. Suppliers do not have the ability to start stock pilling components without receiving orders. This mode of operation puts more emphasis on supply chain performance and the way components are ordered. Supply chain performance and patterns of components orders are directly impacted by management strategy used in a supply chain. The management strategy is affected by the type of support that is provided by decision support system. Different management strategies relying on different types of support from decision support systems result in different component order patterns and thus different supplier capacity utilization patterns.

Figure 12 and figure 13 demonstrate the capacity utilization patterns of suppliers 1 and 2 respectively, who provide component 100 in two distinct supply chains. The main difference between these two supply chains is the type of support that is provided to their decision making process. These two types of support are described in more details in 4.2.

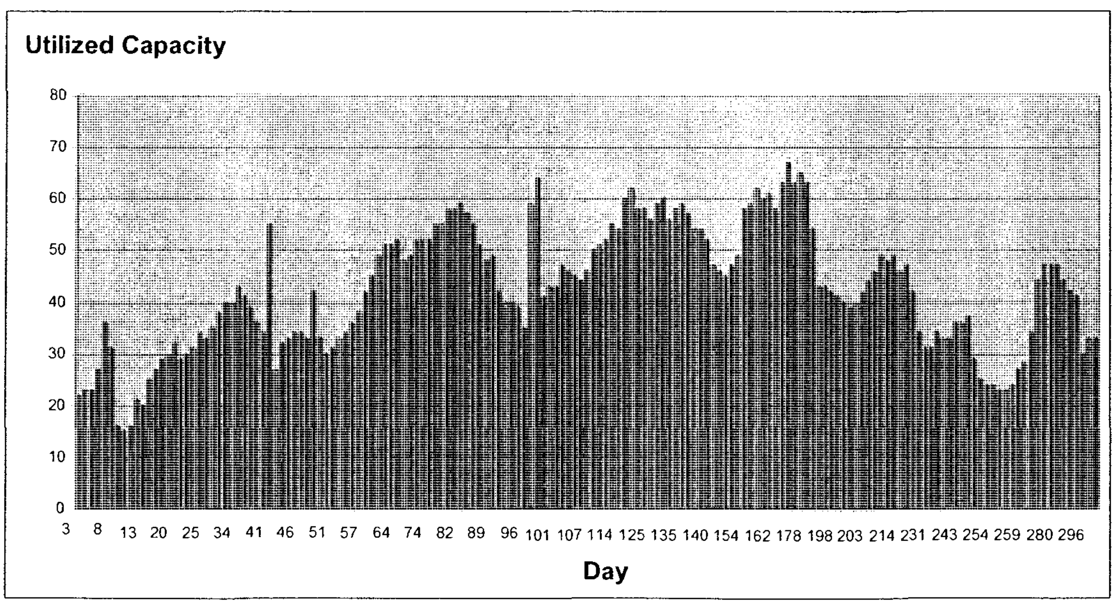


Figure 12: Supplier Capacity Utilization, Supply Chain 1

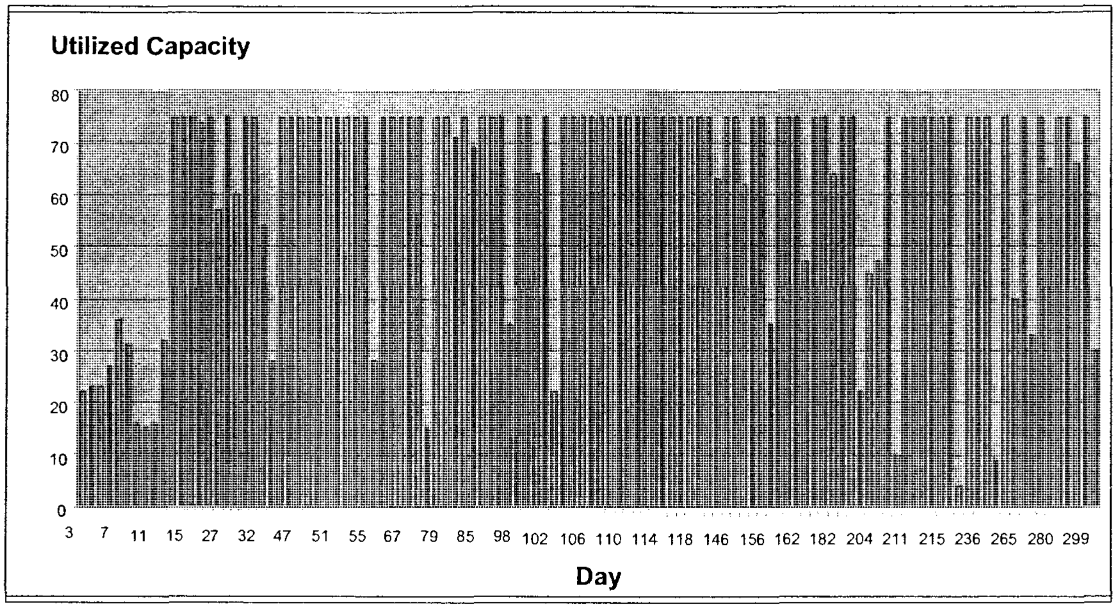


Figure 13: Supplier Capacity Utilization, Supply Chain 2

Supplier capacity could be a bottle neck and a limiting factor for a plant. If demand varies for a component and supplier capacity is limited, supplier might not be able to meet the demand on time. If the demand is not met in a timely fashion, plant will not be able to produce the product that needs the component. If the product is not produced on time, customer will not receive the product before the set due date and plant will end up paying penalty because of late orders.

## 4.2.10. Plant

Plant is the entity that represents a production facility. A plant has an id, a name, and a daily production capacity. Production capacity is measured in cycles. Each product needs a number of cycles to be produced from components. The way plant daily production capacity is consumed depends on the orders that plant has received from customers, components that are available in inventory and production schedule that prioritizes products of which order should be produced first.

Each plant has an initial inventory of components and products. It also has an initial capital. All these values can be set for a plant in the database. Initial conditions of a plant impact the results of simulation. To compare results, the same plant should be used in simulations that are performed on different market types using different supply chain strategies.

We created seven plants with different initial conditions. Running numerous simulations using these plants we noticed that the best set of initial conditions (considering the goals of our research) is an inventory of zero components and zero products. The initial capital does not affect simulation results since we always look at the money made or lost during the course of simulation to compare various supply chain strategies. Based on our observations, we chose to use a plant that has no initial inventory of components and products and no initial capital to get the data we used for this report. The initial inventory of no components and no products provided a level playing field for different supply chain strategies and eliminated the chance of accidentally impacting simulation results because of improper initial conditions.

## 4.3. Designing the situated DSS in the supply chain

Figure 14 shows the architecture of the Supply Chain SDSS and its interfaces with the problem environment. This diagram presents a logical architecture based on the high level layered model of a decision station described in section 3.2.

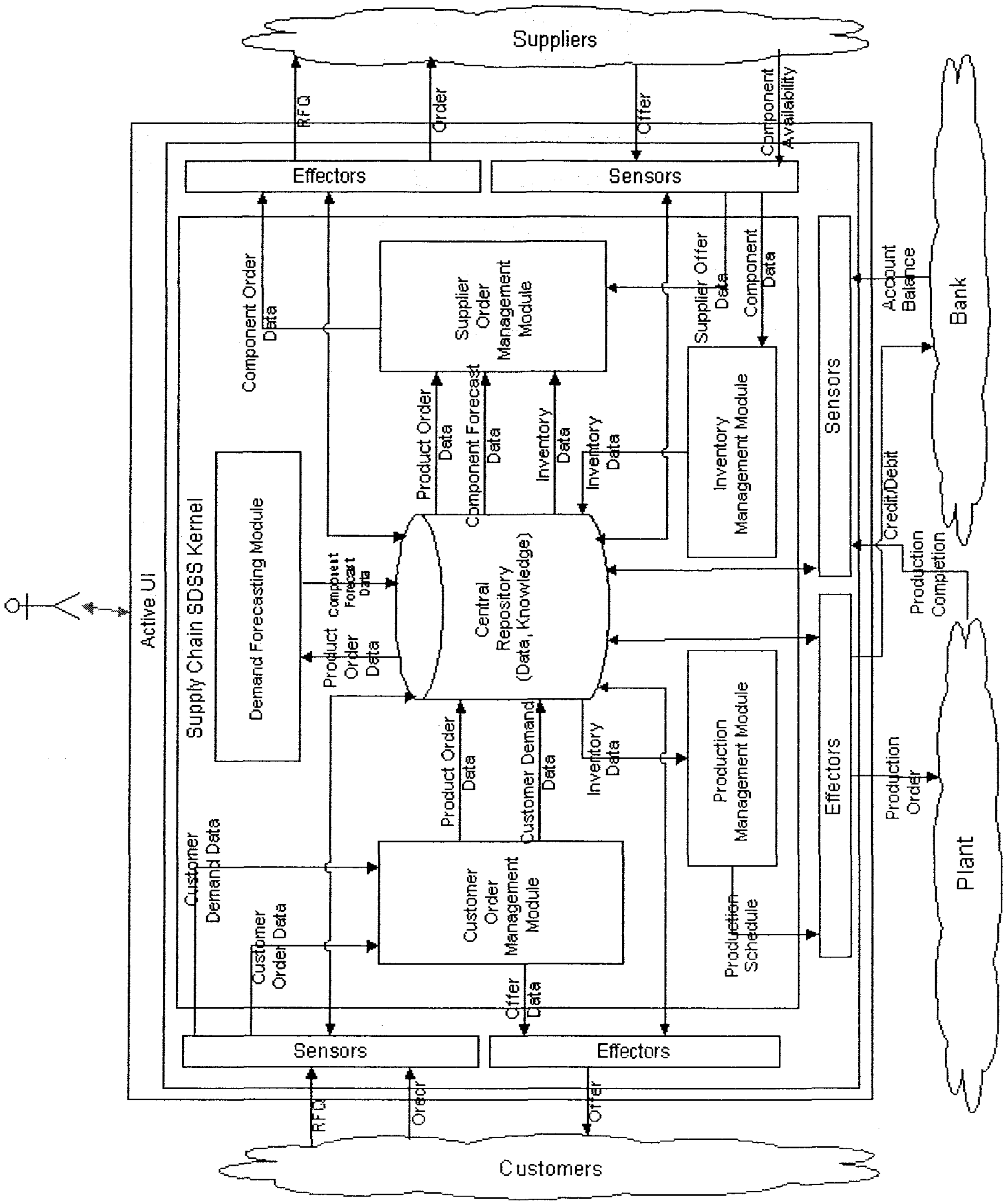


Figure 14: Supply Chain SDSS architecture.

The major components displayed in the above diagram are: SDSS kernel, active user interface, sensors, and effectors. Active user interface as described in section 3.2.3, makes up the judgmental layer of the system and institutes two way communications between people and machines. SDSS kernel makes up the operational layer as defined in section 3.2.2. SDSS kernel components receive data about the problem environment through sensors and impact the problem environment through effectors. Sensors and effectors comprise the reactive layer of the model as described in section 3.2.1.

SDSS kernel has six major components that will be described in more detail in this section.

### 4.3.1. Customer Order Management Module

Customer Order Management (COM) module is designed to handle interactions with customers. COM module receives customer product demand information through sensors. Checking several factors such as profitability, available production capacity, and production liability with the help of sensors, COM module decides if it can respond to an RFQ or if it should ignore it.

