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Supply Chain Risk Assessment for Perishable Products Applying System Dynamics Methodology - A Case of Fast Fashion Apparel Industry

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by

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ABSTRACT

With the fast progress of science and technology and with the continuously growing customer expectations, share of merchandise exhibiting characteristics of perishability is on the rise. Perishable products, through their own nature, are subject to decay, deterioration or obsolescence. As a result, their usefulness, value or functionality is gradually reduced or even lost in a short window of time and cannot be regained if it is not used or sold within a specific time window.

When producing perishable products, all stages of the supply chain are exposed to much higher uncertainty than in the case of durable products, which directly means higher risk. The phases of inventory planning, lead time control, and demand forecasting for perishable products play a critical role in the overall effectiveness of the supply chain.

For this reason, the system dynamics methodology, a simulation and modeling technique developed specifically to address the long term and dynamic management issues, is adopted in this study. The focus of the proposed model is on the interaction between physical processes, information flows and managerial policies of a three-level supply chain for perishable products, in general, and fast fashion apparel supply chain, in particular, so as to create the dynamics of the variables of interest. The values of supply chain key factors such as, for example, inventory, backlogs, stock-outs, forecast error, cost, and profit for each time period are some of the outputs of the proposed model.

Moreover, the Conditional Value at Risk (CVaR) measure is applied to quantify and analyze the risks associated with the supply chain for this type of product and also to determine the expected value of the losses and their corresponding probabilities. With the focus on three prominent categories of risks including risks of delays, forecast, and inventory, multiple business situations for effective strategic planning and decision making are generated and analyzed.

DEDICATION

To my parents who smoothened the path of my dreams and unconditionally supported me through all my walks of life.

To my husband without whose caring support it would have been much more difficult.

To my sisters and brother who believed in me and were always there for me.

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CHAPTER 1
INTRODUCTION

A supply chain is a network of organizations that are involved, through downstream and upstream links, in various activities and processes that create value to consumers (Christopher, 1992). The operation of a supply chain network has many merits, such as lower production and transaction costs, resource sharing, and core business concentration, which provide the enterprises with more profitable opportunities. However, it also involves various risks (Wu and Olson, 2008). Uncertainty in the demand for products is the primary source of risk in the supply chain. In the recent years, several interdependent factors such as higher product variety, shorter product life cycles, increased customer expectations, more complex and longer supply chains, and more global competitions have increased this uncertainty considerably. Moreover, capacity constraints, supply variability, parts quality problems, long lead times, and manufacturing yields besides disruptions due to war and natural disasters are some other sources of risks affecting the supply chain (Sheffi and Rice, 2005).

So far, the study of supply chain risk management (SCRM) has not adequately addressed the challenges associated with increasing supply chain risks (Khan and Burnes, 2007; Thun and Hoenig, 2011). Tang and Musa (2011) studied the research development in SCRM through a comprehensive literature survey relevant to supply chain operations management published between 1995 and 2009. Their investigation reveals that only a small fraction of the papers on SCRM explores the use of quantitative methods and the majority of the literature mainly falls under the category of qualitative approaches. According to their survey, among 138 papers, 78% include only conceptual models, overview and exploratory reviews or empirical studies.

This research is motivated by the need for the development of methodological tools that would quantify the risks associated with the supply chain in order to ease the decision-making process in this field.

Although assessing and managing the supply chain risk is a vital issue for all types of products, the supply chains dealing with perishable products have a need for even higher awareness of this issue due to the particular characteristics of such products. In this research, we investigate the supply chain of fast fashion apparel industry where product life cycles are extremely short and market demand is highly volatile. Low predictability and high level of impulse purchases are the other characteristics of fashion markets. In addition, the fashion industry has recently experienced a great deal of change, particularly with high levels of price competition and global sourcing. All the previously mentioned factors increase the importance of risk assessment for the supply chain of fast fashion products. Despite this potential, we see that the industry has not drawn sufficient attention in terms of supply chain management research and practice (Bruce et al., 2004; Sen, 2008).

The primary modeling and analysis tool used in this research is system dynamics (SD) methodology. Forrester (1961) presented a methodology for the simulation of dynamic models, which is the origin of system dynamics (Sterman, 2000). Since then, SD has been successfully applied to many research fields. System dynamics is considered one of the most effective methods for analyzing complex systems (Campuzano and Mula, 2011).

1.1. Perishability

"Perishable" is an adjective describing something subject to decay, spoilage, obsolescence or destruction. In other words, something cannot be regained when it is not used in time or when it remains unsold. It is a loss of economic opportunity. This phenomenon of perishability can be used to explain the difference between goods, services and information (12 Manage).

Products can have various levels of perishability. For example, tomatoes are highly perishable, because they are subject to natural deterioration/aging process, which reduces their value quickly. A diamond, on other hand, is not perishable at all. Services only have value when they are offered and consumed, so they are always considered perishable. Information also has different levels of perishability. The value of information can vary with time, depending on the sort of information (e.g., news have a different lasting value than encyclopedic knowledge) (12 Manage).

Perishable goods can be broadly classified into two main categories based on: (i) Deterioration (ii) Obsolescence. Deterioration refers to damage, spoilage, vaporization, depletion, decay (e.g., radioactive substances), degradation (e.g., electronic components) and loss of potency (e.g., pharmaceuticals and chemicals) of goods. Obsolescence is loss of value of a product due to arrival of new and better products (Goyal and Giri, 2001). This research is mainly focused on the category of goods for which obsolescence is the cause of perishability.

Sometimes planned obsolescence or built-in obsolescence policy is the cause of perishability, that is, a product with limited useful life is designed and produced so it will become obsolete (unfashionable or unfunctional) after a certain period of time (Bulow, 1986). Planned obsolescence has potential revenue for a producer since in order to acquire ongoing use of the product the consumer is under pressure to buy again, either from the same manufacturer (a replacement part or a newer model), or from a competitor who might also lean on planned obsolescence.

Perishable products have different characteristics that distinguish them from durable items. First of all, they are produced only over a limited period of time and after this time window they are completely purged from the market. The reason is that they soon become obsolete, usually not in terms of their physical features but in terms of brand popularity or evolving technologies. As a matter of fact, these types of products are usually viewed as emotional goods: customers acquire them because of their desire to own and satisfy their huge emotional cravings; brands and popularity play big roles in inducing those desires. Such goods also require and rely on a different logic of selling.

Moreover perishable products, such as fashion goods or electronic devices, whose perishability is primarily determined by the high innovation rate of technology, follow particular purchasing and production logic that must be taken into careful consideration.

Perishability can be attributed to a variety of reasons, including natural decay, seasonality, fashion, technology progress, non-stockability, governmental rules, environmental effects, transportation, and competition. Therefore, a wide range of industries are affected by this phenomenon including: energy; food production, agriculture, plant and animal farming (flowers, vegetables, fruit, and seafood); fashion (garments); high-tech industries such as semiconductors, electronics, computers and bio-techs; health care; travel and entertainment; e-market; fishing; certain blood products, and blood banks; perishable data (earthquake, terrorist attack, etc.).

Service products such as airline seats, hotel rooms, internet bandwidth, and concert/sport event tickets are considered perishable because (a) their quantity is fixed; (b) the inventory can neither be replenished nor stored; and (c) unsold products have little, or no salvage value.

1.2. Supply Chain of Perishable Products

The chain of production, transportation and storage processes from the first supplier to the end consumer has evolved over the years, and progressively shifted from a step-wise chain via a logistical chain into a supply chain. Competition is not between different separate companies but between different supply chains presenting identical goods to the end consumer. Therefore, the center of attention needs to be on the supply chain rather than any individual company.

One main characteristic of perishable products is that their life cycle is fairly short. Companies dealing with short life cycle (SLC) products face a market that operates faster, is more uncertain and unpredictable than the one for more durable goods. The management of supply chains is a challenging issue for companies dealing with this specific type of goods.

The short lifecycle products supply chain is different from the one related to standard life cycle products on a number of counts. The main differences between the two supply chain types are presented in Table 1-1.

Table 1-1. Differences between short and long life cycle product supply chains (Briano et al., 2010)

Activity areas	Supply chain	
	Long life cycle product	Short life cycle product
Planning	- Global/General planning - A single sales forecast is estimated for the company; it is possible with a robust range of products	- Elementary planning - Accurate and separate demand estimation for every product and service, followed by computing a single value for the company
Forecasting	- Quantitative methods - Statistical methods of forecasting	- Heuristic methods of forecasting - Qualitative methods - Forecast by analogy
Manufacturing	- Highly automated systems - Production lines	-Flexible manufacturing systems - Highly automated systems - Manufacturing of a wide range of products - Outsourcing - Hybrid manufacturing processes
Inventories and warehouse management	- Manufacturing for stock - Purchasing of products for stock	- Manufacturing to order - Reducing the number of stored materials and products
Replenishment (suppliers)	-Domestic and local suppliers - Frequent changes of suppliers - Long delivery times - Large number of suppliers - Traditional way of communication, no common and shared information systems	- Global replenishment systems - Long term contracts - Enabling flexible time planning and ordered quantities -Reducing the number of suppliers to those who offer the widest ranges of raw materials - Consolidation of orders from multiple sources

A SLC product requires a more responsive, flexible and agile organization compared to a long life cycle one. A more accurate demand forecasting is needed since it is concentrated in a limited period of time and it must precisely be followed by the production in order neither to result in products shortage nor in overstock, difficult to discard.

The demand pattern for a SLC product is different from the one with a long life cycle. The latter presents a higher variance (a more spread pattern) distributed around a lower peak while SLC products show a more shrunk curve which means a lower variance with a higher peak. This difference arises because a SLC product needs to be sold in a short time period, due to different reasons such as obsolescence, fashion trends or because their market presence is associated with special events (Briano et al., 2010). Spoilage and decay are some other causes of shorter product life cycles (e.g., food industry) which are not in the scope of this study.

1.3. Supply Chain Risks

In the research literature, risk is interpreted in many different ways. Variance-based definitions, which are extracted from classical decision theory, and hazard focused interpretation, common in risk management, are the most widely cited explanations of risk. In the former, risk is the 'variation in the distribution of possible outcomes, their likelihoods and their subjective values'; in the latter, 'Risk = Probability (of a given event) × Severity (negative business impact)' (March and Shapira, 1987). For our purpose, the risk is considered as the prospective loss as a result of unforeseen or random changes in underlying risk factors.

Generally, there are two types of supply chain risk: operational risk and disruption risk (Wakolbinger and Cruz, 2011; Knemeyer et al., 2009; Kleindorfer and Saad, 2005). Operational risk is caused by inadequate or failed processes, people, and systems and is more about supply-demand co-ordination (Bhattacharyya et al., 2010; Lockamy and McCormack, 2010). Quality or delivery problems are some examples of operational risks. Disruption risk results from natural or man-made disasters such as earthquakes, floods, terrorist attacks, and labor strikes. Operational risk is relatively more controllable comparing to disruption risk (Byrne, 2007). However, as stated in a global survey (Byrne, 2007), managers claim that the most fearful and dominant risks affecting their supply chains are the operational ones which are controllable.

Chopra and Sodhi (2004) classified the potential supply chain risks into eight categories of delays, disruptions, forecast inaccuracies, systems breakdowns, intellectual property breaches, procurement failures, inventory problems and capacity issues. Each risk category has its own drivers and mitigation strategies which are listed below.

- Disruptions: natural disaster, supplier bankruptcy, war and terrorism, dependency on a single source of supply, capacity and responsiveness of alternative suppliers.
- Delays: high capacity utilization at supply source, inflexibility of supply source, poor quality or yield at supply source, excessive handling due to border crossings or to change in transportation modes.
- Systems: information infrastructure breakdown, system integration or extensive systems networking, e-commerce.
- Forecast: inaccurate forecasts due to long lead times, seasonality, product variety, short life cycles, small customer base, bullwhip effect or information distortion due to sales promotions, incentives, lack of supply chain visibility and exaggeration of demand in time of product shortages.
- Intellectual Property: vertical integration of supply chain, global outsourcing and markets.
- Procurement: exchange rate risk, percentage of a key component or raw material procured from a single source, industry-wide capacity utilization, long-term versus short-term contracts.
- Receivables: number of customers, financial strength of customers.
- Inventory: rate of product obsolescence, inventory holding cost, product value, demand and supply uncertainty.
- Capacity: cost of capacity, capacity flexibility.

The focus of this research is on operational risk in the supply chain context, three prominent categories of risk which have a high impact on the performance of supply chain are investigated: risk of delays, risk of forecast, and risk of inventory.

1.4. Fast Fashion Apparel Industry

The fashion industry has changed greatly due to the recent success of fast fashion retailers. New firms that emerged in this industry have grown rapidly and persistently and become the market leaders over the past decade. In the first quarter of 2008, the

Spanish Inditex group, owner of the Zara chain, surpassed Gap and became the world's biggest clothing retailer (Carugati et al., 2008). The Swedish chain, H&M, has also become a leading player in this industry. Fast fashion as a relatively new business strategy can be briefly defined as "cutting-edge fashion at an affordable price" for Zara (The Guardian, 2008), or similarly as "fashion and quality at the best price" for H&M (Zara., 2002).

The assortments[1] of fast fashion retailers offer a mix of two product categories including basic items, e.g., a black T-shirt or a pair of plain blue jeans, and fashion items, e.g., the dress celebrities wear in a latest event. As a result, their supply chains are a hybrid combination of an efficient supply chain, which is applied for delivery of basic items, and a responsive supply chain, used for fashion items (H&M, 2007). In this study, the supply chain of fashion items is of primary interest. It is necessary to have a responsive supply chain for fashion items in order to bring the products quickly to the stores if needed, since such fashion is short lasting (highly perishable) and demand for it is highly uncertain. This means a flexible production system is required to minimize the lead time, even at a higher cost. Therefore, the time from design to store including raw materials acquisition, production and distribution should be minimized.

Companies such as Zara and H&M have reduced the design and production lead times to just a few weeks, rather than months, applying flexible supply chain strategies. They introduce new products on a regular basis, e.g., weekly (H&M, 2007). Fashion items, in particular, have a very short life cycle, since they are quickly replaced by the trendier ones. In turn, the fast fashion companies have also changed buying habits of their most devoted customers, creating a virtual and highly competitive cycle.

1.5. Problem Statement

Risk and uncertainty have been part of human life activities since its beginnings, although they have not always been named as such. As long as risk has existed, people have always made an effort to protect themselves from its detrimental effects. Since we

[1] The collection of goods or services that a business provides to consumers.

all agree to the argument that risk matters and that its consequences affect how managers and investors make decisions, hence ability to understand and measure it are essential. To enterprises which aim at increasing the impact of their activities (by minimizing costs and optimizing profits), the need to continuously monitor the risk to be able to make right choices is fundamental, and to carry out such activities effectively, proper and adequate tools (both qualitative and quantitative) are needed. While static assessment of risk is a necessary step towards managing it, it is neither sufficient nor satisfying considering the complex environment of industrial enterprises, operating under dynamically changing conditions.

When producing perishable products, all phases of the supply chain are exposed to much higher uncertainty than in the case of durable products, which directly means higher risk. The supply chains dealing with perishable products need higher awareness of this issue due to the particular characteristics of such products. A perishable product requires a more responsive, flexible and agile organization compared to a durable one. A more accurate demand forecasting is needed since it is concentrated in a limited period of time and it must precisely be followed by the production in order neither to result in products shortage nor in overstock, difficult to discard.

So far, the study of supply chain risk management (SCRM) has not been adequate to meet the challenges associated with increasing supply chain risks. Only a small fraction of the papers on SCRM are based on quantitative methods and the literature mainly falls under the category of qualitative approaches including conceptual models, overview and exploratory reviews or empirical studies.

In fast fashion industry risk effects are compounded by factors, such as, complex supply chains, short product lifecycles, and volatile market demand which make them highly sensitive to exposure of uncertainty, as they operate on the borderline of stability. Despite this potential, we see that the industry has been neglected in terms of supply chain management research and practice.

The interest in the risk measurement for short-life-cycle products, in general, and fast fashion apparel in particular, led us to the review and study of current solutions. Literature survey revealed an existing gap in availability of risk assessment and quantification tools for supply chains operating under these extreme conditions. Thus, the proposed research bridges the gaps remaining in this area for these categories of products.

1.6. Contributions

The original contributions of this study can be summarized as follows:

1.6.1 Modeling the Supply Chain of Fast Fashion Apparel Industry

Taking into account the elevated level of complexity and unpredictability of upcoming events, it is suggestive that traditional approaches and tools are no longer effective. Dynamic supply chain models under uncertainty are required, as well as tools that incorporate the maze of interactions characterizing supply chains and risk origins. To this end, three supply chain models for fast fashion apparel industry are proposed for which system dynamics methodology is applied. Originally, these models were built based on a general supply chain which can also be applied to industries other than fast fashion apparel industry. Afterwards, the models were customized step by step based on the characteristics of the fast fashion apparel industry.

a) The first supply chain model consists of three levels of manufacturer, distributor, and retailer. This model can be used to observe and analyze the effect of any change in one variable or parameter on the behavior of all other variables, simultaneously. The products in apparel industry are categorized based on their features and popularities in order to distinctively investigate the effect of their demand on the model behavior. In this model, the demand for retailer level follows a Poisson distribution.
b) The second model is also a three echelon supply chain with three different product categories in which the Bass diffusion model is applied to generate the demand at retailer level. Then, the performance of retailer level as well as the other two levels of SC is compared with that of the first model.
c) The third supply chain model comprises two levels of manufacturer and retailer. This model has a fair amount of commonality with the famous and successful

case of Zara Company. Applying the model, the net impact of product variety on SC performance and risk is comprehensively studied. Both positive impacts (marketing) and negative impacts (cost) of product variety are included in our analysis.

1.6.2 Quantitative Supply Chain Risk Analysis

The proposed models enable us to conduct comprehensive numerical analysis on the performance of supply chain, and moreover, to identify the factors that have more significant impacts on the risks associated with the supply chain of fast fashion industry. The impact of three prominent categories of risks on the supply chain of this fast fashion apparel industry is quantitatively analyzed in the present research. The coherent risk measure− Conditional Value at Risk (CVaR)− is employed to quantify the risk of each level of supply chain and the whole supply chain.

a) The impact of risk of delay (longer lead times or longer delivery times) on the performance of supply chain is analyzed. How delays in each level of SC affect the same level, other levels and the whole SC performance is investigated. For that reason, different measures including average backlogs, stock-outs, cost, profit, and CVaR are employed.
b) The effect of risk of inventory on SC performance is investigated. To this end, how delays, demand uncertainty, and product variety affect the inventory level and risk of SC is analyzed.
c) The impact of risk of forecast inaccuracy on SC performance is explored. In particular, how demand uncertainty and product variety affect the mean absolute deviation of forecasts and CVaR is explored.

1.7. Organization of Dissertation

This dissertation is divided into seven chapters. Previous literature works is reviewed in Chapter 2. Chapter 3 presents a three-level supply chain model for the fast fashion apparel industry, including its structure, characteristics, and validation process. Chapter 4 provides the numerical analysis pertaining to the performance of SC under risk of delay, risk of forecast, and risk of inventory when the demand at retailer level follows the Poisson distribution. In Chapter 5, the demand at retailer level is remodeled using the Bass diffusion model; the impact of the same categories of risk on the new SC model is analyzed, and compared with the results of previous chapter. A two-level SC model with a number of different characteristics is proposed in Chapter 6 and the impact of product variety on the risk of SC is investigated. Finally, Chapter 7 includes a summary of the present study, its limitations, and the areas of future works.

CHAPTER 2

LITERATURE REVIEW

As mentioned in the previous sections, the purpose of this study is to identify and measure the risks associated with the supply chain of perishable products (fast fashion apparel industry) using system dynamics methodology. Hence, a comprehensive review of the literature in four distinct sections was performed including: supply chain of SLC products, supply chain of apparel and fast fashion industry, supply chain risk measurement, and supply chain modeling through system dynamics methodology.

2.1. Supply Chain of Short Life Cycle Products

Since the main characteristic of perishable products is that their life cycle is short, in this section, the literature on supply chain of SLC products is reviewed. Xu and Song (2007) developed and applied a BASS model for forecasting the demand of SLC products. Xu and Zhang (2008) employed the method of Support Vector Machine (SVM) to predict the demand of SLC products in the conditions of data deficiency. The method examines season factor, products' demand, and demand forecasted by Bass model as influential factors for the demand of SLC products. Zhu and Thonemann (2004) proposed an optimal inventory policy using an adaptive forecasting algorithm and heuristic methods. They modeled the demand applying structural knowledge on the product life cycle, then, combined the actual demand data available after the launch of the product and updated the forecast. Doganis, et al. (2006) suggested a framework to build forecasting models for nonlinear time series sales. They merged two artificial intelligence technologies: a specially designed genetic algorithm (GA) and the radial basis function (RBF) neural network architecture.

Briano, et al. (2010) modeled a supply chain related to short life-cycle products using the system dynamics methodology. They identified and focused on the needs along the supply chain of this specific type of products so as to optimize the total costs and profits of the company. A Mixed Integer Programming model was proposed by Chen et al., (2008) for the supply chain of SLC product which had orders from multiple markets and flows of recycle material. Higuchi and Troutt (2004) applied scenario-based dynamic simulations to investigate the short product life cycle supply chain, demonstrated by the first of the virtual pet toys, Tamagotchi. Feng and Zhao (2008) analyzed the supply chain of SLC products employing a composite modeling method for simulation based on Object-Oriented and Petri Net modeling.

Using the system dynamics model, Kamath and Roy (2007) assessed the dynamics of capacity augmentation for a two-echelon supply chain with the focus on information flows. Leung, et al. (2007) proposed a robust optimization model for perishable products to minimize production costs, inventory costs, labor costs, workforce changing costs, and setup costs in an uncertain environment.

Reiner et al., (2009) analyzed the alternative pricing strategy and their impacts on the service level using a system dynamics model. They also presented a new technique in system dynamics modeling for ensuring the model external validity.

Applying mathematical models, Tomlin (2009) evaluated different disruption-management strategies, such as contingent sourcing, supplier diversification, and demand switching for a two-product newsvendor. Table 2-1 shows the summary of the papers in this section based on the focus of the research.

Table 2-1. Literature review- supply chain of short life cycle products

Research Focus	Papers
Demand/sales forecasting	Briano et al. 2010; Xu and Song 2007; Xu and Zhang 2008; Doganis et al. 2006; Zhu and Thonemann 2004
Capacity planning	Kamath and Roy, 2007
Inventory management	Zhu and Thonemann, 2004
Disruption management	Tomlin, 2009
Production planning	Leung et al., 2007
Service level	Reiner et al., 2009
Recycle strategy	Chen et al., 2008
Supply chain modeling	Briano et al. 2010; Feng and Zhao, 2008; Higuchi and Troutt, 2004

2.2. Supply Chain of Apparel and Fast Fashion Industry

Marufuzzaman and Deif (2010) introduced a metric called “product flow number” for identifying the product flow nature across the apparel supply chain based on mapping the dynamics of fluid flow across a pipe to product flow across a supply chain. The authors illustrated that complex product designs and increasing number of suppliers lead to undesirable dynamics, while production and extending delivery times can result in smooth dynamics.

Wong and Guo (2010) developed a hybrid intelligent (HI) model, composed of a data pre-processing component and a HI forecaster, to solve the medium-term fashion sales forecasting problem. In their model, a new learning algorithm-based neural network is firstly adopted to forecast the initial sales and then a heuristic fine-tuning process is applied to achieve more precise forecasts based on the original ones.

Considering perfect and imperfect quality items, Sana (2011) presented an integrated production-inventory model which can be used in industries such as textile and footwear, food, chemical, etc. They used an analytical approach to optimize the order size for raw material and production rate for maximum expected profit.

Khan et al. (2012) adopted a qualitative approach comprising documentary analysis and structured interviews to assess the role of retail channel alignment in the Italian fashion industry from an operational viewpoint. They suggest a relationship between the degree of alignment, channel type, and lifecycle phase.

Dong et al. (2007) presented a simulation model integrating fuzzy logic to generate a portfolio that meets the apparel customer service level and includes performance index as well as replenishment strategy under different levels of forecasting errors.

With the focus on the time-sensitive casual wear industry, Romano (2009) compared Benetton’s and Zara’s supply networks to understand the justification of their differences in time performance. In the next step, the author applied the fluid dynamics concepts to explain the relations between the business process configuration, supply network structure, and time performance; and then, explained Benetton’s and Zara’s configuration decisions and their effect on time behavior.

Majumder and Srinivasan (2008) built a model to study the price dependent large supply chains which are common in the automobile and apparel industries. They showed that leader position in such networks, which involve long sequences of contracts, as well as contract leadership has a significant effect on the supply chain performance. They developed an algorithm to detect the equilibrium solution, and obtain the optimal location of the leader.

Karabuk (2007) established integer programming models for transportation problems of a textile manufacturer. Their model involves scheduling of pickup and delivery of daily inventory movement between a large numbers of manufacturing facilities in all stages of the manufacturing supply chain.

Pan et al. (2009) applied unified modeling language (UML) to simulate the apparel supply chain processes and explained the relationships between agents (Agents can help automate different tasks and facilitate decision-making). They used genetic algorithm (GA) and fuzzy inference theory for the supply chain agent to optimize the decision about reorder point and replenishment quantity to subsequently minimize the cost of inventory.

Webster and Weng (2008) presented a supply chain model with price sensitive random demand for SLC products like fashion products. They studied two opposite scenarios of manufacturer-controlled and distributor-controlled. They showed that under distributor-controlled scenario, which the distributor controls the supply chain stocking decisions and carries the risk of overstocking, the total supply chain profit is usually higher.

Vaagen and Wallace (2008) integrated Markowitz and the Newsboy models to analyze the optimal portfolio and variety as a result of hedging against uncertainty, while considering demand correlations. They demonstrated that it is necessary to build hedging portfolios with competing items for optimality because of the complex structure of the uncertainty. They also showed that misspecifying the distributions can result in improper hedging and consequently, poor trade-offs between risk and expected return.

In response to specific characteristics of textile–apparel market, Thomassey (2010) proposed different forecasting models applying fuzzy logic, neural networks and data mining methods. They also performed and analyzed a simulation, based on real data, in order to reduce the bullwhip effect and evaluate the advantages of their proposed models.

Douillet and Rabenasolo (2007) discussed the limitation of the standard hypothesis of the knowledge of the uncertain demand modeled in the form of a probability distribution function. The authors adopted Scarf's method to analyze the optimal decision based on some characteristics of the future demand which are practically obtainable.

Eliiyi et al. (2011) formulated the trans-shipment problem of an apparel company with multiple customers and subcontractors, and a trans-shipment depot. They considered total cost of transportation, the customer due dates, and the supplier lead times in their model which can be used for well-timed distribution planning and supplier selection.

Koprulu and Albayrakoglu (2007) investigated the current status of the textile or apparel industry and considering the globalization of the industry, they discussed the key success factors for a supply chain. The authors presented an analytical hierarchy process (AHP) model for supplier selection and based on the results of the model, they created a supplier relationship management (SRM) strategy. Also, they determined strategic priorities for the supplier selection and introduced weights for selecting the right supplier based on the company's strategy.

Burnes et al. (2008) provided a framework for design-led supply chain risk management and presented a case in which design was recognized as a tool to manage risk in supply chains. Their research methodology was based on a longitudinal case study of a major UK retailer. Semi-structured interviews, observation of supplier meetings/workshops were some of the methods used to gather the necessary data.

Sen (2008) reviewed the current operational practices and recent trends for the fashion supply chain in the U.S. They used articles from business journals, industry wide data, industry reviews, extensive interviews with a U.S. department store chain and, an apparel manufacturer in California, to explain how the industry is reconstructing throughout the transition.

Lidia et al. (2012) presented a supply chain model for a small and medium scale enterprise (SME) of an apparel company in Indonesia. They applied System Dynamics (SD) method where data were gathered from a fast fashion company in Indonesia, which produced its own wares, had three stores, a warehouse and was running online sales system.

Cagliano et al. (2011) applied system dynamics (SD) methodology to model warehouse operations at the distribution centre of a fast-fashion vertical retailer. The authors studied the analysis of relationships between the assignment of staff, the flow of items through the warehouse, the order processing tasks, and the inventory management policy. They showed that a flexible usage of human resources, sourcing from reliable manufacturers, and outsourcing of selected warehouse operations, may result in performance improvements for centralized warehousing.

Building on previous research on the impact of RFID technology on retail operations, De Marco et al. (2012) proposed a model using System Dynamics methodology and case exploration of an Italian apparel retailer. They illustrated that RFID implementations are profitable especially when a fashion retailer is focused on clerk-assisted sales strategies. RFID technology can result in faster inventory turnover, better inventory control, and longer time available for store personnel to assist consumers.

Barlas and Aksogan (1997) built a System Dynamics simulation model of a textile and apparel supply chain including the retailing and wholesaling processes to find the inventory policies that result in reduced costs or increased returns for the retailer. More particularly, they examined the effectiveness of the major Quick Response principles in achieving that goal. They also examined the implications of diversification and different hypotheses about the effect of product diversity on inventory levels, customer demand, and possible stockouts.

With reference to Bienayme´–Tchebysheff inequality theory and the fast fashion system, Choi et al. (2010) mathematically derived the optimal retailer's inventory policy. They studied the fast fashion phenomenon in a supply chain with the safety-first objective. The authors showed that the optimal policy was consistent with the one used in the case of fast fashion.

In collaboration with Zara’s pricing team, Caro and Gallien (2012) designed and implemented a process for determining price markdowns which depends on a forecasting model and feeds price optimization model. As part of a controlled field experiment implemented in Belgian and Irish stores during the 2008 fall-winter season, the proposed process increased clearance revenues by approximately 6%. Currently, this process is used worldwide for Zara’s markdown decisions during clearance sales.

Caro and Gallien (2007) focused on dynamic assortment problem faced by fast fashion retailers. They studied a finite horizon multi-armed bandit model with several plays per stage and Bayesian learning. The authors involved the Lagrangian relaxation of weakly coupled dynamic programs (DPs), outcomes related to the emerging theory of DP duality, and different approximations in their study.

With the focus on fast fashion retail stores and in collaboration with Zara, Caro and Gallien (2010) formulated a stochastic model to predict the sales of an article in one store during one replenishment period as a function of demand forecasts, the inventory of available sizes, and the store inventory that is, an article is removed from display if one of its key sizes stocks out. The authors then formulated a mixed-integer program using a piecewise-linear approximation of the first model, which lead to computation of store shipment quantities maximizing overall predicted sales, subject to inventory availability.

Caro and Martinez-de-Albeniz (2009) proposed a model for customer consumption including satiation and multiple competing retailers which helps to determine how often it is necessary to change the assortment in a competitive equilibrium. They also showed that the customers spend a higher share of their budget in stores that renovate the assortment at a faster pace.

Recently, Zara determined the inventory shipments from two central warehouses to its 1,500 stores worldwide deploying operations research models which has increased sales by 3–4 percent. The models employ the link between demand and stock levels to find store replenishment quantities (Caro et al., 2010).

Donohue (2000) worked on developing supply contracts that lead to appropriate coordination of forecast information and production decisions between a distributor and manufacturer of high fashion, seasonal products. They studied two production modes; one that is fairly cheap but requires a long lead-time while the second one is expensive but offers quick turnaround.

Choi (2007) investigated the pre-season inventory and pricing decisions for fashion retailers. The author modeled a dynamic optimization problem and obtained the optimal stocking policy. After the arrival of ordered seasonal product and before the start of the selling season, the retailer can determine the optimal selling price based on the most recent demand information, and the amount of available product.

Iyer and Bergen (1997) built models for the inventory decisions of retailers and manufacturers in the apparel industry both before and after applying Quick Response (QR). Their model showed the winners and losers under QR and suggested actions that lead to Pareto improvement, that is, to make QR profitable for all members of the channel.

Fisher and Raman (1996) modeled the required decisions under Quick Response and presented a framework to estimate the probability distributions of demand. They deployed the method for a skiwear fashion firm that could reduce the cost of current response system and increase the profits by 60%.

Ji and Chen (2012) collected experts' opinions applying the two-stage Delphi method and obtained the hierarchy of risk evaluation indexes by Exploratory Factor Analysis for an apparel supply chain. In the next step, the authors applied AHP to determine the weights of index, combined that with Markowitz's risk price and decision maker's utility function to evaluate the supply chain risk of the enterprise.

Ai-hua et al. (2009) built a retailer-oriented portfolio simulation system including performance index and replenishment strategy under different sales forecasting errors. They validated the process of the simulation with the use of data from an apparel industry.

Hilletofth and Hilmola (2008) discussed that the lean and agile (leagile) approach is not a general solution in the textile and fashion business. The lean approach is more admissible for some fashion and textile companies. Through case study and simulations, the authors showed that the lean and leagile could be employed side-by-side as different strategy substitutes. The following table shows the summary of literature in this section.

Table 2-2. Literature review- supply chain of apparel and fast fashion industry

Research Focus	Papers
Demand/sales forecasting	Wong and Guo, 2010; Dong et al., 2007; Thomassey, 2010; Caro and Gallien, 2010; Ai-hua et al., 2009
Inventory management	Sana 2011; Pan et al., 2009; Cagliano et al., 2011; Choi et al., 2010; Caro and Gallien, 2010; Choi, 2007
Production planning	Sana, 2011
Service level	Dong et al., 2007
Quick response	Barlas and Aksogan, 1997; Iyer and Bergen, 1997; Fisher and Raman, 1996; Hilletofth and Hilmola, 2008
Supply chain modeling	Pan et al., 2009; Lidia et al., 2012
Coordination	Majumder and Srinivasan, 2008; Webster and Weng, 2008; Donohue, 2000
Transportation	Karabuk, 2007; Eliiyi et al., 2011
Risk measurement	Vaagen and Wallace, 2008; Ji and Chen, 2012
Supplier selection	Koprulu and Albayrakoglu, 2007
Retail assortment	Caro and Gallien, 2007; Caro and Martinez-de-Albeniz, 2009
Variety/ diversification	Vaagen and Wallace, 2008; Barlas and Aksogan, 1997
Pricing	Caro and Gallien, 2012; Choi, 2007
Review paper	Sen, 2008

2.3. Supply Chain Risk Measurement

In this section, the research on supply chain risk measurement is presented which is classified based on the risk measurement tools applied.

2.3.1 Utility Maximization

Von Neumann and Morgenstern first presented utility function in 1944 in which the objective was to maximize the decision maker's expected utility (Von Neumann and Morgenstern, 1944).

Goh et al. (2007) considered supply, demand, exchange, and disruption risks and presented a stochastic model of the multi-echelon global supply chain network problem. They designed an algorithm for treating the multi-stage global supply chain network problem with risk minimization and profit maximization objectives and provided a solution methodology applying the Moreau–Yosida regularization.

Agrawal and Seshadri (2000) studied the ordering quantity and the selling price in a single period inventory model in which the utility function of the risk-averse retailer was assumed to be increasing and concave in wealth. They showed that, if price change affects the demand scale, a risk-averse retailer will decrease its price and orders less compared to a risk-neutral retailer; while, a risk- neutral retailer will increase its price if a price change only affects the location of demand distribution.

Chen et al. (2007) proposed a framework to include risk aversion in multi period inventory models with and without inventory and pricing strategy coordination. They analyzed a joint optimization problem on both price and ordering quantity. The authors showed that the optimal policy structure for a decision maker with exponential utility functions is very similar to the structure of the optimal risk neutral inventory policies.

Wang and Webster (2009) modeled a manager's decision-making behavior in the single period newsvendor problem using a type of loss aversion utility function. They showed that a risk-neutral newsvendor may order less than that of a loss-averse newsvendor, if shortage cost is significant. They also found that the loss-averse newsvendor's optimal ordering quantity may decrease in retail price and increase in wholesale price which can never happen in the risk neutral newsvendor model.

Wang and Webster (2007) studied a supply chain with a loss-averse retailer purchasing a perishable product from a risk-neutral manufacturer. Their results signified when retailers are loss-averse, coordinating contracts based on the assumption of risk neutrality may result in noticeably lower supply chain profit.

It is not as easy as anticipated to apply expected utility theory, although it is widely used in the area of supply chain risk management. Because, the decision maker has to determine a utility function which needs additional uncertain procedure such as specifying different parameters and choosing different utility functions and results in more doubtful and inconvenient decision making (Wu et al., 2011).

2.3.2 Mean-Variance Trade-Off

Markowitz (1959) presented a model that selects the best portfolio by analyzing the tradeoffs between risk and return. Such a model, also known as Markowitz's mean-variance, is a particular type of utility function theory in which the utility function is quadratic and the mean-variance objective maximization is equivalent to expected utility maximization (Mossin, 1973).

Ding et al. (2007) applied a mean-variance utility function to model the firm's risk aversion in decision making. The authors analyzed the impact of the delayed allocation option and the financial options on capacity commitment and the firm's performance. They showed that the firm's financial hedging strategy is related to the firm's operational strategy and could affect on it, both quantitatively and qualitatively.

Chen and Federgruen (2000) used mean-variance approach for some basic inventory models. They showed how to conduct a systematic mean-variance trade-off analysis, efficiently. They also showed that the proposed strategies are different from those obtained in standard analysis.

Martinez de Albeniz and Simchi-Levi (2006) studied the behavior of a manufacturer signing a portfolio of option contracts with its suppliers while having access to a spot market applying the mean-variance trade-off method.

Lau and Lau (1999) analyzed a supply chain consisting of a monopolistic supplier and a retailer that apply a return policy and each has a mean-variance objective function. They found the optimal wholesale price and return credit for the supplier to maximize his utility.

Within a mean-variance framework, Buzacott et al. (2011) studied a class of commitment-option supply contracts and demonstrated that the mean-variance objective is convex with respect to both contract commitment portion and option portion.

Choi and Chow (2008), Choi et al. (2008a), Choi et al. (2008b), Choi et al. (2008c), and Wei and Choi (2010) systematically analyzed some problems in inventory and supply chain within a mean-variance framework. The topics involved return policy, the newsvendor problem, channel coordination, etc. They obtained a lot of important results by comparing the traditional performance evaluation with expectation maximization.

Wu et al. (2009) used a mean-variance objective function to model a risk-averse newsvendor problem. They demonstrated that stock-out cost has a large effect on the newsvendor's optimal ordering decisions. That is, with stock-out cost, the risk-averse newsvendor does not essentially order less than that of the risk-neutral newsvendor.

Although the approach of mean-variance trade-off, as a utility function, is broadly used in supply chain risk management, it also suffers two weaknesses. Firstly, it equally penalizes unwanted downside and desirable upside outcomes while decision makers usually care only the downside loss when maximizing profit. Secondly, the relevant risk of an investment by a value-maximizing firm cannot be properly measured by the total variance of the profit from that investment in real world where investors hold diversified portfolios of financial assets. Under such situations, the proper measure of the project's risk aversion of the decision maker may be different from the risk-return trade-off imposed by shareholders, and thus this criterion may entail the existence of agency problems (Wu et al., 2011).

2.3.3 Value at Risk

Value at Risk (VaR) is defined as the expected loss arising from an adverse market movement with specified probability over a period of time (Wu et al., 2011). Artzner et al. (1999) showed that VaR does not meet all the properties needed from a risk measure and should not be used as the only measure of risk exposure. Hence, research of supply chain management applying VaR approach is infrequent. As a rare example, Tapiero (2005) showed that single-period, multi-period, and multi-products inventory problems, besides inventory with price and demand uncertainty can be studied using the VaR approach.

2.3.4 Conditional Value at Risk

The Conditional Value at Risk (CVaR), as a criterion based on VaR, is the conditional expected profit where given profit is below the γ-quantile. Thus, CVaR includes the amount of loss and, as an advantage over VaR, it is a coherent risk measure and is reliable under more general conditions (it is not restricted to Normally distributed returns) (Artzner et al., 1999).

Jammernegg and Kischka (2004) specified the optimal performance measures for an objective function with two risk parameters applying newsvendor model. The first parameter was for the convex integration of two conditional expected values of the profit. The second one discriminated the high profits and low profits by being used as the γ-quantile of the profit distribution.

Wu et al. (2006a) and Wu et al. (2006b) analyzed a pay-to-delay contract, which was originally presented in Brown and Lee (1997) and then studied by Buzacott et al. (2003) applying CVaR approach. They showed the benefits of using the CVaR approach over a mean-variance approach in some conditions. The authors demonstrated that CVaR avoids the shortcoming of the mean-variance approach, which equally penalizes the undesirable downside and the desirable upside outcomes. The CVaR approach also provides an unambiguous solution, which has better computational characteristics.

Zhou et al. (2008) proposed an optimal order model for multi product with CVaR constraints using linear programming. They simulated the model for the case of a newsvendor to investigate to what degree it could succeed.

Chen et al. (2009) investigated the inventory decisions and optimal pricing for both multiplicative and additive demand models. The authors used CVaR to study a risk-averse newsvendor whose demand is stochastic and price dependent.

Goh and Meng (2009) applied CVaR and formulated a stochastic programming for supply chain risk management. They introduced the sample average approximation method for solving the model.

Wu et al. (2010) investigated the impact of risk aversion on the manufacturer's decisions and obtained the manufacturer's optimal decisions. They introduced CVaR as the assessment criterion in a supply contract model. They showed that there is a definitive relationship between the manufacturer's optimal decision and their risk perspective.

Xu (2010) analyzed ordering decisions, the optimal pricing, and the effects of parameter changes for a newsvendor model in which a risk-averse manager encounters a stochastic price dependent demand in either a multiplicative or an additive form. He adopted CVaR as the decision criterion.

2.3.5 Other Risk Measures

Gan et al. (2005) studied how to develop a supply chain contract with a downside risk-averse retailer and a risk-neutral supplier.

Ahmed et al. (2007) investigated the monotonic characteristics of the optimal ordering quantity with regard to the degree of risk aversion for specific risk measures. Moreover, they proposed multi-period inventory models and the classical newsvendors, with a coherent risk measure as the objective function.

Based on a case study in a European toy supply chain, Wong and Hvolby (2007) studied the role of coordination and responsiveness in enhancing supply chain performance and explored consumer and retailer demand patterns and their significance to the manufacturer's supply chains. In this study, the authors concluded that responsiveness and order penetration points (OPP) relocation are advantageous but inadequate in improving the supply chain.

Li et al. (2001) worked on the horizontal coordination between production units positioned in different countries within a supply chain in a changing environment. In the proposed model, they incorporated uncertainties in environmental state, demand and processing times.

