EXTENDED UNDERSTANDING OF THE CAUSES AND CONTROL OF THE BULLWHIP EFFECT IN MULTI-ECHELON SUPPLY CHAINS

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ABSTRACT

One of the most devastating phenomena in a supply chain is the bullwhip effect, i.e. the amplification of demand variability as it progresses up a supply chain. As the bullwhip effect is costly to the supply chain, there is a real cost benefit associated with its reduction. Therefore, this thesis extends the understanding of the causes of the bullwhip effect and develops strategies to reduce the variability of the orders to the upstream echelons.

This thesis consists of four discrete studies. The first study deals with the development of a multi-echelon simulation model, using iThink. It is demonstrated that design parameter values that give very poor dynamics across the whole supply chain do not necessarily yield poor dynamics within a single echelon, so it is essential to consider the whole supply chain when setting parameter values. The compromise between speed of response and stability in the dynamic responses is seen. The second study deals with order batching. It is found that the relationship between batch size and demand amplification is non-monotonic. The results show that when the quotient of the average demand and batch size is integer, demand amplification does not grow with the increase in batch size. The third study explores the stability boundaries of a multi-echelon capacity constrained supply chain and evolves the policies that minimize the backlog bullwhip effect. The last study deals with the net variance ratio induced by different forecasting techniques with an order-up-to level stock replenishment policy. It is seen that the bullwhip effect and inventory variances have distinct properties depending on the demand forecasting technique. Further, it is shown that smoothing the order pattern at the retailer's level increases its net inventory variances. However, the order pattern of the retailer can be smoothed without adversely affecting the net stock level.

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Glossary of Terms

IOBPCS	Inventory and Order Based Production Control System
APIOBPCS	Automatic Pipeline Inventory and Order Based Production Control System
APVIOBPCS	Automatic Pipeline Variable Inventory and Order Based Production Control System
AINV	Actual Inventory
DINV	Desired Inventory
EINV	Error of Inventory
Orate	Order Rate
ComRate	Completion Rate
WIP	Work in Progress
DWIP	Desired Work in Progress
EWIP	Actual Work in Progress
Sales	Actual Customer Demand
SSALES	Smoothed Sales
IEP	Information Enrichment Percentage
Ti	Time to adjust Inventory
Tw	Time to adjust Work in Progress
Tp	Production or Transportation Delay
Tp`	Estimated Pipeline Delay
Ta	Time to Average Sales(Smoothing Constant)
OUT	Order-up-to Level Model
MMSE	Minimum Mean Squared Error Forecasting
SNR	Signal to Noise Ratio
DoF	Degree of Freedom
DOE	Design of Experiments
OA	Orthogonal Arrays
ITAE	Integral of Time Multiplied by Absolute Error
AR	Autoregressive Demand Process
AR(1)	First Order Autoregressive Demand Process

Chapter1: Introduction

1.1 Research Background and Research Need

A supply chain is a network of facilities that together produce raw materials and transform them into intermediate goods and then final products that are delivered to end customers. A supply chain incorporates procurement, manufacturing, and distribution functions, with activities covering local, regional, and increasingly global levels. A supply chain can be composed of many functional levels called echelons or tiers. Each echelon can have numerous facilities. The number of echelons, the different operational policies at different echelons, the material and information flows between these echelons and supply chain uncertainties (demand fluctuations, lead time variations) all contribute to the complexity of a supply chain.

One of the most devastating phenomena in a supply chain is the bullwhip effect, i.e. the amplification of demand variability as it progresses up a supply chain. Slack and Lewis (2002) give an introduction to its causes and remedies. Its effects include inaccurate forecasting leading to periods of low capacity utilisation alternating with periods of not having enough capacity, i.e. periods of excessive inventory caused by over production alternating with periods of stock-out caused by under production. This leads to inadequate customer service and high inventory costs. Since the bullwhip effect is costly to upstream echelons of the supply chain, there is a real cost benefit associated with its reduction. Therefore, this thesis extends the understanding of the causes of the bullwhip effect and develops strategies to reduce the variability of the orders to the upstream echelons. In general, this thesis presents general solutions to the different causes of the bullwhip problem in particular production or distribution ordering procedure. The particular model is powerful because it can represent wide range of supply chain strategies including lean, agile, and vendor managed inventory. Finally, generality of the results is considered and implications for aggregated production/ distribution and inventory control systems are derived in order to control the bullwhip effect. Inventory management problems occur at all levels of multi-echelon supply chain (whether serial or parallel). Hence, the solutions presented in this thesis can be applied to any system where production/ distribution and inventory control systems are integrated.