COM module first checks if the request can be fulfilled directly from inventory. To fulfill a request directly from inventory, there should be enough number of requested products in inventory (explained more in Inventory management module section) that is available and not tied to any specific order. If that is not the case, COM module then treats the issue of selecting orders like a regular knapsack problem. The algorithm that COM module follows to select orders is "Greedy by Profit Density". Since each plant has a limited number of production cycles per day, it makes sense to try to get the most out of each production cycle. The goal of COM module is to select orders that create the maximum profit per cycle. To implement a greedy by profit density selection algorithm, COM module calculates the profit per cycle for all RFQs received on a day. This is done by calculating the profit for the whole order divided by the number of production cycles needed to produce the products of that order. In the next step, COM module selects the RFQ among all RFQs received on that day that has the maximum value for profit per cycle and subtracts the number of cycles required to produce products of that RFQ from plant daily production capacity. COM module keeps repeating this process until the remaining daily production capacity becomes zero or there is no more RFQs left that can be fulfilled using the remaining production capacity.

When COM module chooses an RFQ to be processed, it uses effectors to send an offer to the customer. An offer is a response to an RFQ which carries an "Offered Price" value. The offered price value is the price that COM module is offering to the customer to buy the product at the due date customer has specified. The offered price should be less than the price set by the customer so that the offer has a chance of being accepted and it should also be more than the cost of producing the product so that the offer that is presented to the customer generates revenue and not loss. Since component prices fluctuate, COM module needs to calculate a price for the product that is based on the available information and use that calculated price as a basis for calculating profit or loss values. To make sure the cost of a product is calculated as realistically as possible, COM module uses the component price data obtained through sensors on the day RFQ is received to calculate the price of the product. The real cost of a product can be calculated after the product is produced using the actual component price data of the components in the inventory.

The cost of producing a product is sum of components, labor, transportation, inventory, and etc costs. We use the same COM module for different supply chain management scenarios in our simulations. We have assumed that any cost other than components cost is generally the same for different scenarios and thus we have not included them in our calculations. This assumption gives more weight to the costs of components and the way customer demand is managed and met. This will also eliminate the effects of other costs such as inventory that might be of interest in certain scenarios and environments. This could be considered a restriction of this simulation system and could be a candidate for future work.

### 4.3.2. Demand Forecasting Module

Demand Forecasting (DF) module is only used in scenarios that rely on SDSS. In fact, DF module is one of the differentiating factors that distinguish SDSS from TDSS. This module is in charge of forecasting demand for components based on demand data of previous days obtained through sensors. DF module uses regression analysis to forecast component demand. The module is designed to be adjustable. It can easily use linear regression or non-linear regression with a small code change. When using regression, it is very important to choose a proper regression model. There are various methods to make sure a regression model is appropriate for a given dataset. Based on the patterns observed in the simulation data sets and the number of days we chose as historical data to be used for forecasting demand, one good fit was a regression model that takes advantage of polynomial fitting. We used a polynomial equation of the third degree for this purpose.

DF module uses certain rules to come up with the final number for a component demand. First it uses regression analysis to calculate the demand for the next day. Then it checks the inventory for the component repository and gets the number of components that are not committed to any specific customer order. Based on these values, DF module forecasts the demand for a component.

### 4.3.3. Supplier Order Management Module

Supplier Order Management (SOM) module is in charge of handling all interactions with components suppliers. This module receives the demand for a component generated by DF module and sends RFQs through effectors to suppliers of that component. SOM module sends component type, quantity, and due date to the effector so that RFQs can be generated and sent to suppliers. Suppliers respond to RFQs through offers the next day. Suppliers generate offers considering their capacity for a component, their existing liability for that component, and the due date the component is needed. The offer that suppliers send back contains an "Offered Price" for the component and the quantity that supplier can commit to provide on the due date. The offered price comes from the component price data set which is an element of the simulation data set (see section 4.2.7). All this information is communicated to SOM module through sensors.

In an environment that the capacity of suppliers is infinite, just ordering the amount that is needed on each day will guarantee enough supplies of components for uninterrupted and on-time production. The reality is that suppliers do have a finite capacity and that will limit their ability to respond to component demand. The inability of suppliers to respond to demand could cause components shortages which would impact production and on-time delivery of products. After SOM module sends RFQs based on the demand received from DF module, it also tries to use data captured by sensors to identify late orders and to check shortage of which components caused the delay. SOM Module sends another round of RFQs through effectors to suppliers based on the components needed for late orders considering inventory data of available components. Suppliers will treat these RFQs like the first set of RFQs and will respond with offers considering the same factors mentioned above.

### 4.3.4. Inventory Management Module

Inventory Management (IM) module is in charge of inventory book keeping. IM module records the number and type of components and products that exist in the inventory. IM module also keeps track of the association of components and specific product orders. When a batch of certain component arrives in the inventory, IM module is notified by sensors and checks to see if a number of that batch of component has been ordered specifically for producing a product related to a specific customer order. If that is the case, IM module creates a component liability record for proper number of components and maintains that record until those components are consumed to produce the product that satisfies the customer order. If components that arrive in the inventory are not tied to any specific customer order, there will be no component liability record for them and they are considered component that are available for any purpose. IM module has a similar mechanism for products. Products that are in inventory can be tied to a specific customer order or might be unassociated with specific customer orders. IM module uses product liability record to record this association.

Through liability record mechanism IM module is able to make sure components and products that exist in inventory are actually used to fulfill their specific purpose. Through use of liability records, IM module is capable of determining how many of each type of component and product are available at any point of time for a specific purpose or for any purpose.

Having this capability is important because it allows IM module to answer queries about the number of products that are in inventory and not committed to any customer orders so that COM module can decide which orders can be fulfilled directly from inventory. This capability is also required when DF module queries the inventory level of components to decide if the current level of uncommitted components in inventory is enough to impact the demand forecast.

### 4.3.5. Production Management Module

Production Management (PM) module is responsible for scheduling production of products in the plant. PM module begins with unfulfilled customer orders. Unfulfilled customer orders are offers that have been accepted by customers (which have created commitment on the plant side to provide the ordered products on the due date) but the products mentioned in those are not yet produced and are not yet in inventory. An order can not be processed unless all required components for that order are already available in inventory. The first order of priority for PM module is due date. PM module picks unfulfilled orders based on their due dates and communicates with IM module to see if the required components are available. If components are available, PM module sends the order to plant to be executed through effectors. PM module keeps track of available plant production capacity for the day (which is plant production capacity minus consumed capacity on that day) and keeps sending orders for production to the plant until plant production capacity is fully used or there are no more orders that can be fulfilled in the remaining plant production capacity for the day. We have made an assumption to simplify PM module tasks. We have assumed that the production of the products of an order should be completed in a day and cannot span more than one day. This assumption makes it easier to manage plants and make PM module design much simpler since it always works with one day schedule and does not have to manage production orders that might go on for more than a day. This limitation can be a candidate for future extensions of this research.

### 4.3.6. Central Repository

Central Repository (CR) is the central storage for all data gathered by sensors and all the information generated by components of DSS kernel. CR is responsible for providing storage and retrieval capabilities which are used by various components of DSS kernel as well as sensors and effectors. Data stored in CR can include historic or operational data such as customer demand, supplies' prices, components' availability, observed delays, bank account balance, or paid penalties.

## 4.4. Design and implementation of the simulation system and SDSS

We had various choices considering software system architecture and programming languages. In this section we will describe the software system architecture, the programming language, and the database we used.

### 4.4.1. Software System Architecture

We chose 3-tier architecture to design our system. 3-Tier architecture has three layers:

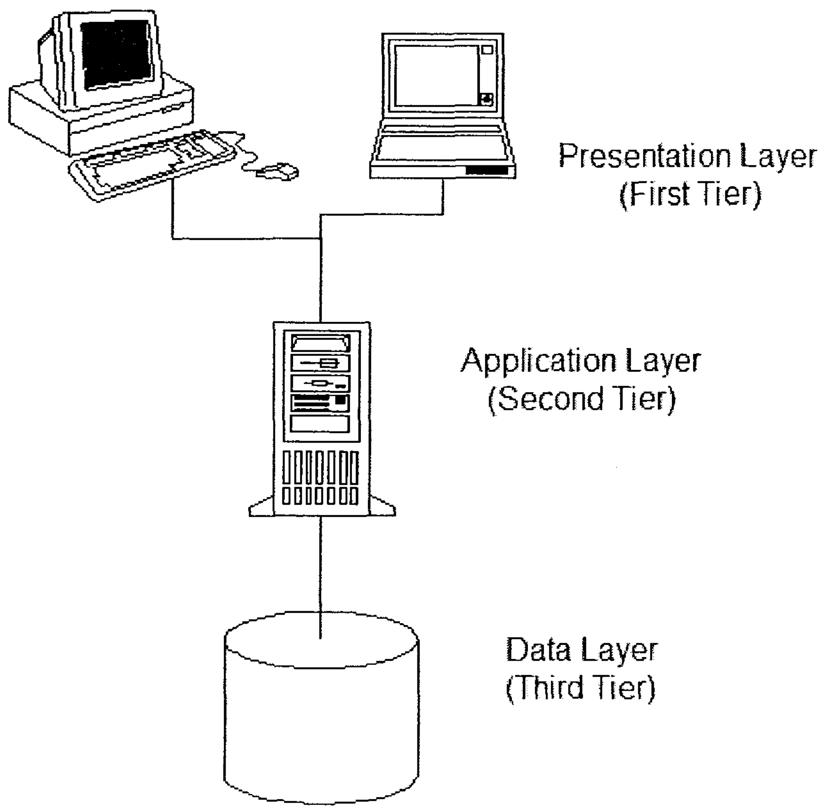


Figure 15: 3-Tier Architecture

Presentation layer is responsible for interacting with user. This tier displays information to the user and receives user requests and generates responses using presentation logic. Application layer contains core business logic. This layer implements the logic that controls all business processes. Data layer is in charge of data persistence and data management.

## 4.4.2. System Implementation

We implemented our system using JAVA programming language following guidelines of J2EE application architecture. The presentation layer of our system has been developed as a web based client that can be viewed using a standard web browser such as Microsoft Internet Explorer (IE) or Mozilla Firefox. A web based client has two main components:

- Static and dynamic web pages containing various types of markup languages (for example HTML, XML, etc.). The dynamic pages are generated by web components (JSPs and servlets)
- A web browser that renders the pages received from the server

Web based clients typically do not execute complex business rules. Heavyweight operations are delegated to application layer to be executed on an application server where they may take advantage of reliability, security and speed of J2EE server-side technologies.

The application layer of our system has been developed as servlets that can run under any J2EE application server. We used Apache Tomcat version 5.5.17 as our application server. The data layer of our system has been designed as a relational database. We had various choices of relational Data Base Management Systems (DBMS). We chose to use MySQL version 5.0.27 to implement the relational data model of the data layer of our system.

# 5. Research Methodology

In this section first we will introduce our research model, variables and measures. Then we will discuss our research hypothesis and the experiment. At the end we will present the results of the experiment and how it is related to our research hypothesis.

## 5.1. Research Model

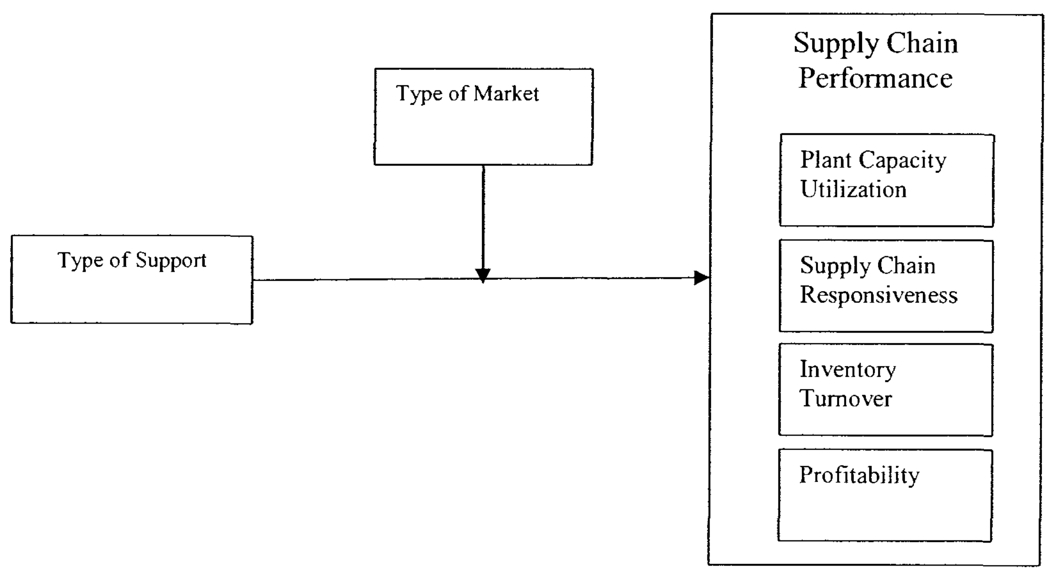


Figure 16: Research Model

The proposed model incorporates the relationship of type of decision support to supply chain performance. This model indicates that the type of decision support which include traditional decision support or situated decision support affects supply chain performance. Supply chain performance is measured through the 4 metrics of plant utilization, customer responsiveness, inventory turnover and profitability. Type of Market is the moderating variable and affects this relationship. Depending on the different market conditions, the relationship between type of support and supply chain performance is different.