Wu (2006) proposed three types of robust optimization models: the robust optimization model with model robustness, the robust optimization model with solution robustness, and the robust optimization model with the trade-off between model robustness and solution robustness. The author proposed a dual-response production loading strategy for company-owned as well as contracted plants to hedge against the short lead time and uncertainty. He showed that the robust optimization models provide a more responsive and flexible system with less risk compared to the results of the two-stage stochastic recourse programming model.

Sounderpandian et al. (2008) considered the optimization of order quantity decisions for the situations that raw material suppliers of a global supply chain are located in developing countries, the lead times are long, and there is the possibility of material losses in transit. Using stochastic programming and employing data from the plywood industry they show that the optimal order quantity of a material need not be monotonic in expected loss of that material.

Nagurney et al. (2005) developed a supply chain network model consisting of three levels of the manufacturers, the distributors, and the retailers, with the random demands in retailer level. In their model, which supply side risk and demand side risk are considered, both physical and electronic transactions were accepted. They modeled the optimizing behavior of the different decision-makers, considering the manufacturers and the distributors as multi-criteria decision-makers and worked on profit maximization and risk minimization.

Tomlin (2006) studied a single-product supply chain in which a firm can source from two suppliers, one that is reliable but expensive and another that is unreliable. Suppliers are capacity constrained, but the reliable supplier may have volume flexibility. They showed that the type of the disruptions (frequent but short versus rare but long) and a supplier's percentage uptime are key elements of the optimal strategy. Further, they stated that if the unreliable supplier has finite capacity or if the firm is risk averse, mixed mitigation strategy (partial sourcing from the reliable supplier and carrying inventory) can be optimal.

Fang and Whinston (2007) proposed a capacity game model in which a monopolistic supplier has to build capacity before observing the uncertain demand. The demand is generated by two potential customers, who privately know their own types. The types could be either high or low, differing in readiness to pay for each unit of demand. To differentiate the customer types, the supplier designs option contracts in a way that only the high type can purchase the options in advance. The supplier profits in three ways: the high type customers pay higher marginal prices on average; they are served as a first priority, allocation efficiency is ensured; the supplier can monitor the number of options being purchased and so determine customer types, and improve capacity investment efficiency.

Martinez-de-Albeniz and Simchi-Levi (2005) developed a framework for supply contracts in which portfolios of contracts can be analyzed and optimized. Their focus is on a multi-period environment with convex contract, inventory holding costs, and spot market. They exclusively practice the case of a portfolio consisting of option contracts and indicate that portfolio contracts can increase the manufacturer's expected profit and reduce its financial risk.

Kremic et al. (2006) statistically studied the contents of 200 publications to categorize if the researches address outsourcing benefits, risks, motivations or decision factors. Each categorization is explained more by the type of risks, benefits, etc. Multivariate analyses consisting of chi-square testing, cross tabulations, and cluster analysis are used for classifying the studies with the aim of discovering relationships among the studies which are not evident when they are considered individually.

Kamrad and Siddique (2004) modeled how flexibility can be simultaneously advantageous to both the suppliers and the producer. They analyzed valued supply contracts in a setting formulated by supplier-switching options, exchange rate uncertainty, profit sharing, order-quantity flexibility, and supplier reaction options applying a real-options (contingent claims) method. The authors adopted basic diversification concepts, from portfolio theory, to analyze risk mitigation. Using this model, they simultaneously solved and examined the dual optimization problem for the suppliers and the producer and endogenize the extent and degree of profit sharing.

Berger et al. (2004) used a decision tree approach to analyze the number of suppliers needed in the presence of risks considering both catastrophic (super-events), which affect many/all suppliers, and unique events that only affect a single supplier. They determined the optimal number of suppliers and the expected cost function by calculating the probabilities of these events, the operating cost of working with multiple suppliers, and the financial loss caused by disasters.

Kirkwood et al. (2005) presented a prepackaged multi-objective decision-analysis framework for IBM's supply-chain to analyze mid-level supply-chain configuration decisions based on 22 considerations covering quality, cost, strategic issues, customer responsiveness, and operating constraints. These multi-attribute utility studies were executed in a spreadsheet environment and included uncertainty via expert estimates of probabilities.

Levary (2007) applied the analytic hierarchy process (AHP) to evaluate and rank potential suppliers and identified the essential characteristics of suppliers that must be considered in the supplier selection process. They described risk to the disruption of company operations as a reliability chain.

Agrell et al. (2004) modeled a three-stage supply chain under stochastic demand and varying coordination and information asymmetry. They used a minimal agency model to contrast known optimal mechanisms with the case study in the telecommunications industry. The authors showed that the observed price–quantity contracts under limited commitment are inadequate under realistic asymmetric information assumptions and the upstream urge to coordinate may further deteriorate performance.

Tapiero (2007) used a Neyman–Pearson quantile risk framework for the statistical control of risks and provided a strategic collaborative approach to risk and quality control in a cooperative supply. In their framework, the supply chain risks depend on the organizational structure, the motivations and the power relationships that exist between members of the supply chain.

Colicchia and Strozzi (2012) presented a new methodology named systematic literature network analysis which allows to classify the paths in which research is moving and thus to detect the streams of most promising research. Wu et al. (2011) reviewed the existing literature on the applications of risk management to supply chains. In their paper, some exemplary works are selected to illustrate the use of different supply chain risk management tools. They divided the literatures in this field into three groups, i.e., financial risk measurement, risk analysis of supply chain models, and disruption management.

Tang (2006) reviewed a range of quantitative models for managing supply chain risks and developed a unified framework for classifying SCRM articles. They also related different supply chain risk management (SCRM) strategies in the literature with actual practices.

Table 2-3. Literature review- supply chain risk measurement

Research Focus	Papers
Inventory management	Chen and Federgruen, 2000; Tapiero, 2005; Chen et al., 2009; Ahmed et al., 2007
Coordination	Wong and Hvolby, 2007; Li et al., 2001; Martinez-de-Albeniz and Simchi-Levi, 2005; Kamrad and Siddique, 2004; Agrell et al., 2004; Wang and Webster, 2007; Martinez de Albeniz and Simchi-Levi, 2006; Lau and Lau, 1999; Wu et al., 2006a; Wu et al., 2006b; Wu et al., 2010; Gan et al., 2005
Supplier selection	Tomlin, 2006; Kamrad and Siddique, 2004; Berger et al., 2004; Levary, 2007; Tapiero, 2007
Capacity Planning	Fang and Whinston, 2007
Pricing	Agrawal and Seshadri, 2000; Chen et al., 2007; Lau and Lau, 1999; Xu, 2010
Robust optimization	Wu, 2006
Order quantity	Sounderpandian et al., 2008; Kamrad and Siddique, 2004; Agrawal and Seshadri, 2000; Chen et al., 2007; Wang and Webster, 2009; Wu et al., 2009; Zhou et al., 2008; Xu, 2010; Ahmed et al., 2007
Review paper	Kremic et al., 2006; Wu et al., 2011; Tang, 2006; Colicchia and Strozzi, 2012

2.4. Supply Chain Modeling Using System Dynamics Methodology

Papers related to the system dynamics simulation of supply chain are not limited. In this section, some representative works are selected for demonstrating various applications of system dynamics approach in supply chains.

Campuzano et al. (2010) constructed a system dynamics model integrating fuzzy estimations for the demand in supply chain. They investigated the behavior of fuzzy estimations instead of exponential smoothing forecasts in a single-item supply chain with two stages. Ge et al. (2004) analyzed the bullwhip effect for a multi-echelon supply chain employing a system dynamics approach. The authors also studied the impact of information delays, demand forecasting and information sharing.

Using a system dynamics model, Janamanchi and Burns (2007) investigated the effect of elongating inventory replenishment times on bullwhip effect. Janamanchi (2009) applied a two echelon system dynamics model to study the impact of different modifications in inventory policies in meeting diverse objectives in supply chains. Yang (2009) utilized system dynamics to build the simulation model of the inventory control in distributor system.

Nuo and Xiao-jie (2010) studied the effect of random demand and bullwhip effect on a multi stage supply chain. Li et al. (2009) investigated the grounds of the bullwhip effect and potential techniques to control it, from the standpoint of the dynamic mechanism of the supply chain.

Rabelo et al. (2011) proposed a new approach to stabilize supply chain systems applying the classical version of particle swarm optimization approach. Their method is drawn from the accumulated deviations from equilibrium. Kumar and Nigmatullin (2011) studied how demand variability and lead-time affect the supply chain performance of a non-perishable product.

Applying a dynamic model of the supply chain, Rabelo et al. (2008) trained a neural network to predict the behavioral changes at an early decision making phase, thus, an enterprise would be able to protect the business against any unsatisfactory condition.

Using the data from TFT LCD industry, Cheng et al. (2008) empirically studied the effect of disruption in the supply chain system through SD approach.

Sundarakani et al. (2010) discussed the method of SD implementation on National Development Index (NDI).

Bhushi and Javalagi (2004) and Angerhofer and Angelides (2000) are two review papers of system dynamics applied to supply chain management. Table 2-4 shows the summary of papers in this section.

Table 2-4. Literature review- Supply Chain Modeling Using System Dynamics Methodology

Research Focus	Papers
Demand/sales forecasting	Campuzano et al., 2010; Ge et al., 2004
Inventory management	Janamanchi, 2009; Yang, 2009
Disruption	Cheng et al., 2008
Supply chain stabilization	Rabelo et al., 2011
Behavioral changes	Rabelo et al., 2008
Bullwhip effect	Ge et al., 2004; Janamanchi and Burns, 2007; Nuo and Xiao-jie, 2010; Li et al., 2009
Review papers	Bhushi and Javalagi, 2004; Angerhofer and Angelides, 2000

CHAPTER 3
APPROACH

Analytical models have different advantages such as presenting the problem concisely, providing a series of closed-form solutions, allowing an easy assessment of the impact caused by changes in inputs on output measures, and offering the possibility of reaching an optimal (or at least sub-optimal) solution. Their main shortcomings relate to the assumptions made to describe a system which may not be very realistic (e.g., oversimplified) and/or the mathematical formulas which can be very complicated and interfere with finding a solution (Campuzano and Mula, 2011).

On the other hand, simulation models can describe highly complex systems, and be used to either experiment with systems that still do not exist or experiment with existing systems without altering them. Among the disadvantages, one is that these models do not present a closed set of solutions. Each change made in the input variables requires a separate solution or a series of runs. Also, complex simulation models may require a long time to be built and run. Moreover, model validation may prove a difficult task (Campuzano and Mula, 2011). Shannon (1975) suggested to study the supply chain applying simulation methods when under one or several of the following conditions:

- The problem has no mathematical formulation.
- There is a mathematical model, but it has no analytical resolution methods.
- There is a model and methods, but the procedures are tedious, and simulation is simpler and less costly.
- When the aim is to observe a simulated history of the supply chain.
- When the aim is to experiment with a model before configuring the supply chain.
- It is impossible to experiment on the real supply chain.
- It is possible to experiment on the supply chain, but ethical reasons hinder this.
- When the aim is to observe very slow supply chain evolution by reducing the time scale.

Due to the complexity of perishable products SC models and in order to prevent making some unrealistic assumptions to make the model simple enough to work with analytical approaches, simulation modeling was selected as the appropriate approach for this study.

Kleijnen and Smiths (2003) presented four different simulation types for supply chains.

- Simulation using a spreadsheet.
- Systems dynamics. In general, the main objective of system dynamics is to understand the structural causes that bring about the behavior of a system (Sterman, 2000).
- Simulation of systems dynamics with discrete events. It can quantify service levels, particularly under uncertainty by focusing on an analytical simulation.
- Business games. They can train users who are active participants in the simulated world. In addition, business games can be involved in investigation to study the effects of the qualitative factors (i.e., the decision system) on benefits, etc. They are also suitable for a distributed virtual environment.

3.1. System Dynamics

In this research, the system dynamics (SD) methodology is adopted. SD is a simulation and modeling technique specifically designed for long term and dynamic management problems (Barlas, 2002). The focus of SD is on the interaction between physical processes, information flows and managerial policies in order to create the dynamic representation of the variables of interest. The structure of the system is defined by the totality of the relationships among these variables. Therefore, the structure of the system operating over time produces patterns of dynamic behavior. It is of significant importance that the model structure validly describes the real world. The main purpose of a SD model is to investigate what and how the dynamics of concern are generated and afterwards search for policies which could improve the system performance (Vlachos et al., 2007).

The significant difference between SD and a traditional simulation method, such as discrete-event simulation, is that the main objective of the latter method is to create a point-by-point match between the real behavior and the model behavior, and effectively, an accurate forecast. However, in an SD study, it is important to generate the major dynamic patterns of concern such as asymptotic growth, collapse, exponential growth, damping or expanding oscillations, S-shaped growth, etc (Sterman, 2000). Hence, it should be noted that the objective of our model is not to predict the total supply chain profit or risk level each week for the coming years, but to reveal under what scenarios and policies the supply chain risk would be lower, supply chain profit would be higher, and if and how can they be controlled.

3.2. The Model

3.2.1 Model Variables

The structure of SD models contains flow (rate) variables, stock (level) variables, and auxiliary variables. Flow variables are the components that determine the variation of stocks (e.g., products entering and leaving the warehouse). Stock variables are the accumulations within the system (e.g., warehouse, backlogged orders). Smoothed stock variables are another type of stocks which are expected values of specific variables acquired by exponential smoothing techniques (e.g., expected/forecasted demand). Auxiliary variables are the remaining elements in the model which represent steps to determine flow variables using stock variables (e.g., orders, lead time). The model variables, their notations and units are listed alphabetically in the following:

i = Product type *i=1(PHD), 2(PMD), 3(PLD)*
j= Supply chain level *j*=1 (Manufacturer), 2(Distributor), 3(Retailer)
t = Time (week) *t=1,2,..., 104*
AT= Apparel type= *HD, LD* (dmnl)
ATn= No. of apparel type (dmnl)
Bcr(j)= Backlogged penalty rate, j=1,2 (dmnl)
BC (ijt)= Backlogged cost, j=1,2 (dollar/week)
BD (ijt)= Backlogged orders delivered, j=1,2 (unit/week)
BIF (ijt)= Backlogged inflow, j=1,2 (unit/week)
BO(ijt)= Backlogged orders, j=1,2 (Unit)
Bt(j)= Backlogged adjustment time, j=1,2 (week)
C= Color= Major, Minor (dmnl)

CA(ij)= Manufacturing Capacity, j=1(unit/week)
CAr(ij)= Product type capacity ratio, j=1 (dmnl)
CSL (j)= Cycle service level, j=2,3 (dmnl)
D(ijt)= Demand for the level j of supply chain (unit/week)
DD(jt)= Delivery delay, j=1,2 (week)
$\mu_{DD(j)}$= Delivery delay mean, j=1,2 (week)
$\sigma_{DD(j)}$= Delivery delay standard deviation, j=1,2 (week)
DE(ijt)= Delivered products (unit/week)
DEt(j)= Min time to delivery (week)
ED(ijt)= Expected demand (unit/week)
F(ijt)= Feasible production rate, j=1 (unit/week)
Fe(ijt)= Forecast error (unit/week)
$\alpha(j)$ = Forecasting adjust factor (week)
FL(ijt)= Flow of products to j=2,3 (unit/week)
FO(ijt)= Firm orders, j=1,2 (unit/week)
FP(ijt)= Manufactured or ready products
h (j)= Holding rate (dmnl)
I(ijt)= Inventory (Unit)
IP(ijt)= Inventory position (unit)
LDr(ijt)= Ratio of lost demand, j=3 (dmnl)
LT(jt)= Lead time (week)
$\mu_{LT(j)}$= Lead time mean (week)
$\sigma_{LT(j)}$= Lead time standard deviation (week)
LTc(j)= Lead time effect on cost, j=1,2 (dmnl)
MDc(ij)= Mean demand constant, j=3 (unit/week)
O(ijt)= Orders (unit/week)
Ot(j)= Orders adjustment time (week)
P(ijt)=Profit (dollar/week)
PCb (ij)= Base product cost, j=1(dollar/unit)
Pr(ij)= Price (dollar/unit)
PrI(ij)= Price increase (dmnl)
R(ijt)= Revenue (dollar/week)
ROP (ijt)= Reorder point, j=2,3 (unit)
S= Number of sizes for each apparel type (AT) (dmnl)
SO(ijt)= Stock-Out, j=3 (unit/week)
SS(ijt)=Safety stock, j=2,3(unit)
TC(ijt)= Total cost (dollar/week)
TCA= Total capacity, j=1 (unit/week)
TRc(j)= Cost per truck (dollar/truck)
TRca=Truck capacity (unit/truck)

TRn (jt)=No. of trucks, j=1,2 (truck/week)
TrnC (ijt)=Transportation cost, j=1,2 (dollar/week)
UC(ij)= Total unit cost (dollar/unit)
UIC(ij)= Unit inventory cost (dollar/unit)
UPC (ij)= Unit product cost (dollar/unit)
UTC (ij) = Unit transportation cost, j=1,2 (dollar/unit)
V= Variety in each apparel type (dmnl)
WIP(ijt)= In process products/ Received Products (Unit)

More detail on model variables, constants, and parameter settings is provided in Tables A-1 to A-3 in the Appendix.

3.2.2 Causal Loop Diagram

The basic SD objective is to understand the structural causes that trigger system performance (Campuzano and Mula, 2011). In SD methodology, causal loop diagram is applied to represent the system. It includes the key factors of the system and the relationships among them based on the causes which have influence on the effects. Causal loop diagrams serve two main purposes. First, they can be applied as conceptual sketches of causal hypothesis during model development and second, they can make a simpler representation of a model. A causal loop diagram describes the major feedback mechanisms which can be either negative or positive. Negative loops play the role of stabilizing elements that lead the model towards a balanced situation. Positive loops make the system unstable, that is, an initial disturbance in the system leads to further change and an instability. The systems usually contain both loop types and the final performance depends on which one is dominant.

The relationships among the variables in causal loop diagram are represented by arrows which come with a + or – sign. The + sign means a positive change in the origin variable of the arrow will produce a positive change in the destination variable. The – sign represents that a positive change in the origin variable will result in a negative change in the destination variable.

As the first modeling step, the relationships among the system operations are captured in a SD manner and the appropriate causal loop diagram is constructed. In order to improve the distinction among the variables, the stock variables are shown in boxes, the smoothed stock variables are written in italics and the rest in small plain letters.

Our supply chain model includes three primary levels, a manufacturer, a distributor, and a retailer. Figures 3-1 to 3-3 show the causal loop diagrams for these three levels.

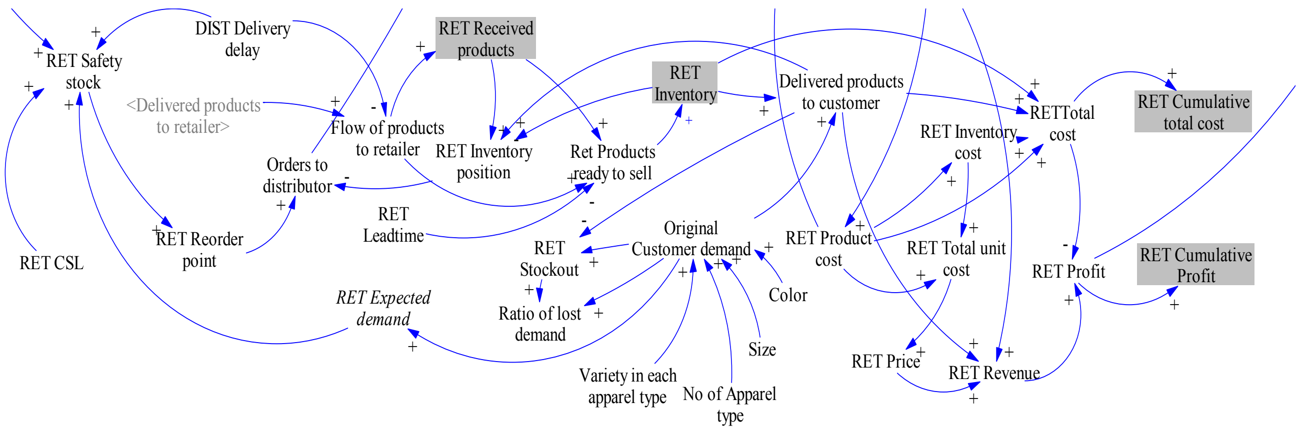


Figure 3-1. Causal loop diagram for retailer level of supply chain

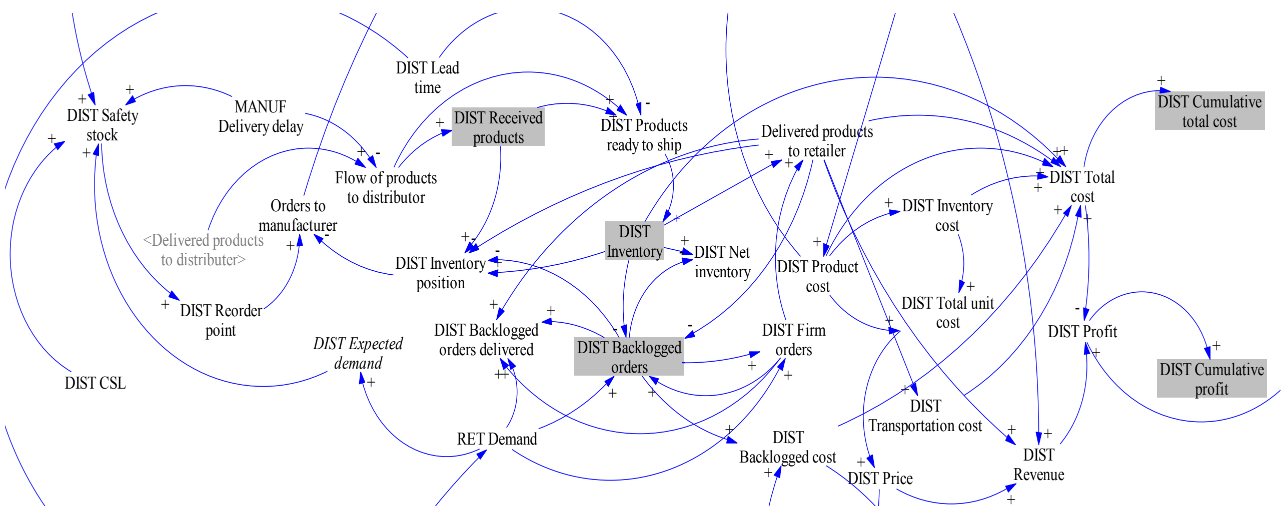


Figure 3-2. Causal loop diagram for distributor level of supply chain

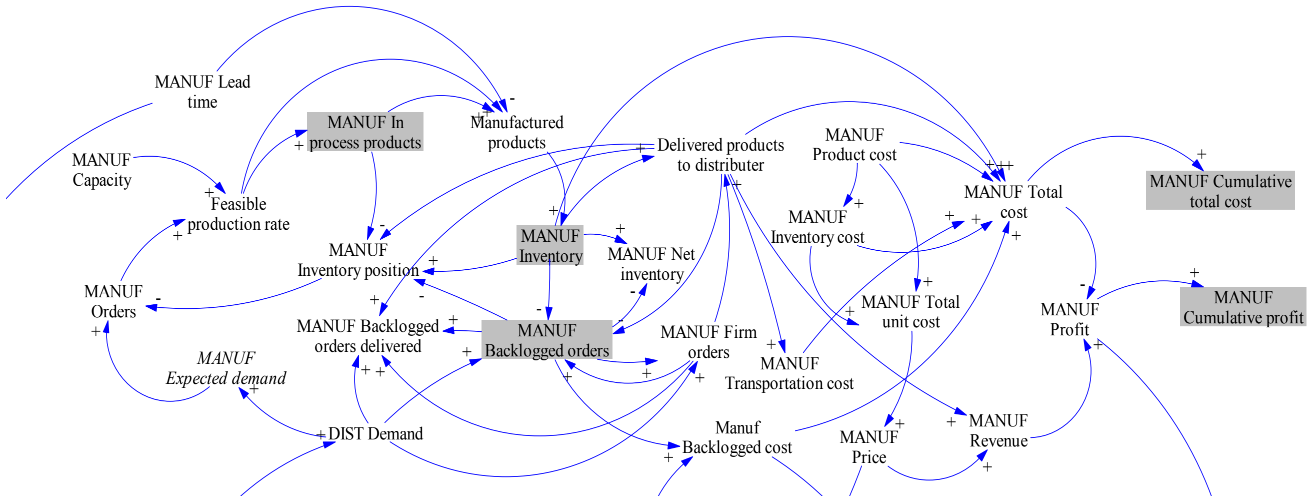


Figure 3-3. Causal loop diagram for manufacturer level of supply chain

3.2.3 Mathematical Formulation/ Stock and Flow Diagram

The next step of SD is to generate the stock and flow diagram. This diagram is a rich visual language which helps to develop the mathematical model and to write a system of differential equations which can be solved via simulation programs.

In this research, Vensim DSS® software is applied to develop the stock and flow diagram. In SD, a special diagramming notation is used for stocks and flows. Stocks are presented by rectangles, inflows are symbolized by a pipe pointing into the stock and outflows by pipes pointing out of stock. Valves control the flows and clouds depict the sources and sinks for flows (Sterman, 2000). It should be mentioned that only the significant delays are included in our model although delays exist in all product flows.

Figure 3-4 shows a high level view of the stock and flow structure of the model using policy structure diagram. This diagram provides an overview of the model for each level of supply chain and highlights the feedback structure without showing all the details (Sterman, 2000). The colored rectangles denote the subunits of the model. The subunits are shown with more detail of corresponding variables and feedback loops, subsequently (Figures 3-6 to 3-9). At the end, the complete stock and flow diagram for all levels of the supply chain is presented in Figure 3-20.

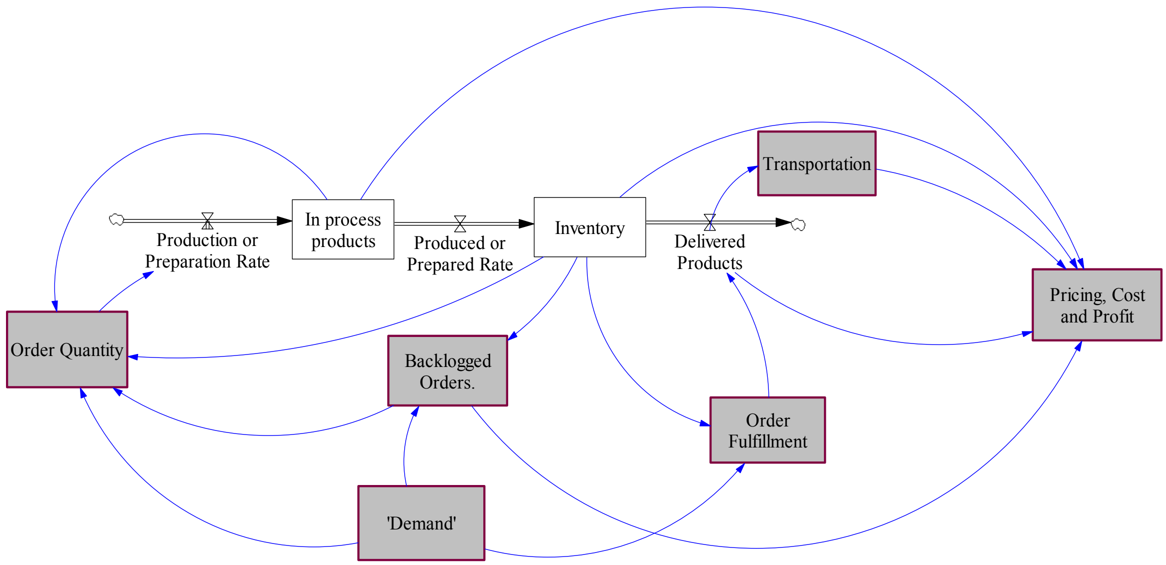


Figure 3-4. The policy structure for each level of supply chain

3.2.3.1 Structure of demand, order fulfillment and backlogged orders

In our model, three categories of products are defined: products with high demand (PHD), products with medium demand (PMD), and products with low demand (PLD) which enables us to simultaneously study the behavior of the model at different demand levels (see Figure 3-5). At the retailer level, the demand for each of these categories of products is a random variable which depends on the variety of products available in the store and it is a factor of different components including ‘number of apparel type’, ‘variety in each apparel type’, ‘color’ and ‘size’ of each apparel type (Eq. 1). The different types of apparel such as skirt, shirt, pants, jacket, etc. are split into two categories of either high demand apparel (HD) or low demand apparel (LD). The parameter ATn (No. of apparel type) contains the number of different apparel types that exist in each of these two categories of garments. The parameter ‘variety in each apparel type’ counts different styles for each apparel type, for example, different types of shirts or pants that are available. The color of apparel is also divided into two sub-categories of major colors (such as white, blue, and black) and minor colors (such as hot pink and neon green) based on its popularity. We defined a parameter named ‘color’ which shows the number of major and minor colors for each apparel. At the end, the parameter ‘size’ shows the number of available sizes for each apparel. The high demand apparels which have a major color are considered as PHD product; the high demand apparels with minor color or the low demand apparels with major color are regarded as PMD products; the low demand apparel with minor color are counted as PLD products. The distributor and retailer demand are basically the orders of the downstream level (Eq. 1).

$$D(ijt) = \begin{cases} O(i(j+1)t) & j = 1,2 \\ Random\ Poisson\ (MDc(ij) \times AT[HD] \times V \times S \times C[major]), & i = 1, j = 3 \\ Random\ Poisson\ \left(MDc(ij) \times \begin{pmatrix} AT[HD] \times V \times S \times C[minor] + \\ AT[LD] \times V \times S \times C[major] \end{pmatrix}\right), & i = 2, j = 3 \\ Random\ Poisson\ (MDc(ij) \times AT[LD] \times V \times S \times C[minor]), & i = 3, j = 3 \end{cases} \quad (1)$$

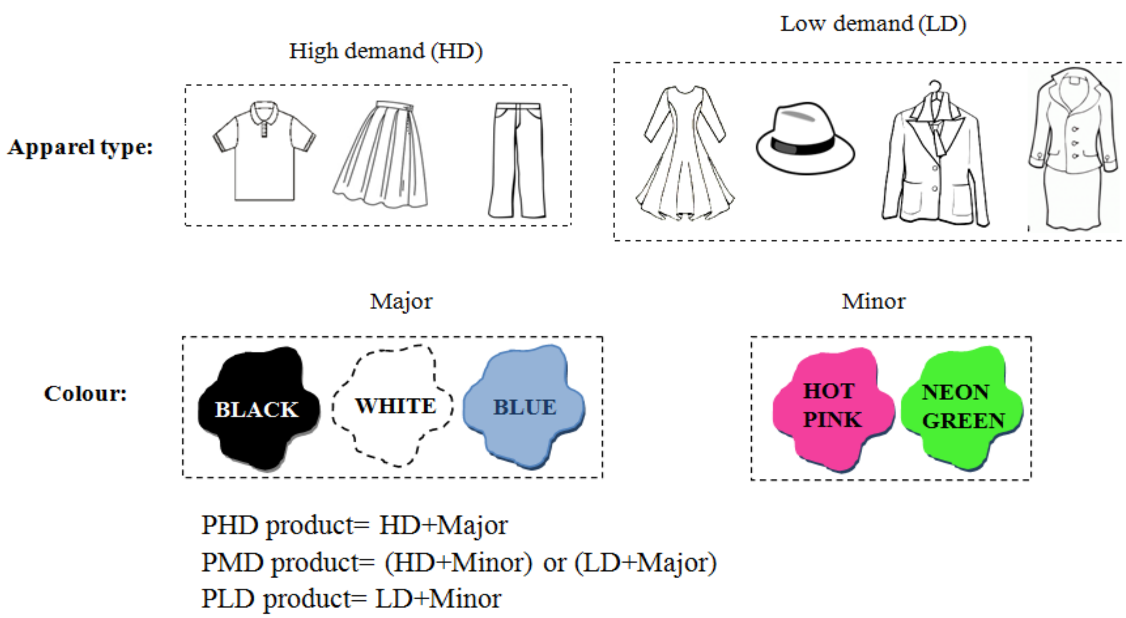


Figure 3-5. Categories of products

Each level of SC receives the demand information and provided that its warehouse (represented by 'inventory') has the required amount available serves the downstream level (Eq. 3). For the manufacturer and distributor levels, if inventory does not have enough stock at the time, the unsatisfied order will be added to the backlogged orders through the variable 'backlogged inflow' (Eq. 4-5). The backlogged orders will be served as soon as the inventory has the indicated level to do so (Eq. 6). The backlogged orders have a negative causal relationship with 'inventory' since any increase in inventory level decreases the backlogged orders.

$$\begin{cases} I(ijt) = I(ij0) + \int_0^t \big(FP(ijt) - DE(ijt) \big) dt, \\ I(ij0) = \begin{matrix} I_{110} = 10{,}000 & I_{120} = 7{,}000 & I_{130} = 4{,}000 \\ I_{210} = 7{,}000 & I_{220} = 3{,}000 & I_{230} = 2{,}500 \\ I_{310} = 1{,}000 & I_{320} = 800 & I_{330} = 400 \end{matrix} \end{cases} \tag{2}$$

$$DE(ijt) = \begin{cases} Min\left(FO(ijt), \frac{I(ijt)}{DEt(ijt)}\right), & j = 1,2 \\ Min\left(D(ijt), \frac{I(ijt)}{DEt(ijt)}\right), & j = 3 \end{cases} \tag{3}$$

$$BIF\ (ijt) = \begin{cases} D(ijt) - DE(ijt), & DE(ijt) < D(ijt) \\ 0, & O.W. \end{cases} \quad j = 1,2 \tag{4}$$

$$BO(ijt) = BO(ij0) + \int_0^t \big(BIF(ijt) - BD(ijt) \big) dt\,; \ \ BO(ij0) = 0 \qquad j = 1,2 \tag{5}$$

$$BD\ (ijt) = \begin{cases} \frac{BO(ijt)}{Bt(j)}, & DE(ijt) = FO(ijt) \\ DE(ijt) - D(ijt), & D(ijt) < DE(ijt) < FO(ijt) \\ 0, & O.W. \end{cases} \quad j = 1,2 \tag{6}$$

At the retailer level, when the customers' need is not satisfied, the customers usually leave the store and do not wait for their need to be fulfilled. Therefore, the constructed model has considered the orders not delivered on time to the final customer as the lost sales at the retailer level and the difference between delivered products and demand will be added to the 'stockout' variable (Eq. 7).

$$SO(ijt) = \begin{cases} D(ijt) - DE(ijt), & D(ijt) > DE(ijt) \\ 0, & O.W. \end{cases} \quad j = 3 \tag{7}$$

$$LDr(ijt) = \begin{cases} \frac{SO(ijt)}{D(ijt)}, & D(ijt) \neq 0 \\ 0, & O.W. \end{cases} \quad j = 3 \tag{8}$$

In the diagram, 'inventory position' variable supplies information on the net inventory level which is a function of 'inventory', 'in process products' and 'backlogged orders' (Eq. 10). Any increment in the first two variables increases the inventory position while an increase in the third variable lowers the inventory position.

$$WIP(ijt) = \begin{cases} WIP(ij0) + \int_0^t \big(F(ijt) - FP(ijt) \big) dt\,; \ WIP(ij0) = 0, \ \ j = 1 \\ WIP(ij0) + \int_0^t \big(FL(ijt) - FP(ijt) \big) dt\,; \ WIP(ij0) = 0, \ \ j = 2,3 \end{cases} \tag{9}$$

$$IP(ijt) = \begin{cases} I(ijt) + WIP(ijt) - BO(ijt), & j = 1,2 \\ I(ijt) + WIP(ijt), & j = 3 \end{cases} \tag{10}$$

For the manufacturer level, the pipe pointing into the ‘in process products’ stock represents the amount of production in each time period which is constrained by the manufacturing capacity (Eq. 12). It should be noted that the manufacturer has a daily capacity, so it can only manufacture the amount of units the factory is capable of. If the manufacturing orders are larger than the manufacturing capacity, the units exceeding this amount are rejected which finally leads to increase in the level of backlogged orders. The capacity is different for each product type and the total capacity of the manufacturer is assigned to each of the three product types based on the demand ratio of the product (Eq. 11).

$$CA(ij) = TCA \times CAr(ij), \qquad j = 1 \tag{11}$$

$$F(ijt) = Min\left(Max\left(ED(ijt) - \frac{IP(ijt)}{Ot(j)}, 0\right), CA(ij)\right), \qquad j = 1 \tag{12}$$

For the distributor and retailer levels, the same pipe shows the flow of products from the upstream level (Eq. 14). This variable adds some delay to the system due to the delivery delay of the upstream level (Eq. 13).

$$DD(jt) = Random\ Normal\big(\mu_{DD(j)}, \sigma_{DD(j)}\big), \qquad j = 1,2 \tag{13}$$

$$FL(ijt) = Delayfixed\Big(DE(i(j-1)t), DD\big((j-1)t\big)\Big), \qquad j = 2,3 \tag{14}$$

The arrival of the manufactured or ready products from the ‘in process products’ stock to the ‘inventory’ stock takes place exactly after the period defined as lead time which is an random variable that changes in different time periods (Eq. 15-16).

$$LT(jt) = Random\ Normal\big(\mu_{LT(j)}, \sigma_{LT(j)}\big) \tag{15}$$

$$FP(ijt) = \begin{cases} Delayfixed\big(F(ijt), LT(jt)\big), & j = 1 \\ Delayfixed\big(FL(ijt), LT(jt)\big), & j = 2,3 \end{cases} \tag{16}$$

The firm orders at each time period is made of backlogged orders and current demand (Eq. 17). There is a positive causal relationship between ‘backlogged orders’, ‘demand’ and ‘firm orders’ since the state of the last variable increases by any increase in the first two variables.

$$FO(ijt) = D(ijt) + \frac{BO(ijt)}{Bt(j)}, \qquad j = 1,2 \tag{17}$$

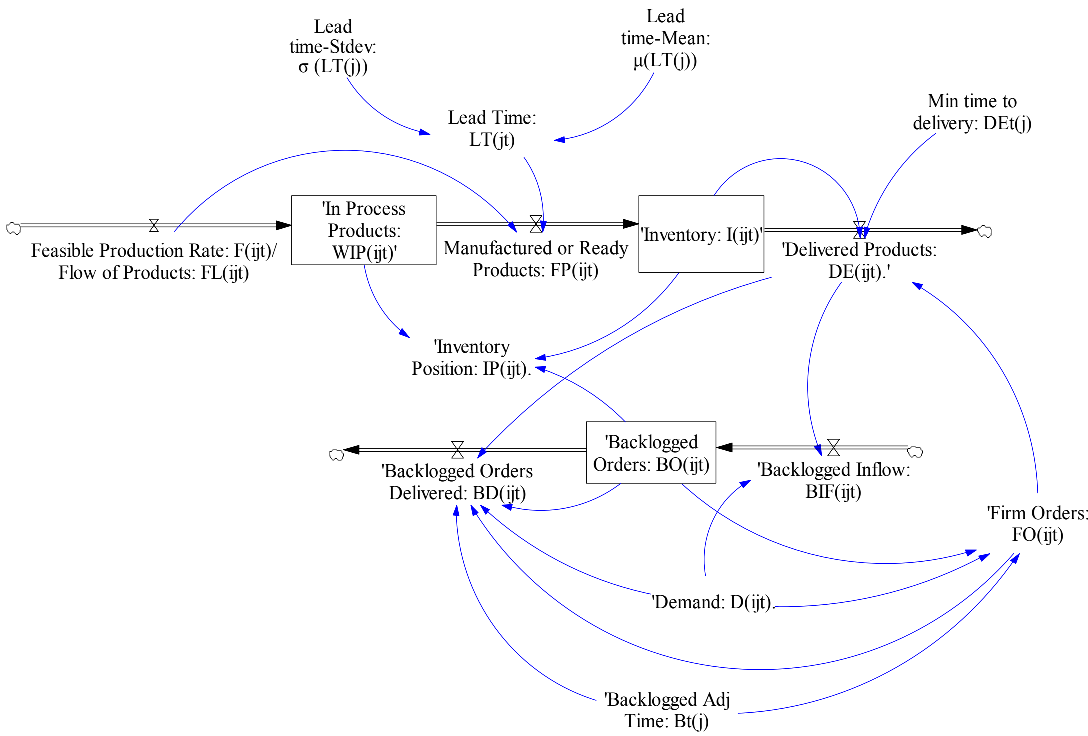


Figure 3-6. Structure of demand, order fulfilment and backlogged orders

3.2.3.2 Structure of order quantity

The demand for each level of the supply chain form part of the data used for forecasting the future demand, referred to as 'expected demand', and will be the information that is considered when placing the orders (Eq. 18). In this research, the continuous review policy (s, S) is applied to inventory replenishment, i.e., the inventory is continuously tracked at each time period and an order is placed when the inventory position drops below reorder point (ROP). An increase in forecasted demand makes the replenishment order size larger since there is positive relationship between expected demand and ROP. To avoid stockouts, the warehouse has a safety stock available whose size depends on Cycle Service Level (CSL: the fraction of replenishment cycles that do not contain a stock out event) as well as the mean and standard deviation of the variables 'expected demand', 'upstream lead time' and 'upstream delivery delay' (Eq. 20). So, ROP is calculated based on safety inventory and expected demand during the lead time of the upstream level considering the delivery delays (Chopra et al., 2004) (Eq. 21). It should be noted that in the supply chain, the more safety inventory the retailer carries, the less safety inventory the distributor needs to carry (Chopra and Meindl, 2010). Thus, two different CSL values are considered for the retailer and distributor levels. The order will be placed when the necessary information is available, that is, current inventory position and reorder point (Eq. 22). The order reaches the distributor as an information flow. It should be mentioned that the variables ‘expected demand SS’, ‘expected demand cumulative’, ‘cumulative demand inflow’, and ‘demand SS inflow’ shown in Figure 3-7 are only the intermediate variables to calculate the average and standard deviation of the expected demand.

$$ED(ijt) = Smooth\big(D(ijt), \alpha(j)\big) \tag{18}$$

$$Fe(ijt) = |D(ijt) - ED(ijt)| \tag{19}$$

$$SS(ijt) = F^{-1}\big(CSL(j)\big) \times \sqrt{\left[(\mu_{LT(j-1)} + \mu_{DD(j-1)}) \times \sigma^2{}_{ED(ijt)}\right] + \left[\mu^2{}_{ED(ijt)} \times \left(\sigma^2{}_{LT(j-1)} + \sigma^2{}_{DD(j-1)}\right)\right]} \quad j = 2,3 \tag{20}$$

$$ROP(ijt) = SS(ijt) + \left[(\mu_{LT(j-1)} + \mu_{DD(j-1)}) \times ED(ijt)\right], \qquad j = 2,3 \tag{21}$$

$$O(ijt) = \begin{cases} \frac{Max(ED\ (ijt) - IP(ijt), 0)}{Ot(j)}, & j = 1 \\ \frac{Max(ROP\ (ijt) - IP(ijt), 0)}{Ot(j)}, & j = 2,3 \end{cases} \tag{22}$$