Next section includes more detailed explanation of the variables and measures used in this model.

## 5.2. Variables and Measures

### Independent variable:

**Type of Support**: this variable indicates the type of decision support used for decision making in managing supply chain. There are 2 main types of support considered in this study: Traditional decision support and situated decision support.

- Traditional Decision Support (TDSS): TDSS is referred to a DSS that takes a more passive approach toward decision making and only provides basic decision support capabilities.
- Situated Decision Support (SDSS): SDSS is referred to a DSS that is situated in the environment and designed to sense the problem environment and offer decision support (Vahidov and Kersten, 2004)

### Moderating variable:

**Type of Market**: this variable is a mediator between the dependent and independent variable and encompasses two different types of changes in the market with regards to variations in customer demand as well as supply availability and prices.

Here we consider two different markets which include:

- Market with stable changes in both customer demand and supply prices
- Market with volatile changes in both customer demand and supply prices

## Dependent variable:

**Supply Chain Performance:** it is an objective measure which indicates the level of performance of the supply chain. Supply chain performance was measured by the following metrics:

- **Plant Capacity Utilization**: capacity utilization is an efficiency metric which shows the degree to which plant's capacity is utilized. Each plant has a fixed daily capacity represented in cycles and each product requires a number of production cycles. Plant capacity represents the maximum daily amount of each product that can be produced with existing equipment. As it was mentioned in section 2.1.1.1. , Plant capacity utilization or the number of consumed cycles is a measure of performance in supply chain production level and indicates the effectiveness of scheduling techniques.
- **Supply Chain Responsiveness (Order fulfillment lead time)**: Supply Chain responsiveness is a very important performance metric which shows the velocity at which a supply chain provides products to the customer. This variable is an indicator of the time it takes for the Supply Chain to respond to significant changes in demand.

  Supply Chain responsiveness can be measured through calculating the order fulfillment lead time. Fulfillment lead time for each order can be determined as [shipment date-due date] of that order. Shipment date is the date that the product is shipped to the customer and due date is the date the customer is expecting the product. This value is always greater or equal to zero. If this value is zero it means that the product is shipped on time and the customer is satisfied. The bigger the value the less satisfied is the customer.
- **Inventory Turnover**: Inventory Turnover is a measure of delivery performance metric in supply chain. Lower inventory turnover is a sign of higher percentage of goods in transit and therefore higher carrying changes. Increase in inventory turns results in reduction of

total carrying charges meanwhile the availability of good to customer increases. This will consequently result in higher supply chain performance.

- **Profitability**: Supply Chain Profitability is a financial performance measure of a supply chain. This variable takes into account the total logistics costs of procurement, flow and storage of materials from point of origin to point of sale and is an indicator of efficiency of a supply chain. In our simulation, this variable can be measured by the amount of money in the bank at the end of the simulation. The final amount is the sum of all payments received from customers for shipped products minus all payments to customers for penalties of late orders, minus payments to suppliers for purchased components.

# 5.3. Research Hypothesis

The essence of our empirical study is to validate the following hypotheses:

**H1a: In a stable market, using SDSS results in equal or higher plant capacity utilization than using TDSS.**

SDSS provides effective decision support by sensing the problem environment. In a stable market since there are no large shifts in customer demand and supply prices, using a SDSS will not necessarily result in higher capacity utilization. But we hypothesize that capacity utilization will not be lower when using a SDD rather than TDSS.

**H1b: In a Volatile market, using SDSS results in higher plant capacity utilization than using TDSS**

In a volatile market, there are large shifts in the customer demand and supply prices. A SDSS is capable of sensing the shifts in the marker and responding to this volatility by providing operation schedules to use plant capacity more efficiently. We hypothesize that in this type of market, using SDSS results in higher plant capacity utilization than using TDSS.

**H2a: In a stable market, using SDSS results in equal or higher supply chain responsiveness than using TDSS.**

The main idea behind a SDSS is to provide more responsiveness to the changes in the market which includes mainly customer demand and supply prices. However, since in a stable market both demand and supply are not changing dramatically, we believe that using a SDSS will not necessarily result in noticeably higher rate of responsiveness but it will not result in lower rate of responsiveness either.

**H2b: In a Volatile market, using SDSS results in higher supply chain responsiveness than using TDSS.**

The unstable and changing rates of both supply and demand in a volatile market requires a type of support that can proactively respond to these changes and provide real time support in order to respond to customer demands effectively. Therefore we believe that a using a SDSS will result in higher supply chain responsiveness than using a TDSS.

**H3a: In a stable market, using SDSS results in equal or higher inventory turnover than using TDSS.**

Stable market is characterized with steady changes in supply and demand. In such a market less aggressive inventory management and optimization is needed (compared to a volatile market) if supply chain is achieving a good inventory turn rate using basic decision support. Therefore, we hypothesize that in a stable market, using SDSS results in equal or higher inventory turnover than using TDSS.

**H3b: In a Volatile market, using SDSS results in higher inventory turnover than using TDSS.**

To achieve a higher inventory turnover, an organization needs to effectively plan both components procurement and production and delivery planning. This will be more challenging when supply prices and customer demand are constantly changing. We believe that using a SDSS will result in inventory cost reductions through demand and supply visibility. A SDSS is capable of sensing, forecasting and responding to market changes more effectively in order to maximize inventory efficiency. We hypothesize that using a SDSS will result in higher inventory turnover than using a TDSS.

**H4a**: **In a stable market, using SDSS results in equal or higher profitability than using TDSS.**

One of the main goals of any supply chain management strategy is to generate profit and avoid loss. The profit is sum of all money received (from customers for shipped products) minus all money paid (for purchase of components and penalties of late orders). The more efficient a supply chain is, it is in a better position to generate more revenue by producing more products in a period of time and incur less cost for components and less cost for penalties since it should be able to respond to customer orders in relatively timely manner. We believe that using a SDSS in a stable market will not necessarily result in noticeably higher profitability compared to using TDSS but it will not result in lower profitability either.

**H4b**: **In a Volatile market, using SDSS results in higher profitability than using TDSS.**

The dynamic nature of a volatile market requires a type of support that can proactively respond to the changes in customer demand and supply prices and thus generate more revenue by taking advantage of market opportunities and avoid falling victim to market fluctuations. We believe using a SDSS will result in higher profitability compared to using a TDSS.

# 5.4. Experiment

We performed several experiments to investigate the effectiveness of our Situated DSS (SDSS) vs. traditional DSS (TDSS).

## 5.4.1. Input Data

The first step in our experiment is generating the input data. Using our Input data manager (Fig. 17), we create 2 demand datasets to represent the demands in the stable market and in the volatile market.

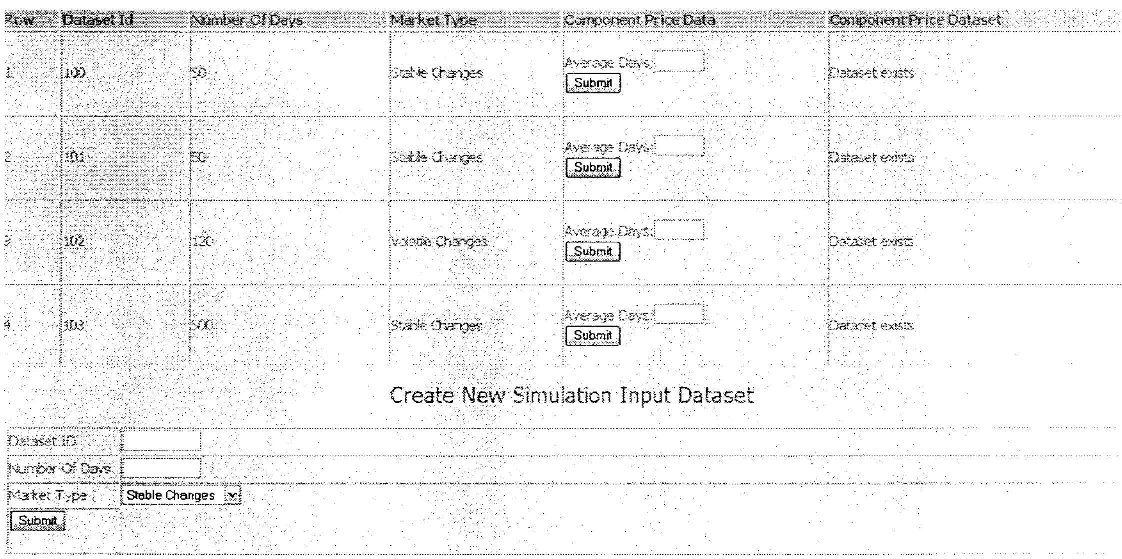


Figure 17: Input data manager

Figure 18 shows the demand for product 1 in steady market and figure 19 shows the demand for product 1 in volatile market. Appendix A includes the demand data for more products.

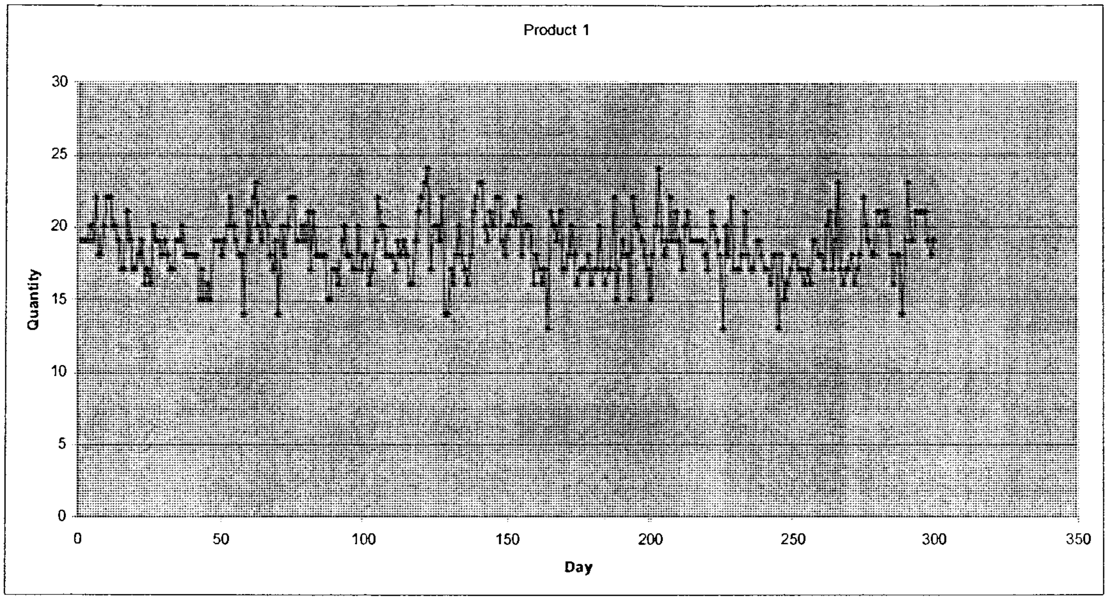


Figure 18: Demand data for product 1 in stable market

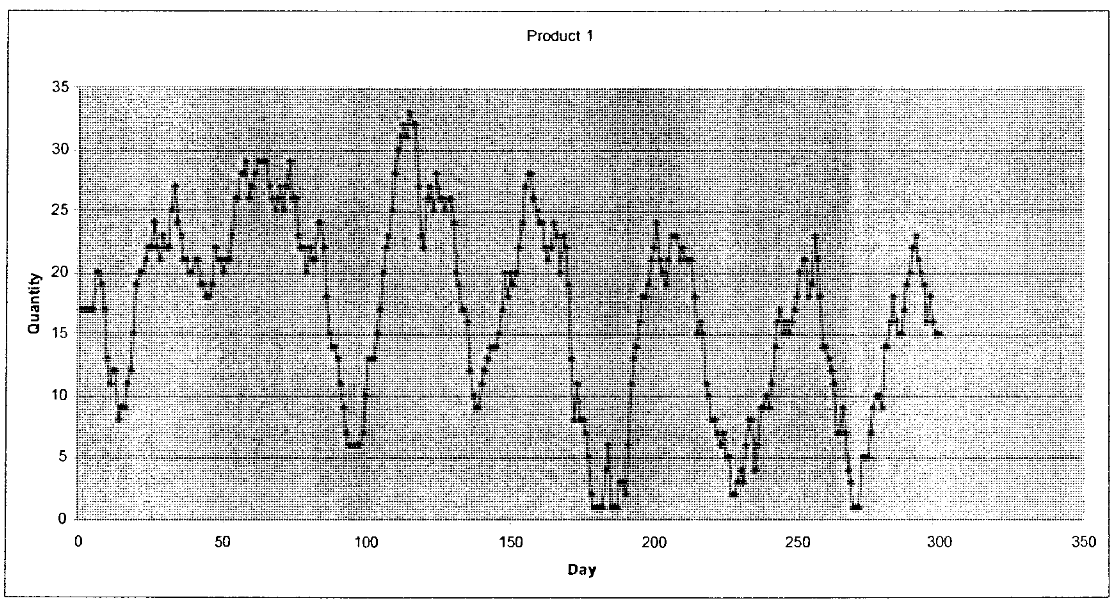


Figure 19: Demand data for product 1 in volatile market

When the demand data is produced, supply data is generated based on the demand of the products.

Product 1 in constructed from four components: 100, 200, 300, and 400.

Figures 20 and 21 show the supply prices of each product 100 in steady and volatile markets. Appendix B includes the supply prices for the more components.

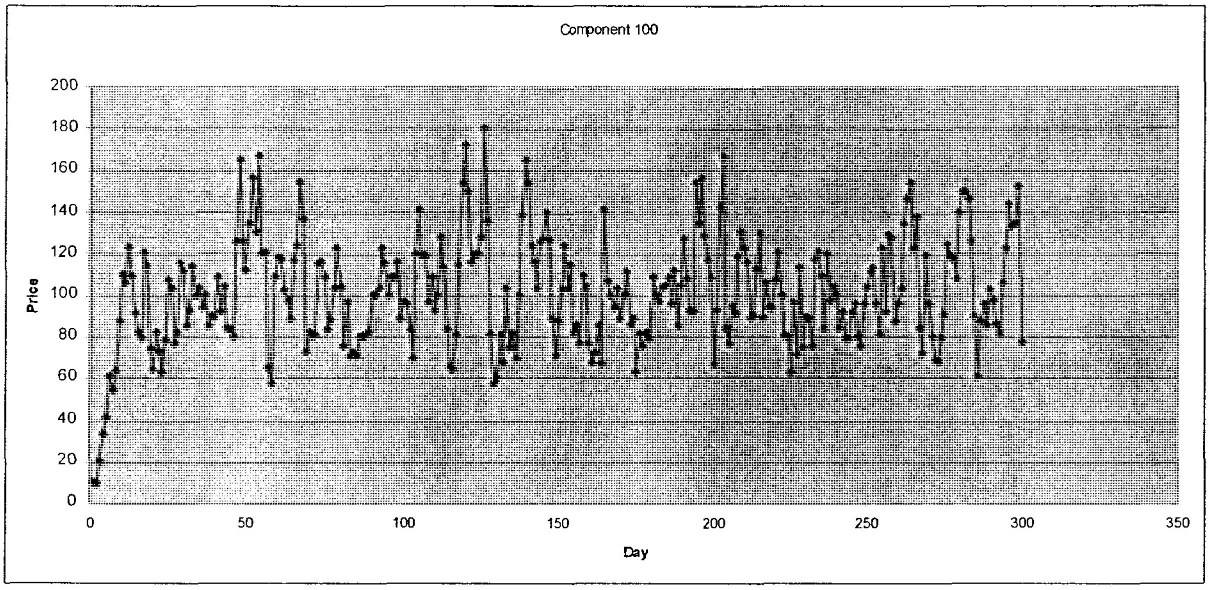


Figure 20: Supply prices for component 100 in steady market

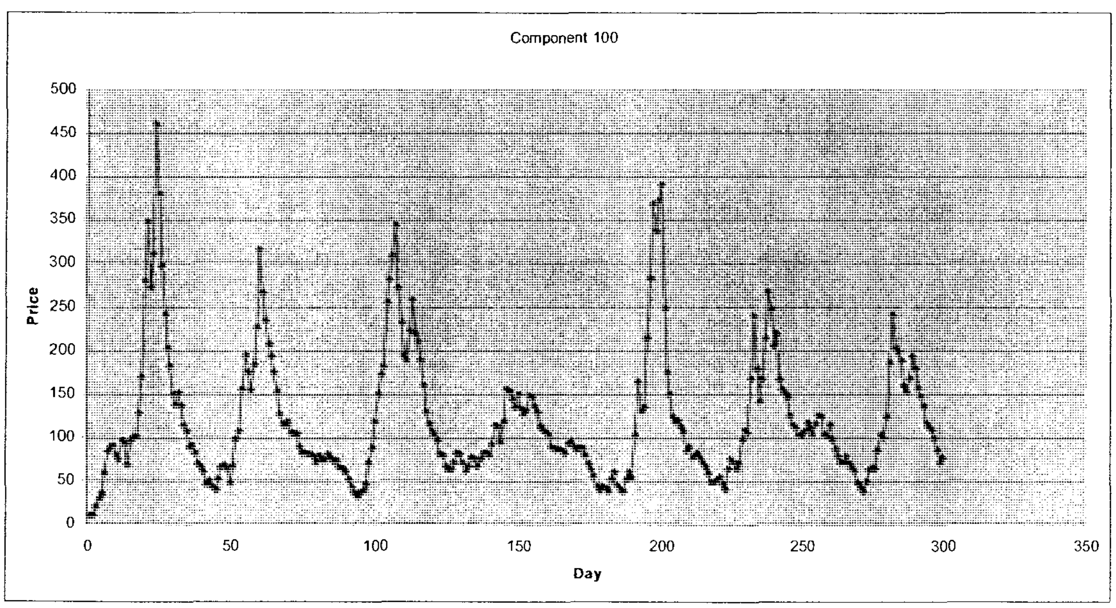


Figure 21: Supply prices for component 100 in volatile market

At the end of this step we have the demand and supply input data for an experiment.

## 5.4.2. Simulation Sessions

When demand and supply data are available for both types of markets, we are ready to perform our experiments using our simulation session coordinate (figure 22).

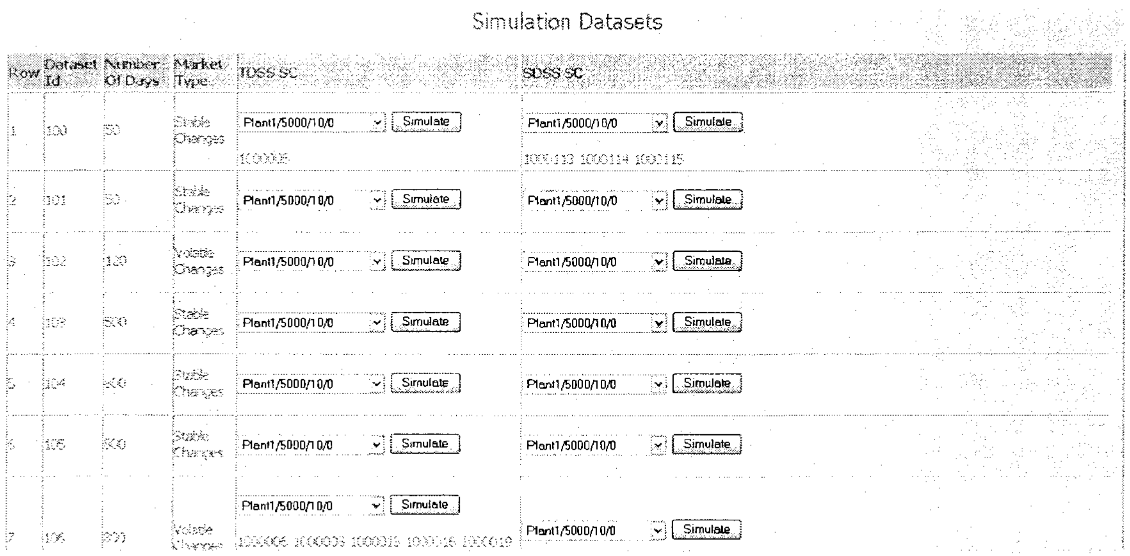


Figure 22: Simulation Session Coordinator

At this point we run the simulation in each type of market for 300 days; once using the tradition DSS (TDSS) and once using the Situated DSS (SDSS). In each simulation we use we use Plant 7 which has an initial inventory of zero components and zero products. At the end of the experiment we have 4 result sets. Result set 1 needs to be compared against result set 2. And result set 3 needs to be compared against result set 4.

| | TDSS | SDSS |
|---|---|---|
| Steady Market | Result set ID (simulation ID) 1 | Result set ID (simulation ID) 2 |
| Volatile Market | Result set ID (simulation ID) 3 | Result set ID (simulation ID) 4 |

Table 3: **Result set matrix**

Each of the three variables- plant capacity utilization, order fulfillment lead time and inventory Turnover- are measured at the end of each day of the simulation session. However profitability or the final balance is measured at the end of each simulation session. Therefore, in order to have a larger sample size, we performed 60 simulations; 30 simulations on stable markets and 30 simulations on volatile market. Each group of 30 simulation includes 15 simulation using TDSS and 15 simulation using SDSS.

## 5.5. Results

In the section we discuss the result of the experiment. In order to test each hypothesis, we use independent sample t-tests to check if the variations between two groups (SDSS and TDSS) for each variable in each type market are significant. Before performing the t-tests, we also use ANOVA in order to test for differences among the four groups mentioned in table 3.

Table 4 shows the results of ANOVA for On Time Fulfillment rate among the 4 groups.

**ANOVA**

Ontime Fullfillment Rate

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 1449.755 | 3 | 483.252 | 342.614 | .000 |
| Within Groups | 10131.517 | 7183 | 1.410 | | |
| Total | 11581.273 | 7186 | | | |

Table 4: ANOVA result- On time Fulfillment Rate

The results show that there is a significant difference for On Time Fulfillment rate among the groups tested, $F\ (3, 7183) = 342.614, p < .05$.

Table 5 shows the results of ANOVA on Inventory Turnover rate between the 4 groups.

**ANOVA**

Inventory Turnover

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 103.631 | 3 | 34.544 | 95.740 | .000 |
| Within Groups | 423.229 | 1173 | .361 | | |
| Total | 526.860 | 1176 | | | |

Table 5: ANOVA result- Inventory Turnover

The results show that there is a significant difference for Inventory Turnover rate among the groups tested, $F\ (3, 1173) = 95.740, p < .05$.