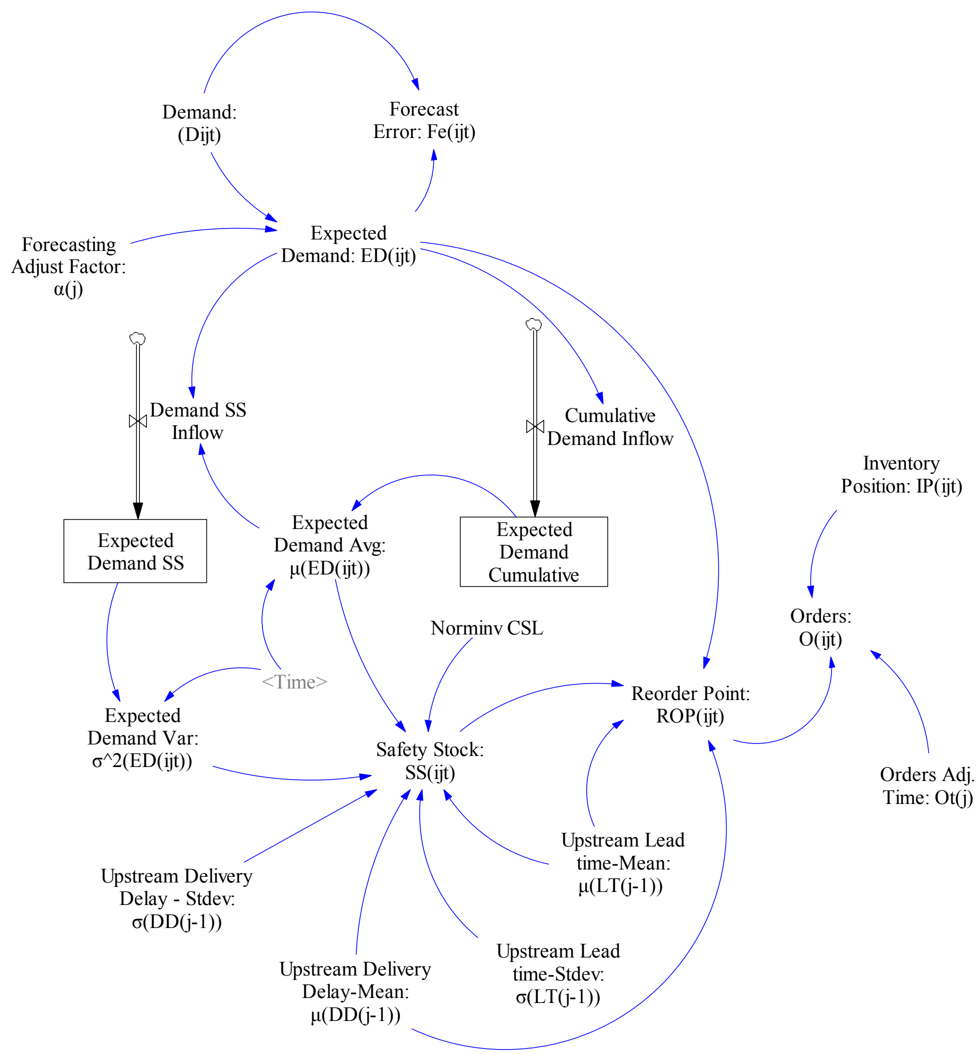


Figure 3-7. Structure of order quantity

3.2.3.3 Structure of transportation

In this model, it is considered that each truck can carry all three types of products needed to be delivered in each time period: $\sum_{i=1}^{3} DE(ijt)$. Therefore, the information needed to calculate the number of necessary trucks is: total delivery of all product types as well as truck capacity. Equation 23 shows the formula used to calculate the number of trucks. The part $Integer\left(\frac{\sum_{i=1}^{3} DE(ijt)}{TRca}\right)$ counts the number of full trucks needed. Then, if the remaining products are more than half of the capacity of one truck, another truck will be added. Otherwise, the products will be distributed among the existing trucks.

$$TRn(jt)=\begin{cases} 0, & \frac{\sum_{i=1}^{3} DE(ijt)}{TRca}=0 \\ 1, & 0<\frac{\sum_{i=1}^{3} DE(ijt)}{TRca}<1 \\ Integer\left(\frac{\sum_{i=1}^{3} DE(ijt)}{TRca}\right)+1, & Integer\left(\frac{\sum_{i=1}^{3} DE(ijt)}{TRca}\right)-\frac{\sum_{i=1}^{3} DE(ijt)}{TRca}>0.5 \\ Integer\left(\frac{\sum_{i=0}^{3} DE(ijt)}{TRca}\right), & O.W. \end{cases} \quad j=1,2$$

(23)

Weekly cost of transportation for each product type depends on the number of trucks, cost per truck, and quantity of delivered products from each product type (Eq. 24). As explained above, the number of trucks is for all product types. However, there is need to compute the transportation cost for each product type, distinctively. Therefore, the ratio $\frac{DE(ijt)}{\sum_{i=1}^{3} DE(ijt)}$ in Equation 24 is used.

$$TrnC(ijt)=\begin{cases} \frac{DE(ijt)}{\sum_{i=1}^{3} DE(ijt)}\times TRn(jt)\times TRc\,(j), & \sum_{i=1}^{3} DE(ijt)\neq 0 \\ 0, & O.W. \end{cases} \quad j=1,2 \qquad (24)$$

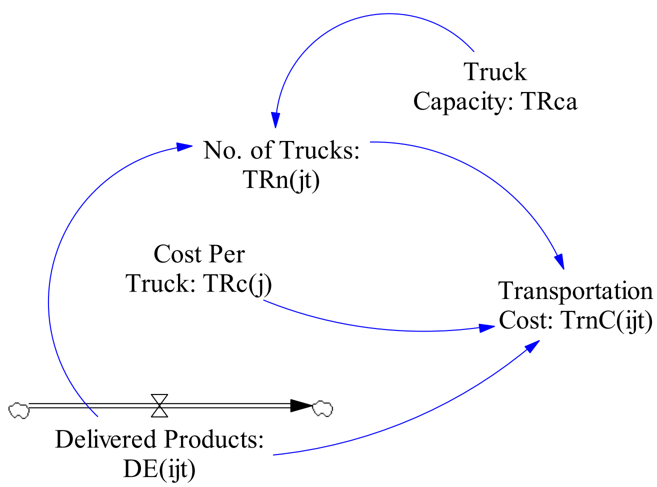


Figure 3-8. Structure of transportation

3.2.3.4 Structure of pricing, cost and profit

One of the main criteria applied to evaluate the entire supply chain performance is the profit in each level of supply chain and total supply chain profit. In our model, the profit follows the standard formulation of revenue minus cost (Eq. 25).

$$P(ijt)=R(ijt)-TC(ijt) \qquad (25)$$

Most of the cost parameters employed are the typical ones used in supply chain management including inventory holding cost, production/product cost, transportation cost, and cost of backlogs. Inventory holding cost is a fraction of product cost (Eq. 28). Depending on the category of products, different product costs are specified for them. Backlogs cost is the penalty the upstream level should pay and is a proportion of product cost at the current level of supply chain and amount of backlogs inflow in each period (Eq. 30). For each level of supply chain, total cost per time period is calculated using the variable 'total cost' and is the summation of all abovementioned costs (Eq. 31).

For most of the businesses, decreasing the lead time below a certain point is a costly process. Thus, the impact of the lead time changes on the production/product cost is also included in our model which is presented in equations 26 and 27.

$$LTc\ (j) = \begin{cases} \begin{cases} 1.1, & \mu_{LT(j)} \leq 1.5 \\ 1, & 1.5 < \mu_{LT(j)} \leq 2.5 \\ 0.9, & O.W. \end{cases} & j = 1 \\ \begin{cases} 1.1, & \mu_{LT(j)} \leq 0.28 \\ 1, & O.W. \end{cases} & j = 2 \end{cases} \tag{26}$$

$$UPC\ (ij) = \begin{cases} PCb(ij) \times LTc(j), & j = 1 \\ Pr\big(i(j-1)\big) \times LTc(j), & j = 2 \\ Pr\big(i(j-1)\big), & j = 3 \end{cases} \tag{27}$$

$$UIC(ij) = h(j) \times UPC(ij) \tag{28}$$

$$UC(ij) = \begin{cases} UIC(ij) + UPC(ij) + UTC(ij), & j = 1,2 \\ UIC(ij) + UPC(ij), & j = 3 \end{cases} \tag{29}$$

$$BC\ (ijt) = Bcr\ (j) \times UPC\ \big(i(j+1)\big) \times BIF(ijt), \qquad j = 1,2 \tag{30}$$

$$TC(ijt) = \begin{cases} \big[UIC(ij) \times \big(I(ijt) + WIP(ijt)\big)\big] + [UPC(ij) \times DE(ijt)] + BC(ijt) + TrnC(ijt), & j = 1,2 \\ \big[UIC(ij) \times \big(I(ijt) + WIP(ijt)\big)\big] + [UPC(ij) \times DE(ijt)], & j = 3 \end{cases} \tag{31}$$

As the pricing strategy, higher mark-ups are considered for the products with small volume of demand (Sen, 2008). Furthermore, the mark-up for each category of product is selected in such a way that the product's final price in retailer level does not exceed a normal limit in apparel industry. ‘Price’ and ‘price inc.’ in the pricing diagram are the variables used for pricing calculations (Eq. 32).

$$\Pr(ij) = PrI(ij) \times UC(ij) \tag{32}$$

The revenue is calculated based on the amount of delivered products to the downstream level and their prices (Eq. 33).

$$R(ijt) = \Pr(ij) \times DE(ijt) \tag{33}$$

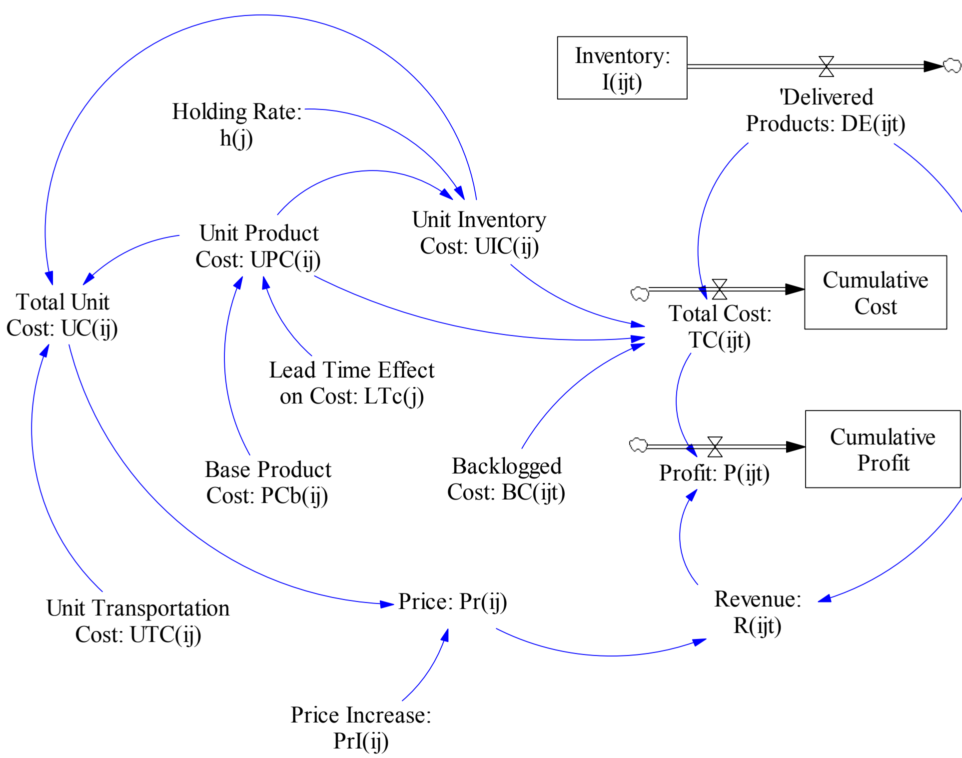


Figure 3-9. Structure of pricing, cost and profit

3.3. Model Validation

It is vital to establish the validity of the structure of SD model which is the validity of the set of equations used in the model. Structure validity is followed by checking the accuracy of model behavior. However, it should be noted that a point-by-point match between the real behavior and the model behavior is not as important as it is in classical forecasting modeling (Barlas, 2000; Forrester and Senge, 1980). There are many tests of model structure and behavior for SD models which are not doable with other types of models. Contrarily, some commonly used tests for other models are inappropriate for SD models (Forrester and Senge, 1980).

Forrester and Senge (1980) suggested a number of direct structure tests, for example, structure and parameter verification tests, extreme conditions test, and dimensional consistency test. In this study, the structure test is conducted by comparing the model equations with the existing knowledge on the system in the literature. A parameter verification test was carried out by evaluating the constant parameters used in the models against the knowledge of fast fashion apparel industry. Finally, dimensional consistency test for all model equations as well as extreme conditions test is conducted.

Tests of model behavior evaluate the adequacy of model structure through analysis of the behavior generated by the structure (Forrester and Senge, 1980). Some of these tests which are conducted in this study include extreme policy, behavior sensitivity and behavior anomaly. The behavior anomaly test is extensively used in both phases of model development and model validation. After discovering some model behavior which significantly conflicts with behavior of the real system, the abnormal behavior was traced to find the obvious flaws in the model or assumptions.

The results of extreme policy test (Scenario 4, 5, and 6), extreme conditions tests (Scenario 7) and behavior sensitivity to some key factors of model (scenarios 1, 4, and 7) are shown in Table 3-1 as well as Tables A-5 and A-6 in the Appendix.

Table 3-1. Structure and behavior validation of the model under seven scenarios (PHD products)

Variable name	Scenario / Level	1: Base scenario	2: Seasonal demand	3: 25% increase in lead-time of all levels	4: Extreme high demand	5: Extreme low demand	6: Base model with Zero capacity	7: Base model with Zero inventory in Manufacturing level
Average weekly demand	Retailer	7,872	8,144	7,872	39,384	1,568	7,872	7,872
	Distributor	3,866	4,093	4,164	20,581	776	8,238	8,356
	Manufacturer	3,952	4,703	5,264	241,499	876	416,521	438,026
Stdev of weekly demand	Retailer	96	752	96	184	38	96	96
	Distributor	1,375	1,510	1,675	4,844	273	892	641
	Manufacturer	8,128	8,669	10,612	23,196	1,586	254,174	255,314
Average weekly sales	Retailer	3,842	3,864	4,123	17,947	768	221	125
	Distributor	3,854	3,847	4,184	18,288	734	180	83
	Manufacturer	3,936	3,876	5,277	18,674	721	94	0
Average weekly inventory	Retailer	3,916	3,919	4,341	17,947	812	221	125
	Retailer (Received)	840	842	1,038	3,963	159	40	18
	Distributor	38,867	33,278	51,402	18,288	6,263	205	108
	Distributor (Received)	1,846	1,778	3,110	8,621	321	44	0
	Manufacturer (finished products)	5,232	5,420	6,044	18,674	2,964	171	0
	Manufacturer (WIP)	8,274	8,808	13,201	40,760	1,539	0	0
Average weekly backlogs	Distributor	2,782	2,969	3,514	220,998	544	397,473	418,563
	Manufacturer	14,701	14,833	25,413	11,460,053	2,165	14,011,650	15,104,441
Average weekly stockout	Retailer	4,031	4,280	3,749	21,437	800	7,652	7,748
Average ratio of lost demand	Retailer	0.512	0.521	0.476	0.544	0.510	0.972	0.984
Average weekly cost	Retailer	100,387	100,903	108,489	468,139	20,121	5,730	3,226
	Distributor	77,846	73,090	94,674	210,054	13,886	29,485	29,150
	Manufacturer	29,073	29,751	39,805	336,934	6,407	397,012	417,000
Average weekly Profit	Retailer	19,058	19,905	20,000	88,788	3,803	28,516	28,816
	Distributor	12,074	17,300	3,792	418,146	3,270	371,051	389,749
	Manufacturer	8,399	7,146	10,432	-159,157	456	-396,114	-417,000
	Supply chain	39,531	44,352	34,224	347,777	7,529	3,453	-18,562
Stdev of weekly profit	Retailer	4,825	5,044	4,958	10,064	938	2,272	1,546
	Distributor	36,155	33,320	49,669	82,404	6,803	236,688	240,297
	Manufacturer	20,906	20,771	23,811	15,111	4,757	242,650	243,059
	Supply chain	46,071	42,883	56,909	64,758	9,400	13,100	8,401

Scenarios 4 and 5 present business conditions in which the supply chain is subjected to extremely high demand and extremely low demand from the final customer at the retailer level. Scenario 6 represents the behavior of the system when the manufacturing capacity is equal to zero. Scenario 7 is used to test the model structure by changing a stock variable that is inventory. The purpose is to see how an extreme condition on a stock variable affects the rest of flow and auxiliary variables in between. In this scenario, manufacturing inventory is assumed to be zero with no initial inventory available. Furthermore, some of the key factors including lead time and customer demand are selected to perform the sensitivity analysis.

Figures 3-10 through 3-16 illustrate the weekly inventory at all three levels of the apparel supply chain plotted for a period of 104 weeks (two years) for all seven scenarios.

Tables 3-1, A-5, A-6 and Figures 3-10 through 3-16 show the anticipated behavior of the studied supply chain. For instance, under zero capacity and zero manufacturing inventory scenarios, "average weekly sales" is zero for manufacturer and it drops to a value close to zero for the other two SC levels. Since these two levels can use their initial inventory in the earlier time periods their average sales is not zero. Under these two scenarios, the level of backlogged orders increases exponentially; and average ratio of lost demand approaches 1. Due to the penalty the manufacturer needs to pay to the downstream level, the cost at manufacturer level increases, significantly. Average weekly profit for retailer and distributor increases because of the backlogged penalty they earn from the upstream level. However, manufacturer's average profit decreases remarkably since they do not have any revenue and they have to pay the penalty rate of the backlogs.

When we inject extreme high demand to the retailer level (extreme high demand scenario) we can see that the demand at upstream levels increases as well which consequently leads to increase in average weekly sales. Under this scenario, all SC levels have to deal with higher amount of inventory. Since production capacity is kept the same under this scenario, the number of backlogs in both distributor and manufacturer levels increases significantly. The cost in all three SC levels shows a high increase due to higher backlogs, inventory, and product costs. When we compare the behavior of the model under extreme low demand scenario and extreme high demand scenario, as expected it can be seen that the model shows an opposite behavior.

By increasing the lead time of all three SC levels, we can see that the inventory of all SC levels increase. The increase in backlogs is another impact of higher lead times. Therefore, higher costs happen due to higher inventories and backlogs. Consequently, longer lead times result in significantly lower profit for distributor as well as higher variation in profit of all supply chain levels.

Moreover, the apparel supply chain portrays the 'bullwhip effect' that is, increasing demand variability from retailer to the upstream levels. It can be seen in Tables 3-1, A-5, and A-6, in the values of Stdev of weekly demand. Based on the results presented, it can be concluded that the proposed model is valid, both behaviorally and structurally.

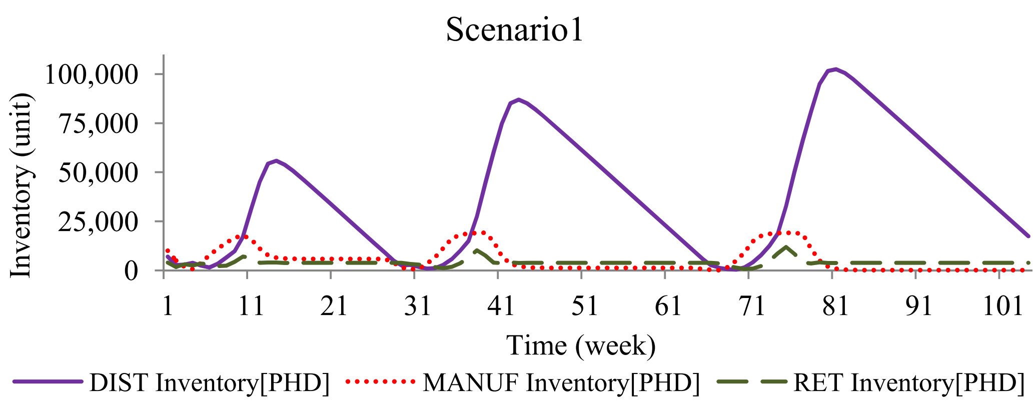


Figure 3-10. Weekly inventory level for three SC levels under scenario 1, base model

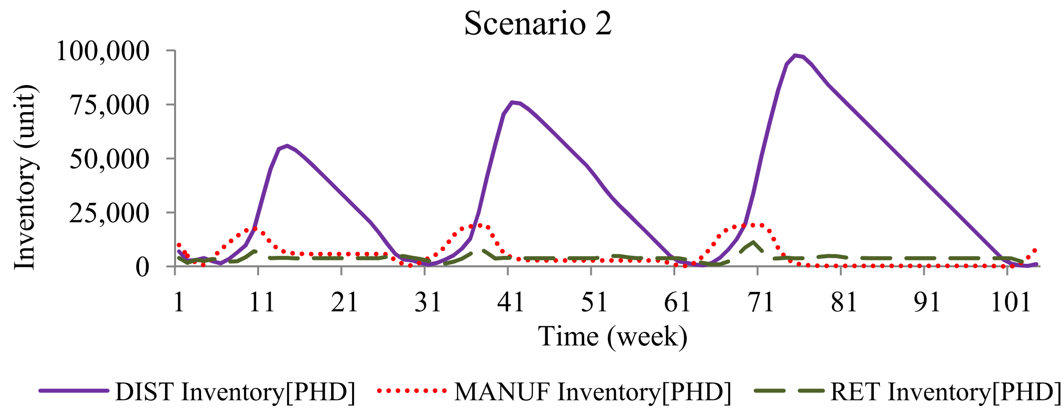


Figure 3-11. Weekly inventory level for three SC levels under scenario 2, seasonal demand

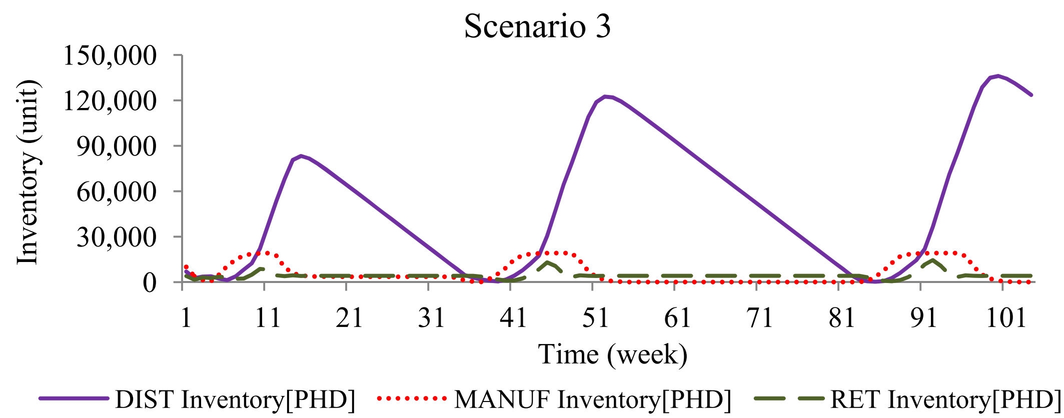


Figure 3-12. Weekly inventory level for three SC levels under scenario 3, 25% increase in lead-time of all levels

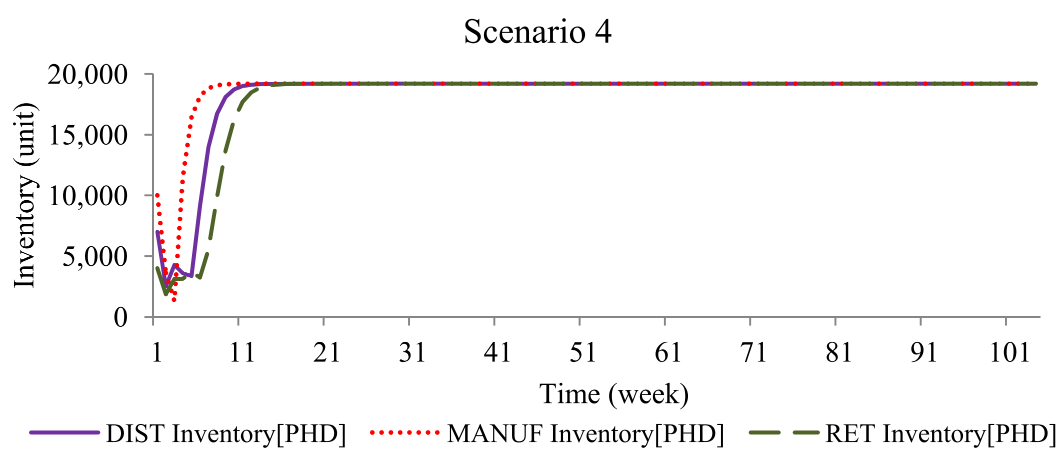


Figure 3-13. Weekly inventory level for three SC levels under scenario 4, extreme high demand

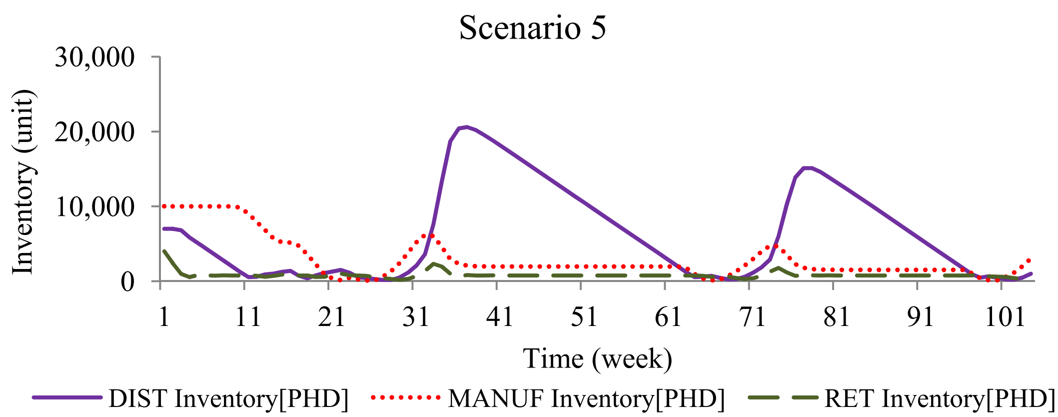


Figure 3-14. Weekly inventory level for three SC levels under scenario 5, extreme low demand

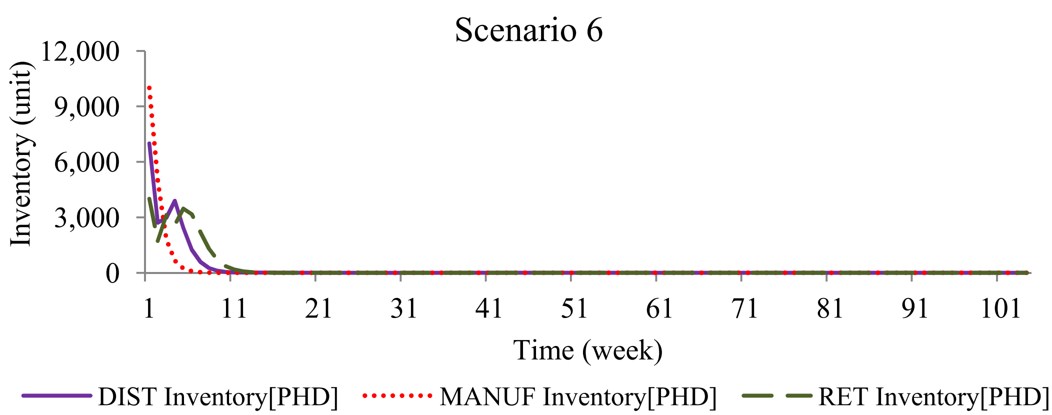


Figure 3-15. Weekly inventory level for three SC levels under scenario 6, base model with zero capacity

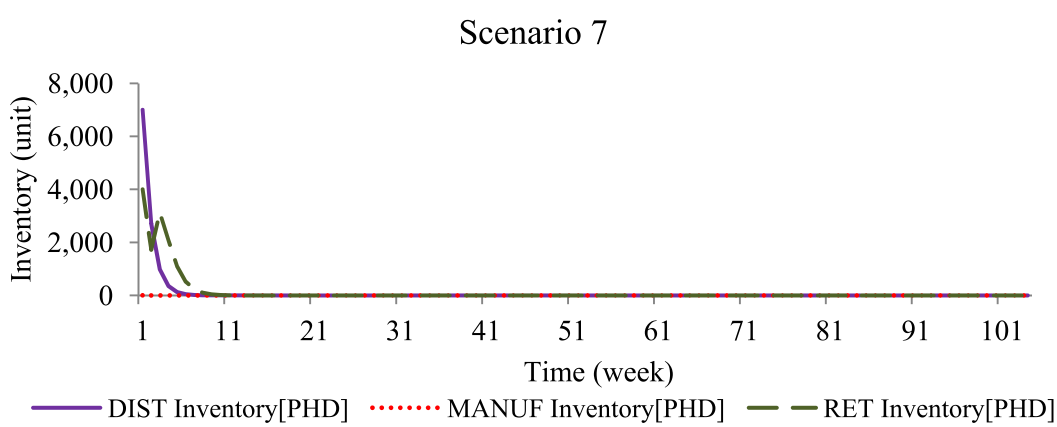


Figure 3-16. Weekly inventory level for three SC levels under scenario 7, base model with zero inventory in manufacturing level

3.4. Risk Measurement

Uncertainty and risk have always been part of human life and, in turn, people have been trying to protect themselves against their consequences. As early as 1000 BC, the Babylonians developed a system where merchants who borrowed money to fund shipments could pay an extra amount to cancel the loan if the shipment was stolen (Damodaran, 2008). From the business point of view, risk has to be factored in by managers and investors when making decisions. Therefore, it follows logically that measuring risk is an essential step towards managing it.

The focus of traditional supply chain management is mainly on minimizing the expected cost or maximizing the expected profit. Those methods of management did not take into account the decision maker's risk preference toward risk which plays an important role in more recent risk measurement methods. Risk averse, risk neutral and risk taking are three groups of decision makers based on their preference on risk (Wu et al., 2011). The origin of almost all methods of risk measurement in supply chain management stems from economics and finance including theory of utility function (Von Neumann and Morgenstern, 1944), mean-variance trade-off (Markowitz, 1959), Value at Risk (VaR) model and Conditional Value at Risk (CVaR) model (Wu et al., 2011). The aim of the theory of utility function is maximization of the decision maker's expected utility.

Mean-variance trade-off was first introduced by Markowitz (1959); it is a special form of utility function theory when the payoffs are normally distributed. In this case, the mean-variance preference (MV) is:

$$MV = \mu - \frac{\gamma}{2}\sigma^2 \tag{34}$$

where μ is the expected payoff, σ^2 is its variance and γ is the coefficient of decision maker's risk aversion. Any increase in the mean payoff increases the expected utility while increases in variance or greater coefficient of risk aversion decrease the expected payoff (Kouvelis et al., 2011). That is, the higher the expected payoff, the higher the risk. However, majority of decision makers are risk averse and for a given payoff they would want as low a risk as possible and for a given risk level they want the expected payoff to be as high as possible. Risk in Markowitz's model is defined by the variance of the profit of different investments. In order to select the optimal portfolio of products, possible portfolios should be presented by a point on a risk-return graph. Then, the optimal portfolio can be derived by fitting the MV line on the mean-variance efficient frontier, which is made of the portfolios that lie on the northwestern frontier of risk-return graph.

VaR is defined as the expected loss occurring due to an adverse market movement with specified probability over a period of time. In some respects, VaR is a natural progression from earlier mean-variance framework (Dowd, 2005). Yet there are also important differences between them:

- Mean-variance framework interprets risk in terms of standard deviation of the return, while VaR methods define it in terms of the maximum likely loss. The VaR perception of risk is more intuitive and easier for non-professional and beginners to understand.
- Mean-variance framework presumes that returns are normally (or near normally) distributed, whereas VaR approaches can cover a very wide range of possible distributions.
- VaR approaches can be reasonably used for a vast range of problems.

The VaR has a number of significant benefits over traditional risk measures (Dowd, 2005):

- VaR provides a common consistent measure of risk for different positions and risk factors. It can be used for any type of portfolio, and it provides the means to compare the risks of different portfolios.
- VaR permits to combine the risks of sub-positions into an overall measure of portfolio risk, and be fully aware of the ways in which different risk factors interrelate or correlate with each other.
- VaR is holistic in that it quantifies all driving risk factors.
- VaR is probabilistic, and provides a risk manager with practical information on the probabilities related to specific loss amounts.
- VaR is presented in the simplest and most easily understood unit of measure, that is, 'lost money'.

However, the VaR also has its shortcomings. VaR estimates can be exposed to error, and VaR systems can be subject to model risk (i.e., the risk of errors originated from models built on incorrect assumptions) or implementation risk (i.e., the risk of errors stemmed from the way in which systems are implemented). Nonetheless, such problems are common to many if not all risk measurement systems, and are not exclusive to VaR ones. Yet the VaR also has its own unique limitations as a risk measure. One important drawback is that the VaR only tells us the most we can lose if a tail event does not occur (e.g., it tells us the most we can lose 95% of the time); if a tail does not occur, we can anticipate to lose more than the VaR, but the VaR itself gives us no suggestion of how much that might be. This failure of VaR implies that two positions can have the same VaR– and therefore appear to have the same risk– and yet have very different risk vulnerability. This can result in some detrimental outcomes. Therefore, the VaR has some serious disadvantages as a risk measure. When dealing with elliptical distributions[2] VaR has proven a good measure of risk in many ways. However, in such circumstances, VaR is simply a transformation of standard deviation and does not contain more information than what can be found from mean-variance framework. The main purpose of advancing from the mean-variance framework to something more general is to be able to measure the risks associated with seriously non-normal distributions. The VaR enables us to do this, but it is in exactly these conditions that the VaR is not consistent. So, an alternative framework is required to measure the risk in a seriously non-normal environment (Dowd, 2005).

3.4.1 Coherent Risk Measures:

Now we move to the next risk measurement paradigm: the theory of coherent risk measures proposed by Artzner et al. (1999). This approach provides the first mathematically grounded theory of financial risk. The starting point is a simple but insightful one: that even though we all have an instinctive sense of what financial risk involves, it is not easy to give a quantitative assessment of financial risk unless we indicate what we basically mean by a measure of risk. The concept of risk itself is

[2] An elliptical distribution is any member of a broad family of probability distributions that generalize the multivariate normal distribution and inherit some of its properties (http://en.wikipedia.org/wiki/Elliptical_distribution).

difficult to conceive without a clear idea of what we mean by a measure of risk. Artzner et al. (1999) theorized a set of axioms- the axioms of coherency- to shed light on these issues and started to develop its implications.

If X and Y are the future values of two risky positions, a risk measure $\rho(\cdot)$ is said to be coherent if it fulfills the following properties for any number n and positive number t:

Sub-additivity: $\rho(X) + \rho(Y) \leq \rho(X + Y)$ (35)

Positive homogeneity: $\rho(tX) = t\rho(X)$ (36)

Monotonicity: $\rho(X) \geq \rho(Y), if\ X \leq Y$ (37)

Translational invariance: $\rho(X + n) = \rho(X) - n$ (38)

The first condition, sub-additivity, means that aggregating individual risks does not increase the overall risk. The second and third conditions are justifiable conditions to establish a priori, and together denote that the function $\rho(\cdot)$ is convex. The Translational invariance condition means that the addition of a sure amount n to our position will reduce the risk because it will increase the value of our end-of-period portfolio.

It should be noted that VaR is not usually sub-additive, and can only be made to be sub-additive under the assumption that returns are normally distributed (Artzner et al., 1999). However, in the real world non-normal distributions are the norm rather than exception.

3.4.2 The Conditional Value at Risk (CVaR):

The CVaR is perhaps the most common coherent risk measure. This measure usually goes by different names in the literature including expected shortfall (ES), expected tail loss (ETL), tailVaR, tail conditional expectation and worst conditional expectation (Dowd, 2005).

If we have a confidence level α and set $p=1-\alpha$, and if q_p is the p-quantile of prospective profit/loss (P/L) over some holding period, then VaR at that confidence level and holding period is equal to (Dowd, 2005):

$$VaR = -q_p \quad (39)$$

The CVaR is the expected value of our losses, L, if we get a loss in excess of VaR:

$$CVaR = E[L|L > VaR] \tag{40}$$

or

$$CVaR_\alpha = \frac{1}{1-\alpha}\int_\alpha^1 q_p dp \tag{41}$$

If the loss distribution is discrete, then the CVaR is the discrete equivalent of Equation (41):

$$CVaR_\alpha = \frac{1}{1-\alpha}\sum_{p=0}^{\alpha}[pth\ highest\ loss] \times [probability\ of\ pth\ highest\ loss] \tag{42}$$

The CVaR has many of the advantages of VaR: it provides a common consistent risk measure for different positions, it quantifies the correlations in a correct way, and it has many of the same applications as VaR. However, the CVaR is also a better risk measure than the VaR for the following reasons (Dowd, 2005):

- The CVaR measures what to expect in bad (i.e., tail) states - it gives an idea of how bad it might be - whilst the VaR only tells to expect a loss higher than the VaR itself.
- A CVaR-based risk–expected decision rule is reliable under more general conditions than a VaR-based risk–expected decision rule.
- Because it is coherent, the CVaR always meets sub-additivity. The CVaR therefore has the various attractions of sub-additivity.
- The CVaR does not discourage risk diversification, and the VaR sometimes does.
- Finally, the sub-additivity of CVaR implies that the portfolio risk surface will be convex, and convexity ensures that portfolio optimization problems using CVaR measures will always have a unique well-behaved optimum.

Thus, in this research, CVaR is applied as the risk measurement method.

In the following, it is illustrated how the output of the system dynamics model is applied to measure the risk associated with supply chain. The supply chain profit values (P/L) for a period of 104 weeks (two years) are extracted from the proposed SD model. Then, applying equation (41), the values of VaR and CVaR for different confidence levels are calculated. It should be mentioned that the general behavior of VaR and CVaR is almost the same. However, the risk values are obviously larger when CVaR is applied as the risk measure (Figures 3-17 to 3-19). Figure 3-17 shows the distribution of supply chain profit over a two years period as well as VaR and CVaR for a 95% confidence level. The negative values show the profit and positive values present the loss in the supply chain.