Table 6 shows the results of ANOVA for Consumed Cycles rate among the 4 groups.

**ANOVA**

ConsumedCycles

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 554304.4 | 3 | 184768.129 | 18.469 | .000 |
| Within Groups | 11545139 | 1154 | 10004.453 | | |
| Total | 12099443 | 1157 | | | |

Table 6: ANOVA result- Consumed Cycles

The results show that there is a significant difference for Consumed Cycles rate among the groups tested, $F\ (3, 1154) = 18.469, p < .05$.

H1a states that in a stable market, using SDSS results in equal or higher plant capacity utilization than using TDSS. We used simulation result set 1 and 2 (table 3). We performed an independent sample t-test to compare the mean scores of two groups on Plant Capacity Utilization (or consumed cycles) in a stable market.

Group Statistics

| | Simulation id | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Consumed Cycles | 1 | 294 | 457.80 | 88.822 | 5.180 |
| | 2 | 290 | 467.31 | 98.618 | 5.791 |

Table 7: Mean comparison for Plant Capacity Utilization in stable market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| Consumed Cycles | Equal variances assumed | 1.327 | 0.250 | -1.226 | 582 | 0.110 | -9.518 | 7.764 | -24.767 | 5.732 |
| | Equal variances not assumed | | | -1.225 | 574.023 | 0.110 | -9.518 | 7.770 | -24.779 | 5.743 |

Table 8: Independent Samples Test on Plant Capacity Utilization in stable market

The results indicate that there was no significant difference in performance between TDSS (ID 1) and SDSS (ID 2), $t$ (574) = 1.22, $p$ = 0.11. That is, the average plant utilization capacity of TDSS ($M$ = 458, SD = 89) was not significantly lower than that of SDSS ($M$ = 467, SD = 99). Therefore, H1a is supported.

H1b states that in a volatile market, using SDSS results in higher plant capacity utilization than using TDSS. We used simulation result set 3 and 4. We performed an independent sample T tests to compares the mean scores of two groups on Plant capacity utilization (or consumed cycles) in a volatile market.

**Group Statistics**

| | Simulation id | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Consumed Cycles | 3 | 293 | 412.24 | 103.227 | 6.031 |
| | 4 | 281 | 430.73 | 108.749 | 6.487 |

Table 9: Mean comparison for Plant Capacity Utilization in volatile market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| Consumed Cycles | Equal variances assumed | 0.859 | 0.354 | -2.090 | 572 | 0.018 | -18.491 | 8.848 | -35.869 | -1.113 |
| | Equal variances not assumed | | | -2.088 | 567.002 | 0.018 | -18.491 | 8.857 | -35.888 | -1.093 |

Table 10: Independent Samples Test on Plant Capacity Utilization in volatile market

The results indicate that there was significant difference in performance between TDSS (ID 3) and SDSS (ID 4), $t$ (567) = 2.08, $p$ = 0.01. That is, the average plant capacity utilization of

SDSS ($M = 430$, SD = 109) was significantly higher from that of TDSS ($M = 412$, SD = 103). Therefore, H1b is supported.

H2a states that in a stable market, using SDSS results in equal or higher supply chain responsiveness than using TDSS. We used simulation result set 1 and 2. We performed an independent sample T tests to compares the mean scores of two groups on Supply Chain online fulfillment rate in a stable market. As mentioned before, Supply Chain responsiveness is measured through online fulfillment rate. The lower the Supply Chain online fulfillment rate the higher is the Supply Chain responsiveness.

**Group Statistics**

| | Simulation id | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| On time fulfillment rate | 1 | 2,565 | 0.84 | 1.089 | 0.021 |
| | 2 | 2,571 | 0.73 | 1.061 | 0.021 |

Table 11: Mean comparison for On Time Fulfillment rate in stable market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| On time fulfillment rate | Equal variances assumed | 0.197 | 0.657 | 3.722 | 5,134 | 0.000 | 0.112 | 0.030 | 0.053 | 0.170 |
| | Equal variances not assumed | | | 3.722 | 5,129.936 | 0.000 | 0.112 | 0.030 | 0.053 | 0.170 |

Table 12: Independent Samples Test for On Time Fulfillment rate in stable market

The results indicate that there was significant difference in performance between TDSS (ID 1) and SDSS (ID 2), $t$ (5130) = 3.72, $p$ = 0.00. That is, the average supply chain online fulfillment rate of TDSS ($M$ = 0.84, SD = 1.08) was significantly higher than that of SDSS ($M$ = 0.73, SD = 1.06). This implies that, supply chain responsiveness of TDSS was significantly lower than that of SDSS Therefore, H2a is supported.

H2b states that in a volatile market, using SDSS results in higher supply chain responsiveness than using TDSS. We used simulation result set 3 and 4. We performed an independent sample T tests to compare the mean scores of two groups on Supply Chain online fulfillment rate in a volatile market.

**Group Statistics**

| | Simulation id | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| On time fulfillment rate | 3 | 1,024 | 2.08 | 1.279 | 0.040 |
| | 4 | 1,027 | 1.13 | 1.569 | 0.049 |

Table 13: Mean comparison for On Time Fulfillment rate in volatile market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| On time fulfillment rate | Equal variances assumed | 95.890 | 0.000 | 15.050 | 2,049 | 0.000 | 0.952 | 0.063 | 0.828 | 1.076 |
| | Equal variances not assumed | | | 15.055 | 1,970.910 | 0.000 | 0.952 | 0.063 | 0.828 | 1.075 |

Table 14: Independent Samples Test for On Time Fulfillment rate in volatile market

The results suggests that there was significant difference in performance between TDSS (ID 3) and SDSS (ID 4), $t$ (1971) = 15.055, $p$ = 0.00. That is, the average supply chain online fulfillment rate of SDSS ($M$ = 1.13, SD = 1.56) was significantly lower than that of TDSS ($M$

= 2.08, SD = 1.27). This implies that, supply chain responsiveness of SDSS was significantly higher than that of TDSS. Therefore, H2b is supported.

H3a states that in a stable market, using SDSS results in equal or higher inventory turnover than using TDSS. We used simulation result set 1 and 2. We performed an independent sample T tests to compares the mean scores of two groups on Inventory Turnover in a stable market.

**Group Statistics**

| | Simulation Id | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Inventory Turnover | 1 | 294 | 0.65 | 0.293 | 0.017 |
| | 2 | 294 | 1.00 | 0.362 | 0.021 |

Table 15: Mean comparison for on Inventory Turnover rate in stable market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference Lower | Upper |
| Inventory Turnover | Equal variances assumed | 19.948 | 0.000 | -12.813 | 586 | 0.000 | -0.348 | 0.027 | -0.401 | -0.295 |
| | Equal variances not assumed | | | -12.813 | 561.362 | 0.000 | -0.348 | 0.027 | -0.401 | -0.295 |

Table 16: Independent Samples Test on Inventory Turnover rate in stable market

The results suggests that there was significant difference in performance between TDSS (ID 1) and SDSS (ID 2), $t$ (561) = 13, $p$ = 0.00. That is, the average Inventory Turnover of TDSS ($M$ = 0.65, SD = 0.293) was significantly lower than that of SDSS ($M$ = 1.0, SD = 0.362). Therefore, H3a is supported.

H3b states that in a Volatile market, using SDSS results in higher inventory turnover than using TDSS. We used simulation result set 3 and 4. We performed an independent sample T tests to compares the mean scores of two groups on Inventory Turnover in a volatile market.

**Group Statistics**

| | Simulation Id | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Inventory Turnover | 3 | 295 | 1.18 | 0.667 | 0.039 |
| | 4 | 294 | 1.47 | 0.883 | 0.052 |

Table 17: Mean comparison for on Inventory Turnover rate in volatile market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference Lower | Upper |
| Inventory Turnover | Equal variances assumed | 13.386 | 0.00 | -4.477 | 587 | 0.000 | -0.289 | 0.065 | -0.415 | -0.162 |
| | Equal variances not assumed | | | -4.475 | 545.290 | 0.000 | -0.289 | 0.065 | -0.416 | -0.162 |

Table 18: Independent Samples Test on Inventory Turnover rate in volatile market

The results suggests that there was significant difference in performance between TDSS (ID 3) and SDSS (ID 4), t (545) = 4.47, p = 0.00. That is, the average Inventory Turnover of SDSS (M = 1.18, SD = 0.667) was significantly higher than that of TDSS (M = 1.46, SD = 0.883). Therefore, H3b is supported.

H4a states that in a stable market, using SDSS results in equal or higher supply chain profitability than using TDSS.

**Group Statistics**

| | Type of support | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Final Balance | 1 | 15 | 484,654,507.07 | 4,017,399.057 | 1,037,287.976 |
| | 2 | 15 | 495,524,358.07 | 7,478,930.825 | 1,931,051.636 |

Table 19: Mean comparison for on Final Balance in stable market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | 95% Confidence Interval of the Difference | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| Final Balance | Equal variances assumed | 5.275 | 0.029 | -4.959 | 28 | 0.000 | -10,869,851 | 2,192,014.3 | -15,359,988.8 | -6,379,713.2 |
| | Equal variances not assumed | | | -4.959 | 21.45 | 0.000 | -10,869,851 | 2,192,014.3 | -15,422,473.9 | -6,317,228.1 |

Table 20: Independent Samples Test on Final Balance in stable market

The results suggests that there was significant difference in performance between TDSS (Type of support 1) and SDSS (Type of support 2), t (21) = 4.95, p = 0.00. That is, the average final balance of TDSS (M = 495,524,358.07, SD = 7,478,930.825) was significantly lower than that of SDSS (M = 484,654,507.07, SD = 4,017,399.057). Therefore, H4a is supported.

H4b states that in a Volatile market, using SDSS results in higher supply chain profitability turnover than using TDSS.

**Group Statistics**

| | Type of Support | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Final Balance | 1 | 15 | 411,523,084.4 | 19,762,872.8 | 5,102,751.8 |
| | 2 | 15 | 456,460,288.4 | 16,103,109.7 | 4,157,805.1 |

Table 21: Mean Comparison for on Final Balance in volatile market

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (1-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| Final Balance | Equal variances assumed | 0.867 | 0.360 | -6.827 | 28 | 0.000 | -44,937,204.0 | 6,582,204.7 | -58,420,239.2 | -31,454,168.9 |
| | Equal variances not assumed | | | -6.827 | 26.903 | 0.000 | -44,937,204.0 | 6,582,204.7 | -58,445,062.7 | -31,429,345.4 |

Table 22: Independent Samples Test on Final Balance in volatile market

The results suggests that there was significant difference in performance between TDSS (Type of support 1) and SDSS (Type of support 2), $t(27) = 6.82$, $p = 0.00$. That is, the average final balance of SDSS ($M = 456,460,288.4$, $SD = 16,103,109.7$) was significantly higher than that of TDSS ($M = 411,523,084.4$, $SD = 19,762,872.8$). Therefore, H4b is supported.

# 6. Conclusions

Advanced decision support and software agents are promising in the area of supply chain management and have the potential for improving different supply chain processes.

In this research we presented a holistic view about applications of these technologies in the area of supply chain management and their great potential to overcome different limitation of supply chain management in supporting both customer responsiveness and supplier synchronization. We also presented a model of agent-based DSS called Situated Decision Support System (SDSS) which is integrated with the supply chain environment and is capable of sensing the stimuli and acting upon them. The ultimate aim of this model is to provide a higher level of integration with the business environment to enable the supply chain achieve the capability of fast adaptation to unforeseen changes, market fluctuations and new customer requirements. This capability is defined as agility.

We observed from the result of our experiments that using SDSS results in higher supply chain performance. Based on our findings, the effectiveness of SDSS is more significant in volatile markets than stable markets. This can be explained through the ability of SDSS to sense and respond quickly and effectively to changing market conditions. In a stable market since there are no sharp changes in the environment, there is not necessarily a significant difference between the performance of TDSS and SDSS, provided that TDSS offers optimal support in response to stable market demands and supply availability.

For practitioners in the area of supply chain management, the implementation of the proposed SDSS is considered a way to increase the effectiveness of their decision making process and enhance the level of supply chain flexibility and agility.

One major concern that needs to be discussed is feasibility of such systems. Feasibility can be discussed in terms of complexities of development and implementation. Although development of such complex systems requires a lot of effort, the advancement in new software engineering methodologies and tools and the movement toward non-monolithic architectures make the development of such systems possible.

This work does not provide a detailed architecture of a supply chain decision station; instead it provides a basis for such DSS, its major components and their required capabilities. Much more work is needed to actually provide a detailed design and implementation.

The main limitation of this study is the lack of human subject in the experiments. Due to time and resource constraints we had to simulate the actions of the human subject in the context of both TDSS and SDSS. As we have mentioned before, we support a two way interaction between the SDSS and the user and we argue that the SDSS is not fully capable of undertaking its tasks without human intervention. One of the important reasons that prevented us from involving humans in the experiment was the lack of human subject with supply chain management expertise. However, the main reason for excluding human user in the experiments was the time restriction that human factor would impose on the experiments. In order to achieve a viable result, we needed to perform supply chain activities for a relatively long period of time. In each experiment we ran the simulation for 300 days for each market type and support type. Involving human factor would have limited this period to only 20 or 30 days based on our time and budget restrictions. Even if we overlook these restrictions, involving human subject without any supply chain expertise would not have added any value to the experiments.

Another area of improvement of this study is related to the nature of the simulation systems. The scenario that we have simulated captures many challenges for decision making in the area of supply chain management specially the fluctuations in the demand and supply.

However there are many possible extensions to the simulated scenarios. Something that can be incorporated in the simulation environment for future work is operational contingencies. In current simulation system we have accounted for limitations in the production capacity of the plant and also capacity of supplier's production. However, no unforeseen event such as delays in supply delivery, losses of capacity, or quality problems has been included in the simulated scenarios.