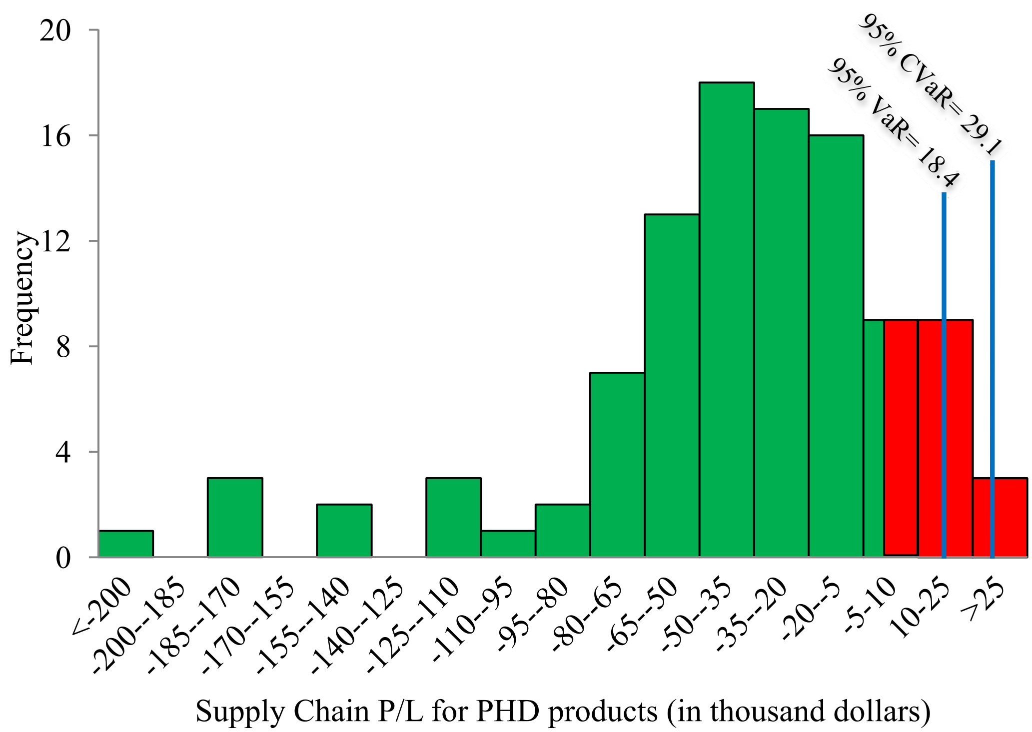


Figure 3-17. Supply chain return/profit distribution based on the output of system dynamics model- scenario: case 1 (Profit: - and Loss: +); 95% VaR and CVaR values

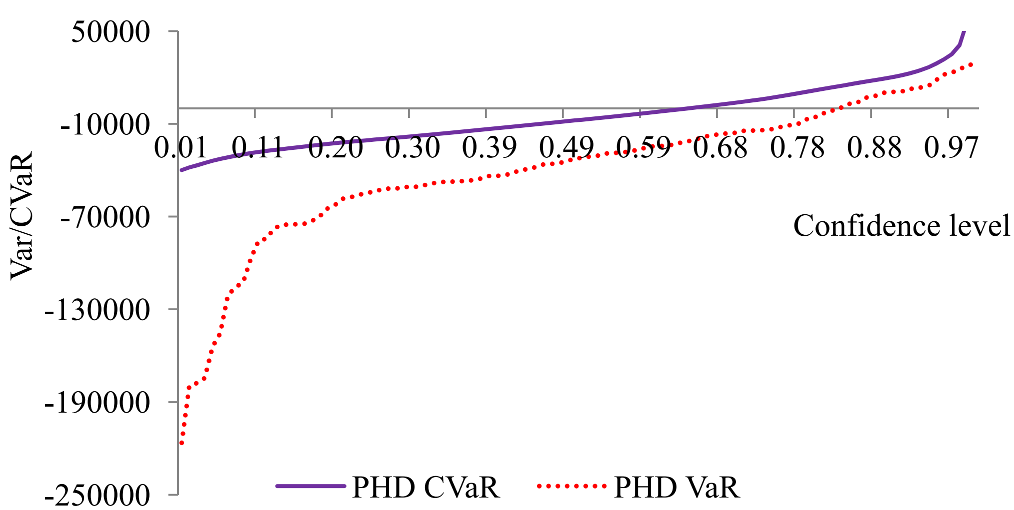


Figure 3-18. VaR /CVaR and confidence level curve for supply chain profit of PHD products

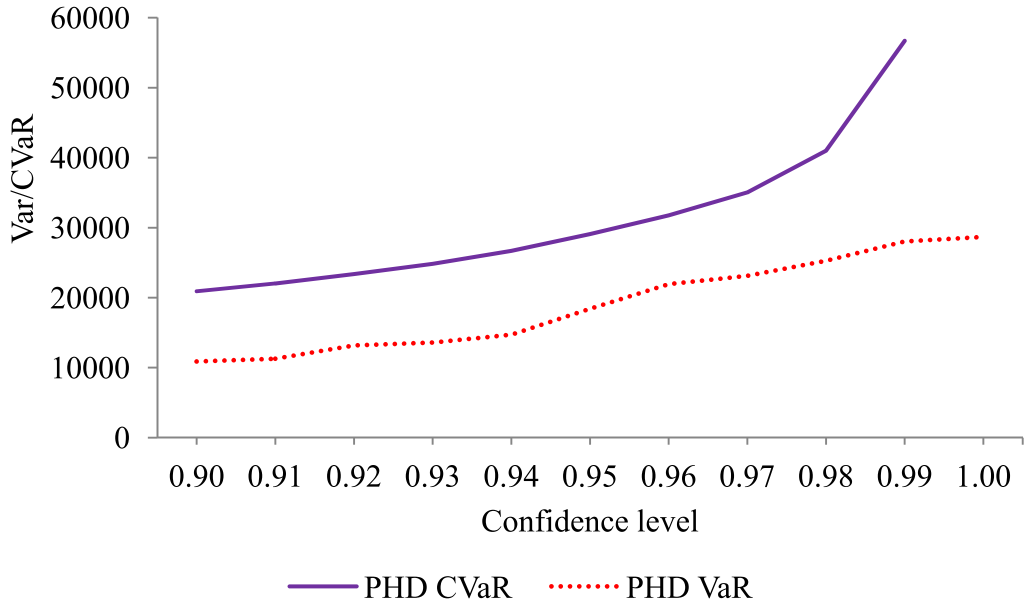


Figure 3-19. VaR /CVaR and confidence level higher than 90% for supply chain profit of PHD products

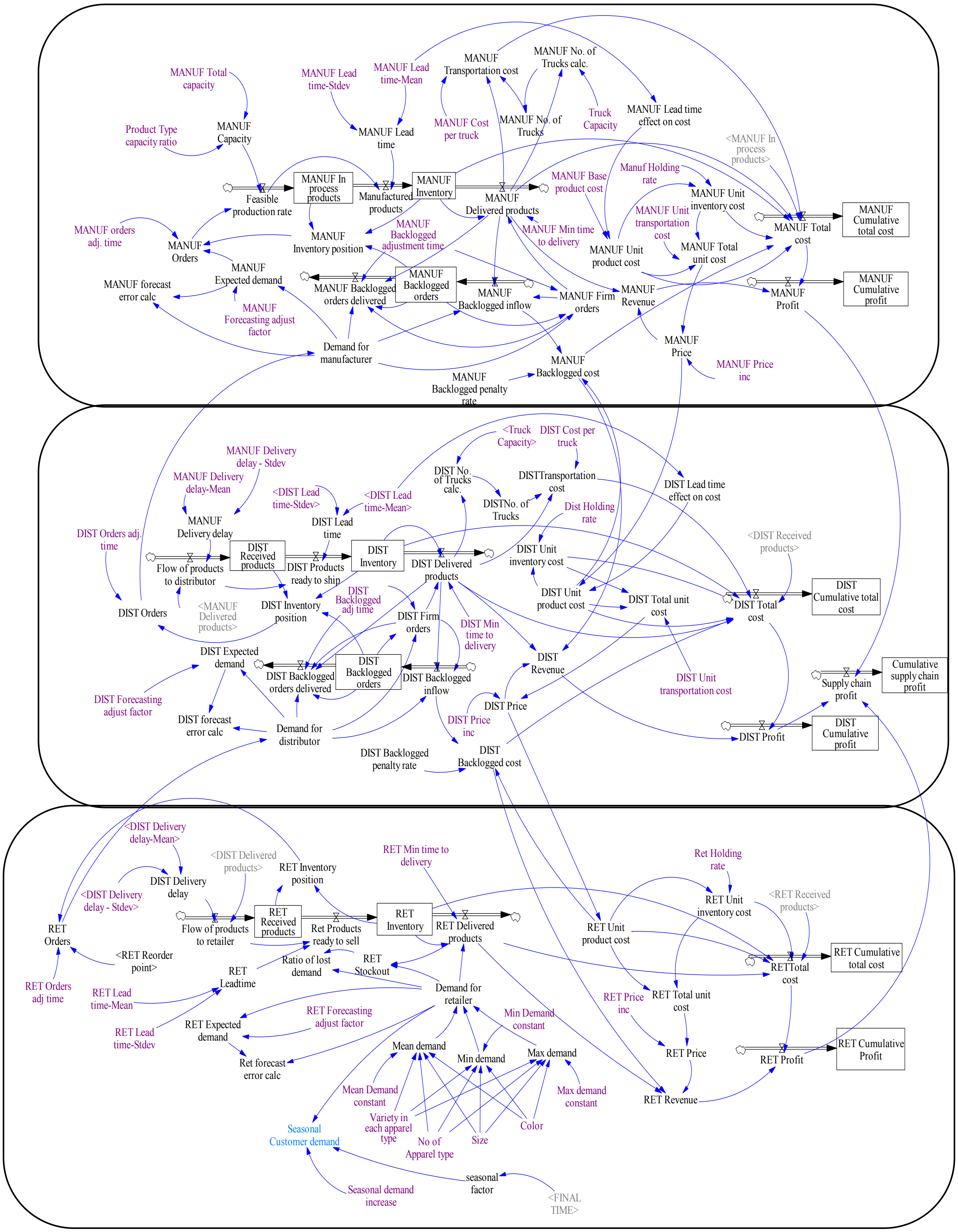


Figure 3-20. The stock and flow diagram for all levels of supply chain of fast fashion apparel industry

CHAPTER 4

NUMERICAL RESULTS

In this chapter, the performance of supply chain under different categories of risks is analyzed. In particular, we investigate how delays, demand forecasts, and inventory levels affect the SC performance considering average backlog, stock-out, cost, and profit of each level of SC as the performance metrics. In addition, CVaR is applied as the tool to measure the risk of SC.

4.1. Risk of Delay

This section compares the performance of SC under different lead-time and delivery delay scenarios. In particular, it is shown how the LT and delivery delay of each SC level affects the backlogged orders, stock-out and cost of all SC levels. In addition, the effect of LT and delivery delay on profit and risk of each SC level and the whole SC is analyzed.

In order to carry out the necessary analysis, different scenarios were defined with different lead-times for each level of SC and separate scenarios for their delivery delays. Table 4-1 shows the detail for each of 35 scenarios and the notations used.

Table 4-1. Notation and detail of scenarios defined to study the performance of supply chain

		$\mu_{LT(j)}$ $j=1$	$\mu_{LT(j)}$ $j=2$	$\mu_{LT(j)}$ $j=3$	$\mu_{LT(j)}$ $j=1,2\&3$	$\mu_{DD(j)}$ $j=1$	$\mu_{DD(j)}$ $j=2$
	Base:	2	0.5	0.14	(2,0.5,0.14)	0.5	0.5
		MLT	DLT	RLT	ALT	MDD	DDD
1	10% increase	2.2	0.55	0.154	(2.2,0.55,0.154)	0.55	0.55
2	20% increase	2.4	0.6	0.168	(2.4,0.6,0.168)	0.6	0.6
3	40% increase	2.8	0.7	0.196	(2.8,0.7,0.196)	0.7	0.7
4	2 days increase	2.28	0.78	0.42	(2.28,0.78,0.42)	0.78	0.78
5	20% decrease	1.6	0.4	0.112	(1.6,0.4,0.112)	0.4	0.4
6	2 days decrease	1.72	0.22	_	(1.72,0.22,0.001)	0.22	0.22

The first row of Table 4-1 shows which parameter(s) changed. For example, $\mu_{LT(j)}$ $j=1,2\&3$ denotes that the lead-time mean of all three levels of SC changed and

$\mu_{DD(j)}$ *j=1* stands for change in delivery delay mean of the manufacturer level. Row 2 shows the values of LT and delivery delay for the base scenario. Row 3 shows the abbreviations used for naming the scenarios. For example, DLT means change in distributor's lead-time, ALT means change in all levels lead-time, and MDD means change in manufacturer's delivery delay. Finally, rows 4 to 9 demonstrate the amount and direction of change. As an example, the highlighted cells should be read as follows: Scenario ALT3- 40% increase in lead-time means of all levels of SC.

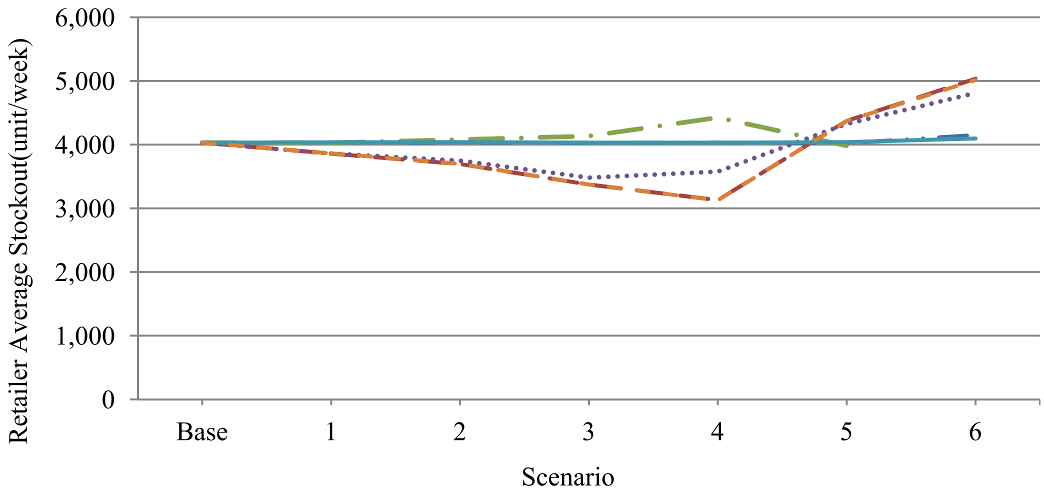
It should be noted that all the figures in this section only show the performance of SC for PHD products (i=1). The general trend of behavior is almost the same for the other two types of products. However, the amount of increase or decrease is different in some cases for which the results for PMD and PLD products are presented in brackets in the text as well as Tables A-7 to A-13 in the Appendix.

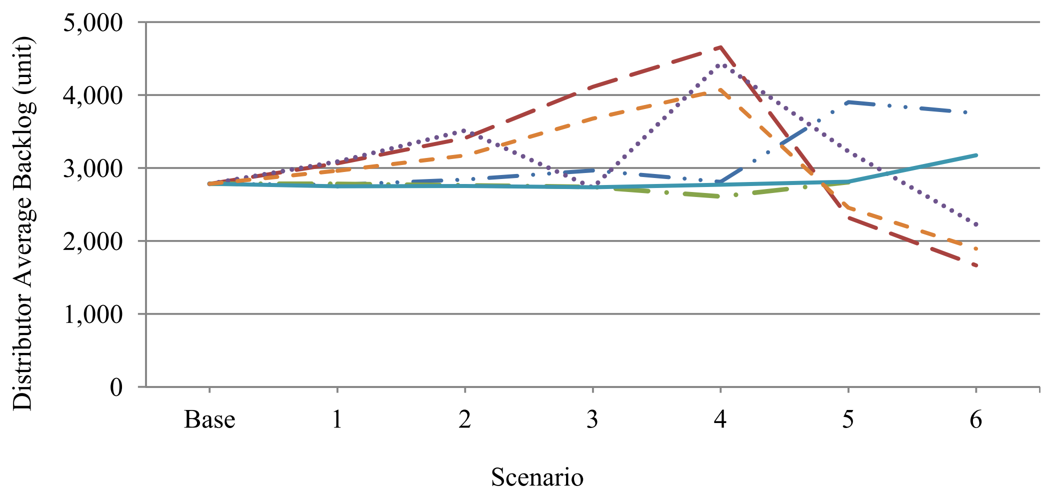
4.1.1 The Effect of Lead Time and Delivery Delay on Stock-Out and Backlogged Orders

Figure 4-1 shows that the average amount of stock-out in retailer level is mainly affected by the LT and the delivery delay of the distributor– a negative correlation between these two factors. That is, the higher the LT or delivery delay of distributor the lower the amount of stock-out. The reason is that the demand for retailer for all the scenarios in this chapter is kept the same. However, with the increase in LT or delivery delay of the upstream level, the retailer orders boost and lead to increase in the retailer's inventory. Consequently, with higher inventory and the same demand the amount of stock-out decreases.

Based on the results shown in Figure 4-1, it can be concluded that the average amount of distributor's backlogged orders is the most sensitive to the distributor's LT and delivery delay. Two days increase in distributor's lead-time (DLT4) leads to 67% [PMD: 62%, PLD: 66%] increase in the average backlogged orders of distributor.

For the manufacturer, the ALT scenarios have the highest impact on the amount of backlogged orders. Two-day increase in LT of all SC levels (ALT4) results in 113% [PMD: 88%, PLD: 104%] increase in manufacturer's average backlogged orders. On the other hand, a two-day decrease in the same parameters (ALT6) only decreases the manufacturer's backlogged orders by 36% [PMD: 37%, PLD: 35%].





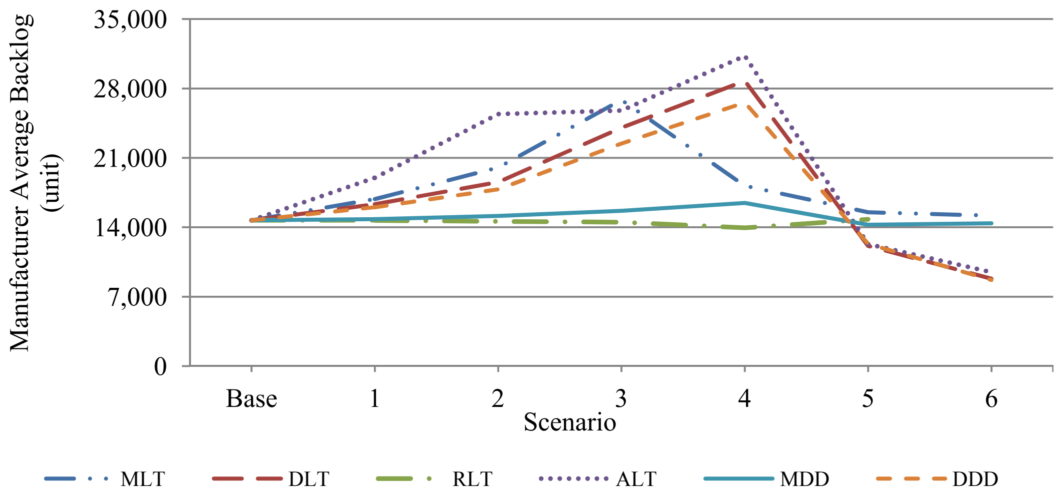


Figure 4-1. The effect of lead time and delivery delay on stock-out and backlogged orders

4.1.2 The Effect of Lead Time and Delivery Delay on Cost

Figure 4-2 shows how the changes in lead time and delivery delay of different supply chain levels change the average total cost of each level of supply chain. It can be seen that, in general, distributor's lead time and delivery delay has a very high impact on the cost of all three supply chain levels. Two days increase in distributor's lead time or delivery delay (DLT4 or DDD4) leads to 25% [PMD: 24%, PLD: 25%] increase in average cost for retailer level, 58% [PMD: 37%, PLD: 39%] increase in distributor's average cost and 40% [PMD: 44%, PLD: 45%] increase in manufacturer's average cost. However, when there is two days decrease in distributor's lead time or delivery delay, retailer's average cost decreases by 29% [PMD and PLD: 26%], distributor's decreases by 28% [PMD: 27%, PLD: 25%] and manufacturer's decreases by 24% [PMD and PLD: 22%]. So, all three levels show almost the same sensitivity to the decrease in distributor's lead time or delivery delay.

After DLT and DDD scenarios, ALT sets of scenarios play a major role in altering the average cost. Manufacturer's delivery delay (MDD) and retailer's lead time (RLT) have the least impact on the cost.

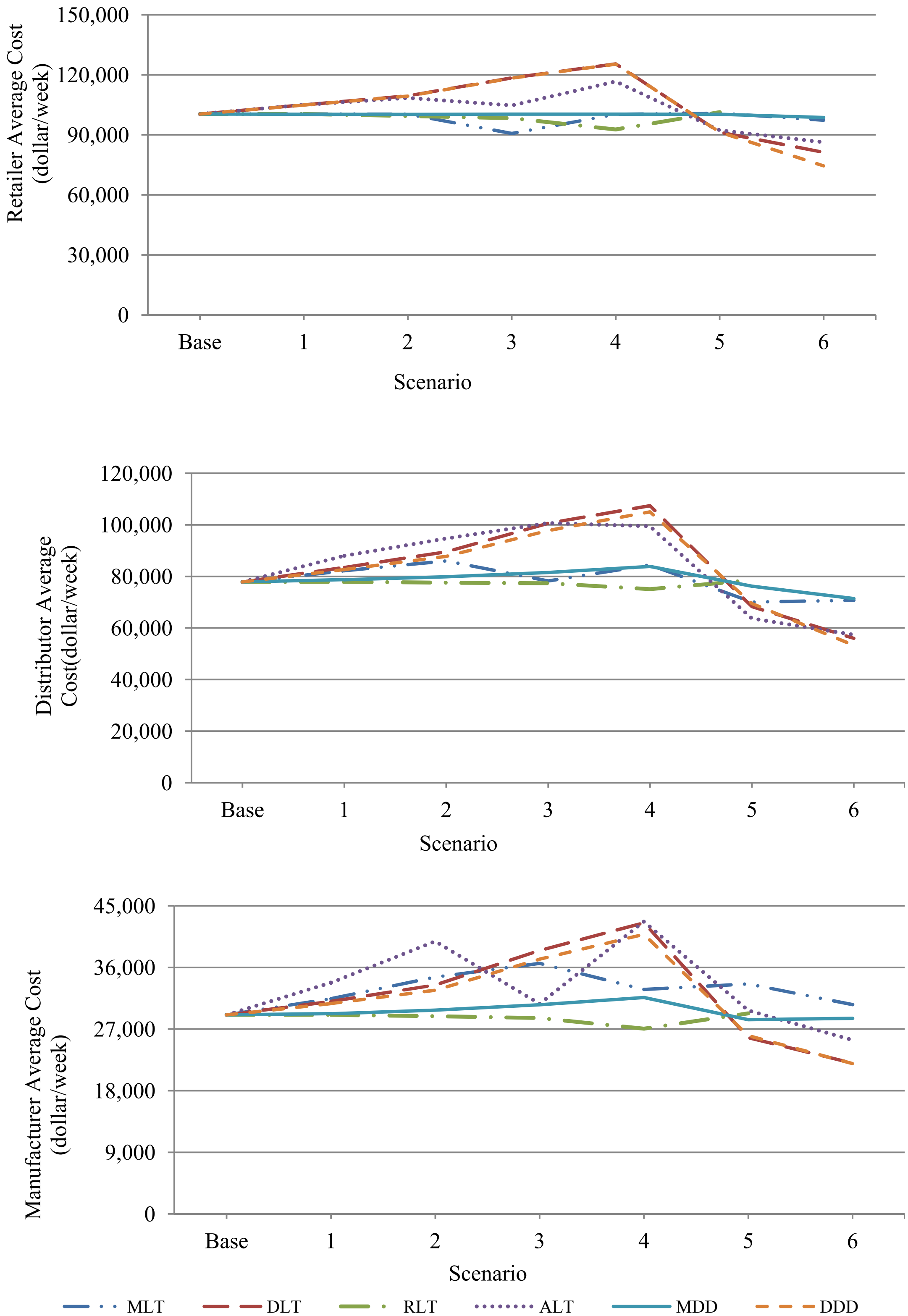


Figure 4-2. The effect of lead time and delivery delay on cost

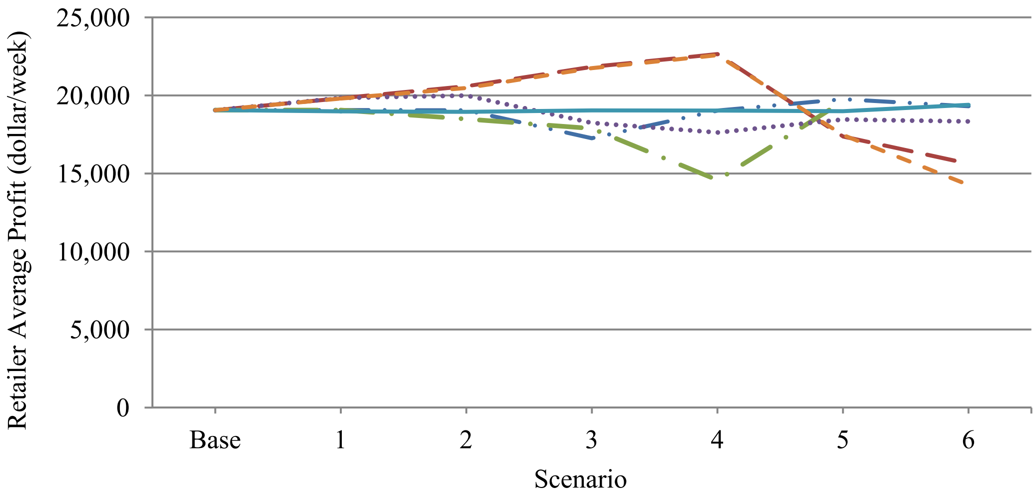
4.1.3 The Effect of Lead Time and Delivery Delay on Profit

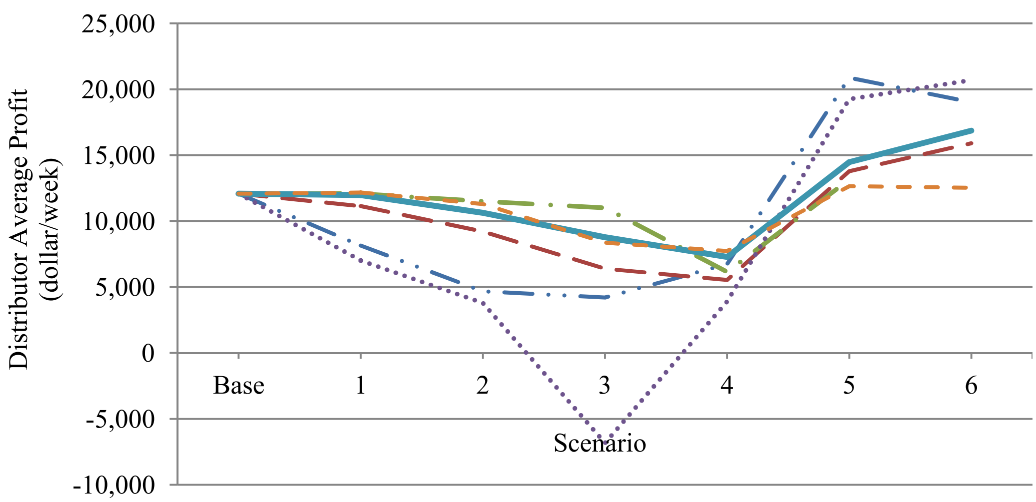
Increase in distributor's lead time or delivery delay increases the average profit of both retailer and manufacturer. For the reason that the sales rises by higher distributor's lead time or delivery delay and the raise in revenue is more than the corresponding cost increase, it finally leads to higher profit. However, for the distributor, increase in lead time or delivery delay of this level results in higher increase in cost (due to higher backlogs and inventory cost) comparing to increase in revenue (due to increase in sales). Thus, distributor's average profit decreases. Two days increase in distributor's lead time or delivery delay (DLT4 or DDD4) causes 18% [PMD: 20%, PLD: 21%] increase in retailer's average profit and 55% [PMD: 43%, PLD: 49%] increase in manufacturer's, but, 54% [PMD: 26%, PLD: 24%] decrease in distributor's average profit (Figure 4-3).

Distributor's profit shows the highest sensitivity to ALT scenarios where lead time of all supply chain levels change at the same time. The higher the lead time or delivery delay, the lower the distributor's profit. 40% increase in lead time of all supply chain levels (ALT3) results in 157% [PMD: 53%, PLD: 85%] decrease in distributor's profit. Some other results drawn from Figure 4-3 are in the following:

- Two days decrease in distributor's lead time or delivery delay (DLT6 or DDD6) leads to 25% [PMD and PLD: 25%] decrease in retailer's average profit and 48% [PMD: 40%, PLD: 41%] decrease in manufacturer's average profit.
- Two days increase in retailer's lead time (RLT4) decreases the retailer's average profit by 24% [PMD: 21%, PLD: 18%].
- 20% decrease in manufacturer's lead time (MLT5) causes 73% [PMD: 46%, PLD: 40%] increase in distributor's profit.
- Two days decrease in lead time of all supply chain level (ALT6) increases the distributor's profit by 71% [PMD: 49%, PLD: 37%].

Figure 4-3 also shows the behavior of supply chain profit under different scenarios. It can be seen that ALT and MLT scenarios have more significant impact on supply chain profit. 40% increase in lead time of all supply chain levels (ALT3) decrease the average profit of supply chain by 54% [PMD: 20%, PLD: 32%]. 20% decrease in manufacturer's lead time (MLT5) increases the supply chain average profit by 31% [PMD: 22%, PLD: 18%].





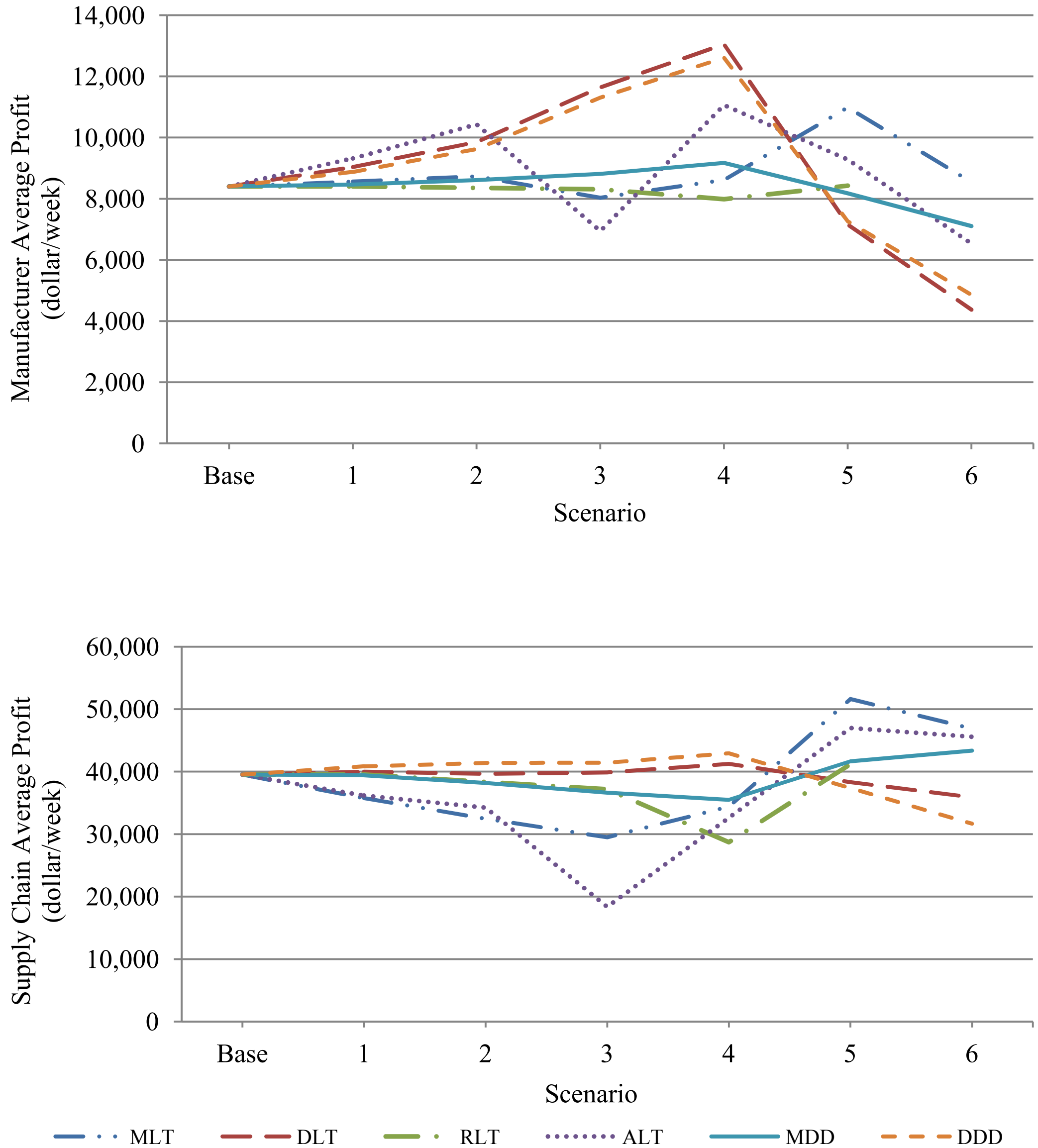
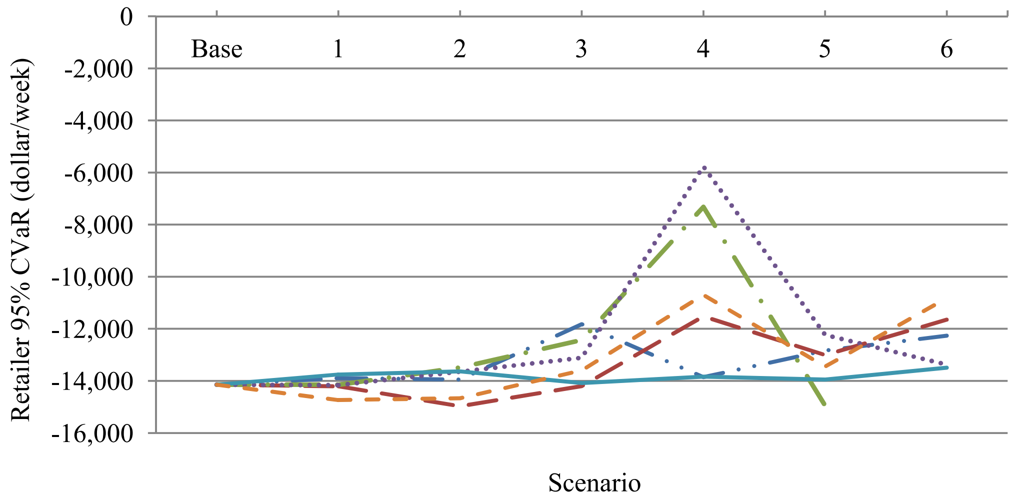
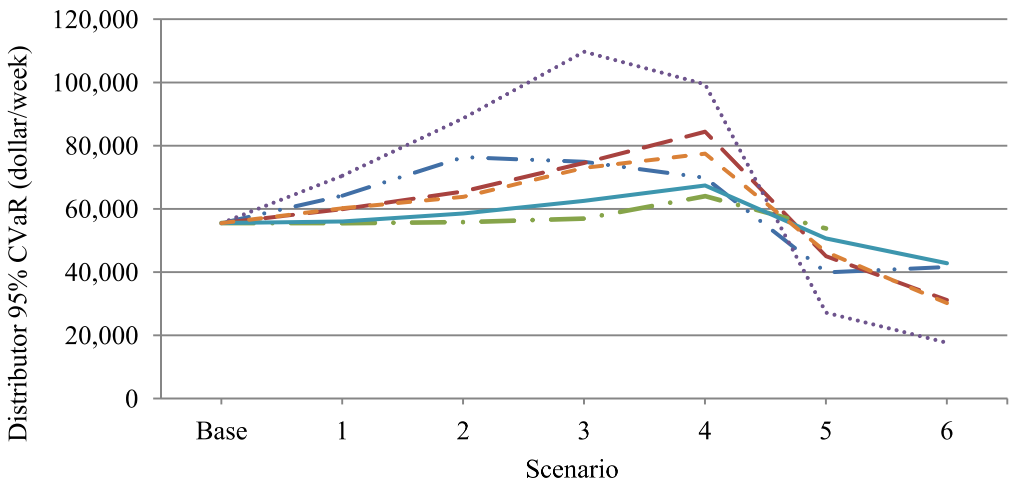


Figure 4-3. The effect of lead time and delivery delay on profit

4.1.4 The Effect of Lead Time and Delivery Delay on Risk

Figure 4-4 shows the 95% CVaR for each level of supply chain and Figure 4-5 depicts the 99% CVaR. It can be seen that the general behavior of each level of supply chain under different scenarios is almost the same between 95% CVaR and 99% CVaR. However, both sets of graphs are presented in this section to compare the risk values which are obviously larger for the case of 99% CVaR. For example, the 99% CVaR of distributor level under ALT3 scenario is $188,893 which is much higher than 95% CVaR under the same scenario that is $109,697.





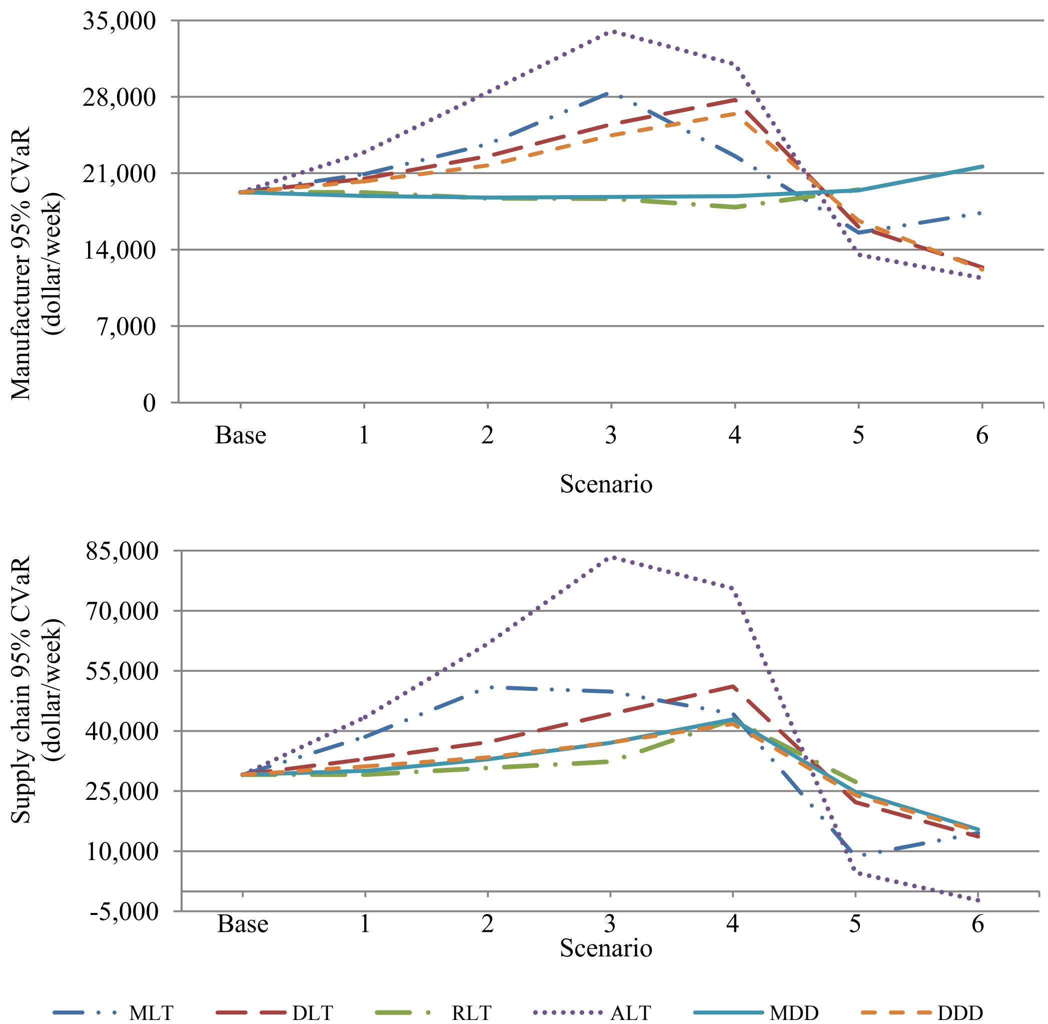
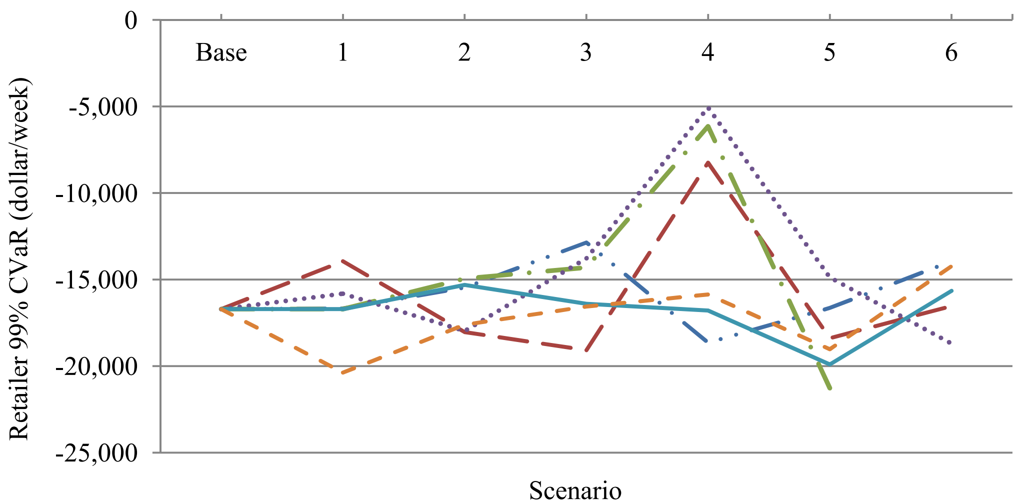


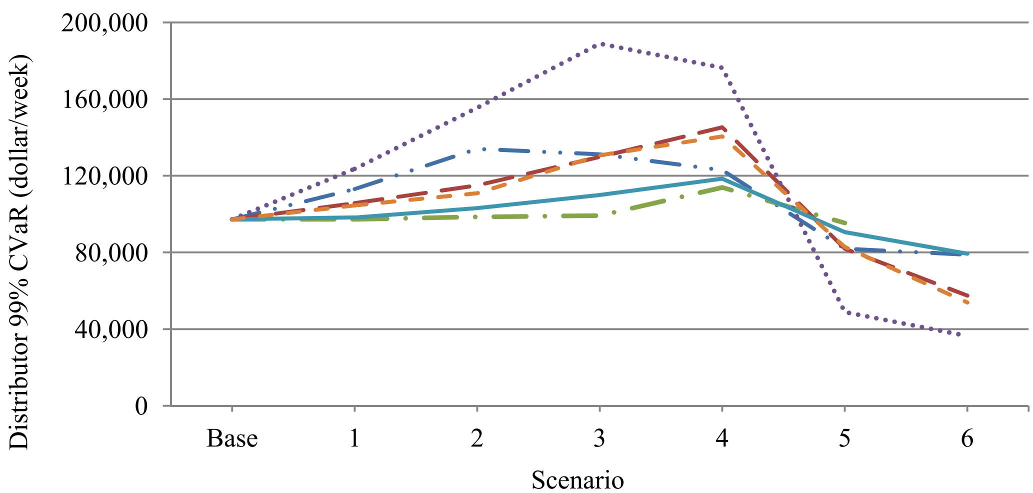
Figure 4-4. The effect of lead time and delivery delay on risk (95% CVaR)

For retailer's level, the CVaR values are negative which means the values at the tail of retailer P/L distribution are positive and basically, the retailer is making profit and there is negative loss or risk for them.

Based on the results shown on the graphs related to CVaR values, all supply chain levels as well as the whole supply chain risk are the most sensitive to ALT scenarios. Retailer's lead time and manufacturer's delivery delay have the lowest impact on the risk of manufacturer, distributor and the whole supply chain. For example, 40% increase in lead time of all supply chain levels (ALT3) leads to 94% [PMD: 78%, PLD: 114%] increase in risk of distributor (99% CVaR), 95% [PMD: 79%, PLD: 77%] increase in risk of manufacturer and 158% [PMD: 176%, PLD: 643%] increase in supply chain risk.

Two days decrease in lead time of all supply chain levels (ALT6) results in 63% [PMD: 59%, PLD: 77%] decrease in distributor's risk, 40% [PMD and PLD: 33%] decrease in manufacturer's and 97% [PMD: 119%, PLD: 379%] decrease in supply chain's risk.





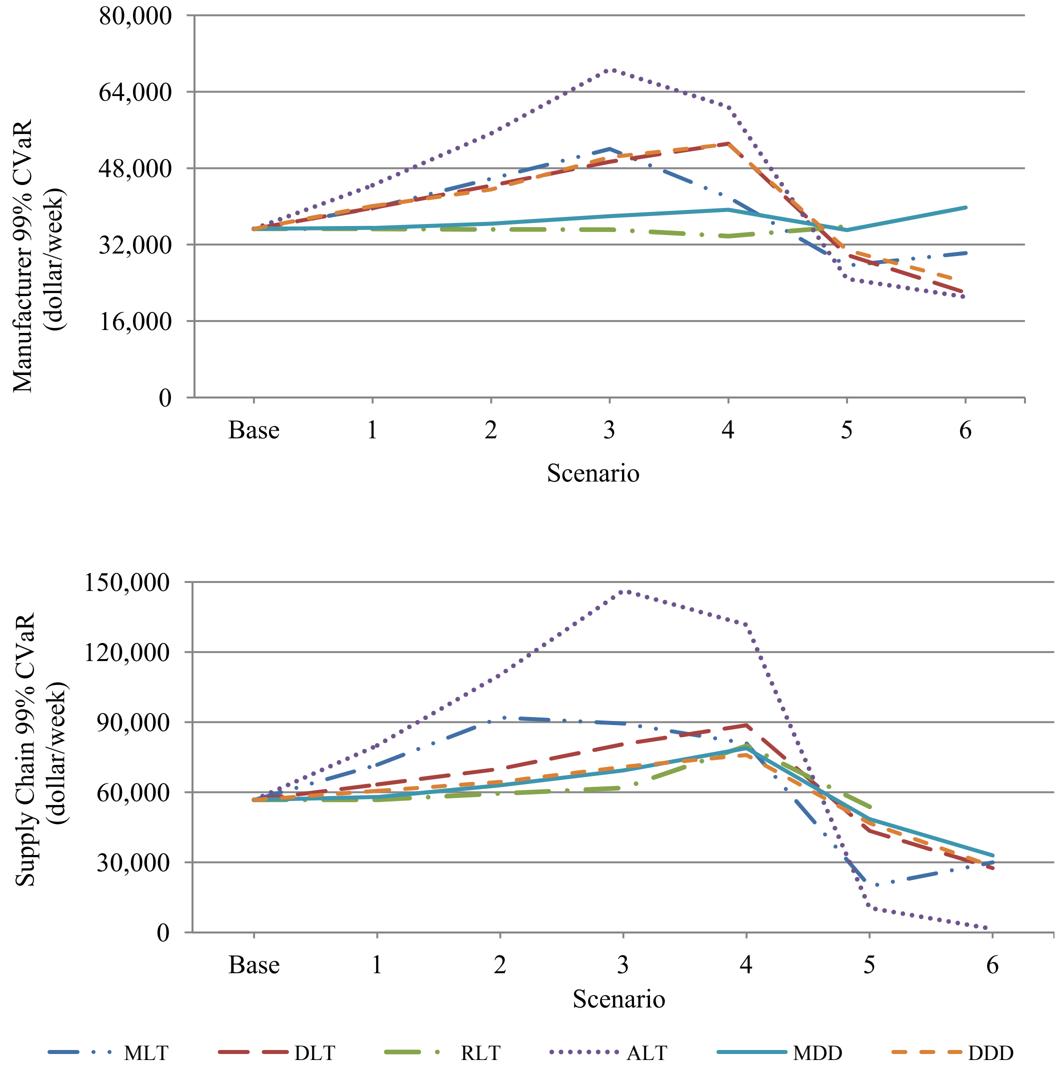


Figure 4-5. The effect of lead time and delivery delay on risk (99% CVaR)

4.2. Risk of Forecast

Any mismatch between the company's estimation and real demand leads to forecast risk. If forecasts are too low, products might not be on hand to sell while too high forecasts result in overload inventories, and unavoidably, price mark-downs. Long lead times, seasonal demand, high product variety and smaller product life cycles are all drivers of forecast risk (Chopra and Sodhi, 2004). In this section, the impact of lead times on forecast risk is particularly studied and in chapter 5, the impact of demand uncertainty on the risk of forecast is assessed.

The Mean Absolute Deviation (MAD) is selected as the measure of forecast error in this study (Chopra and Meindl, 2010):

$$MAD(ij) = \frac{1}{104}\sum_{t=1}^{104}|Fe(ijt)| \quad (43)$$

Figure 4-6 simultaneously depicts how manufacturer's lead time affects the forecast error measure (MAD) and risk measure (95% CVaR) of all three SC levels. It can be seen that the forecast error of the retailer level is insensitive to manufacturer's lead time. However, when the lead time of manufacturer increments from 2 weeks up to 2.8 weeks, both MAD and CVaR values increase. In other words, higher lead time leads to higher forecast error and higher risk in supply chain.

The reason why MAD values are lower for the cases of manufacturer's LT=1.6 and 1.72 is that the time window considered in this study is 104 weeks and very low levels of lead time changes the structure of demand in manufacturer and distributor levels (one high pick is added toward the end of the time window). Demand estimation has a smoothing delay of 7 days (1 week) and prior to reaching this smoothing delay, the time window ends and causes a large gap between the estimated demand and the actual demand at the last few time periods of the time window.

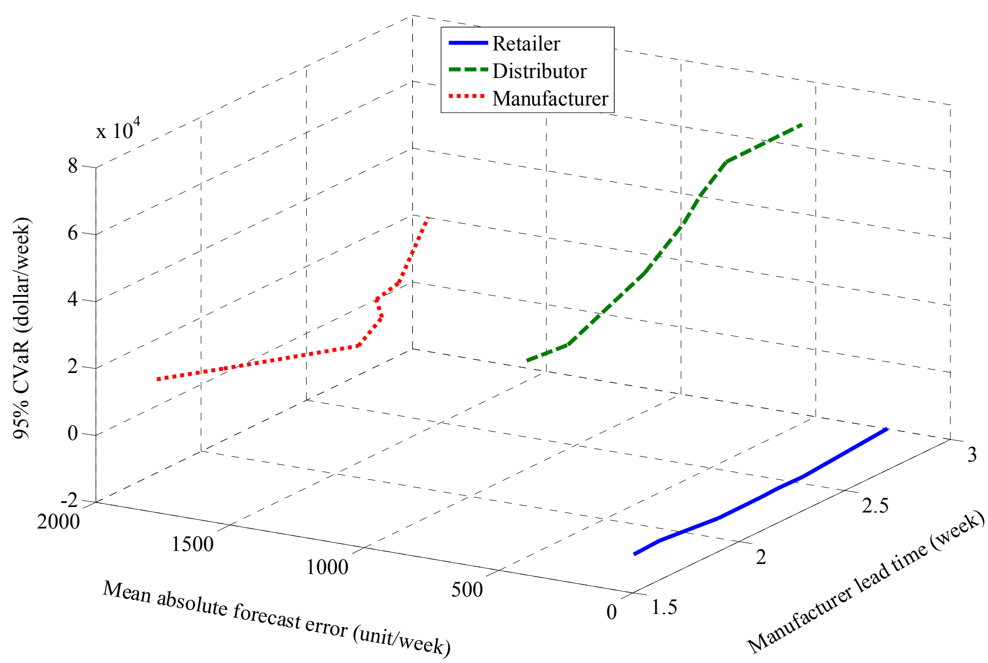


Figure 4-6. Relationship between forecast error and risk of each supply chain level under different manufacturer lead times for PHD products

Figure 4-7 illustrates how distributor's lead time affects the forecast error and risk of each SC level. The same trend of behavior can be observed that is the MAD values increase by any elevation in distributor lead time which consequently leads to increased risk. The detail of MAD and 95% CVaR values under different manufacturer and retailer lead time for all three types of products is presented in table 4-2.

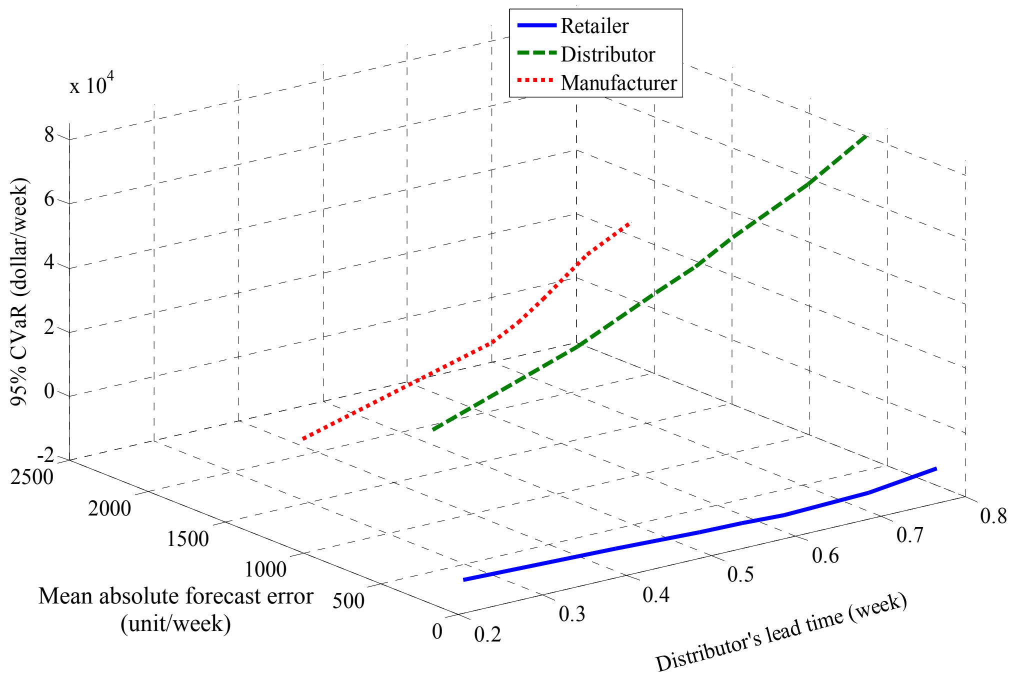


Figure 4-7. Relationship between forecast error and risk of each supply chain level under different distributor lead times for PHD products

Table 4-2. Relationship between forecast error and risk of each supply chain level under different manufacturer and distributor lead times for all three types of products

	Product Type	SC level	Manufacturer's lead time							Distributor's lead time						
			1.6	1.72	2	2.2	2.28	2.4	2.8	0.22	0.4	0.5	0.55	0.6	0.7	0.78
Mean absolute forecast error	PHD	Retailer	75	75	75	75	75	75	75	75	75	75	75	75	75	75
		Distributor	476	415	349	360	365	361	394	272	321	349	378	405	466	512
		Manufacturer	1,851	1,697	1,415	1,484	1,568	1,577	1,783	1,111	1,321	1,415	1,517	1,629	1,884	2,035
	PMD	Retailer	54	54	54	54	54	54	54	54	54	54	54	54	54	54
		Distributor	238	224	179	181	183	185	187	127	172	179	192	196	215	243
		Manufacturer	877	877	659	699	716	731	800	500	666	659	692	745	829	941
	PLD	Retailer	24	24	24	24	24	24	24	24	24	24	24	24	24	24
		Distributor	45	39	36	37	37	37	38	26	32	36	38	39	45	49
		Manufacturer	177	160	139	148	150	156	172	98	125	139	144	155	175	197
95% CVaR	PHD	Retailer	-12,837	-12,265	-14,150	-13,893	-13,855	-13,949	-11,820	-11,649	-13,010	-14,150	-14,207	-14,973	-14,198	-11,522
		Distributor	39,947	41,607	55,478	64,184	69,833	76,386	74,920	31,146	45,061	55,478	59,930	65,516	74,540	84,395
		Manufacturer	15,563	17,381	19,247	20,917	22,567	23,670	28,441	12,377	16,087	19,247	20,498	22,566	25,492	27,711
	PMD	Retailer	-11,741	-11,467	-12,388	-12,447	-12,381	-12,204	-10,890	-10,898	-11,251	-12,388	-12,935	-13,361	-14,472	-14,066
		Distributor	27,576	28,149	37,648	43,043	46,199	50,560	58,383	19,501	31,406	37,648	39,529	43,800	49,458	53,279
		Manufacturer	10,095	11,185	12,648	13,985	14,895	15,828	17,363	7,741	12,160	12,648	13,189	13,774	15,794	17,717
	PLD	Retailer	-3,833	-3,847	-4,196	-4,208	-4,200	-4,122	-3,603	-3,495	-3,761	-4,196	-4,353	-4,382	-4,685	-4,817
		Distributor	5,983	6,068	8,553	10,612	11,553	12,838	12,995	3,557	6,702	8,553	9,379	11,044	12,680	13,631
		Manufacturer	2,532	2,780	2,948	3,332	3,645	3,868	4,631	1,664	2,597	2,948	3,105	3,509	4,006	4,478

4.3. Risk of Inventory

Since excess inventory has a detrimental impact on financial performance, risk of inventory is another category of risk investigated in this study. In this section, the impact of long lead times on inventory level and risk measure is mainly analyzed. In chapter 5, the impact of demand uncertainty on the risk of inventory is assessed.

Figure 4-8 illustrates how the changes in lead time and delivery delay affect the average total inventory (in process products and finished products over a period of 104 weeks) of each supply chain level. The same sets of scenarios presented in Table 4-1 are used.

According to the results, the higher the lead time, the larger the inventory amount is. Also, it can be seen that the inventory of all SC levels is most sensitive to ALT sets of scenarios (when the lead time of all supply chain levels change at the same time). There is 72% [PMD: 46%, PLD: 63%] increase in the inventory of the distributor for the scenario ALT3 (when there is 40% increase in lead time of all supply chain levels). On the other hand, when there is two days decrease in lead time of all SC levels (scenario ALT6), the distributor's inventory decreases by 45% [PMD: 44%, PLD: 46%]. For the retailer, the highest amount of inventory is for the scenario ALT4 (two days increase in lead time of all supply chain levels) which changes by 46% [PMD: 43%, PLD: 45%]. Since the lead time at retailer level is short, all supply chain levels are least sensitive to RLT scenarios.

The inventory of distributor and manufacturer shows the highest sensitivity to the LT of their own level, after ALT scenarios. For the manufacture, the inventory of PHD and PLD products increases the most (59% and 58%, respectively) when the LT of manufacturer increases by 40% (MLT3). However, for PMD products, ALT3 has the highest impact on manufacturer's inventory, which leads to a 72% increase.

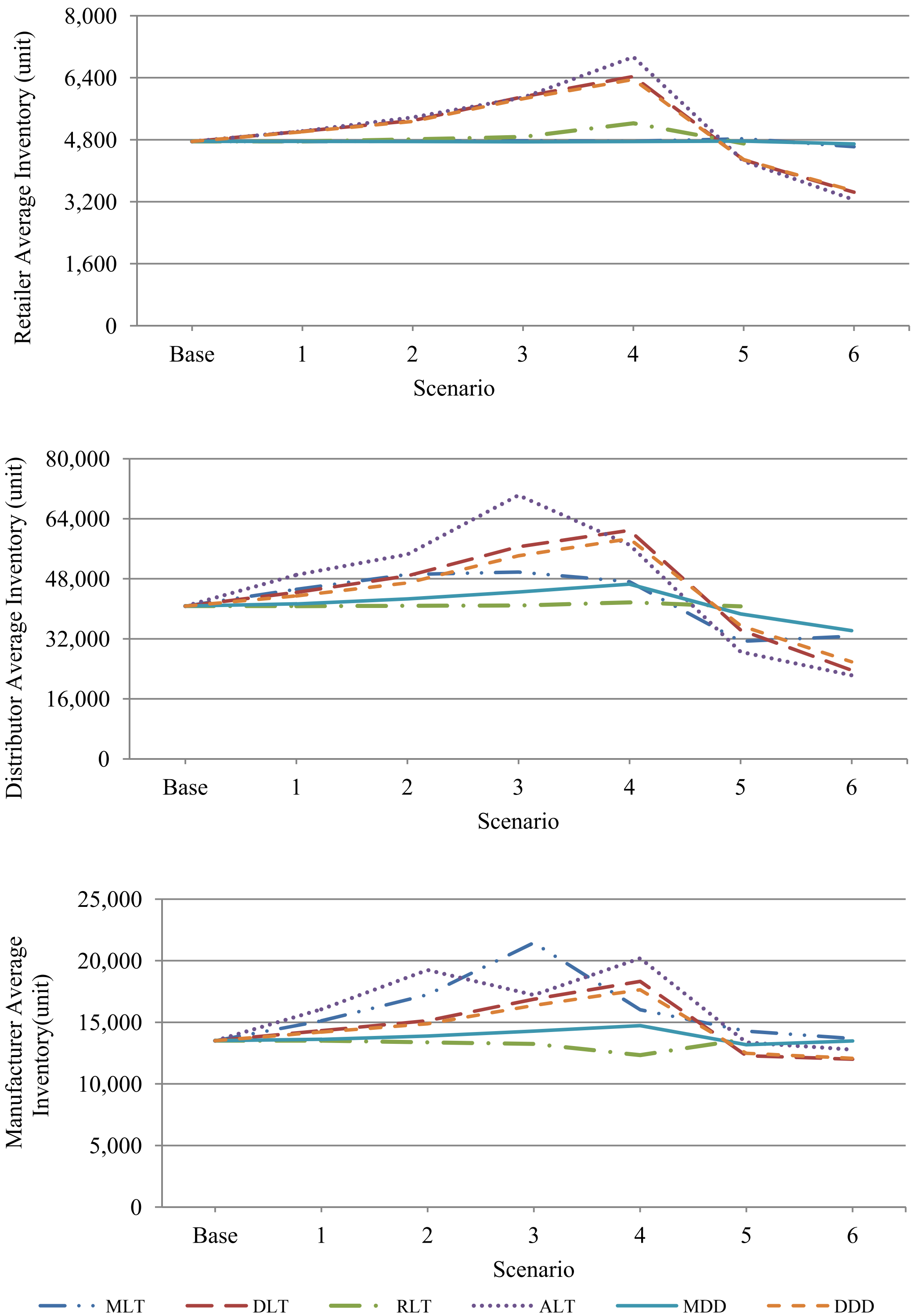


Figure 4-8. The effect of lead time and delivery delay on inventory

Figures 4-9 through 4-11 simultaneously show the inventory amount and risk measure of each SC level under the most significant sets of scenarios, which are MLT, DLT, and ALT ones. It should be mentioned that Scenario 0 in these figures is equivalent to the “base” scenario of Table 4-1. The values used to draw these figures are extracted from Tables A-7 to A-13 in the Appendix. The behavior of the risk measure toward the inventory level can be seen in these figures. It can be noticed that the larger amount of inventory generally results in higher risk levels.

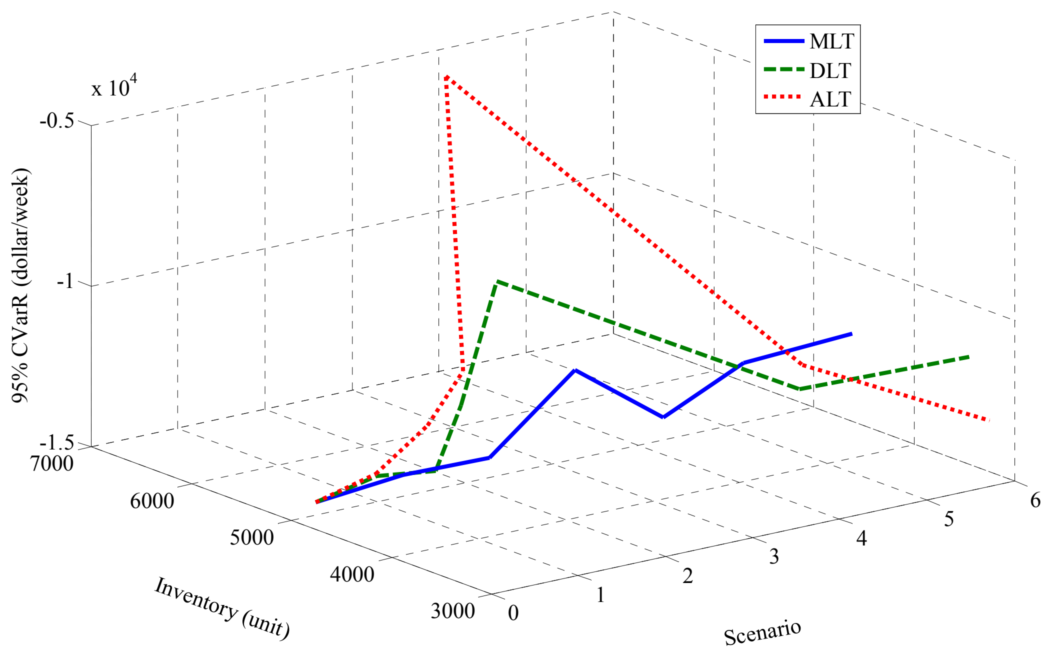


Figure 4-9. Effect of MLT, DLT, and ALT scenarios on inventory and risk of retailer level for PHD products

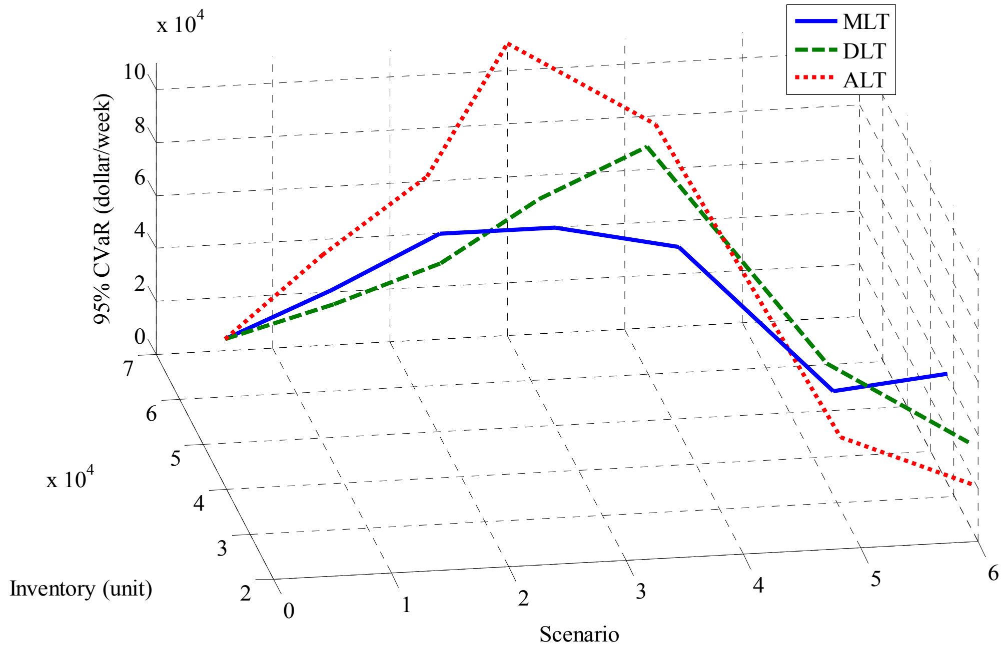


Figure 4-10. Effect of MLT, DLT, and ALT scenarios on inventory and risk of distributor level for PHD products

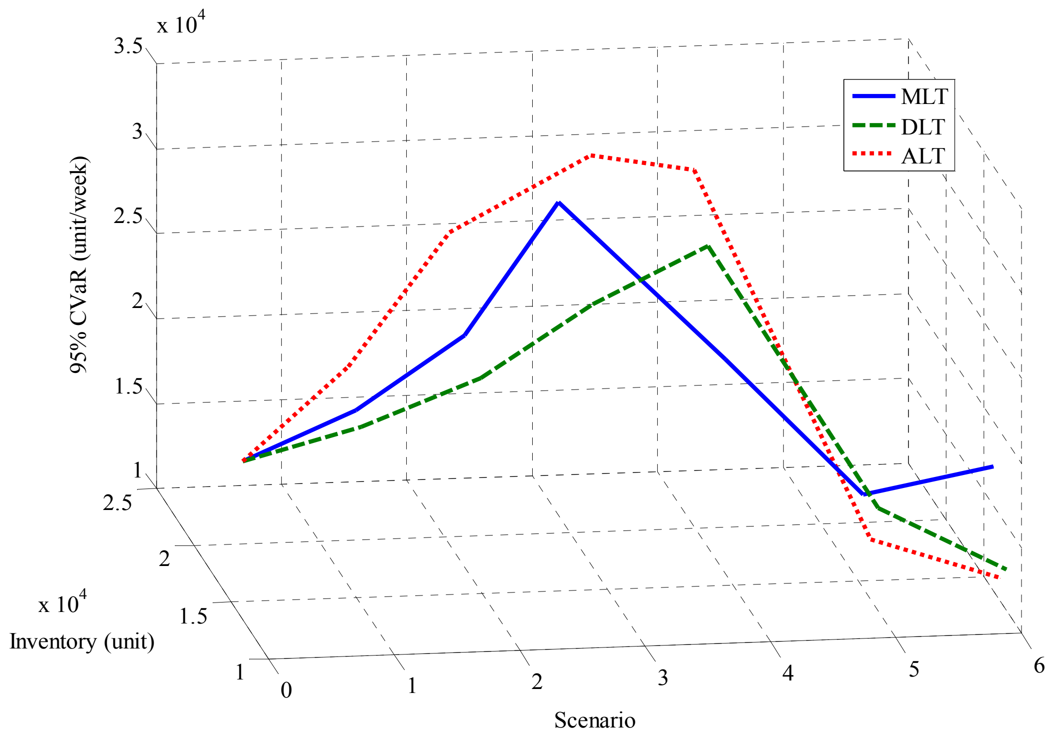


Figure 4-11. Effect of MLT, DLT, and ALT scenarios on inventory and risk of manufacturer level for PHD products

CHAPTER 5
BASS MODEL AND NUMERICAL RESULTS

In the literature, there exists another stream of forecasting methods applied for products with short life cycles called the Bass diffusion model. The Bass model, published in 1969, is recognized as the originator of analytical diffusion models to describe new-product diffusion and has been broadly used in forecasting since then (Bass, 1969). This model presents the underlying principle of how current adopters and potential adopters of a product interact. The basic argument of the model is that adopters can be categorized as innovators or as imitators and the rate and timing of adoption relies on their level of innovativeness and imitation among adopters. That is, the path of cumulative adoptions of a product follows a function whose momentary growth rate depends on two parameters, one of which captures a consumer's natural tendency to buy and is independent of the number of preceding adopters, being called the coefficient of innovation. The other parameter considers a positive force of influence on a consumer by previous adopters, being called the coefficient of imitation (Chen and Chen, 2007).

In this chapter, we apply the Bass model to generate the customer demand at retailer level and analyze the risk of each SC level under this type of demand. Figure 5-1illustrates the behavioral rationale of Bass terminology using the stock and flow diagram. In general, imitators purchase the product based on positive word of mouth influences from current customers, while innovators do not need such special incentive. The number of innovators is likely to increase with consumers' access to product-related information from product advertising and/or sales off promotion.

The model variables defined for Bass demand at retailer level, their notations and units are presented in alphabetical order as follows:

AC(ijt)= Active customers, j=3 (person)
AdC(ijt)= Advertisement cost, j=3 (dollar/week)
AdCr(ijt)= Rate of advertisement cost, j=3 (dmnl)
AdE(ij)=Advertisement effectiveness, j=3 (1/week)
AUt(j)= Average duration of active use, j=3 (week)
COr(j)= Contact rate, j=3 (1/week)
CRd(j)= Customer return delay, j=3 (week)

CRf(j)= Customer return fraction, j=3 (dmnl)
CRr (ijt)= Customer return Rate, j=3 (person/week)
D(ijt)= Demand for Ret, j=3 (unit/week)
DCf(j)= Discontinuation fraction, j=3 (dmnl)
DCr(ijt)= Discontinuation rate, j=3 (person/week)
FC(ijt)= Former customers, j=3 (person)
PC(ijt)= Potential customers, j=3 (person)
POP (j)= Total population, j=3 (person)
PuAd(ijt)= Purchase due to advertisement, j=3 (person/week)
PuWoM(ijt)= Purchase due to word of mouth, j=3 (person/week)
PUf(ij)= Purchase fraction, j=3 (dmnl)
PUr(ijt)= Purchase rate, j=3 (person/week)

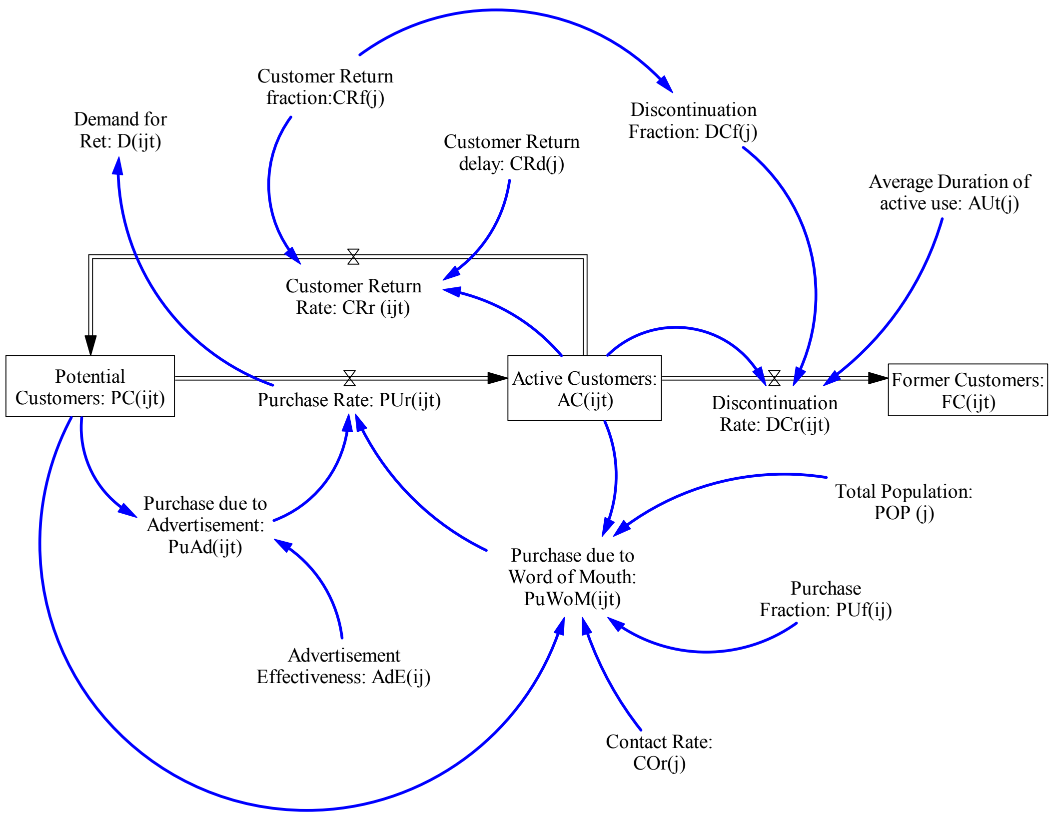


Figure 5-1. Stock and flow diagram for Bass demand at retailer level of SC

As shown in Figure 5-1, "purchase rate" is a function of "purchases due to word of mouth"– representing the imitators– and "purchases due to advertisement"– representing the innovators (Eq. 45).

$$D(ijt) = PUr(ijt), \quad j = 3 \tag{44}$$

$$PUr(ijt) = PuAd(ijt) + PuWoM(ijt), \quad j = 3 \tag{45}$$

$$PuAd(ijt) = PC(ijt) \times AdE(ij), \quad j = 3 \tag{46}$$

For many products, people's inclination to generate word of mouth and their persuasiveness and interest, change over time. Generally, word of mouth decreases as people become accustomed to a product. For that reason, the customers who have purchased a product are divided into two categories of "active customers" and "former customers" (Eq. 48 and 53). Therefore, "purchase due to word of mouth" would only be generated by the population of active customers (Sterman, 2000) (Eq. 49).

$$PC(ijt) = PC(ij0) + \int_0^t CRr\ (ijt) - PUr(ijt),\ PC(ij0) = POP\ (j) \quad j = 3 \tag{47}$$

$$AC(ijt) = AC(ij0) + \int_0^t PUr(ijt) - DCr(ijt) - CRr\ (ijt), AC(ij0) = 0 \quad j = 3 \tag{48}$$

$$PuWoM(ijt) = \frac{(AC(ijt) \times PUf(ij) \times COr(j) \times PC(ijt))}{POP\ (j)}, \quad j = 3 \tag{49}$$

Number of people an active customer is in contact with during each time period, "contact rate", ratio of contacted people who would become new customers, "purchase fraction", and "total population" are the other factors affecting the "purchase due to word of mouth" variable.

In our model, we have also considered the repeat purchases which are common in fast fashion apparel industry. "Customer return rate" is dependent on the ratio of active customers who return to the purchase loop, "customer return fraction", and the time period it takes for them to come back to the retailer store, "customer return delay" (Eq. 50).

$$CRr\ (ijt) = \frac{(AC(ijt) \times CRf(j))}{CRd(j)}, \quad j = 3 \tag{50}$$

The rest of active customers build the "former customers" stock through the "discontinuation rate" flow (Eq. 51-53).

$$DCf(j) = 1 - CRf(j), \quad j = 3 \tag{51}$$

$$DCr(ijt) = \frac{(AC(ijt) \times DCf(j))}{AUt(j)}, \quad j = 3 \tag{52}$$

$$FC(ijt) = FC(ij0) + \int_0^t DCr(ijt)\ , FC(ij0) = 0 \quad j = 3 \tag{53}$$

The parameter setting for the Bass demand is shown in Table 5-1. In order to be able to compare the performance of supply chain based on Bass demand and Poisson demand, which was presented in the previous chapter, the parameters in this section are selected in such way that the average Bass demand for each product type is very close to the average values of Poisson demand at retailer level. Figure 5-2 depicts the demand for PHD products based on Poisson and Bass model.

Table 5-1. Bass demand constants and parameter setting

Notation	Name in Vensim	Value	Unit
AdE(ij) j=3	Advertisement Effectiveness [PHD, PMD, PLD]	0.009,0.004,0008	1/week
AdCr(ijt) j=3	Rate of advertisement cost	0.04	dmnl
AUt(j) j=3	Average Duration of active use	6	week
COr(j) j=3	Contact Rate	15	1/week
CRd(j) j=3	Customer Return delay	6	week
CRf(j) j=3	Customer Return fraction	0.8	dmnl
PUf(ij) j=3	Purchase Fraction	0.014,0.0097,0.0078	dmnl
POP (j) j=3	Total Population	350,000	person

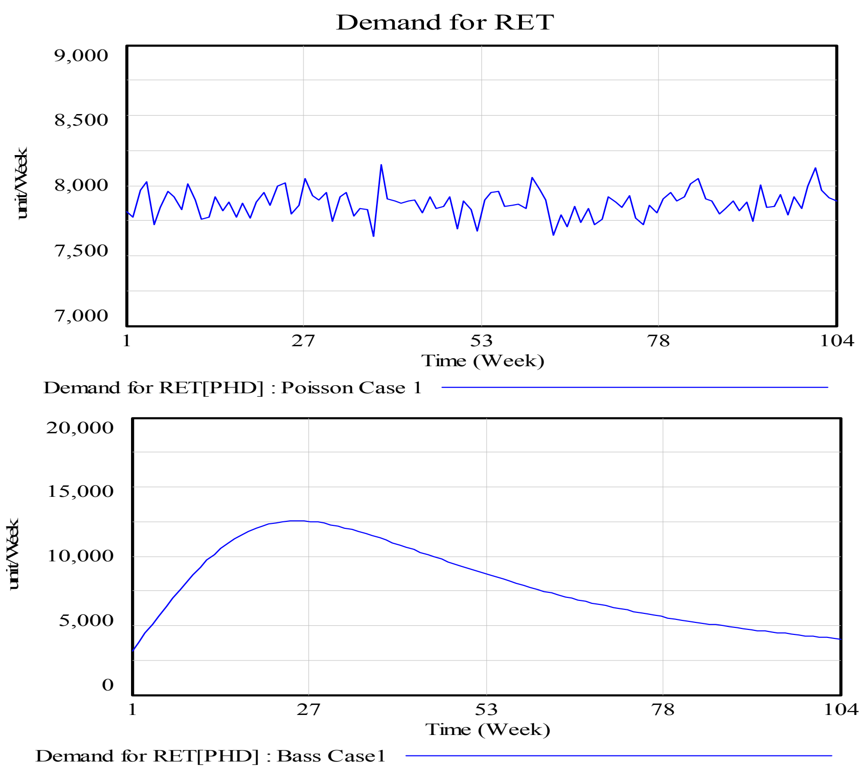


Figure 5-2. Poisson and Bass demand at retailer level for PHD products

In the presented model, it is assumed that the retailer pays the costs related to the advertisement which is proportionate to its revenue (Eq. 54-55).

$$AdC(ijt) = R(ijt) \times AdCr(ijt), \quad j = 3 \tag{54}$$

$$TC(ijt) =$$

$$\left[UIC(ij) \times \left(I(ijt) + WIP(ijt)\right)\right] + [UPC(ij) \times DE(ijt)] + AdC(ijt), j = 3 \tag{55}$$

In the rest of this chapter, the impact of three categories of risk is investigated including risk of delay, risk of inventory, and risk of forecast on the performance of supply chain under Bass model demand at retailer level. Moreover, the results are compared with the corresponding ones presented in the previous chapter.

5.1. Risk of Delay

In this section, the impact of LT and delivery delay on the SC performance (backlogged orders, stock-out, cost, profit, and CVaR) is analyzed. The scenarios used are similar to the ones presented in Table 4-1.

5.1.1 The Effect of Lead Time and Delivery Delay on Stock-Out And Backlogged Orders

Figure 5-3 depicts the average stock-out at retailer level and average backlogged orders at distributor and manufacturer levels. Comparison of this figure and the corresponding one for Poisson demand (Figure 4-1) shows that both the behavior of stock-out and its amount under all scenarios are very similar. However, some differences for the case of backlogged orders can be seen. The range of average backlogged orders is slightly higher under Bass demand: distributor's backlogged orders under Poisson demand is in the interval of [1666 - 4653] and under Bass demand belongs to the interval of [2,117 – 4,310]. For manufacturer level, the Poisson interval is [9471 – 31282] and the Bass interval is [10,598 – 37,466].

Although similar to the case of Poisson demand DLT scenarios have the highest impact on distributor's backlogs and ALT scenarios affect the manufacturer's backlogs the most, the intensity of their impact is different between Poisson and Bass demand. For example, two-day increase in distributor's lead-time (DLT4) leads to 23% [PMD: 44%, PLD: 51%] increase in the average backlogged orders of distributor which is less than the corresponding value under Poisson demand (67%). For manufacturer, the highest level of backlog increase is under ALT3 by 73% [PMD: 73%, PLD: 59%] which is again less than the equivalent value for Poisson demand which was 113% under ALT4.

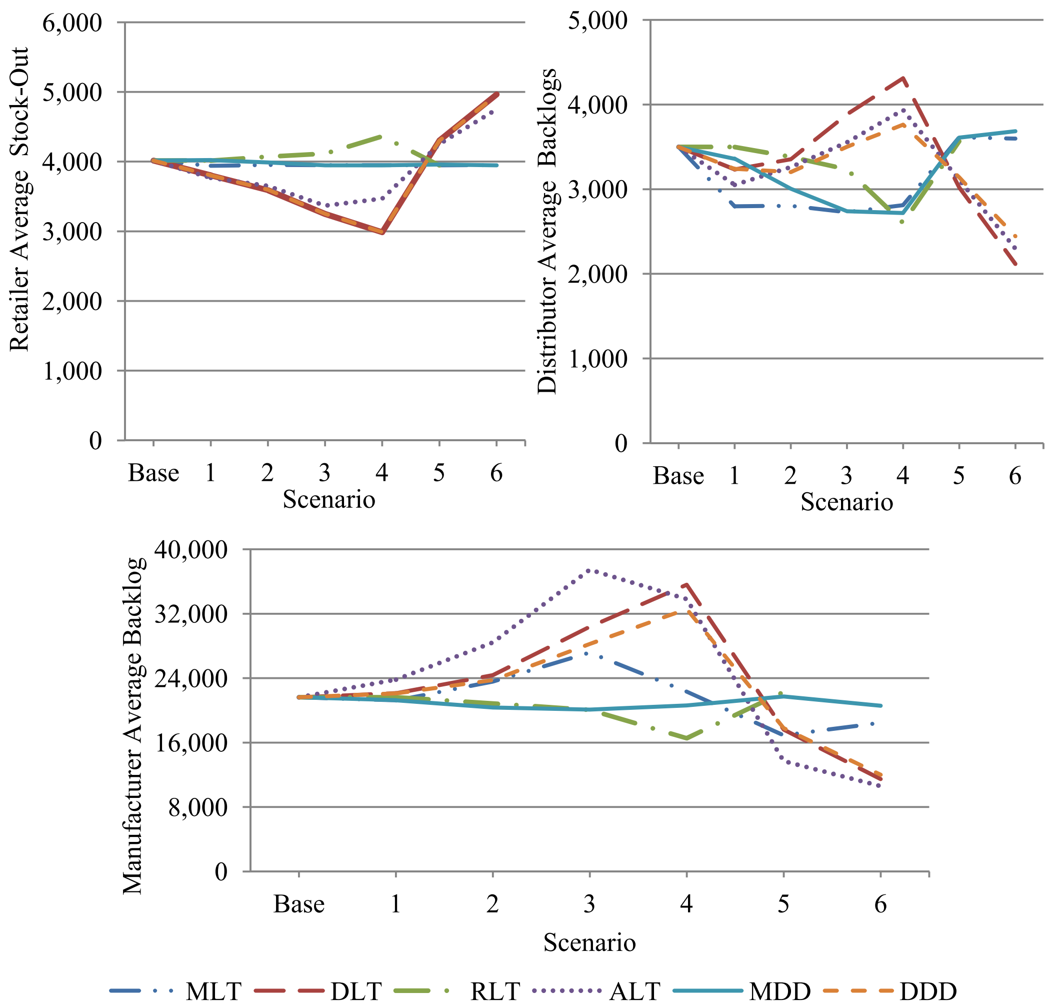


Figure 5-3. The effect of lead time and delivery delay on stock-out and backlogged orders

5.1.2 The Effect of Lead Time and Delivery Delay on Cost

The impact of lead time and delivery delay on the average total cost of each SC level is shown in Figure 5-4. The results obtained in this subsection are compared with the equivalent values shown in Figure 4-2. In general, the range of total cost under Bass demand is higher for all SC levels yet again the retailer depicts a very similar behavior under both types of demand. Range of distributor's total cost under Poisson demand is

[55,997 – 107,403] and under Bass demand is [67,755 – 134,798]. For manufacturer, this range changes from [22,017 – 42,517] under Poisson to [25,237 – 38,790] under Bass demand.