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# 8. Appendices

## Appendix A:

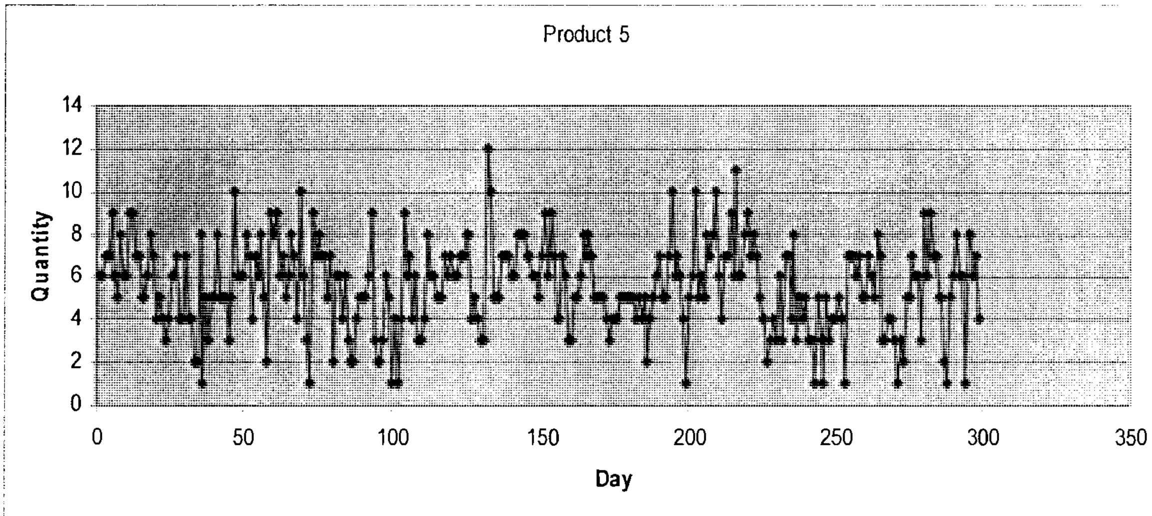


Figure 23: Demand data for product 5 in Stable market

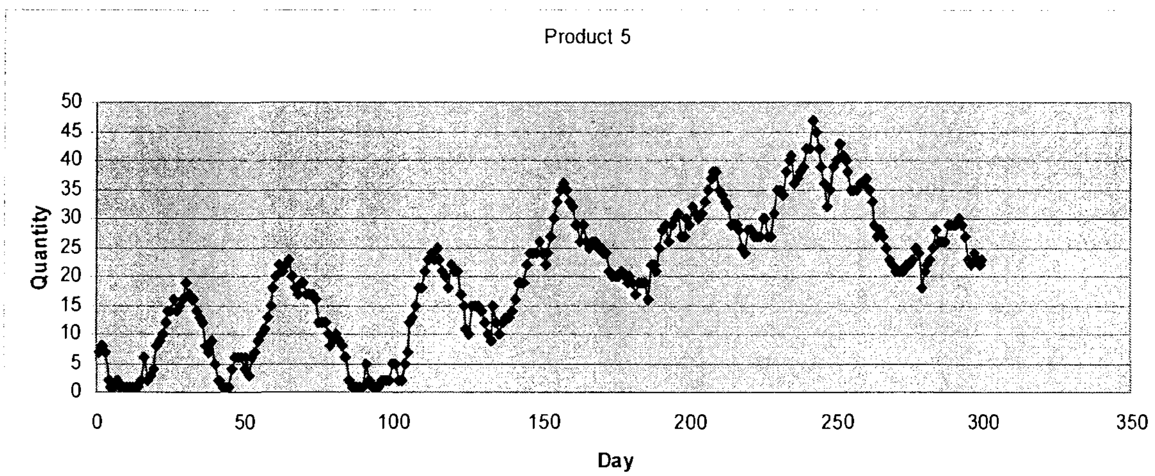


Figure 24: Demand data for product 5 in volatile market

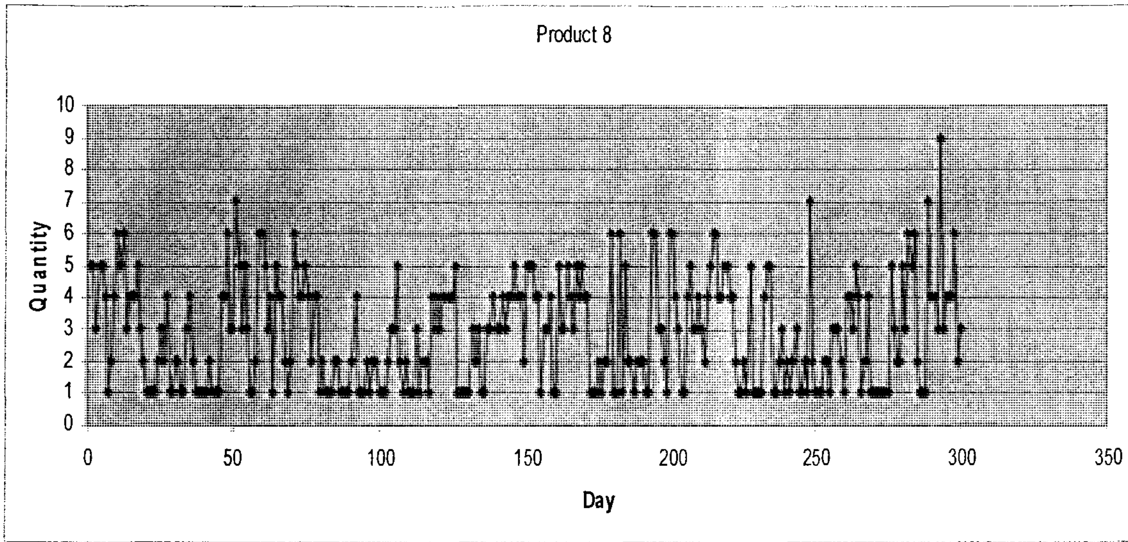


Figure 25: Demand data for product 8 in Stable market

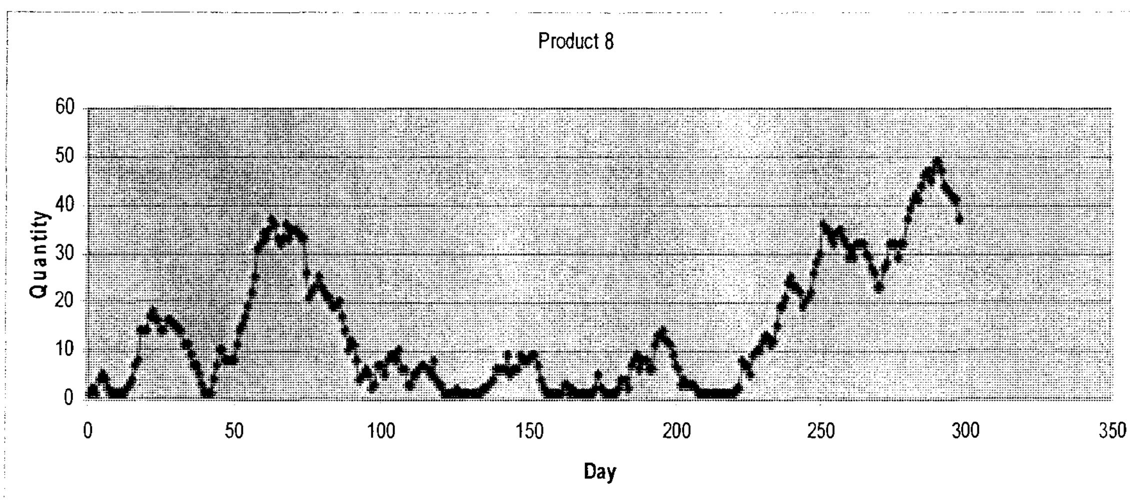


Figure 26: Demand data for product 8 in volatile market

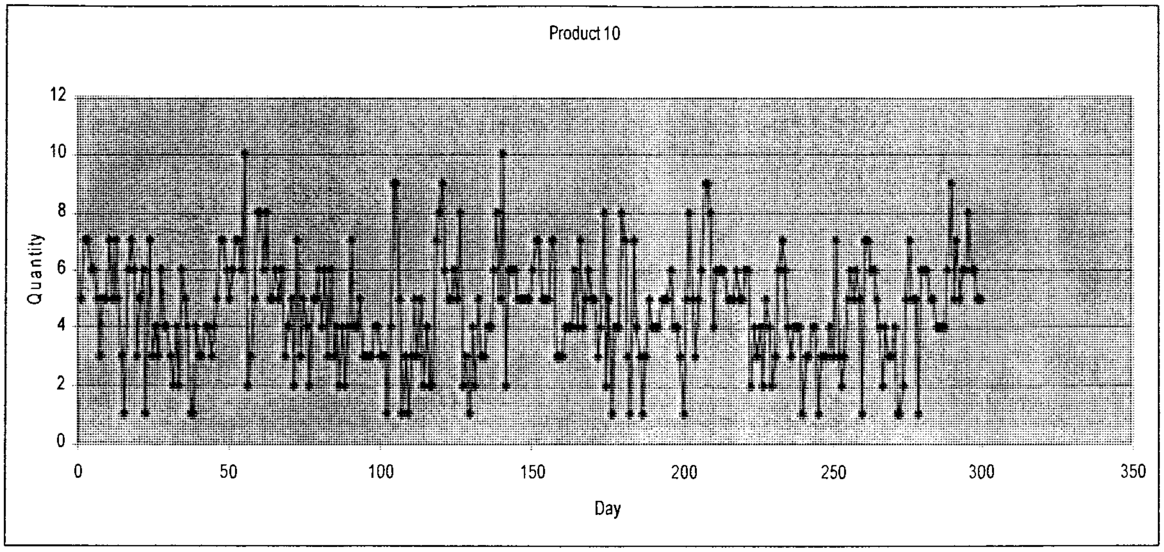


Figure 27: Demand data for product 10 in Stable market

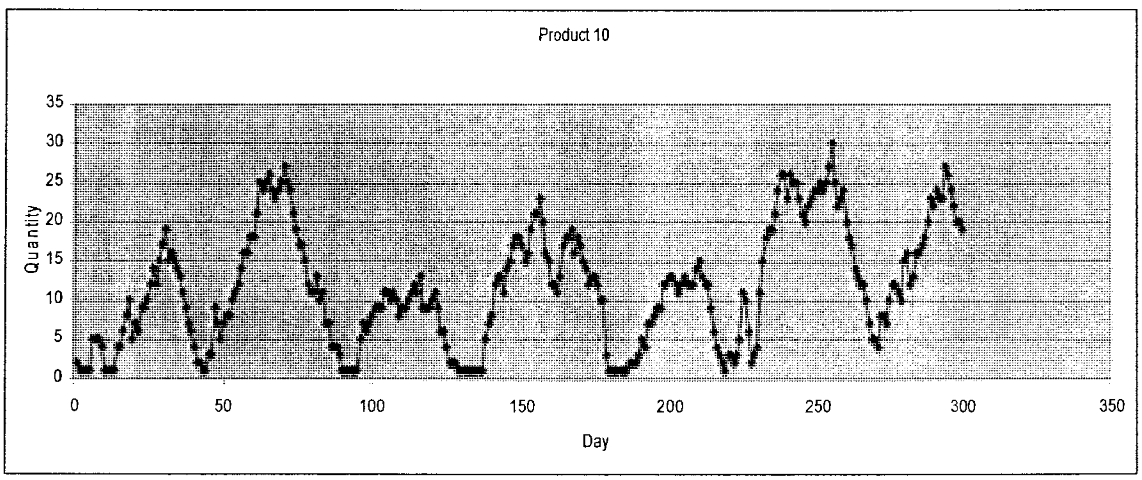


Figure 28: Demand data for product 10 in volatile market

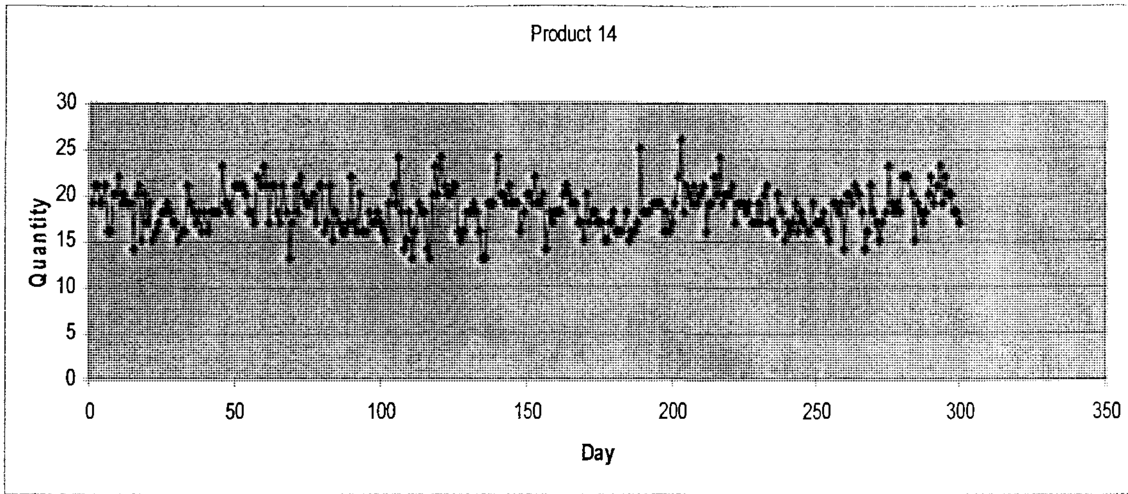


Figure 29: Demand data for product 14 in Stable market

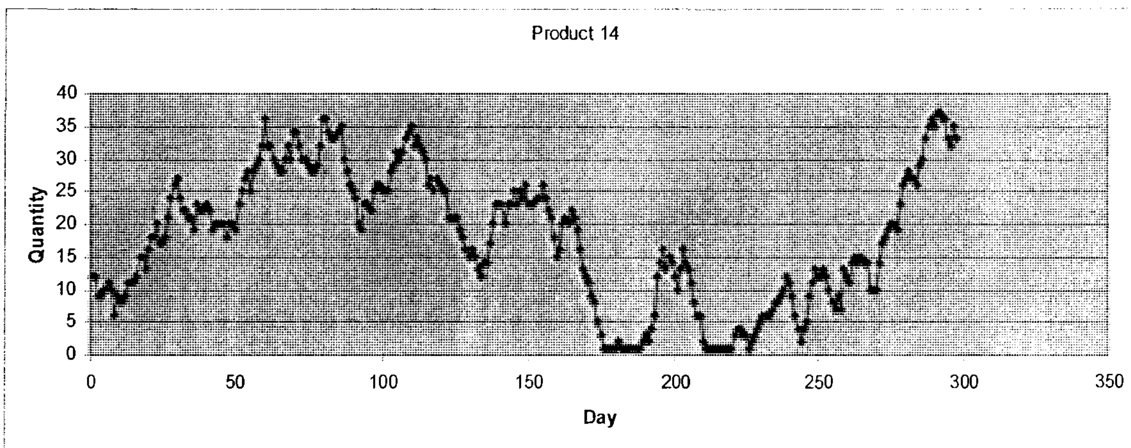