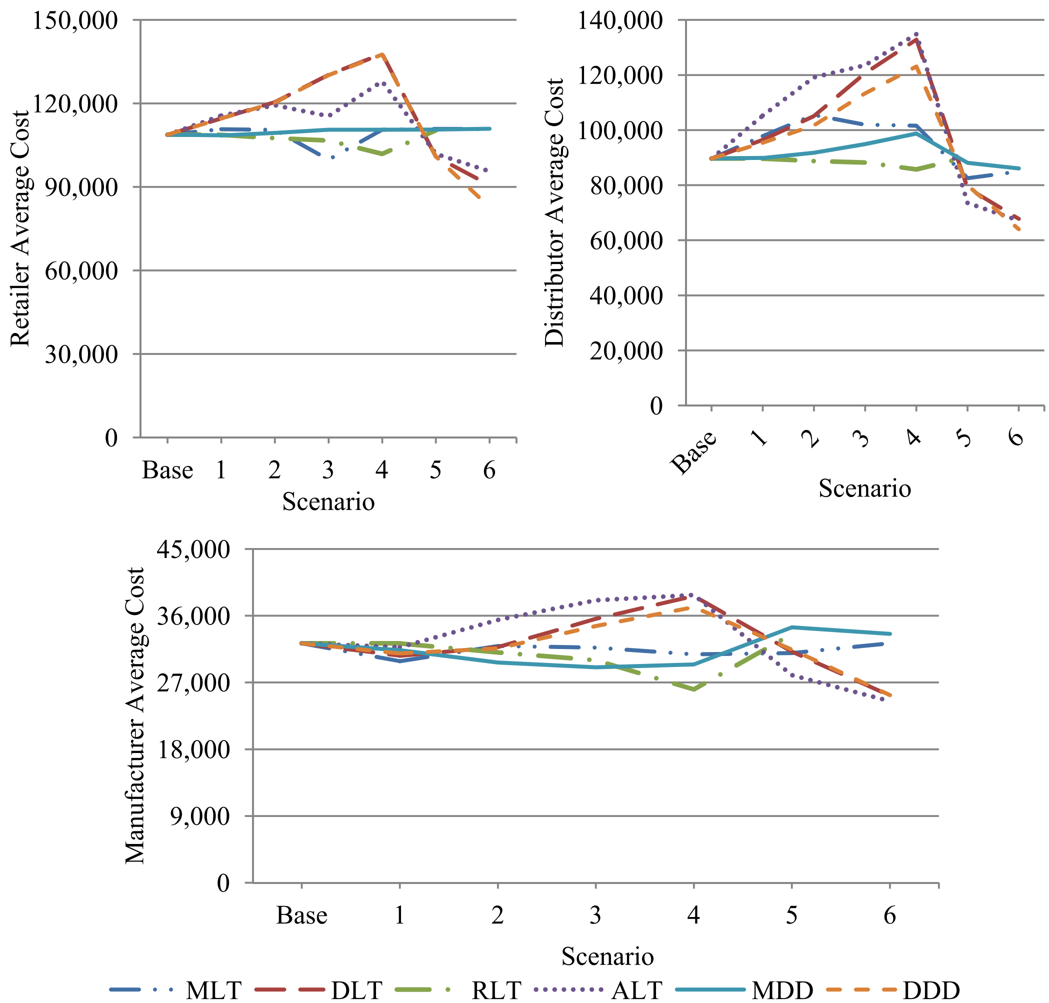


Figure 5-4. The effect of lead time and delivery delay on cost

The most impactful sets of scenarios for distributor and manufacturer, ALT and DLT scenarios, switch their order when comparing the total cost under Bass and Poisson demand. Two days increase in LT of all SC levels (ALT4) leads to 50% [PMD: 19%, PLD: 22%] increase in average cost for distributor level, 20% [PMD: 33%, PLD: 45%] increase in manufacturer's average cost.

5.1.3 The Effect of Lead Time and Delivery Delay on Profit

Again, at retailer level, the changes in averages follow an identical trend to Poisson demand (compare Figure 5-5 with Figure 4-3). However, the profit range under Bass demand is lower in comparison with Poisson demand. Poisson profit range is [14,576 – 22,575] and Bass profit belongs to the interval of [10,670 –17,604].

Similarly, distributor's, manufacturer's and consequently, supply chain's average profit is lower in the case of Bass demand: SC average profit interval under Poisson is [18,353 – 51,620] while under Bass is [-2,482 – 36,508].

For distributor level, ALT scenarios have the highest impact on profit of this level. 40% increase in lead time of all supply chain levels (ALT3) results in 627% [PMD: 160%, PLD: 69%] decrease in distributor's profit which is significantly higher than the equivalent decrease from the case of Poisson demand which was 157%.

The average profit at manufacturer level is most sensitive to DLT and DDD scenarios. For instance, DLT4 increases the manufacturer's profit by 32% [PMD: 30%, PLD: 35%] which is less than that of Poisson demand (54%).

Similar to the case of Poisson demand, ALT sets of scenarios have the highest impact on supply chain profit following the MLT scenarios. Under ALT3, SC average profit goes down by 109% [PMD: 55%, PLD: 29%] which is far above the case of Poisson demand (54% decrease). 20% decrease in lead time of all supply chain levels (ALT5) leads to 27% [PMD: 10%, PLD: 17%] increase in SC profit. Based on the above results, it can be stated that the profit of SC is much more sensitive to lead time increases under the Bass demand.

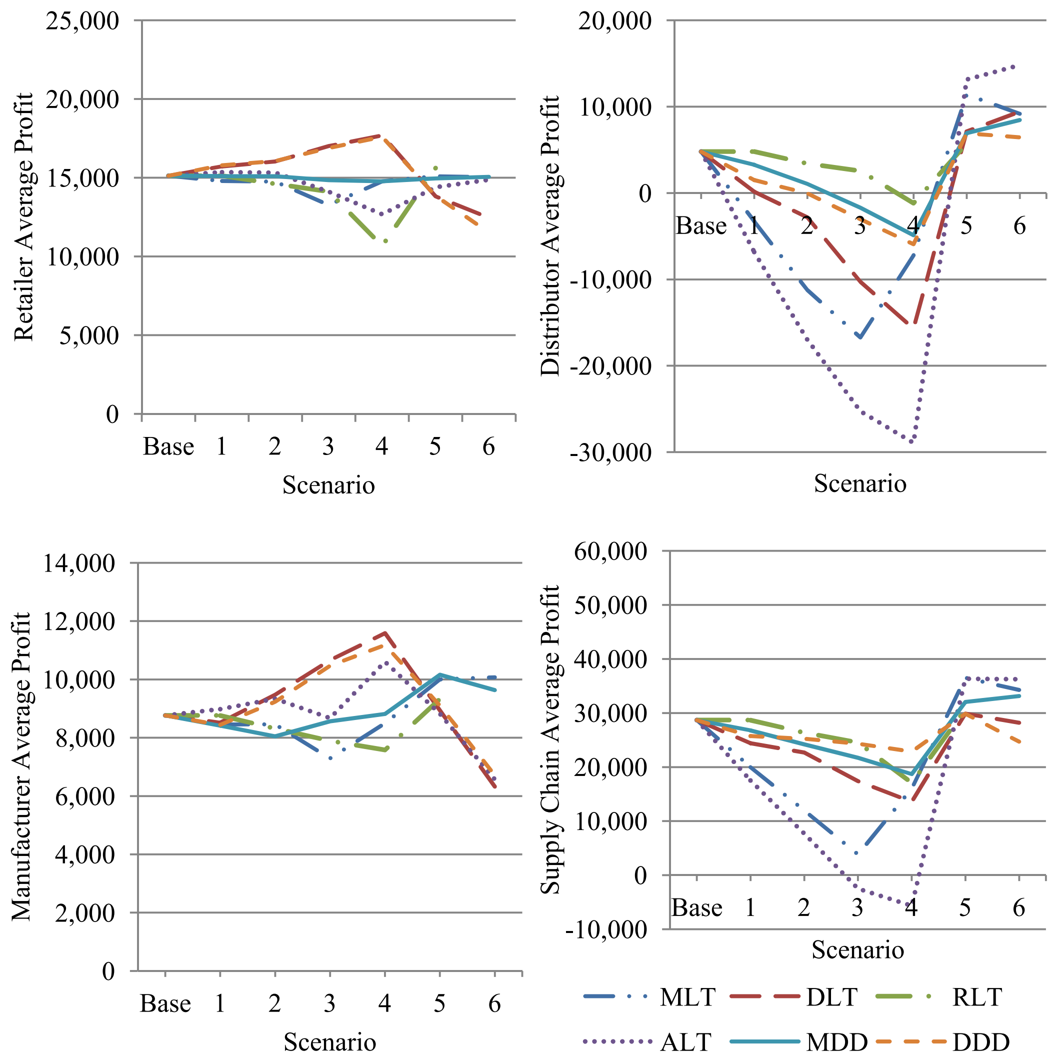


Figure 5-5. The effect of lead time and delivery delay on profit

5.1.4 The Effect of Lead Time and Delivery Delay on Risk

Figure 5-6 shows the 95% CVaR for each level of supply chain and Figure 5-7 depicts the 99% CVaR. Unlike the case of Poisson demand whose 99% CVaR values at retailer level were all negative – there was no risk of loss at that level of SC– it can be seen in Figure 5-6 that the corresponding risk measures under Bass demand include positive values. For example, 99% CVaR for ALT4 scenario equals to -5,059 under Poisson demand whereas it is 22,284 under the Bass demand. Besides the retailer, level of risk for distributor, manufacturer, and accordingly, supply chain is higher when demand is generated based on Bass model. The range of supply chain risk measure (99%

CVaR) falls in the interval of [1,465 – 146,321] under the Poisson demand, while that of Bass demand belongs to the [42,229 – 260,121] interval.

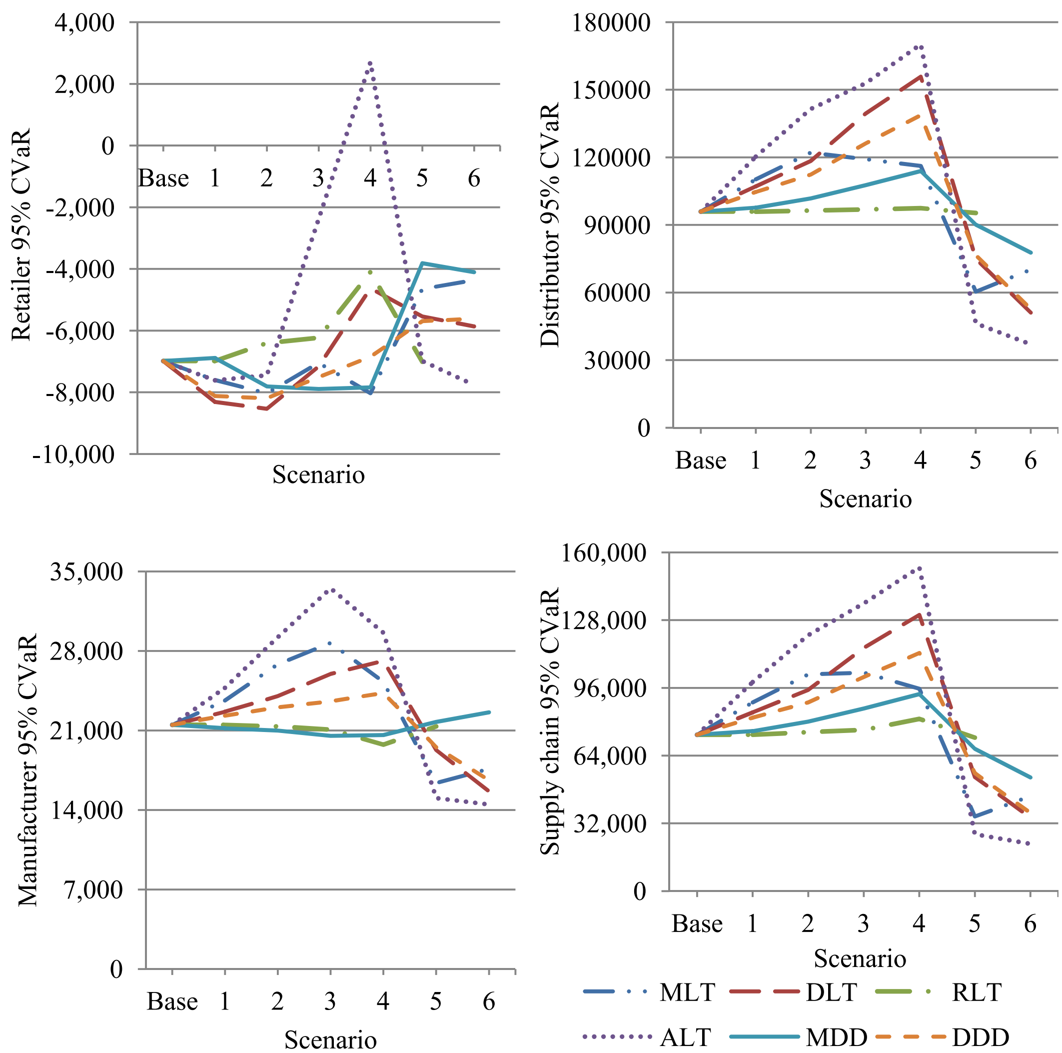


Figure 5-6. The effect of lead time and delivery delay on risk (95% CVaR)

Similar to the case of Poisson demand, all SC levels as well as the whole supply chain risk are the most sensitive to ALT sets of scenarios. Based on Figure 5-7, two days increase in lead time of all SC levels (ALT4) leads to 397% [PMD: 136%, PLD: 31%] increase in risk of retailer, 74% [PMD: 62%, PLD: 95%] increase in risk of distributor, 24% [PMD and PLD: 32%] increase in risk of manufacturer and 103% [PMD: 73%, PLD: 291%] increase in supply chain risk. Two days decrease in lead time of all supply chain levels (ALT6) results in 62% [PMD: 65%, PLD: 76%] decrease in distributor's risk, 33% [PMD: 31%, PLD: 36%] decrease in manufacturer's and 67% [PMD: 92%, PLD: 154%] decrease in supply chain's risk.

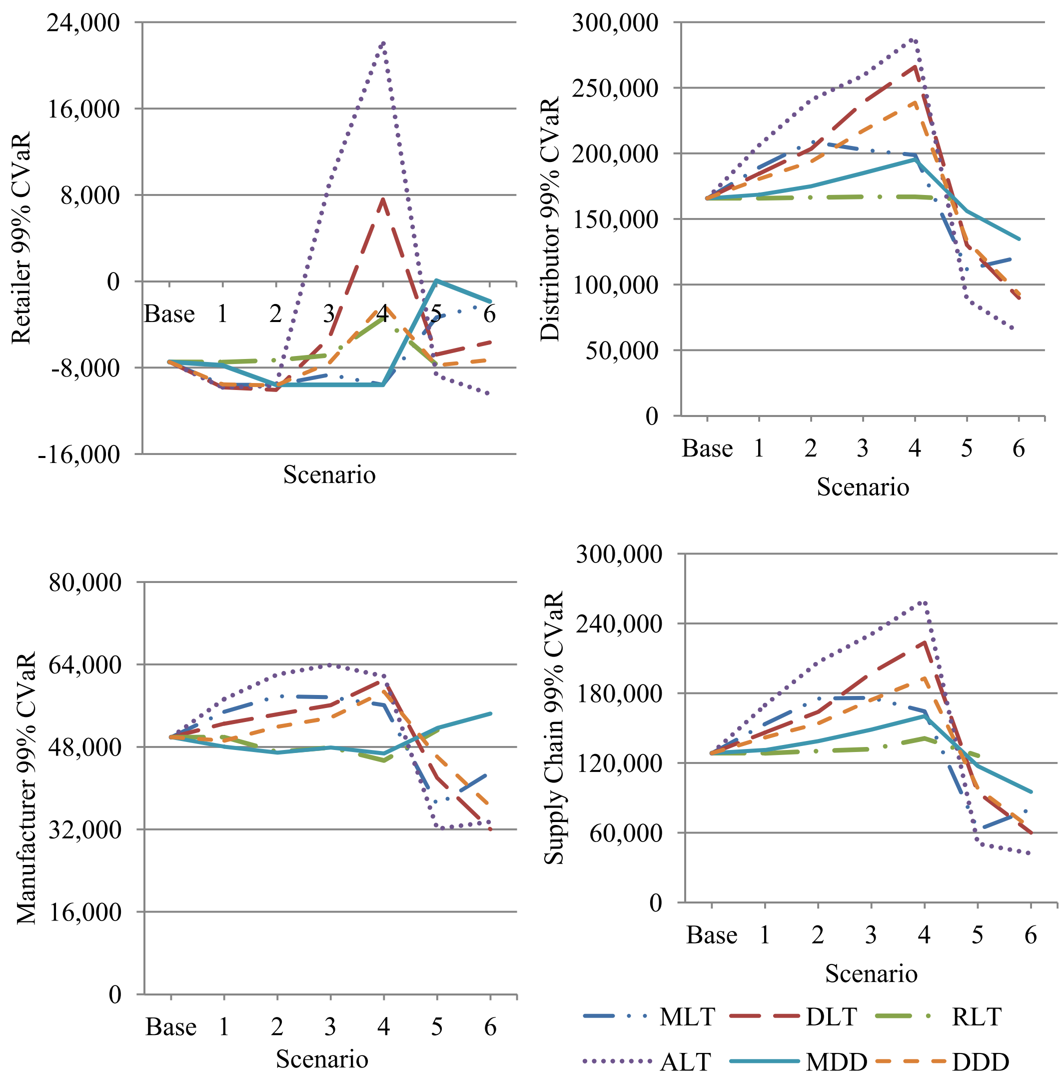


Figure 5-7. The effect of lead time and delivery delay on risk (99% CVaR)

5.2. Risk of Forecast

In chapter 4, it was analyzed how long lead times affect the forecast error and risk of each SC level. It was shown that higher lead time leads to higher forecast error and higher risk in supply chain. In this section, by comparing three measures of demand standard deviation, forecast error (MAD), and risk measure (95% CVaR), the impact of demand uncertainty on the risk of forecast under two types of demands– Poisson and Bass– is explored.

Figure 5-8 shows demand standard deviation, forecast error, and risk of each SC level for PHD products under the base scenarios of Bass and Poisson demands. It can be seen that, for all levels of supply chain, the uncertainty level of demand for the case of Bass model is higher than Poisson. That is, by comparing the forecast error and risk measure of Poisson and Bass demand, essentially, the impact of demand uncertainty on these two measures is being compared.

Based on the results shown on the graph in the middle and right side of Figure 5-8, it can be concluded that the higher the demand uncertainty, the higher the forecast error and risk are for all SC levels. Table 5-2 shows the detail values of demand standard deviation, MAD, and 95% CVaR for all product types and all three SC levels.

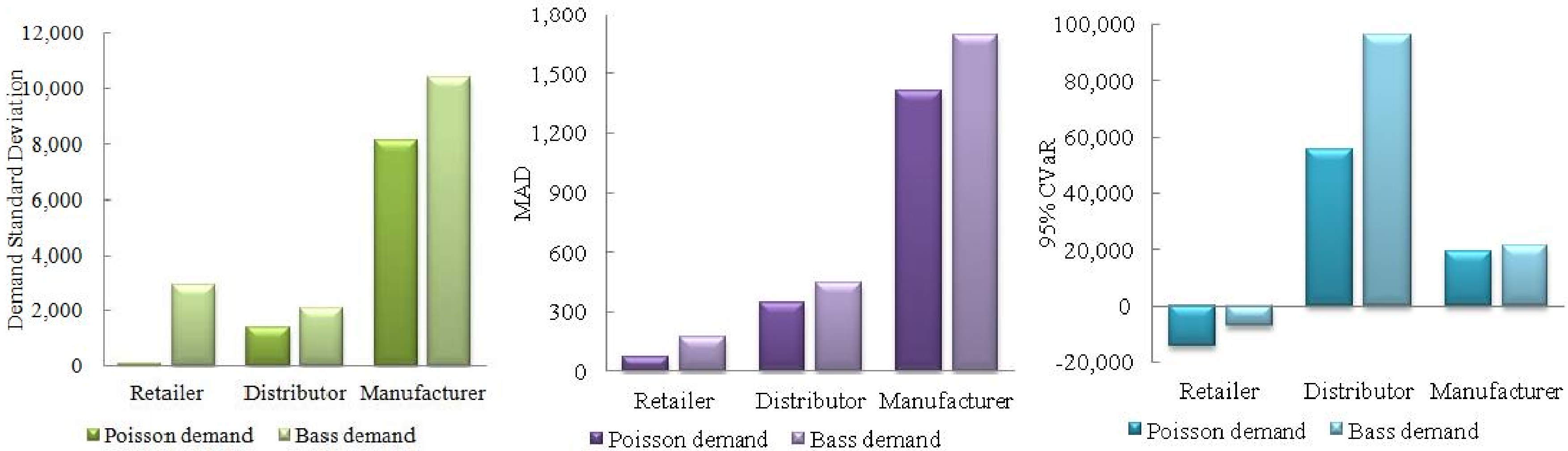


Figure 5-8. Relationship between demand uncertainty, forecast error and risk of each SC level for PHD products (comparison of Poisson and Bass demand)

Table 5-2. Relationship between demand uncertainty, forecast error and risk of each SC level for all product types (comparison of Poisson and Bass demand)

Variable	Product type	PHD			PMD			PLD		
	SC level	Retailer	Distributor	Manufacturer	Retailer	Distributor	Manufacturer	Retailer	Distributor	Manufacturer
Demand standard deviation	Poisson demand	96	1,375	8,128	68	658	3,890	29	127	770
	Bass demand	2,880	2,066	10,406	690	804	4,293	131	153	833
Forecast error (MAD)	Poisson demand	75	349	1,415	54	179	659	24	36	139
	Bass demand	171	448	1,697	43	206	768	6	38	142
Risk measure (95% CVaR)	Poisson demand	-14,150	55,478	19,247	-12,388	37,648	12,648	-4,196	8,553	2,948
	Bass demand	-6,984	95,899	21,486	-6,543	42,765	12,837	-2,159	9,842	3,359

5.3. Risk of Inventory

Figure 5-9 depicts how the changes in lead time and delivery delay affect the average total inventory of each SC level. The behavior of average inventory for all SC levels is similar to Poisson demand (compare with Figure 4-8). However, under the Bass demand, the inventory amount is higher to some extent.

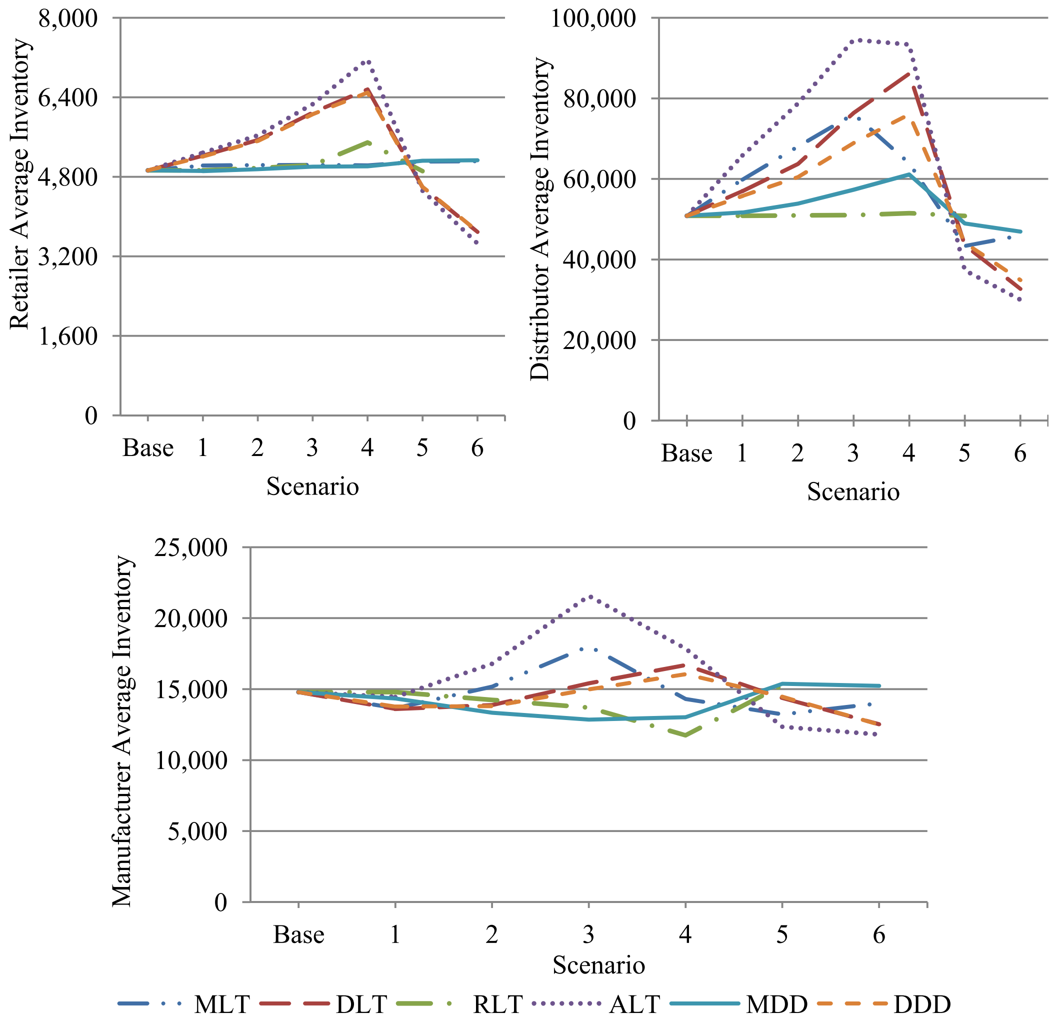


Figure 5-9. The effect of lead time and delivery delay on inventory.

ALT scenarios have the highest impact on inventory of all SC levels followed by DLT scenarios for retailer and distributor levels and MLT scenarios for manufacturer level. For instance, 40% increase in LT of all SC levels (ALT3) causes 86% [PMD:

75%, PLD: 50%] increase in average invetory of distributor and 46% [PMD: 27%, PLD: 32%] increase in manufacturer's average inventory. ALT4, the most impactful scenario for retailer level, increases its average inventory by 45% [PMD: 43%, PLD: 44%].

Demand uncertainty is another driver of risk of inventory in supply chain. As stated before, since the Bass demand has a larger standard deviation than Poisson demand, comparing these two models is equivalent to the study of demand uncertainty. Figure 5-10 simultaneously compares the demand uncertainty, average inventory and risk of each SC level for PHD products. The graph in the middle illustrates that the inventory of all SC levels are higher for the case of Bass demand which has higher demand uncertainty. Also, it can be seen that demand uncertainty has the highest impact on inventory and risk of distributor level, because it holds the highest amount of inventory in supply chain. Table 5-3 shows the detail values of average inventory for all product types and all three SC levels.

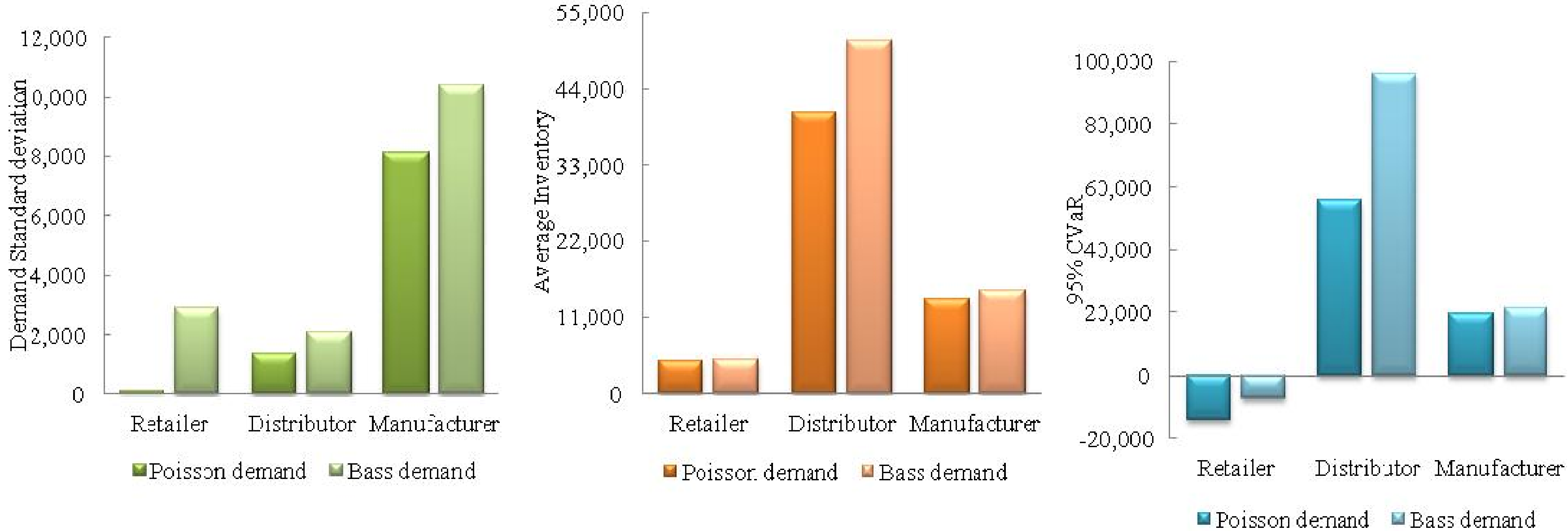


Figure 5-10. Relationship between demand uncertainty, inventory amount and risk of each SC level for PHD products (comparison of Poisson and Bass demand)

Table 5-3. Relationship between demand uncertainty, inventory amount and risk of each SC level for all product types (comparison of Poisson and Bass demand)

	Product type	PHD			PMD			PLD		
Variable	SC level	Retailer	Distributor	Manufacturer	Retailer	Distributor	Manufacturer	Retailer	Distributor	Manufacturer
Average Inventory	Poisson demand	4,756	40,713	13,506	2,278	19,310	5,980	453	3,835	1,279
	Bass demand	4,929	50,841	14,792	2,314	20,789	7,073	450	4,000	1,301

CHAPTER 6

IMPACT OF PRODUCT VARIETY ON SUPPLY CHAIN RISK

The main purpose of this chapter is investigating the impact of product variety as another driver of risk on the performance of supply chain. While considering positive impacts of product variety on demand, it is particularly shown that how product variety affects the risk of inventory and forecast. A new system dynamics model – a simplified version of the one presented in chapter four– is proposed which has more common characteristics with the case of Zara Company.

6.1. Introduction

Contemporary customers change their product preferences rapidly and are inclined to purchase only what they need or want. In response, the companies need to increase their product variety to improve market share and remain globally competitive.

Apparel industry, viewed as one of outstanding economic engines in history, has been radically evolving over the past 25 years due to retail consolidation, globalization and e-commerce. Challenges specific to fast fashion apparel industry include tremendous product variety and very short product life cycles. In such environment, it is of high importance to effectively manage trade-offs between variety benefits and inventory and/or other risks arising from variety increase.

Carugati et al. (2008) classified the companies in apparel industry into three market segments based on their competitive strategy: cost advantage, speed, and brand equity. The key to success for the second market segment is providing customers with the most fashionable clothes in the shortest time. Fashion items, in particular, have a very short life cycle, since they are routinely substituted by trendier ones. As a result, every year, a fast fashion firm offers a much larger variety of products in comparison with a traditional retailer. Therefore, for a category of apparel variants differentiated by some attributes such as color, style or size, detailed modeling is required to investigate the effect of product variety on performance of an apparel supply chain.

6.2. Product Variety

Among several definitions available in the literature, the present study considers the definition of product variety as the number of different versions of a product offered by a firm at a single point in time (Randall and Ulrich, 2001). According to product characteristics, there are different drivers for product variety such as form (size, shape, and structure), feature (options provided), and style (color, appearance) (Park et al., 2005).

Product variety directly affects several departments in a firm such as, for example, marketing, logistics and manufacturing. Increasing product variety in style, size, package, function, etc., can result in improved customer satisfaction, higher market share and enhanced competitiveness (Park et al., 2005). Product variety also changes consumer purchase style and welfare. The needs and wishes of divergently distributed consumers are better satisfied by higher product variety. In addition, consumers can benefit from a diversity of options through "variety seeking" behavior, which satisfies rational inquisitiveness (Kahn, 1998). Thus, increasing product variety augments consumer welfare (Brynjolfsson et al., 2003). In contrast, a reduction in variety has an adverse impact on both purchase quantity and shopping iteration (Borle et al., 2005). On the other hand, increasing availability of product variety also changes consumer behavior, requiring, for example, better product choice selection strategies, and in the long run creating much more sophisticated and savvy customer (Iyengar and Kamenica, 2010).

Increasing variety has impact on logistics operations and costs as well. Variety induces different indirect costs that are difficult to capture, and are often neglected when making the decision about introducing variety (Martin and Ishii, 1996). Raw material costs, work-in-process (WIP), finished goods, and post-sales service inventories, and logistics costs are some examples of costs arising from increased variety. The inventory of finished goods and WIP for a firm with higher product variety is more than a firm with lower level of variety as a result of the uncertainty in forecasting demands (Forza and Salvador, 2002).

The more challenging issue is to ensure operational efficiency when the variety level is increasing (McCutcheon et al., 1994; Åhlström and Westbrook, 1999). A broader product line can result in higher costs, essentially because of increases in overhead expenses, material costs and labor costs (Hayes and Wheelwright, 1984; Abegglen and Stalk, 1985). In particular, the impact of product variety on cost is considerably higher than that proposed by the risk-pooling[3] literature for completely flexible manufacturing processes when setup times are significant (Thonemann and Bradley, 2002).

Most of the times, the objectives of marketing and manufacturing are contradictory (Crittenden, 1993). Although increasing product variety might lead to increased sales, it has its disadvantages so that it might not be economically viable. Thus, a challenge faced by companies is to maintain the competitive price and quality while offering variety in order to satisfy customer's needs and wants.

The net impact of product variety on supply chain performance is uncertain when considering both the positive impact of variety on sales and the negative impact of the increased inventory and out-of-stock due to high product variety. The determination depends on the trade-off between these positive and negative effects. Thus, in this chapter, both types of impacts are explored, simultaneously. The literature review reveals that previous research incidentally studied the impact of product variety on business functions and mostly focused on the impact of product variety on individual functional areas (Wan, 2011).

Therefore, the main contribution of this chapter is in simultaneously capturing the impacts of variety in product on demand and risk outcomes. Integrating marketing factors (demand) and operational factors (costs/risks) within a company is an important, and at the same time challenging issue.

The subject of analysis here is a (simplified) supply chain with a single manufacturer and a single retailer. First, the performance of supply chain is investigated disregarding the effect of product variety on the lead time. Then, the effect of product variety is

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[3] Risk pooling suggests that demand variability is reduced if one aggregates demand across locations because as demand is aggregated across different locations, it becomes more likely that high demand from one customer will be offset by low demand from another. This reduction in variability allows a decrease in safety stock and therefore reduces average inventory (Simchi-Levi et al., 2007).

analyzed when it impacts the manufacturer's lead time. Although, many industries are under pressure for higher variety and faster delivery (McCutcheon et al., 1994; Pil and Holweg, 2004), distinct recognition of the lead time-variety trade-off can rarely be found the literature. It is demonstrated that disregarding the effect of product variety on lead time can lead to poor decisions and can lead companies to offer product variety that is higher than economically feasible.

6.3. The Model

The structure of stocks and flows in the proposed model here is similar to that of chapter four with few differences in model characteristics which are presented below.

- Supply chain is with a single manufacturer and a single retailer.
- The distributor is part of the manufacture level that is, the finished apparel, after being packed, will be sent to distribution centre through underground conveying belt.
- Periodic review policy is applied as the inventory replenishment system, e.g., the inventory status is checked every three days and an order is placed to increase the level of inventory to match the expected demand for three days.
- The stock of the initial inventory for the manufacturer level is 6,000 units and for the retailer 2,000 units.
- The manufacturing capacity is 28,800 units per time period.
- The manufacturer lead time in the base model is 14 days for production and 1 day for delivery.
- The adjust factor for forecasting is equal to 3.
- Distributions are made twice a week.

Figure 6-1 depicts the stock and flow diagram of the two echelon SC model.

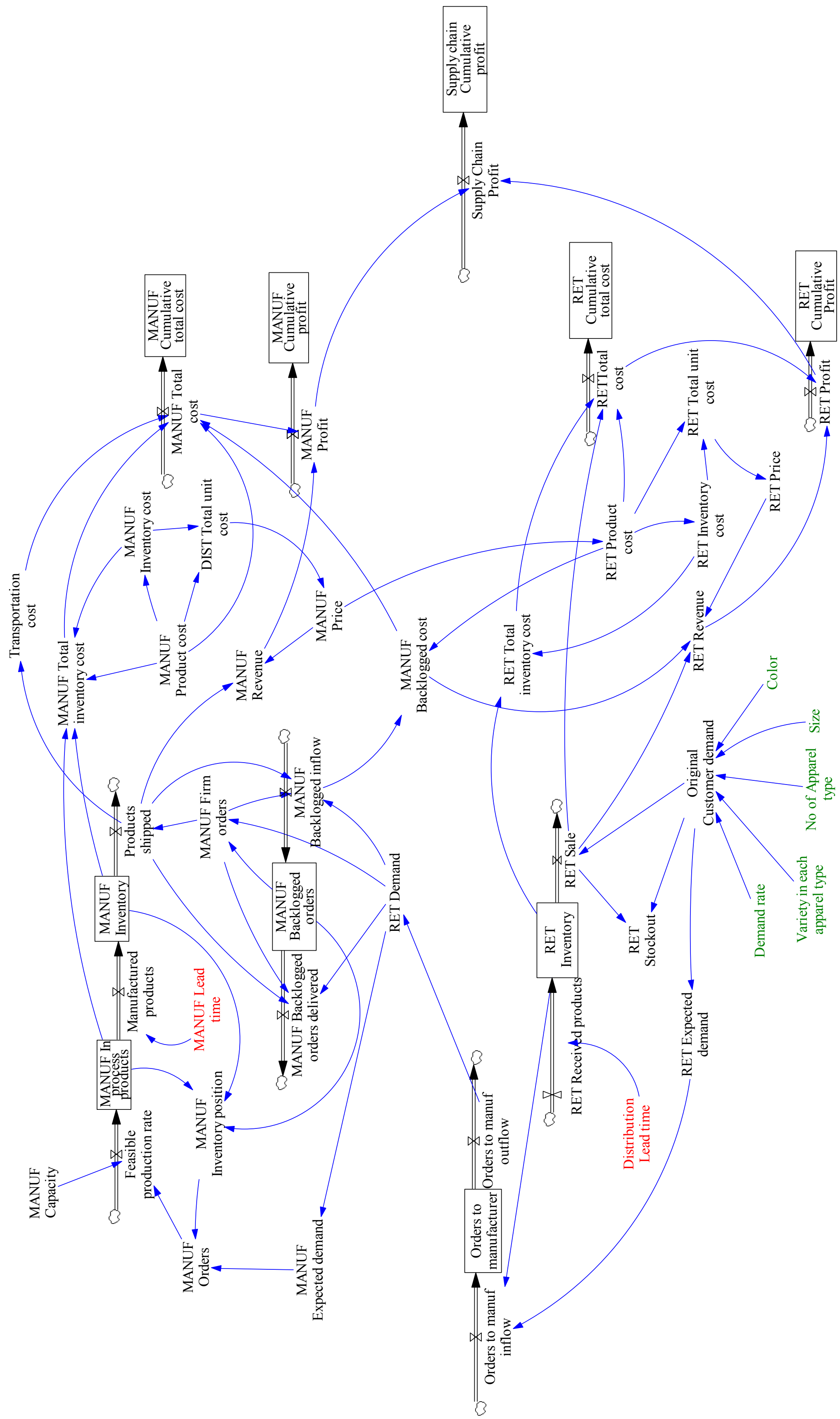

Figure 6-1. The stock and flow diagram of the two-echelon supply chain

6.4. Numerical Results

As stated before, the present chapter explores the effect of product variety on the supply chain of a fast fashion apparel industry. Average cost, average profit, mean absolute deviation (MAD) of forecast, 99% CVaR, and average inventory are selected as the performance measures. Our numerical analysis is divided into two subsections: first, the impact of product variety on the SC performance under the assumption that increases in product variety have no effect on LT is assessed. In the second subsection, the cases that product variety significantly affects the LT are considered and simultaneous impact of variety and LT on the performance of SC is analyzed.

6.4.1 Variety Does Not Affect the Lead Time

In this section, it is assumed that increasing product variety does not affect the lead time. That is, the manufacturer's LT for all levels of product variety is the same. Table 6-1 shows the detail of 10 scenarios with different variety levels, VM1 to VM10.

Table 6-1. Product variety and lead time for scenarios

Scenario	No. of apparel type	Variety in each apparel type	Size	Color	Scenario	Manuf. lead time (days)
VM1	4	3	3	3	VL1	12
VM2	6	5	4	5	VL2	14
VM3	7	6	4	5	VL3	16
VM4	9	8	4	5	VL4	18
VM5	10	9	7	8	VL5	20
VM6	12	11	10	10	VL6	22
VM7	14	13	11	11	VL7	24
VM8	13	13	13	13	VL8	26
VM9	14	14	14	14	VL9	28
VM10	15	15	14	14	VL10	30

Figure 6-2 shows the impact of product variety on average cost, revenue, and profit of both SC levels. It can be seen that increasing variety will lead to increase in revenue of manufacturer up to a certain level of variety which is the point that the manufacturer reaches the production capacity (VM7). However, the cost of manufacturer increases even after VM7 since the unsatisfied demand is increasing which leads to higher backlogged cost. Therefore, the profit decreases after VM7. Due to significant increase in manufacturer's backlogs and the penalty they should pay to the retailer, the retailer's revenue increases even after VM7, although the sales remain the same for this SC level.

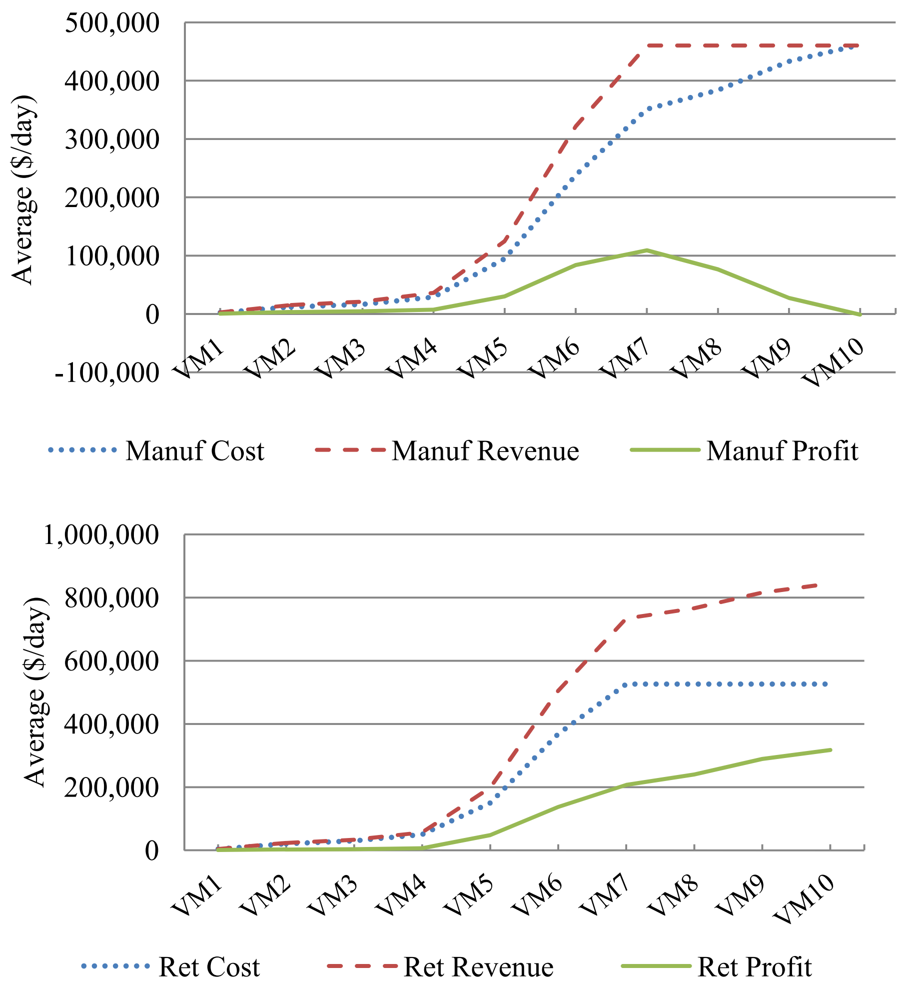

Figure 6-2. The effect of product variety (VM scenarios) on manufacturer's and retailer's cost, revenue, and profit

The simultaneous impact of product variety on measure of forecast error (MAD) and measure of risk (99% CVaR) for both manufacturer and retailer is illustrated in Figure 6-3. It can be seen that by increasing the variety through scenarios of VM1 to VM10, the forecast error of both SC levels as well as their risk measures go up and the level of increase is more significant for the manufacturer. The detail of values used for this figure is presented in Table 6-2.

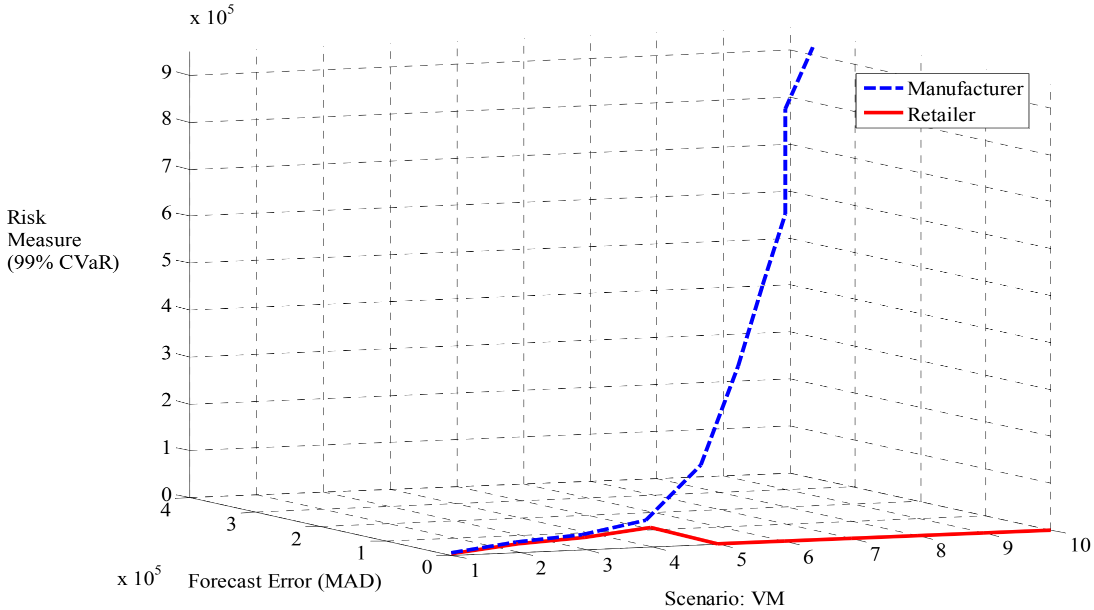

Figure 6-3. The effect of product variety (VM Scenarios) on forecast error and risk of manufacturer and retailer

Similarly, Figure 6-4 simultaneously shows the impact of product variety on average inventory and risk measure of manufacturer and retailer. As expected, the higher levels of variety leads to higher inventory levels– up to the point that the manufacturer reaches the production capacity– which consequently increases the risk of both SC levels.

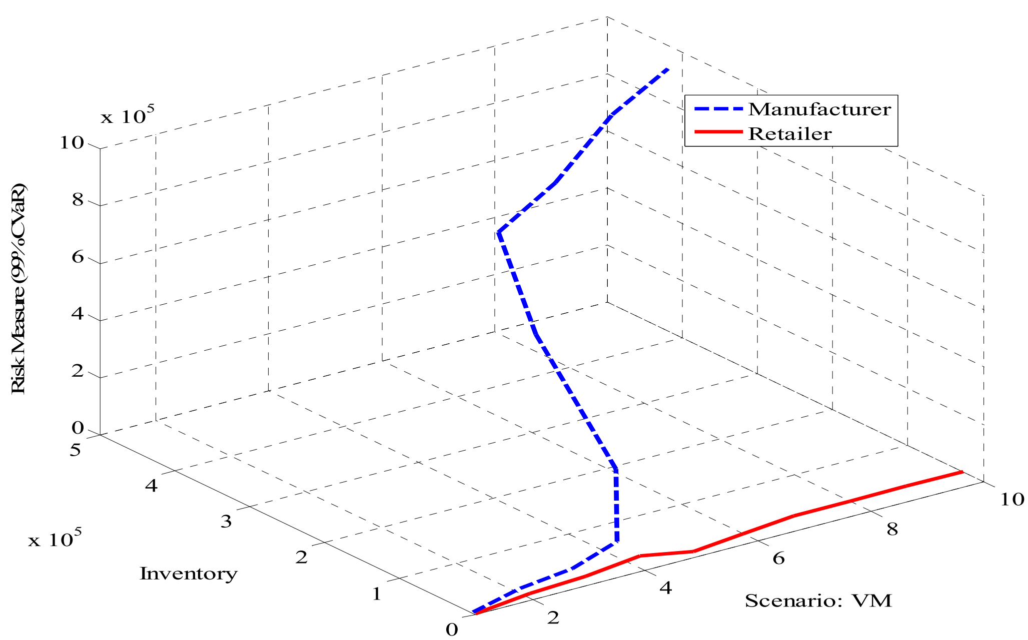

Figure 6-4. The effect of product variety (VM Scenarios) on average inventory and risk of manufacturer and retailer

Table 6-2. The effect of product variety (VM Scenarios) on MAD, 99% CVaR, and average inventory

Variety Scenario	Forecast error (MAD)		Risk Measure: 99% CVaR			Average Inventory	
	Manufacturer	Retailer	Manufacturer	Retailer	Supply Chain	Manufacturer	Retailer
VM1	558	16	4,500	2,417	5,647	2,812	394
VM2	3,202	40	21,542	17,781	24,767	15,309	2,366
VM3	4,392	45	29,807	25,457	34,864	20,763	3,397
VM4	7,534	60	53,786	42,002	58,426	37,106	5,586
VM5	26,841	109	160,168	0	69,335	113,593	10,214
VM6	71,167	179	351,159	0	123,790	294,297	19,048
VM7	134,851	236	499,761	0	129,600	419,030	27,244
VM8	202,953	268	623,303	0	129,600	419,030	27,244
VM9	305,617	310	809,502	0	129,600	419,030	27,244
VM10	364,816	333	916,898	0	129,600	419,030	27,244

6.4.2 Variety Affects the Lead Time

For the manufacturers whose setup time is significant, increasing product variety considerably affects the lead time. Therefore, in this section, 10 new scenarios, named VL1 to VL10, are defined. The levels of variety in these scenarios are the same as previous ones. However, there is increase in lead times by any increase in variety (see Table 6-1).

Figure 6-5 depicts the effect of product variety on manufacturer's and retailer's cost, revenue, and profit. It shows that the increase in manufacturer's cost is significantly higher than the VM scenarios, because higher lead time increases the backlogged orders as well as WIP (inventory) and, consequently, their corresponding cost. Thus, under lower levels of product variety, the profit starts to decrease and the rate of decrease is steeper. However, at the retailer level, there is only a slight change (there is no backlog or WIP in this level).

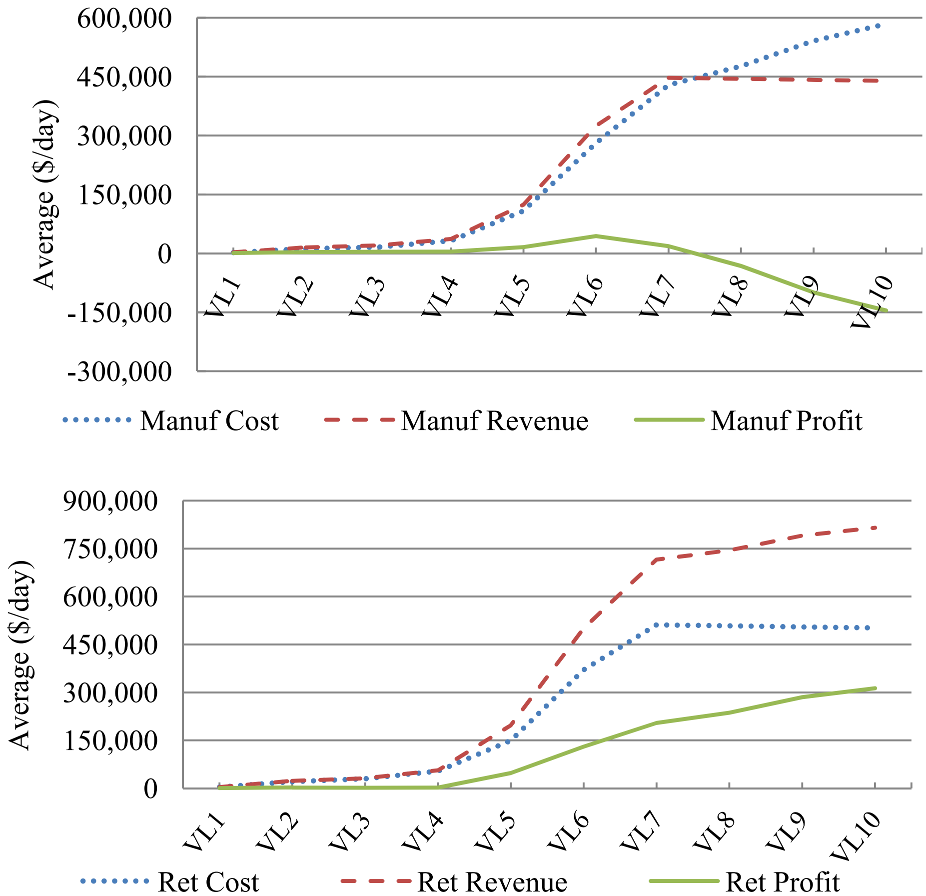

Figure 6-5. The effect of product variety (VL scenarios) on manufacturer's and retailer's cost, revenue, and profit

Table 6-3 shows the effect of product variety on MAD, 99% CVaR, and average inventory under VL sets of scenarios. Similar trend under these scenarios can be observed. That is, the higher the product variety, the higher the MAD, average inventory and CVaR values. However, the intensity of increase is different from VM set of scenarios.

Table 6-3. The effect of product variety (VL Scenarios) on MAD, 99% CVaR, and average inventory

Variety Scenario	Forecast error (MAD)		Risk Measure: 99% CVaR			Average Inventory	
	Manufacturer	Retailer	Manufacturer	Retailer	Supply Chain	Manufacturer	Retailer
VL1	504	16	4,500	3,223	5,700	2,450	407
VL2	3,202	40	21,542	17,781	24,767	15,309	2,366
VL3	4,922	45	28,451	35,522	44,548	23,199	3,664
VL4	9,090	60	59,890	64,616	82,948	46,747	7,171
VL5	34,705	109	194,287	0	103,491	159,239	10,375
VL6	98,367	179	394,937	0	210,190	458,189	19,177
VL7	203,143	236	599,887	0	237,600	688,488	26,455
VL8	324,134	268	755,857	0	259,200	741,432	26,297
VL9	515,806	310	942,126	0	280,800	794,061	26,139
VL10	650,555	333	1,081,994	0	302,400	846,375	25,981

Figure 6-6 compares the impact of product variety on manufacturer's forecast error and risk under VM and VL scenarios. According to the graph, VL scenarios, when product variety affects the LT, have more significant impact on both MAD and CVaR measures. The impact of product variety on average inventory and risk of manufacturer under VM and VL scenarios are shown in Figure 6-7. In the same way, it can be seen that manufacturer's inventory is more sensitive to the VL scenarios.

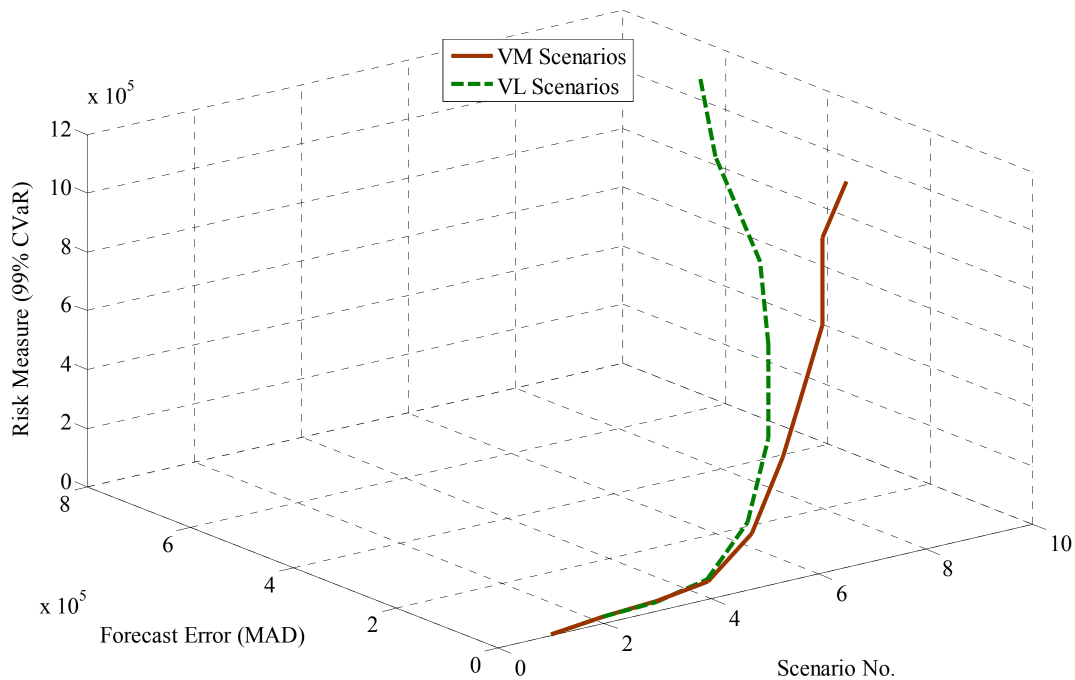

Figure 6-6. Comparison of the effect of product variety on forecast error and risk of manufacturer under VM and VL scenarios

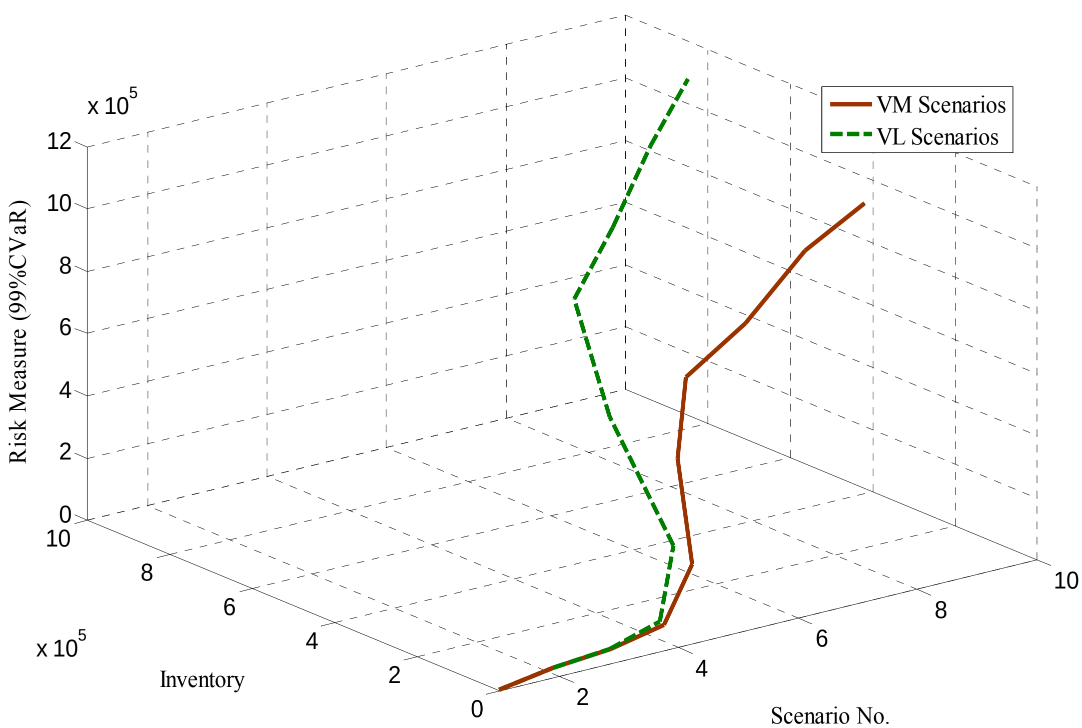

Figure 6-7. Comparison of the effect of product variety on average inventory and risk of manufacturer under VM and VL scenarios

Figure 6-8 illustrates the supply chain risk under two sets of scenarios (VM1-10 & VL1-10). It can be seen that under VL scenarios, the supply chain risk increases faster in comparison with VM scenarios which means supply chain risk is much more sensitive to product variety when it also affects the lead time. Based on all the results discussed above, it can be concluded that for the systems with a significant setup time in which increasing variety affects the lead time, firms should consider this effect. Otherwise, they might offer a variety level which is far above economically feasible.

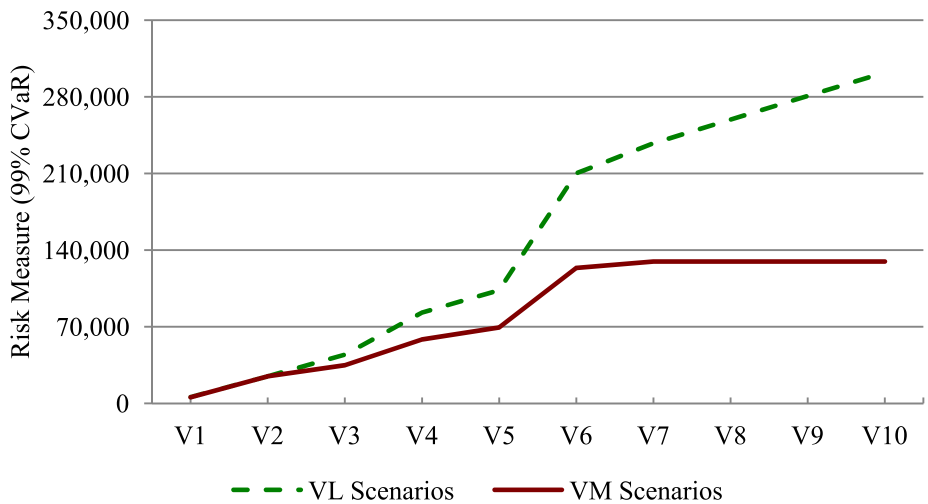

Figure 6-8. Comparison of the effect of product variety on supply chain risk (99% CVaR) under VM and VL scenarios

CHAPTER 7

CONCLUSIONS

7.1. Summary

This research was motivated by the fact that companies develop strategies to adapt to supply chain dynamics and mitigate disruptions. However, existing research has been mostly concentrated on the supply chain optimization stage. Studies on supply chains dynamics and risk management comprise a very small share of supply chain management research. At the same time, empirical studies reveal that supply chain managers spend a significant proportion of their working time handling risks/disruptions. As an outcome of this apparent gap between practice and theory, decisions in the areas of supply chains dynamics and disruption management are often isolated from the planning level and mainly based on expert knowledge with restricted application of quantitative analysis tools. The main purpose of this study was to develop a dynamic model for the supply chain of perishable products in general and fast fashion apparel industry in particular and to quantitatively analyze the risks associated with the corresponding supply chain.

In order to observe and analyze the processes and relationships in the supply chain of fast fashion industry, system dynamics methodology was applied and three different models were presented. Applying the proposed models and conditional value at risk measure, the risk associated with the supply chain was quantified that can be widely used in decision making process.

In particular, the impact of three prominent categories of risk− risk of delay, risk of forecast, and risk of inventory− on the performance of supply chain were analyzed. The other measures employed to conduct our comprehensive quantitative analysis, besides CVaR, included average backlogged orders, stock-outs, inventory, total cost, profit, and mean absolute deviation for forecasts.

The impact of lead-time and delivery delay on the SC performance was investigated. The numerical analysis showed how delays in each level of SC affected the risk of that same level, other levels, and the whole SC. Although the behavior of each SC level toward each performance metric is different, it can be concluded that the supply chain risk is most sensitive to ALT scenarios in which the lead-time of all SC levels change at the same time. It was shown that the higher the delays, the higher the risk in the SC. For example, when the lead time of all SC levels were increased by 40%, there was 94% increase in distributor's risk, 95% increase in manufacturer's risk, and 158% increase in supply chain's risk for products with high demand. The delays at manufacturer's level (MLT) also had a high impact on SC risk after the ALT cases.

A new version of the original model was proposed which used the Bass diffusion model to generate the demand at retailer level. Comparing this model and the original one, which used Poisson distribution for demand at retailer level, enabled us to study the impact of demand uncertainty− a key driver of risk− on the SC performance since both models had different standard deviations of demand.

The analysis related to the impact of demand uncertainty, product variety, and lead time on the risk of inventory showed that these three factors significantly affect the inventory amount and consequently the risk measure of each SC level. That is, higher uncertainty of demand, product variety, and longer lead times result in higher inventory levels and larger CVaR values. Similarly, it was illustrated that demand uncertainty, product variety, and lead time have negative effect on the risk of forecast inaccuracy in supply chain. For instance, 50% increase in standard deviation of distributor's demand leads to 28% increase in forecast inaccuracy for distributor and 73% increase in distributor's risk.

Moreover, the net impact of product variety on the performance of supply chain was explored considering that product variety has positive effect on sales and revenue, at the same time, negative effect on inventory, backlogs, and cost. Through a simplified version of main SD model which has specific characteristics similar to the case of Zara, the effect of different levels of product variety on supply chain risk was analyzed. It was shown that the systems with a significant setup time in which increasing variety affects the lead time are more sensitive to the variety level.

7.2. Limitations

In this research, accurate industry-specific parameter values were not available. Therefore, some of the absolute numbers that this model presented are used for comparative analysis of different scenarios. It should be mentioned that our scenarios covered the most possible parameter ranges and the results followed the general patterns in this industry. Nevertheless, the model helps to conduct comparative analysis, to study the relationships between SC levels, and to investigate the effect of changes in variables of interest on the model performance.

As another limitation of this study we can mention that the main focus was on fast fashion products and their corresponding supply chain. However, large apparel companies require to have a portfolio of supply chains that work jointly to serve different segments based on different markets, consumers, products, or seasons. For example, one supply chain for basic products which are constantly in demand, one for seasonal products that need to be updated four times a year, and one for the fashion products.

7.3. Future Work

The present research mainly focuses on the impact of selected categories of risk, i.e. risks of inventory, forecast, and delay on the SC performance. The impact of other risk categories such as, for example, risks of capacity, procurement, receivables and disruptions can be assessed by extending the proposed model and adding the necessary variables and causal loops.

The proposed SC model consists of three levels of manufacturer, distributor, and retailer. It is assumed that the raw materials required in manufacturer level are always available. Introducing another level in the supply chain as the supplier can be another stream of future studies. Furthermore, increasing the number of distributors and retailers in the supply chain and analyzing the system behavior based on different modes of transport and different policies constitutes a future endeavor.

In the past, materials, energy, and other resources were used inefficiently in the apparel industry, causing unsustainable levels of waste generation. The companies did not adopt the strategies such as Post-purchase or disposal of products during the design and production stages. Nowadays, apparel companies are becoming more aware of their environmental impact and are employing sustainability programs to prevent these issues. Therefore, introducing the factors which can be used to analyze and measure the overall sustainability of supply chain in the proposed model is an interesting issue to consider for future studies.

A wide range of companies are involved with the phenomenon of perishability. This research was specifically focused on the fast fashion apparel industry. High-tech, plant farming, health care, and travel businesses are some other instances of the industries dealing with perishability and the associated risks. They can be modeled and investigated by applying the proposed model as the base model and including necessary changes according to specific industry and policy settings.

The developed model was validated applying different structural and behavioral tests including extreme condition, dimensional consistency, extreme policy, behavior sensitivity, and behavior anomaly tests. The policies and approaches used in the current study can be further validated based on industrial data and practitioners' insight and perspective.

In chapter 6 a new case study of the model was proposed which had a fair amount of commonality with Zara Company. For example, the distributor was considered part of the manufacturer level. However, Zara's supply chain is vertically integrated which makes it the world's largest fashion retailer and leads to high level of transparency in information flows. Therefore, Zara is able to control the current information and predict the future demand with very high level of accuracy and in a short period of time. Thus, the bullwhip effects are much diminished in its supply chain compared to the other fashion retailers. The model in this research can be modified accordingly to include more features of Zara's responsive supply chain which differentiates them from their competitors.

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APPENDICES

Table A-1. List of Stock variables and their definitions

Notation	Name in Vensim	Definition	Unit
WIP (ijt):	Manuf. in process products Dist./ Ret. received products	Manuf: inventory of raw materials or work in process in manufacturing level. Dist/Ret: inventory of products in distributor or retailer level which are not ready to be sold due to shelving, unpacking, repacking activities or etc. The outputs of these variables depend on the lead time of the corresponding level.	Unit
BO(ijt) *j=1,2*	Manuf./ Dist. backlogged orders	Unsatisfied orders placed by the downstream level of chain which will be served in forthcoming period when the inventory would be available.	Unit
—	Manuf./ Dist./ Ret. cumulative profit	Accumulation of profit in each level of supply chain from the first time period to the last one in the model.	Dollar
—	Manuf./ Dist./ Ret. cumulative total cost	Accumulation of total cost in each level of supply chain from the first time period to the last one.	Dollar
I(ijt)	Manuf./ Dist./ Ret. inventory	Inventory of all finished products and available for delivery to the downstream level of supply chain upon its request.	Unit
ED(ijt)	Manuf./ Dist./ Ret. expected demand	Forecast of orders of the level immediately before that being considered using simple or exponential smoothing technique with the corresponding forecasting adjust factor.	Unit/week

- *t* = Time *t=1,2,..., 104*
- *i* = Product type *i=1(PHD), 2(PMD), 3(PLD)*
- *j*= Supply chain level *j*=1 (Manufacturer), 2(Distributor), 3(retailer)

Table A-2. List of material flow variables and their definitions

Notation	Name in Vensim	Definition	Unit
DE(ijt)	Delivered products to distributor/ retailer/ customer	Quantity delivered from level j of supply chain to the immediately downstream level (Sale of level j).	Unit/week
FP(ijt)	Final products: Manufactured products/ Dist. products ready to ship/ Ret. products ready to sell	Manuf.: Flow of finished products to the manufacturer inventory which is conditioned by the manufacturer's lead time and introduces a delay to the system/ Dist./ Ret.: Flow of products that have undergone the unpacking and repacking process which are conditioned by distributor's or retailer's lead time and introduce a delay to the system.	Unit/week
F(ijt) *j=1*	Feasible production rate	Amount of production in each time period which is constrained by the manufacturing capacity.	Unit/week
FL(ijt) *j=2,3*	Flow of products to distributor/ retailer	Flow of products to the level that has ordered the products. It modifies the state of the corresponding stock variable related to 'received products'. This variable adds some delay to the system due to the delivery delay of the upstream level.	Unit/week

Table A-3. List of auxiliary and information flow variables and their definitions

Notation	Name in Vensim	Definition	Unit
LT(jt)	Manuf./Dist./Ret. lead time	Manuf: time period between receiving the raw material from the supplier until it is a finished product. Dist./ Ret.: time period needed to unpack and repack the products to prepare them based on the orders received from the downstream level of the chain.	Week
LTc(j)	Lead time effect on cost	If the lead time is longer or shorter than a threshold, it will affect the unit product cost. The shorter the lead time, the higher the unit product cost will be.	Dmnl
ROP(ijt) *j=2,3*	Dist./ Ret. reorder point	The point in which the inventory position should not be lower than that and an order needs to be placed. It is calculated based on expected demand during the lead time of the upstream level and safety inventory. Note: Since no upstream level for the manufacturer is considered in our model there is no lead time for that. Thus, Manuf. reorder point is not included in this study.	Unit
SS(ijt) *j=2,3*	Dist./Ret. safety stock	The level of extra stock to mitigate the risk of backlogged orders/stockout.	Unit
BC(ijt)	Manuf./ Dist. Backlogged cost	The penalty that should be paid to the downstream level due to the delay to deliver the products which is proportional to the product cost and amount of backlogged orders.	Dollar/week
DD(jt) *j=1,2*	Manuf./ Dist. delivery delay	Time period needed to deliver the material to the immediately downstream level. It is assumed that each supply chain level is responsible to deliver the products it sells.	Week
FO(ijt) *j=1,2*	Manuf./ Dist. firm orders	Supplies information about the demand of products and backlogged orders that are still to be served.	Unit/week
IP(ijt)	Manuf./ Dist./ Ret. Inventory position	Supplies information to manage the demand. It increases by the inventories (unfinished and finished products) and decreases by backlogged orders.	Unit

Table A-3 Cont'd. List of auxiliary and information flow variables and their definitions

TrnC(ijt) *j=1,2*	Manuf./ Dist. transportation cost	Weekly cost of transportation for each product type which depends on number of trucks, cost per truck, and quantity of delivered products from each product type. Note: cost per truck depends on the distance between supply chain levels. It is assumed that the distance between manufacturer and distributor is 50 km and the distance between distributor and retailer is 250 km.	Dollar/week
TRn(jt) *j=1,2*	Manuf./ Dist. No. of trucks	Number of trucks needed for transportation of all product types which depends on the quantity of delivered products and truck capacity. It is assumed that the capacity of each LTL (less than truckload) carrier is 2500 piece of garment.	Truck/week
Fe(ijt)	Manuf./ Dist./ Ret. forecast error calc.	Absolute value of the difference between expected demand and real demand in each level of supply chain.	Unit/week
UIC(ijt)	Manuf./ Dist./ Ret. Unit inventory cost	Inventory cost for each unit of product which is a fraction of product cost.	Dollar/unit
Pr(ij)	Manuf./ Dist./ Ret. price	Selling price to apply on products delivered to the downstream level.	Dollar/unit
UPC(ij)	Manuf./ Dist./ Ret. unit product cost	The cost to produce or purchase each product unit.	Dollar/unit
P(ijt)	Manuf./ Dist./ Ret. profit	Profit earned at each level of supply chain at each time period.	Dollar/week
TC(ijt)	Manuf./ Dist./ Ret. total cost	Total cost at each level of supply chain at each time period.	Dollar/week
O(ijt)	Manuf./ Dist./ Ret. orders	Manuf.: Supplies information about the products that must be manufactured to meet the future demands Dist./ Ret.: Supplies information about the products must be ordered to the upstream level to meet future demand of the SC level which placed the order.	Unit/week
D(ijt)	Demand for Manuf./ Dist./ Ret.	The demand for the level j of supply chain is calculated based on the orders from the downstream level.	Unit/week
SO(ijt) *j=3*	Ret. stockout	Unsatisfied or lost demand due to insufficient inventory in retailer level.	Unit/week

Table A-3 Cont'd. List of auxiliary and information flow variables and their definitions

CA(ij) *j=1*	Manuf. capacity	The total capacity of the manufacturer is assigned to each product type based on the demand ratio of the product.	Unit/week
UC(ij)	Manuf./ Dist./ Ret. total unit cost	Total cost for each unit of product which depends on inventory cost, transportation cost and production/purchase cost.	Dollar/unit
BD(ijt) *j=1,2*	Manuf./ Dist. backlogged orders delivered		Unit/week
BIF(ijt) *j=1,2*	Manuf./ Dist. backlogged inflow		Unit/week
R(ijt)	Revenue		Dollar/week
LDr *j=3*	Ratio of lost demand		Dmnl

Table A-4. Model constants and parameter setting

Notation	Name in Vensim	Value	Unit
$PCb(ij)$ $j=1$	Manuf. Base product cost [PHD, PMD, PLD]	5,7,9	dollar/unit
$Bcr(j)$ $j=1$	Backlogged penalty rate	0.1	dmnl
$TRc(j)$ $j=1$	Manuf. Cost per truck	230	dollar/truck
$CAr(ij)$ $j=1$	Product Type capacity ratio [PHD, PMD, PLD]	0.64, 0.3, 0.06	dmnl
$\sigma_{DD(j)}$ $j=1$	Manuf. Delivery delay - Stdev	0.28	week
$\mu_{DD(j)}$ $j=1$	Manuf. Delivery delay-Mean	0.5	week
$\alpha(j)$ $j=1$	Manuf. Forecasting adjust factor	1	week
$h(j)$ $j=1$	Manuf. Holding rate	0.1	dmnl
$\mu_{LT(j)}$ $j=1$	Manuf. Lead time-Mean	2	week
$\sigma_{LT(j)}$ $j=1$	Manuf. Lead time-Stdev	0.5	week
$PrI(ij)$ $j=1$	Manuf. Price inc[PHD, PMD, PLD]	1.7,1.8,1.9	dmnl
TCA $j=1$	Manuf. Total capacity	30,000	unit/Week
$UTC(ij)$ $j=1$	Manuf. Unit transportation cost	0.1	dollar/unit
$Bcr(j)$ $j=2$	Backlogged penalty rate	0.15	dmnl
$TRc(j)$ $j=2$	Dist. Cost per truck	300	dollar/truck
$\sigma_{DD(j)}$ $j=2$	Dist. Delivery delay - Stdev	0.14	week
$\mu_{DD(j)}$ $j=2$	Dist. Delivery delay-Mean	0.5	week
$\alpha(j)$ $j=2$	Dist. Forecasting adjust factor	1	week
$h(j)$ $j=2$	Dist. Holding rate	0.1	dmnl
$\mu_{LT(j)}$ $j=2$	Dist. Lead time-Mean	0.5	week
$\sigma_{LT(j)}$ $j=2$	Dist. Lead time-Stdev	0.28	week
$CSL(j)$ $j=2$	Dist. CSL	0.4	dmnl
$PrI(ij)$ $j=2$	Dist. Price inc[PHD, PMD, PLD]	2.15,2.25,2.35	dmnl
$UTC(ij)$ $j=2$	Dist. Unit transportation cost	0.11	dollar/unit
$Bt(j)$ $j=1,2$	Dist./MANUF Backlogged adjustment time	1	week
$MDc(ij)$ $j=3$	Mean Demand constant [PHD, PMD, PLD]	35, 10, 5	unit/Week
$\alpha(j)$ $j=3$	Ret. Forecasting adjust factor	1	week
$h(j)$ $j=3$	Ret. Holding rate	0.12	dmnl
$\mu_{LT(j)}$ $j=3$	Ret. Lead time-Mean	0.14	week
$\sigma_{LT(j)}$ $j=3$	Ret. Lead time-Stdev	0.07	week
$CSL(j)$ $j=3$	Ret. CSL	0.6	dmnl
$PrI(ij)$ $j=3$	Ret. Price inc [PHD, PMD, PLD]	1.2,1.25,1.3	dmnl
$TRca$	Truck Capacity	2500	unit/truck
V	Variety in each apparel type	5	dmnl
S	Size	5	dmnl
ATn	No of Apparel type [HD, LD]	3, 2	dmnl
$DEt(j)$	Dist./ Manuf./ Ret. Min time to delivery	1	week
$Ot(j)$	Manuf./Dist./ Ret. orders adj. time	1	week
AT	Apparel Type [HD,LD]	__	dmnl
C	Color [major, minor]	3,3	dmnl
__	Min Demand constant	0	unit/Week
__	Max demand constant [PHD, PMD, PLD]	55, 25, 8	unit/Week
__	SAVEPER	1	week
__	TIME STEP	0.03125	week
__	FINAL TIME	104	week
__	INITIAL TIME	1	week

Table A-5. Structure and behavior validation of the model under seven scenarios (PMD products)

	Scenario	1: Base scenario	2: Seasonal demand	3: 25% increase in lead-time of all levels	4: Extreme high demand	5: Extreme low demand	6: Base model with Zero capacity	7: Base model with Zero inventory in Manufacturing level
Variable name	Level							
Average weekly demand	Retailer	3,755	3,885	3,755	18,753	750	3,755	3,755
	Distributor	1,836	1,902	1,976	9,937	365	3,893	3,975
	Manufacturer	1,839	2,119	2,350	125,614	407	193,760	208,764
Stdev of weekly demand	Retailer	68	376	68	140	26	68	68
	Distributor	658	768	758	2,171	128	512	334
	Manufacturer	3,890	4,554	4,762	15,151	682	120,711	121,585
Average weekly sales	Retailer	1,836	1,887	1,968	8,442	369	133	65
	Distributor	1,826	1,889	1,976	8,591	345	100	33
	Manufacturer	1,836	2,111	2,345	8,788	339	70	0
Average weekly inventory	Retailer	1,880	2,003	2,053	8,442	401	133	65
	Retailer (Received)	398	410	492	1,861	75	22	7
	Distributor	18,451	23,554	24,368	8,591	2,488	114	47
	Distributor (Received)	859	989	1,394	4,050	152	32	0
	Manufacturer (finished products)	2,173	2,389	2,841	8,788	1,823	143	0
	Manufacturer (WIP)	3,807	4,404	5,841	19,106	664	0	0
Average weekly backlogs	Distributor	1,301	1,528	1,547	115,313	242	184,813	199,525
	Manufacturer	7,086	9,279	11,055	5,730,982	938	6,442,347	7,202,181
Average weekly stockout	Retailer	1,919	1,999	1,787	10,312	381	3,622	3,690
Average ratio of lost demand	Retailer	0.511	0.508	0.476	0.550	0.507	0.965	0.982
Average weekly cost	Retailer	73,832	76,161	79,554	338,710	14,902	5,294	2,592
	Distributor	54,374	62,827	65,785	146,462	8,967	21,560	21,234
	Manufacturer	18,762	21,585	24,837	245,876	4,463	272,546	293,105
Average weekly Profit	Retailer	17,561	17,909	18,484	81,971	3,484	21,130	21,299
	Distributor	11,078	5,119	5,474	318,217	3,405	253,896	273,038
	Manufacturer	7,012	8,056	8,085	-122,488	294	-271,560	-293,105
	Supply chain	35,652	31,084	32,043	277,700	7,183	3,466	1,233
Stdev of weekly profit	Retailer	4,269	4,225	4,132	4,172	795	1,505	753
	Distributor	27,197	33,722	34,766	64,352	4,295	164,972	168,836
	Manufacturer	15,529	16,556	17,250	17,571	3,519	170,263	170,705
	Supply chain	34,538	40,923	41,004	48,875	6,350	12,314	6,447

Table A-6. Structure and behavior validation of the model under seven scenarios (PLD products)

Variable name	Scenario / Level	1: Base scenario	2: Seasonal demand	3: 25% increase in lead-time of all levels	4: Extreme high demand	5: Extreme low demand	6: Base model with Zero capacity	7: Base model with Zero inventory in Manufacturing level
Average weekly demand	Retailer	749	775	749	3,754	151	749	749
	Distributor	369	382	397	1,989	73	782	793
	Manufacturer	373	390	495	25,505	72	39,197	41,341
Stdev of weekly demand	Retailer	29	76	29	57	13	29	29
	Distributor	127	132	154	439	25	93	71
	Manufacturer	770	754	990	3,127	139	24,180	24,304
Average weekly sales	Retailer	365	374	392	1,685	74	23	13
	Distributor	369	375	395	1,717	70	18	9
	Manufacturer	375	366	491	1,752	64	10	0
Average weekly inventory	Retailer	373	381	412	1,685	79	23	13
	Retailer (Received)	80	82	98	372	15	4	2
	Distributor	3,659	3,318	4,826	1,717	618	22	13
	Distributor (Received)	176	172	291	808	29	5	0
	Manufacturer (finished products)	493	492	576	1,752	307	20	0
	Manufacturer (WIP)	786	783	1,235	3,821	125	0	0
Average weekly backlogs	Distributor	263	256	325	23,439	44	37,395	39,498
	Manufacturer	1,407	1,369	2,380	1,165,702	178	1,310,808	1,419,418
Average weekly stockout	Retailer	384	401	357	2,070	77	726	736
Average ratio of lost demand	Retailer	0.512	0.513	0.476	0.551	0.507	0.970	0.982
Average weekly cost	Retailer	20,729	21,227	22,383	95,374	4,233	1,301	758
	Distributor	14,753	14,246	17,770	39,646	2,669	6,056	6,004
	Manufacturer	4,982	4,936	6,712	66,073	1,053	74,568	78,549
Average weekly Profit	Retailer	5,949	6,139	6,301	27,759	1,202	6,015	6,024
	Distributor	3,909	4,728	2,333	90,274	882	69,298	72,974
	Manufacturer	2,135	2,024	2,626	-32,792	155	-74,373	-78,549
	Supply chain	11,993	12,890	11,261	85,241	2,239	939	450
Stdev of weekly profit	Retailer	1,390	1,403	1,389	895	281	359	337
	Distributor	7,421	7,028	9,468	18,408	1,406	44,732	45,519
	Manufacturer	4,647	4,611	5,200	4,474	1,050	46,111	46,178
	Supply chain	10,173	9,645	11,693	15,550	2,076	3,407	2,185