Figure 30: Demand data for product 14 in volatile market

# Appendix B:

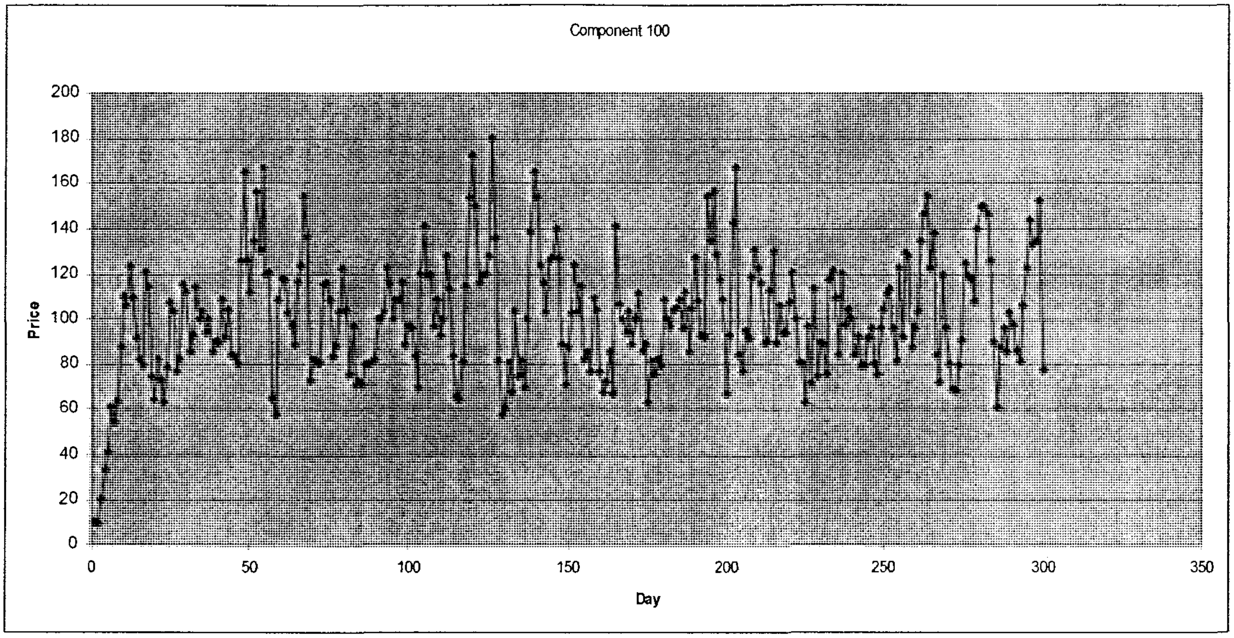


Figure 31: Component 100 Price Pattern, Stable Market

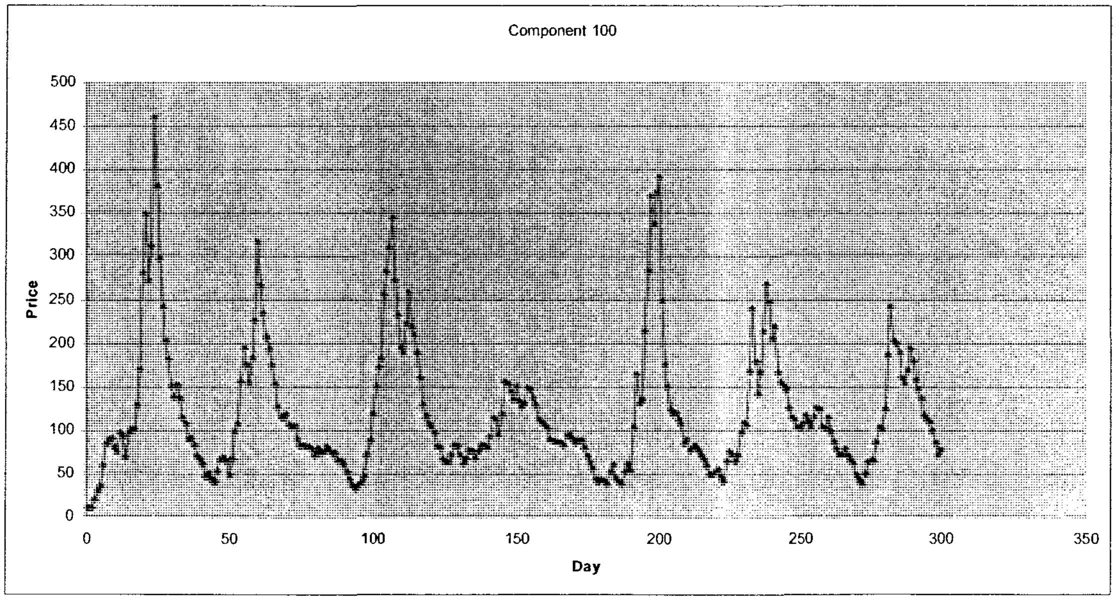


Figure 32: Component 100 Price Pattern, Volatile Market

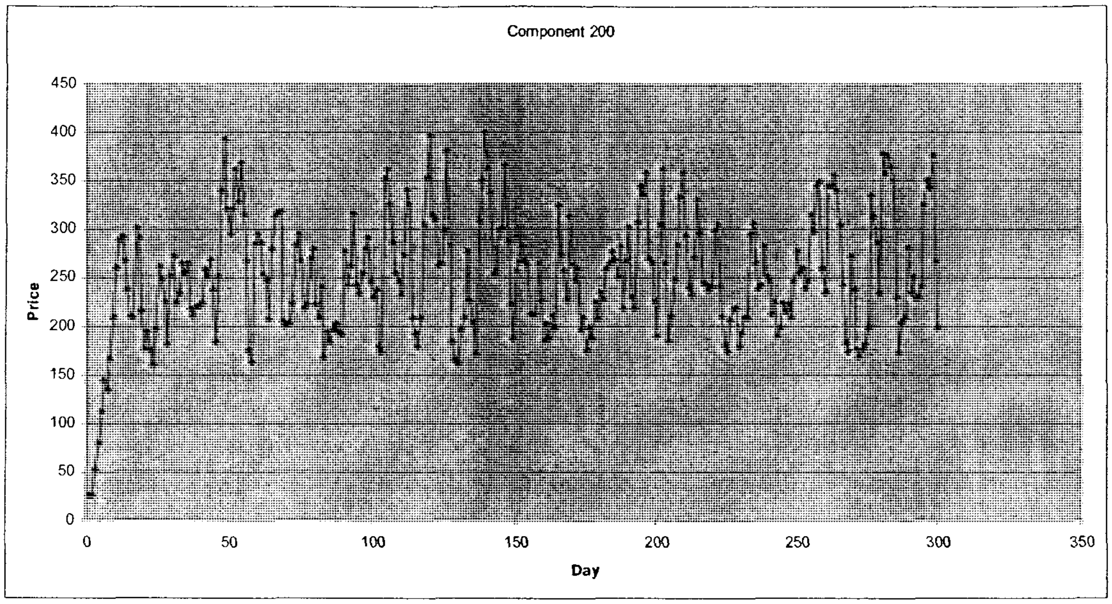


Figure 33: Component 200 Price Pattern, Stable Market

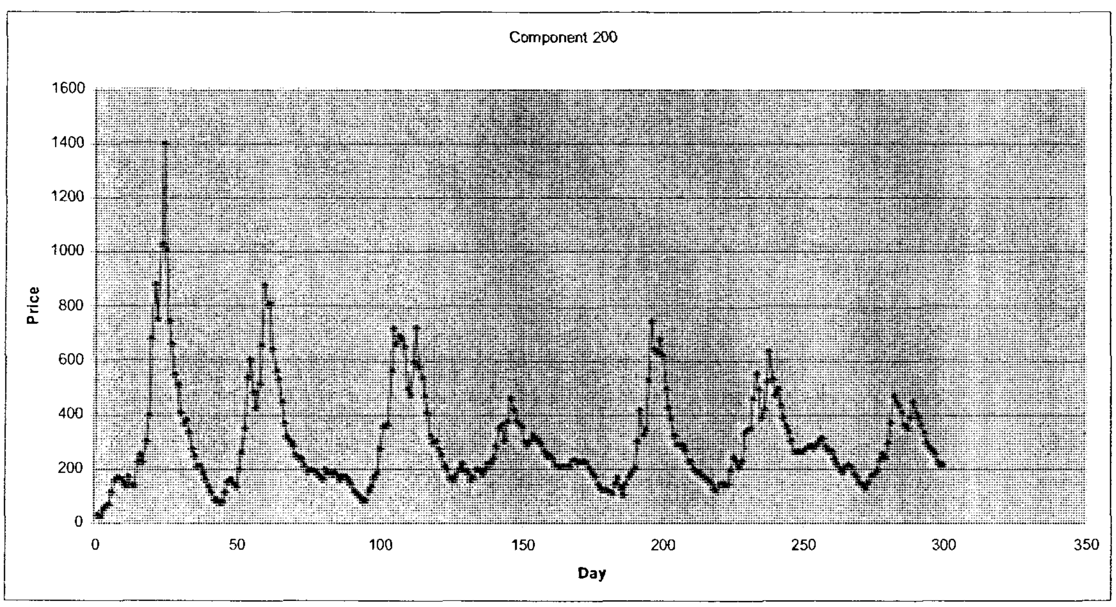


Figure 34: Component 200 Price Pattern, Volatile Market

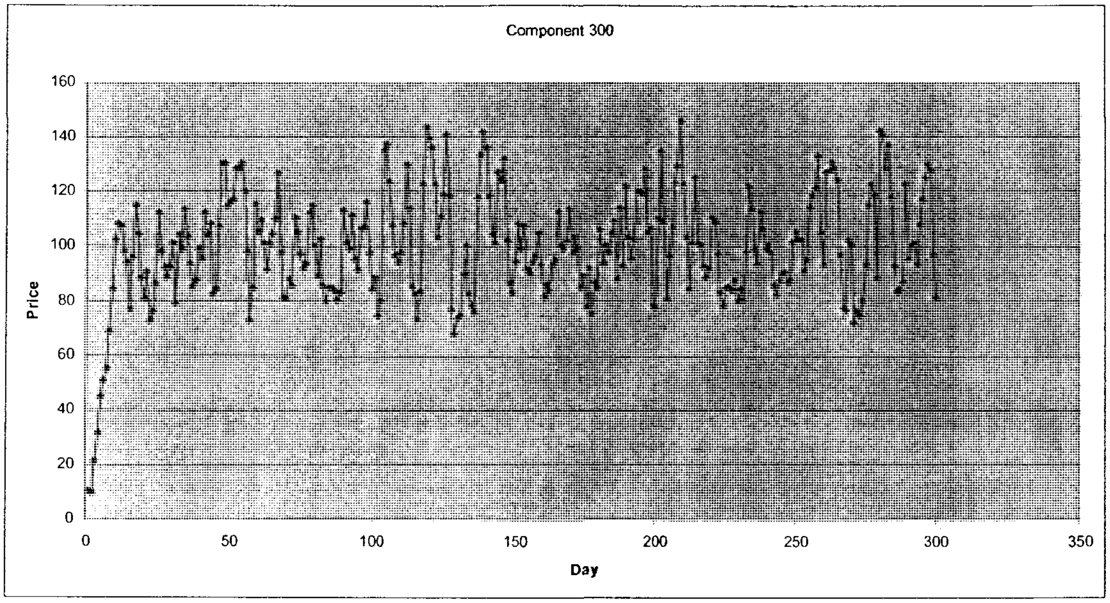


Figure 35: Component 300 Price Pattern, Stable Market

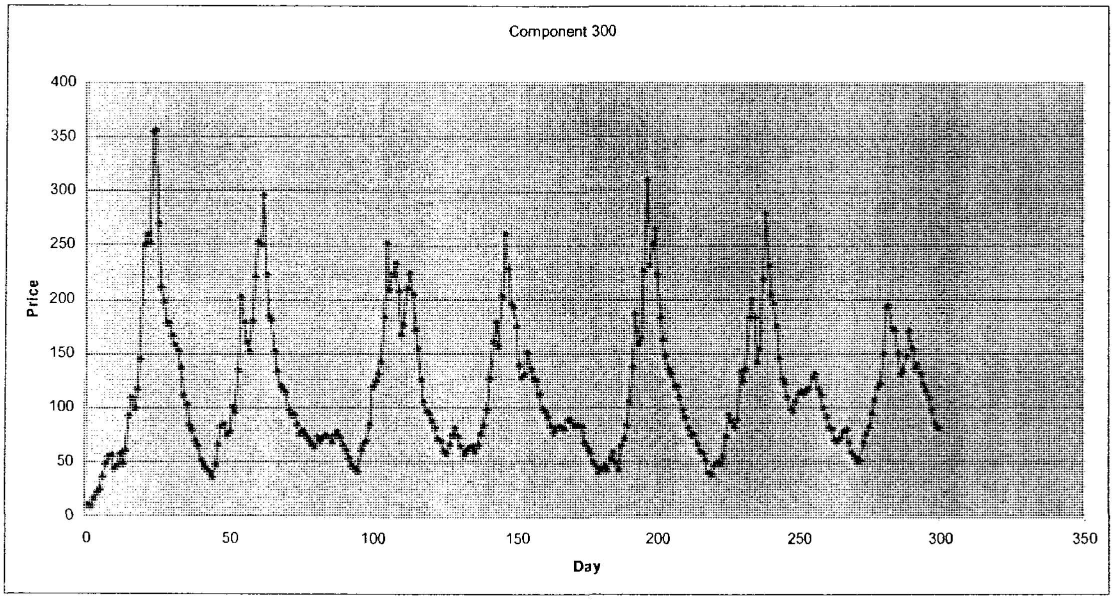


Figure 36: Component 300 Price Pattern, Volatile Market

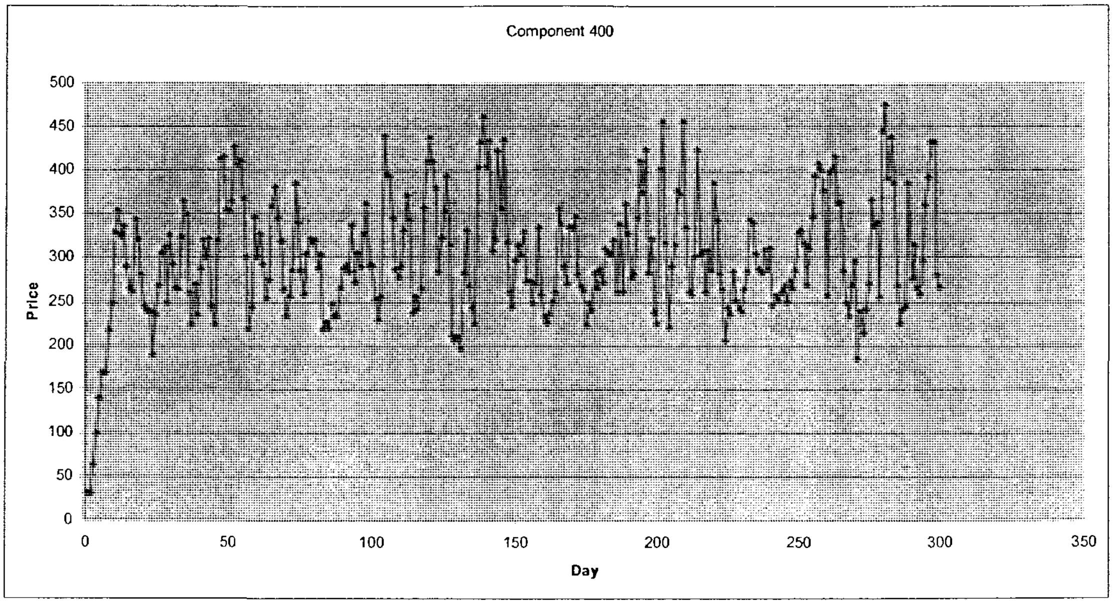


Figure 37: Component 400 Price Pattern, Stable Market

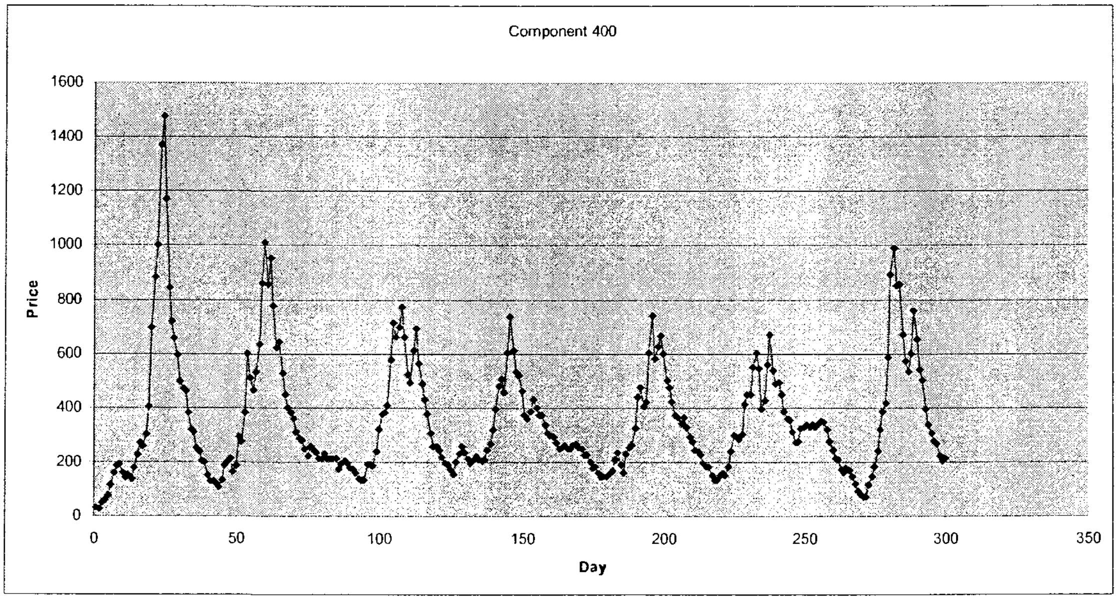


Figure 38: Component 400 Price Pattern, Volatile Market