Vensim Equations

Retailer Level

Demand for RET[Product type]=random poisson(Min demand[Product type],Max demand[Product type], Mean demand[Product type],0,1,2)

Flow of products to retailer[Product type]= DELAY FIXED(DIST Delivered products[Product type], DIST Delivery delay, 0)

Max demand[PHD]=Max demand constant[PHD]*No of Apparel type[HD]*Variety in each apparel type*Size*Color[Major]

Max demand[PMD]=Max demand constant[PMD]*(No of Apparel type[HD]*Variety in each apparel type*Size*Color[Minor]+ No of Apparel type[LD]*Variety in each apparel type*Size*Color[Major])

Max demand[PLD]=Max demand constant[PLD]*No of Apparel type[LD]*Variety in each apparel type*Size*Color[Minor]

Mean demand[PHD]=Mean Demand constant[PHD]*No of Apparel type[HD]*Variety in each apparel type*Size*Color[Major]

Mean demand[PMD]=Mean Demand constant[PMD]*(No of Apparel type[HD]*Variety in each apparel type*Size*Color[Minor]+ No of Apparel type[LD]*Variety in each apparel type*Size*Color[Major])

Mean demand[PLD]=Mean Demand constant[PLD]*No of Apparel type[LD]*Variety in each apparel type*Size*Color[Minor]

Min demand[PHD]=Min Demand constant[PHD]*No of Apparel type[HD]*Variety in each apparel type*Size*Color[Major]

Min demand[PMD]=Min Demand constant[PMD]*(No of Apparel type[HD]*Variety in each apparel type*Size*Color[Minor]+ No of Apparel type[LD]*Variety in each apparel type *Size*Color[Major])

Min demand[PLD]=Min Demand constant[PLD]*No of Apparel type[LD]*Variety in each apparel type*Size*Color[Minor]

Ratio of lost demand[Product type]=XIDZ(RET Stockout[Product type],Demand for RET [Product type], 0)

RET Average profit[Product type]=XIDZ(RET Cumulative Profit[Product type],Time,0)

RET Cumulative Profit[Product type]= INTEG (RET Profit[Product type],RET Profit[Product type])

RET Cumulative total cost[Product type]= INTEG (RET Total cost[Product type], RET Total cost [Product type])

RET Delivered products[Product type]= MIN(Demand for RET[Product type], RET Inventory [Product type]/RET Min time to delivery)

RET Demand SS inflow[Product type]= SIMULTANEOUS ((RET Expected demand[Product type]-RET Expected demand-Avg[Product type])^2,100)

RET Expected demand[Product type]=SMOOTH (Demand for RET[Product type], RET Forecasting adjust factor)

RET Expected demand (cumulative)[Product type]= INTEG (RET Sum demand inflow[Product type], RET Sum demand inflow[Product type])

RET Expected demand-Avg[Product type]= SIMULTANEOUS (XIDZ(RET Expected demand (cumulative)[Product type],Time,0),0.8)

RET Expected demand-SS[Product type]= INTEG (RET Demand SS inflow[Product type], RET Demand SS inflow[Product type])

RET Expected demand-Var[Product type]= XIDZ(RET Expected demand-SS[Product type], Time,0)

Ret forecast error calc[Product type]= ABS(Demand for RET[Product type]-RET Expected demand [Product type])

RET Inventory[PHD]= INTEG (Ret Products ready to sell[PHD]-RET Delivered products [PHD], 4000)

RET Inventory[PMD]= INTEG (-RET Delivered products[PMD]+Ret Products ready to sell [PMD], 2500)

RET Inventory[PLD]= INTEG (-RET Delivered products[PLD]+Ret Products ready to sell [PLD] ,400)

RET Inventory position[Product type]= RET Inventory[Product type]+RET Received products [Product type]

RET Lead time= random normal(0.0001,52 ,RET Lead time-Mean ,RET Lead time-Stdev, 3)

RET Orders[Product type]=(Max(RET Reorder point[Product type]-RET Inventory position[Product type],0))/RET Orders adj. time

RET Price[Product type]=RET Total unit cost[Product type]*RET Price inc[Product type]

Ret Products ready to sell[Product type]= DELAY FIXED (Flow of products to retailer[Product type] , RET Lead time , 0)

RET Profit[Product type]=RET Revenue[Product type]-RET Total cost[Product type]

RET Profit SS[Product type]= INTEG ((RET Profit[Product type]-RET Average profit[Product type])^2,(RET Profit[Product type]-RET Average profit[Product type])^2)

RET Profit Var[Product type]=XIDZ(RET Profit SS[Product type],Time,0)

RET Received products[Product type]= INTEG (Flow of products to retailer[Product type]-Ret Products ready to sell[Product type],0)

RET Reorder point[Product type]= (DIST Delivery delay-Mean+DIST Lead time-Mean)*RET Expected demand[Product type]+RET Safety stock[Product type]

RET Revenue[Product type]= (RET Delivered products[Product type]*RET Price[Product type])+DIST Backlogged cost[Product type]

RET Safety stock[Product type]=RET Norminv CSL[Product type]*SQRT(((DIST Lead time-Mean+DIST Delivery delay-Mean)*RET Expected demand-Var[Product type]) +((RET Expected demand-Avg[Product type])^2*(DIST Lead time-Stdev^2+DIST Delivery delay - Stdev^2)))

RET Stockout[Product type]=IF THEN ELSE(Demand for RET[Product type]>RET Delivered products[Product type], Demand for RET[Product type]-RET Delivered products[Product type] , 0)

RET Sum demand inflow[Product type]=RET Expected demand[Product type]

RET Total unit cost[Product type]= RET Unit Inventory cost[Product type]+RET Unit Product cost[Product type]

RET Total cost[Product type]= ((RET Inventory[Product type]+RET Received products[Product type])*RET Unit Inventory cost[Product type])+(RET Unit Product cost[Product type]*RET Delivered products[Product type])

RET Unit Inventory cost[Product type]=Ret Holding rate*RET Unit Product cost[Product type]

RET Unit Product cost[Product type]= DIST Price[Product type]

seasonal factor= PULSE TRAIN(24,3,26,FINAL TIME)

Seasonal RET demand [Product type]= IF THEN ELSE(seasonal factor=0, Demand for RET [Product type], Demand for RET [Product type]*Seasonal demand increase)

Distributor Level

Demand for DIST[Product type]=RET Orders[Product type]

DIST Backlogged cost[Product type]=DIST Backlogged penalty rate*RET Unit Product cost[Product type]*DIST Backlogged inflow[Product type]

DIST Backlogged inflow[Product type]=IF THEN ELSE(DIST Delivered products [Product type] <Demand for DIST[Product type], Demand for DIST[Product type]-DIST Delivered products[Product type], 0)

DIST Backlogged orders[Product type]= INTEG (DIST Backlogged inflow[Product type]-DIST Backlogged orders delivered[Product type],0)

DIST Backlogged orders delivered[Product type]=IF THEN ELSE(DIST Delivered products [Product type]=DIST Firm orders[Product type] , DIST Backlogged orders[Product type] / DIST Backlogged adjustment time, IF THEN ELSE(DIST Delivered products[Product type]>Demand for DIST[Product type], DIST Delivered products[Product type]-Demand for DIST[Product type], 0))

DIST Cumulative profit[Product type]= INTEG (DIST Profit[Product type], DIST Profit [Product type])

DIST Cumulative total cost[Product type]= INTEG (DIST Total cost[Product type], DIST Total cost[Product type])

DIST Delivered products[Product type]=MIN(DIST Firm orders[Product type], DIST Inventory[Product type]/DIST Min time to delivery)

DIST Delivery delay=random normal(0.0001,52 ,DIST Delivery delay-Mean , DIST Delivery delay - Stdev,4)

DIST Demand SS inflow[Product type]=(DIST Expected demand[Product type]-DIST Expected demand-Avg[Product type])^2

DIST Expected demand[Product type]=SMOOTH(Demand for DIST[Product type], DIST Forecasting adjust factor)

DIST Expected demand (cumulative)[Product type]= INTEG (DIST Sum demand inflow[Product type], DIST Sum demand inflow[Product type])

DIST Expected demand-Avg[Product type]= XIDZ(DIST Expected demand (cumulative)[Product type],Time,0)

DIST Expected demand-SS[Product type]= INTEG (DIST Demand SS inflow[Product type], DIST Demand SS inflow[Product type])

DIST Expected demand-Var[Product type]= XIDZ(DIST Expected demand-SS[Product type],Time,0)

DIST Firm orders[Product type]= DIST Backlogged orders[Product type]/DIST Backlogged adjustment time + Demand for DIST[Product type]

DIST forecast error calc[Product type]=ABS(Demand for DIST[Product type]-DIST Expected demand[Product type])

DIST Inventory[PHD]= INTEG ((DIST Products ready to ship[PHD]-DIST Delivered products [PHD]),7000)

DIST Inventory[PMD]= INTEG (-DIST Delivered products[PMD]+DIST Products ready to ship [PMD] ,3000)

DIST Inventory[PLD]= INTEG (-DIST Delivered products[PLD]+DIST Products ready to ship [PLD],800)

DIST Inventory position[Product type]= DIST Inventory[Product type]+DIST Received products [Product type]-DIST Backlogged orders[Product type]

DIST Lead time= random normal(0.0001,52 ,DIST Lead time-Mean ,DIST Lead time-Stdev, 5)

DIST Lead time effect on cost=IF THEN ELSE(DIST Lead time-Mean<=0.28, 1.1, 1)

DIST No. of Trucks calc.=sum(DIST Delivered products[Product type!])/Truck Capacity

DIST Orders[Product type]= (Max(DIST Reorder point[Product type]-DIST Inventory position [Product type],0))/DIST Orders adj. time

DIST Price[Product type]=DIST Total unit cost[Product type]*DIST Price inc[Product type]

DIST Products ready to ship[Product type]= DELAY FIXED (Flow of products to distributor [Product type],DIST Lead time, 0)

DIST Profit[Product type]=DIST Revenue[Product type]-DIST Total cost[Product type]

DIST Received products[Product type]= INTEG (Flow of products to distributor[Product type]-DIST Products ready to ship[Product type],0)

DIST Reorder point[Product type]= (MANUF Delivery delay-Mean+MANUF Lead time-Mean)*DIST Expected demand[Product type]+DIST Safety stock[Product type]

DIST Revenue[Product type]= (DIST Delivered products[Product type]*DIST Price[Product type])+MANUF Backlogged cost [Product type]

DIST Safety stock[Product type]=DIST Norminv CSL[Product type]*SQRT(((MANUF Lead time-Mean +MANUF Delivery delay-Mean)*DIST Expected demand-Var[Product type])+((DIST Expected demand-Avg[Product type])^2*(MANUF Lead time-Stdev^2+MANUF Delivery delay - Stdev^2)))

DIST Sum demand inflow[Product type]=DIST Expected demand[Product type]

DIST Total cost[Product type]=DIST Transportation cost[Product type]+DIST Backlogged cost [Product type]+((DIST Inventory[Product type]+DIST Received products[Product type])*DIST Unit Inventory cost [Product type])+(DIST Unit Product cost [Product type]*DIST Delivered products[Product type])

DIST Total unit cost[Product type]=DIST Unit Inventory cost[Product type]+DIST Unit Product cost [Product type]+DIST Unit transportation cost

DIST Unit Inventory cost[Product type]=Dist Holding rate*DIST Unit Product cost[Product type]

DIST Unit Product cost[Product type]=MANUF Price[Product type]*DIST Lead time effect on cost

DIST No. of Trucks=IF THEN ELSE(INTEGER(DIST No. of Trucks calc.)>=1, IF THEN ELSE((DIST No. of Trucks calc.-INTEGER(DIST No. of Trucks calc.))>0.5,((INTEGER(DIST No. of Trucks calc.))+1), (INTEGER(DIST No. of Trucks calc.))), IF THEN ELSE(DIST No. of Trucks calc.<0.001, 0, 1))

DIST Transportation cost[Product type]=XIDZ(DIST Delivered products[Product type], sum (DIST Delivered products[Product type!]), 0)*DISTNo. of Trucks*DIST Cost per truck

Flow of products to distributor[Product type]= DELAY FIXED(MANUF Delivered products [Product type], MANUF Delivery delay, 0)

Manufacturer Level

Demand for MANUF[Product type]=DIST Orders[Product type]

Feasible production rate[Product type]=MIN(MANUF Capacity[Product type], MANUF Orders [Product type])

MANUF Backlogged cost[Product type]=MANUF Backlogged penalty rate*DIST Unit Product cost[Product type]*MANUF Backlogged inflow[Product type]

MANUF Backlogged inflow[Product type]= IF THEN ELSE(MANUF Delivered products [Product type]<Demand for MANUF[Product type], Demand for MANUF[Product type]-MANUF Delivered products[Product type], 0)

MANUF Backlogged orders[Product type]= INTEG (MANUF Backlogged inflow[Product type]-MANUF Backlogged orders delivered[Product type],0)

MANUF Backlogged orders delivered[Product type]= IF THEN ELSE(MANUF Delivered products [Product type]=MANUF Firm orders[Product type] , MANUF Backlogged orders [Product type]/MANUF Backlogged adjustment time, IF THEN ELSE(MANUF Delivered products[Product type]>Demand for MANUF[Product type], MANUF Delivered products[Product type]-Demand for MANUF[Product type], 0))

MANUF Capacity[Product type]= MANUF Total capacity*Product Type capacity ratio[Product type]

MANUF Cumulative profit[Product type]= INTEG (MANUF Profit[Product type], MANUF Profit [Product type])

MANUF Cumulative total cost[Product type]= INTEG (MANUF Total cost[Product type], MANUF Total cost[Product type])

MANUF Delivered products[Product type]=MIN(MANUF Firm orders[Product type], MANUF Inventory[Product type]/MANUF Min time to delivery)

MANUF Delivery delay=random normal(0.0001,52,MANUF Delivery delay-Mean , MANUF Delivery delay - Stdev,6)

MANUF Expected demand[Product type]= SMOOTH(Demand for MANUF[Product type], MANUF Forecasting adjust factor)

MANUF Firm orders[Product type]=Demand for MANUF[Product type]+MANUF Backlogged orders [Product type]/MANUF Backlogged adjustment time

MANUF forecast error calc[Product type]=ABS(Demand for MANUF[Product type]-MANUF Expected demand[Product type])

MANUF In process products[Product type]= INTEG (Feasible production rate[Product type]-Manufactured products[Product type],0)

MANUF Inventory [PHD]= INTEG (Manufactured products[PHD]-MANUF Delivered products [PHD],10000)

MANUF Inventory[PMD]= INTEG (Manufactured products[PMD]-MANUF Delivered products [PMD],7000)

MANUF Inventory[PLD]= INTEG (Manufactured products[PLD]-MANUF Delivered products [PLD],1000)

MANUF Inventory position[Product type]=MANUF Inventory[Product type]+MANUF In process products[Product type]-MANUF Backlogged orders[Product type]

MANUF Lead time= random normal(0.0001,52 ,MANUF Lead time-Mean ,MANUF Lead time-Stdev,7)

MANUF Lead time effect on cost= IF THEN ELSE(MANUF Lead time-Mean<=1.5, 1.1, IF THEN ELSE(MANUF Lead time-Mean>1.5:AND:MANUF Lead time-Mean<=2.5, 1, 0.9))

MANUF No. of Trucks calc.= sum(MANUF Delivered products[Product type!])/Truck Capacity

MANUF No. of Trucks= IF THEN ELSE(INTEGER(MANUF No. of Trucks calc.)>=1, IF THEN ELSE((MANUF No. of Trucks calc.-INTEGER(MANUF No. of Trucks calc.))> 0.5,((INTEGER(MANUF No. of Trucks calc.))+1), (INTEGER(MANUF No. of Trucks calc.))), IF THEN ELSE(MANUF No. of Trucks calc.<0.001, 0, 1))

MANUF Orders[Product type]=Max(MANUF Expected demand[Product type]-MANUF Inventory position[Product type],0)/MANUF Orders adj. time

MANUF Price[Product type]=MANUF Total unit cost[Product type]*MANUF Price inc[Product type]

MANUF Profit[Product type]= MANUF Revenue[Product type]-MANUF Total cost[Product type]

MANUF Revenue[Product type]=MANUF Delivered products[Product type]*MANUF Price [Product type]

MANUF Total cost[Product type]= MANUF Transportation cost[Product type]+((MANUF Inventory [Product type]+MANUF In process products [Product type])*MANUF Unit Inventory cost[Product type])+(MANUF Unit product cost[Product type]*MANUF Delivered products[Product type])+MANUF Backlogged cost[Product type]

MANUF Total unit cost[Product type]=MANUF Unit Inventory cost[Product type]+MANUF Unit product cost[Product type]+MANUF Unit transportation cost

MANUF Transportation cost [Product type]=XIDZ(MANUF Delivered products[Product type], sum(MANUF Delivered products [Product type!]), 0)*MANUF No. of Trucks*MANUF Cost per truck

MANUF Unit Inventory cost[Product type]=Manuf Holding rate*MANUF Unit product cost [Product type]

MANUF Unit product cost[Product type]= MANUF Base product cost[Product type]*MANUF Lead time effect on cost

Manufactured products[Product type]=DELAY FIXED (Feasible production rate[Product type], MANUF Lead time, 0)

Supply Chain

Supply chain profit[Product type]= DIST Profit[Product type]+MANUF Profit[Product type] + RET Profit[Product type]

Cumulative supply chain profit[Product type]= INTEG (Supply chain profit[Product type], Supply chain profit[Product type])

Table A-7. The effect of lead time and delivery delay on inventory

	Level	Manufacturer						Distributor						Retailer					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	13,506	13,506	13,506	13,506	13,506	13,506	40,713	40,713	40,713	40,713	40,713	40,713	4,756	4,756	4,756	4,756	4,756	4,756
	1	15,110	14,318	13,506	16,051	13,612	14,203	45,191	44,380	40,713	49,041	41,309	43,442	4,754	5,018	4,756	5,021	4,756	5,007
	2	17,230	15,129	13,376	19,245	13,879	14,880	49,153	48,770	40,795	54,513	42,631	46,902	4,761	5,295	4,813	5,379	4,754	5,273
	3	21,454	16,870	13,240	17,217	14,279	16,364	49,800	56,544	40,891	70,289	44,479	54,127	4,773	5,909	4,872	5,889	4,746	5,860
	4	16,017	18,316	12,331	20,185	14,729	17,634	47,210	60,903	41,691	57,067	46,560	58,677	4,761	6,431	5,225	6,937	4,753	6,357
	5	14,288	12,290	13,641	13,360	13,172	12,482	31,356	34,334	40,647	28,536	38,624	35,491	4,828	4,278	4,703	4,247	4,767	4,285
	6	13,678	12,006	_	12,779	13,481	12,067	32,696	23,623	_	22,275	34,170	25,883	4,621	3,446	_	3,250	4,691	3,476
PMD	1	6,701	6,387	5,980	7,169	6,025	6,318	21,533	20,819	19,310	22,911	19,657	20,393	2,275	2,398	2,278	2,393	2,277	2,395
	2	7,650	6,813	5,913	8,682	6,145	6,675	23,406	22,253	19,422	25,762	20,425	21,438	2,274	2,522	2,306	2,545	2,277	2,511
	3	9,656	7,710	5,848	10,315	6,326	7,464	24,550	25,351	19,540	28,284	21,367	23,799	2,269	2,782	2,330	2,810	2,272	2,759
	4	7,095	8,441	5,424	9,351	6,541	8,090	22,433	28,330	20,606	28,112	22,276	26,555	2,275	3,027	2,504	3,257	2,272	2,990
	5	6,454	5,540	6,049	5,957	5,900	5,454	15,680	16,374	19,197	14,419	18,111	17,024	2,314	2,033	2,253	2,040	2,278	2,054
	6	6,573	5,638	_	5,928	6,481	5,283	15,823	11,413	_	10,818	16,005	13,039	2,276	1,659	_	1,556	2,216	1,650
PLD	1	1,434	1,353	1,279	1,517	1,286	1,335	4,283	4,170	3,835	4,612	3,888	4,068	453	477	453	477	453	477
	2	1,633	1,434	1,266	1,812	1,308	1,398	4,637	4,575	3,839	5,118	4,016	4,343	454	503	458	510	452	500
	3	2,018	1,590	1,254	1,723	1,345	1,536	4,678	5,269	3,845	6,256	4,209	4,982	454	560	463	548	452	554
	4	1,517	1,730	1,174	1,932	1,385	1,650	4,460	5,735	3,912	5,445	4,377	5,448	453	610	497	655	452	601
	5	1,346	1,181	1,292	1,280	1,256	1,213	2,931	3,243	3,835	2,637	3,654	3,362	460	407	448	405	453	408
	6	1,259	1,204	_	1,235	1,243	1,145	3,100	2,459	_	2,066	3,308	2,502	439	330	_	310	452	332

Table A-8. The effect of lead time and delivery delay on backlog and Stock-out

	Level	Manufacturer Backlog						Distributor Backlog						Retailer Stockout					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	14,701	14,701	14,701	14,701	14,701	14,701	2,782	2,782	2,782	2,782	2,782	2,782	4,031	4,031	4,031	4,031	4,031	4,031
	1	16,846	16,319	14,701	18,992	14,817	16,026	2,770	3,065	2,782	3,087	2,748	2,961	4,030	3,859	4,031	3,860	4,036	3,863
	2	20,027	18,561	14,601	25,413	15,146	17,820	2,840	3,410	2,761	3,514	2,754	3,171	4,033	3,697	4,081	3,749	4,039	3,698
	3	26,835	24,050	14,509	25,777	15,659	22,454	2,966	4,113	2,739	2,732	2,735	3,675	4,030	3,375	4,136	3,481	4,032	3,374
	4	18,188	28,765	13,944	31,282	16,449	26,580	2,810	4,653	2,608	4,436	2,769	4,067	4,035	3,129	4,426	3,576	4,033	3,128
	5	15,518	12,124	14,812	12,300	14,255	12,336	3,901	2,318	2,806	3,226	2,811	2,455	4,021	4,374	3,982	4,327	4,038	4,371
	6	15,173	8,812	_	9,471	14,399	8,690	3,750	1,666	_	2,227	3,175	1,892	4,149	5,037	_	4,812	4,098	5,017
PMD	1	8,063	7,783	7,086	8,828	7,155	7,659	1,290	1,426	1,301	1,414	1,286	1,378	1,920	1,843	1,919	1,842	1,922	1,840
	2	9,314	8,498	7,041	11,055	7,348	8,246	1,293	1,557	1,291	1,547	1,294	1,453	1,922	1,758	1,943	1,787	1,921	1,761
	3	11,851	10,294	6,996	15,868	7,597	9,627	1,288	1,828	1,279	1,912	1,288	1,624	1,920	1,609	1,965	1,688	1,919	1,600
	4	8,585	12,647	6,739	13,332	7,884	11,498	1,295	2,104	1,214	1,928	1,296	1,812	1,920	1,484	2,106	1,702	1,920	1,490
	5	7,567	6,062	7,137	6,024	6,912	6,002	1,845	1,139	1,312	1,533	1,324	1,153	1,915	2,094	1,897	2,057	1,920	2,079
	6	7,990	4,072	_	4,488	7,489	4,451	1,844	779	_	1,046	1,670	949	1,945	2,390	_	2,289	1,971	2,397
PLD	1	1,632	1,562	1,407	1,820	1,419	1,527	263	289	263	290	259	278	384	367	384	368	384	368
	2	1,942	1,768	1,397	2,380	1,454	1,674	269	321	260	325	259	295	384	351	389	357	384	351
	3	2,556	2,243	1,389	2,515	1,511	2,062	275	382	259	283	258	338	384	321	393	338	383	321
	4	1,760	2,711	1,340	2,869	1,572	2,433	266	436	246	402	259	373	384	299	420	340	384	297
	5	1,497	1,157	1,420	1,200	1,367	1,182	373	220	265	311	266	234	385	416	379	411	384	416
	6	1,396	839	_	917	1,318	835	342	160	_	216	280	181	395	478	_	458	385	477

Table A-9. The effect of lead time and delivery delay on cost

	Level	Manufacturer						Distributor						Retailer					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	29,073	29,073	29,073	29,073	29,073	29,073	77,846	77,846	77,846	77,846	77,846	77,846	100,387	100,387	100,387	100,387	100,387	100,387
	1	31,440	31,030	29,073	33,771	29,242	30,724	82,178	83,462	77,846	88,002	78,719	82,640	100,399	105,002	100,387	104,993	100,255	104,887
	2	34,595	33,425	28,874	39,805	29,769	32,672	85,996	89,534	77,540	94,674	79,848	87,786	100,352	109,459	99,405	108,489	100,183	109,358
	3	36,586	38,471	28,610	30,690	30,544	37,208	78,244	100,570	77,340	100,690	81,537	97,775	90,678	118,460	98,303	104,720	100,325	118,333
	4	32,781	42,517	27,058	42,691	31,610	40,829	84,445	107,403	75,055	99,465	83,837	104,994	100,292	125,466	92,667	116,684	100,326	125,285
	5	33,590	25,733	29,285	29,726	28,379	26,042	70,054	68,283	78,564	63,689	76,228	69,500	100,802	91,258	101,350	92,255	100,239	91,354
	6	30,565	22,017	_	25,378	28,559	21,949	70,737	55,997	_	57,362	71,425	53,297	97,325	81,240	_	86,273	98,668	74,457
PMD	1	20,221	20,047	18,762	21,550	18,904	19,856	57,666	57,931	54,374	60,774	54,905	57,302	73,767	76,992	73,832	76,988	73,701	77,087
	2	22,048	21,310	18,577	24,837	19,267	20,908	60,200	61,306	54,336	65,785	56,027	59,994	73,697	80,474	73,094	79,554	73,751	80,341
	3	23,097	24,096	18,437	24,777	19,806	23,276	55,792	68,038	54,075	64,797	57,312	65,806	66,504	86,772	72,440	75,884	73,797	86,986
	4	21,004	26,965	17,401	27,683	20,406	25,750	58,943	74,313	53,654	70,827	58,581	71,596	73,757	92,178	68,224	85,539	73,773	91,814
	5	22,172	16,950	18,934	19,472	18,416	16,838	50,097	47,646	54,748	46,040	52,800	48,705	74,108	66,681	74,487	67,997	73,786	67,261
	6	21,390	14,611	_	16,740	19,792	14,347	50,500	39,683	_	40,610	49,682	38,340	72,905	60,169	_	63,570	71,738	54,470
PLD	1	5,411	5,307	4,982	5,775	5,010	5,235	15628	15,718	14,753	16,536	14,868	15,529	20,749	21,689	20,729	21,687	20,722	21,654
	2	5,948	5,690	4,938	6,712	5,091	5,530	16284	16,817	14,665	17,770	15,063	16,335	20,753	22,678	20,521	22,383	20,728	22,627
	3	6,234	6,488	4,902	5,430	5,226	6,214	14744	18,809	14,570	18,236	15,397	18,279	18,711	24,448	20,330	21,244	20,769	24,441
	4	5,639	7,199	4,667	7,424	5,376	6,823	15935	20,255	14,119	18,856	15,751	19,706	20,726	25,858	19,235	24,089	20,747	25,904
	5	5,696	4,451	5,031	5,192	4,897	4,542	13184	12,907	14,821	11,988	14,376	13,176	20,737	18,853	20,961	19,086	20,741	18,864
	6	5,135	3,909	_	4,454	4,813	3,776	13351	11,115	_	10,827	13,678	10,222	20,107	16,888	_	17,848	20,696	15,421

Table A-10. The effect of lead time and delivery delay on profit

	Level	Manufacturer						Distributor						Retailer					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	8,399	8,399	8,399	8,399	8,399	8,399	12,074	12,074	12,074	12,074	12,074	12,074	19,058	19,058	19,058	19,058	19,058	19,058
	1	8,562	9,034	8,399	9,318	8,463	8,876	8,140	11,135	12,074	7,006	11,975	12,168	19,061	19,817	19,058	19,838	18,978	19,802
	2	8,728	9,852	8,355	10,432	8,608	9,625	4,676	9,209	11,500	3,792	10,629	11,296	19,051	20,588	18,491	20,000	18,949	20,476
	3	8,031	11,641	8,307	6,943	8,813	11,308	4,206	6,383	11,012	-6,834	8,779	8,365	17,255	21,834	17,883	18,244	19,046	21,746
	4	8,612	13,051	7,986	11,062	9,172	12,611	6,742	5,542	6,147	3,905	7,287	7,736	19,032	22,655	14,567	17,627	19,029	22,575
	5	10,985	7,157	8,428	9,281	8,178	7,262	20,877	13,788	13,151	19,248	14,477	12,641	19,757	17,367	19,613	18,462	18,988	17,460
	6	8,544	4,373	_	6,532	7,103	4,855	19,017	15,905	_	20,693	16,859	12,533	19,311	15,625	_	18,339	19,405	14,264
PMD	1	7,172	7,527	7,012	7,580	7,102	7,449	8,366	10,826	11,078	7,932	10,724	11,508	17,541	18,214	17,561	18,240	17,483	18,222
	2	7,337	7,913	6,945	8,085	7,229	7,772	5,786	10,736	10,640	5,474	9,768	11,768	17,510	18,972	17,094	18,484	17,495	18,914
	3	6,665	8,846	6,934	6,033	7,408	8,557	4,113	9,522	9,844	5,193	8,409	11,965	15,866	20,236	16,678	17,214	17,550	20,279
	4	7,245	10,017	6,623	9,333	7,616	9,600	7,170	8,187	5,518	4,270	7,181	10,788	17,549	21,187	13,935	17,008	17,541	21,019
	5	9,181	5,766	7,027	7,812	6,611	6,050	16,143	11,175	12,032	14,983	12,692	10,736	18,061	16,223	17,981	16,925	17,666	16,172
	6	7,994	4,186	_	5,564	6,273	4,185	16,372	13,473	_	16,468	14,509	9,277	17,800	14,356	_	16,704	17,756	13,356
PLD	1	2,215	2,282	2,135	2,368	2,142	2,249	3132	3,721	3,909	2,885	3,835	3,950	5,963	6,210	5,949	6,220	5,947	6,191
	2	2,288	2,451	2,122	2,626	2,180	2,389	2474	3,407	3,748	2,333	3,534	3,856	5,968	6,480	5,808	6,301	5,949	6,449
	3	2,166	2,840	2,101	1,653	2,226	2,721	2224	3,024	3,574	603	3,127	3,698	5,393	6,889	5,676	5,902	5,975	6,879
	4	2,248	3,179	2,022	3,008	2,293	3,024	2752	2,955	2,558	2,280	2,878	3,624	5,962	7,164	4,869	5,929	5,962	7,187
	5	2,629	1,836	2,151	2,353	2,096	1,856	5490	3,981	4,010	5,190	4,180	3,790	6,063	5,434	6,108	5,699	5,958	5,452
	6	2,108	1,258	_	1,714	1,943	1,346	4951	3,898	_	5,372	4,642	3,448	5,959	4,853	_	5,578	6,010	4,456

Table A-11. The effect of lead time and delivery delay on 95% CVaR

	Level	Manufacturer						Distributor						Retailer					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	19,247	19,247	19,247	19,247	19,247	19,247	55,478	55,478	55,478	55,478	55,478	55,478	-14,150	-14,150	-14,150	-14,150	-14,150	-14,150
	1	20,917	20,498	19,247	22,915	18,916	20,255	64,184	59,930	55,478	70,479	56,003	60,203	-13,893	-14,207	-14,150	-14,163	-13,755	-14,737
	2	23,670	22,566	18,703	28,413	18,771	21,723	76,386	65,516	55,815	88,652	58,543	63,836	-13,949	-14,973	-13,488	-13,648	-13,632	-14,669
	3	28,441	25,492	18,676	34,014	18,827	24,471	74,920	74,540	56,916	109,697	62,526	72,962	-11,820	-14,198	-12,430	-13,113	-14,083	-13,596
	4	22,567	27,711	17,891	30,965	18,896	26,434	69,833	84,395	64,007	99,379	67,394	77,484	-13,855	-11,522	-7,319	-5,763	-13,837	-10,697
	5	15,563	16,087	19,507	13,532	19,437	16,640	39,947	45,061	53,784	27,181	50,654	46,337	-12,837	-13,010	-14,950	-12,235	-13,950	-13,452
	6	17,381	12,377	_	11,400	21,610	12,169	41,607	31,146	_	17,648	42,803	30,183	-12,265	-11,649	_	-13,377	-13,493	-10,822
PMD	1	13,985	13,189	12,648	14,797	12,450	12,462	43,043	39,529	37,648	45,896	37,736	39,691	-12,447	-12,935	-12,388	-12,695	-12,569	-12,650
	2	15,828	13,774	12,480	17,618	12,215	13,340	50,560	43,800	38,144	58,136	39,562	40,304	-12,204	-13,361	-12,048	-12,788	-12,461	-13,189
	3	17,363	15,794	12,456	23,402	12,141	14,646	58,383	49,458	38,673	67,024	42,599	43,901	-10,890	-14,472	-11,435	-11,366	-12,476	-13,933
	4	14,895	17,717	11,868	18,759	12,140	16,840	46,199	53,279	43,897	70,559	45,701	48,666	-12,381	-14,066	-8,046	-9,357	-12,361	-14,075
	5	10,095	12,160	12,795	8,921	12,770	11,483	27,576	31,406	36,541	19,956	33,447	32,513	-11,741	-11,251	-13,088	-11,270	-12,398	-11,487
	6	11,185	7,741	_	7,999	14,604	10,145	28,149	19,501	_	13,678	28,908	25,662	-11,467	-10,898	_	-12,407	-11,212	-9,847
PLD	1	3,332	3,105	2,948	3,527	2,838	3,118	10612	9,379	8,553	11,576	8,682	9,147	-4,208	-4,353	-4,196	-4,255	-4,274	-4,250
	2	3,868	3,509	2,882	4,401	2,761	3,314	12838	11,044	8,725	14,714	9,261	10,087	-4,122	-4,382	-4,096	-4,123	-4,244	-4,291
	3	4,631	4,006	2,811	6,030	2,817	3,888	12995	12,680	8,879	18,518	10,370	11,710	-3,603	-4,685	-3,822	-4,183	-4,169	-4,449
	4	3,645	4,478	2,801	4,887	2,859	4,164	11553	13,631	10,642	17,235	11,220	12,599	-4,200	-4,817	-2,990	-3,270	-4,201	-4,603
	5	2,532	2,597	2,955	2,139	3,042	2,669	5983	6,702	8,423	3,684	7,765	6,901	-3,833	-3,761	-4,354	-3,673	-4,189	-4,006
	6	2,780	1,664	_	1,822	3,426	1,981	6068	3,557	_	1,581	6,664	4,559	-3,847	-3,495	_	-4,078	-4,020	-3,535

Table A-12. The effect of lead time and delivery delay on 99% CVaR

	Level	Manufacturer						Distributor						Retailer					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	35,296	35,296	35,296	35,296	35,296	35,296	97,235	97,235	97,235	97,235	97,235	97,235	-16,708	-16,708	-16,708	-16,708	-16,708	-16,708
	1	39,615	39,692	35,296	44,422	35,487	40,077	113,043	105,661	97,235	123,584	98,195	104,493	-16,671	-13,946	-16,708	-15,819	-16,715	-20,376
	2	45,800	44,352	35,175	55,275	36,388	43,558	133,970	114,931	98,493	155,406	103,150	110,836	-15,466	-18,037	-14,952	-17,970	-15,308	-17,618
	3	52,037	49,335	35,130	68,744	37,962	50,332	131,119	129,836	99,177	188,893	109,957	130,676	-12,861	-19,084	-14,304	-13,774	-16,402	-16,561
	4	41,912	53,133	33,778	60,843	39,290	53,019	122,922	145,282	113,844	176,314	118,494	140,469	-18,645	-8,252	-6,148	-5,059	-16,793	-15,867
	5	27,598	29,853	35,814	24,833	35,053	30,864	81,916	81,911	95,382	48,856	90,610	82,797	-16,640	-18,393	-21,274	-14,881	-19,906	-19,032
	6	30,221	21,961	_	21,041	39,762	24,180	78,822	57,458	_	36,429	79,358	53,862	-13,947	-16,533	_	-18,700	-15,651	-14,230
PMD	1	26,447	25,154	23,650	27,214	23,451	24,446	75,845	69,784	65,217	81,418	66,223	68,621	-16,897	-15,923	-16,352	-16,384	-14,253	-15,709
	2	30,366	25,798	22,638	32,969	22,942	24,583	89,860	76,535	66,619	102,041	70,272	72,024	-13,118	-17,768	-17,725	-17,988	-14,566	-16,429
	3	33,194	30,305	23,387	42,450	22,167	29,791	101,416	88,067	67,988	115,951	75,533	80,970	-14,610	-20,765	-13,556	-15,392	-17,766	-17,352
	4	28,209	35,381	22,491	37,065	22,311	35,216	81,819	92,941	78,358	123,782	81,346	87,269	-17,043	-18,014	-7,832	-13,527	-16,990	-18,929
	5	18,518	21,351	23,415	16,775	23,871	21,738	53,315	55,868	63,666	36,772	60,254	58,215	-16,240	-15,042	-19,854	-15,873	-17,164	-16,776
	6	20,304	14,903	_	15,768	26,356	18,667	52,153	36,675	_	26,556	52,450	45,850	-13,743	-14,740	_	-17,925	-14,617	-12,432
PLD	1	6,742	6,199	5,836	6,799	5,829	6,066	18791	16,677	15,013	20,522	15,512	16,504	-5,468	-5,003	-5,588	-5,680	-6,091	-5,666
	2	7,686	6,409	5,901	8,169	5,670	6,232	22809	19,355	15,475	26,257	16,500	17,521	-5,495	-5,803	-5,115	-5,926	-5,079	-5,509
	3	8,558	7,693	5,777	10,342	5,649	7,979	23700	22,534	16,036	32,180	18,469	20,956	-5,135	-6,432	-4,919	-4,787	-6,367	-5,731
	4	6,948	8,985	5,295	9,385	5,540	8,933	20574	23,396	19,138	31,650	19,909	22,716	-6,098	-5,475	-3,529	-4,680	-5,835	-5,064
	5	4,898	4,983	5,757	4,253	6,182	5,205	13492	12,169	14,743	7,404	14,005	12,636	-5,053	-5,726	-5,899	-5,324	-4,969	-5,571
	6	5,085	3,549	_	3,883	6,525	3,958	11149	7,005	_	3,431	13,366	8,077	-5,091	-4,807	_	-6,342	-5,701	-5,429

Table A-13. The effect of lead time and delivery delay on supply chain profit & CVaR

	Level	Supply Chain Profit						Supply Chain 95% CVaR						Supply Chain 99% CVaR					
	Scenario	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD	MLT	DLT	RLT	ALT	MDD	DDD
PHD	Base	39,531	39,531	39,531	39,531	39,531	39,531	29,091	29,091	29,091	29,091	29,091	29,091	56,714	56,714	56,714	56,714	56,714	56,714
	1	35,763	39,986	39,531	36,162	39,416	40,846	38,574	33,008	29,091	43,467	30,028	31,178	71,713	63,284	56,714	80,004	57,916	60,600
	2	32,454	39,649	38,347	34,224	38,186	41,396	50,906	37,228	30,769	61,832	32,953	33,420	91,935	70,054	59,454	110,299	63,001	64,431
	3	29,492	39,858	37,201	18,353	36,638	41,419	49,832	44,241	32,337	83,478	37,056	37,089	89,399	80,570	61,825	146,321	69,329	70,877
	4	34,386	41,248	28,701	32,593	35,487	42,922	44,272	51,131	42,855	75,541	42,902	41,767	80,912	88,632	79,882	131,653	78,867	75,918
	5	51,620	38,311	41,192	46,991	41,644	37,363	8,694	22,229	27,300	4,648	24,786	23,991	19,740	43,430	53,696	10,413	48,441	46,768
	6	46,872	35,902	_	45,564	43,367	31,652	14,534	13,696	_	-2,245	15,426	15,005	29,967	27,456	_	1,465	32,896	28,251
PMD	1	33,080	36,568	35,652	33,752	35,309	37,179	19,663	15,163	13,381	21,894	14,258	13,855	37,899	30,971	27,889	41,375	29,150	28,971
	2	30,633	37,621	34,679	32,043	34,492	38,454	27,805	16,496	14,688	33,570	16,733	14,332	51,379	32,892	30,124	60,987	33,506	30,343
	3	26,644	38,604	33,456	28,440	33,366	40,801	37,258	20,127	15,974	43,400	19,696	14,683	66,201	39,049	32,292	77,224	37,951	31,213
	4	31,964	39,391	26,077	30,611	32,338	41,407	23,334	23,034	24,784	47,564	23,378	16,111	43,412	44,010	46,559	83,622	43,732	33,829
	5	43,385	33,163	37,040	39,720	36,969	32,957	439	10,631	11,995	-2,369	10,020	11,792	3,114	22,232	25,514	-3,159	21,862	24,436
	6	42,165	32,015	_	38,735	38,538	26,818	3,702	2,832	_	-5,921	3,609	10,216	10,892	7,579	_	-5,242	11,151	19,877
PLD	1	11,310	12,213	11,993	11,472	11,924	12,389	2,891	1,317	692	3,464	1,000	907	6,221	3,746	2,569	7,104	3,123	3,066
	2	10,731	12,339	11,678	11,261	11,663	12,693	5,177	2,080	1,121	6,493	1,646	1,048	9,975	4,909	3,302	12,162	4,278	3,441
	3	9,783	12,753	11,351	8,158	11,328	13,298	5,159	2,708	1,523	10,608	2,669	1,358	9,585	5,813	4,027	19,083	5,817	4,303
	4	10,962	13,299	9,448	11,217	11,133	13,834	3,919	3,638	4,017	8,526	3,640	1,592	7,787	7,157	8,591	16,534	7,406	4,038
	5	14,182	11,252	12,269	13,242	12,234	11,098	-2,992	-170	327	-3,419	-64	178	-3,914	950	2,039	-5,051	1,361	1,547
	6	13,018	10,009	_	12,664	12,595	9,250	-1,936	-1,882	_	-4,737	-1,669	-564	-1,770	-2,880	_	-7,157	-1,273	-365

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