Like much system dynamics research, the main portion of this thesis uses the widely referenced 'beer game' model since this reflects validated decision rules in a real-world supply chain. Decision rules are validated by proving the existence of amplifications and oscillations in the order rate of the supply chain. The beer game is a simplified but still realistic representation of a multi-echelon supply chain consisting of a retailer, wholesaler, distributor, and factory (beer brewer). Sterman (1989) originally developed a multi-echelon beer game and this policy has been termed the *Automatic Pipeline Inventory and Order Based Production Control System* (APIOBPCS) by Naim and Towill (1995); this model combines the *make to stock* and *make to order* control manufacturing production strategies. APIOBPCS is a general rule for issuing orders on the basis of forecasted sales, error of the inventory, and error of the work in progress. By incorporating a variable desired inventory level as a function of demand, APIOBPCS can be changed into the *Automatic Pipeline Variable Inventory and Order Based Production Control System* (APVIOBPCS).

Different analytical techniques have been used to investigate the beer game model but none of these are fully satisfactory (White et al, 2006). One of the most commonly applied methodologies to study the various aspects of APIOBPCS and

APVIOBPCS is the control theoretic approach. It is clear that the control theoretic approach normally involves linearization through the use of linear models in presenting a view of the whole system. Transferring function analysis, applied in control theory, can analyze a model with more than five parameters if all parameters are independent of each other. The order of the system increases with each new parameter and it is extremely difficult to convert the transfer function of greater than fifth order between the transfer function domain and the time domain (Holweg et al, 2005). Control strategies can be designed to achieve specific performance levels (e.g reducing the bullwhip effect), but it is difficult to deal with the complex issues such as non-linearities, stochastic behavior, adaptive control and multi-echelon systems seen in supply chain modeling (Agaran et al, 2007).

Previous research involving the APIOBPCS production and inventory control system is based on various unrealistic assumptions, such as deterministic demand, no capacity constraints, and no batching, to keep the supply chain model analytically solvable and tractable. There is a need to study the model under more realistic assumptions of stochastic demand process, batch ordering and capacity constraints. Riddalls and Bennett (2001) pointed out that control theorists are unable to optimize batch size. Potter and Disney (2006) mentioned that the impact of order batching on bullwhip has not been clearly explored. They pointed out that studying the impact of batch size on APVIOBPCS, under a stochastic demand process, using the transform techniques of control theory is extremely challenging. Further, Riddalls et al (2002) and White et al (2006) pointed out that control theorists are dealing with the linearity of the model as there are no capacity constraints.

System dynamics simulation, as applied in this thesis, then seems an appropriate methodology to investigate the impact of batch size and capacity constraints on the dynamic response of the system. It allows one to use a systems approach in visualizing and solving a problem holistically. Simulation can better deal with stochastic conditions, batch ordering, capacity constraints, multi-performance criteria, and other realistic assumptions of supply chain models. It is necessary to shift from analytical models to system dynamics simulation-based research due to the complexity of the interactions among different parameters, as well as the randomness of demand and extensive non-linearties in the supply chain models (Sahin and Robinson, 2002).

Most of the previous research into the effects of parameter values of production control systems was focused on single echelons (John et all 1994, Riddalls et al 2002), whereas this thesis studies the effects on the dynamic performance of a whole supply chain. Production and inventory control systems seldom exist in isolation, but are connected in series and in parallel to form a complex supply chain. Significant benefits can be gained by doing what is best for the overall supply chain rather than what is best solely for the single echelon. Focusing on the design of a single echelon in isolation without reference to the rest of the supply chain can lead to poor performance overall.

Multi-echelon supply chains consist of many interacting parameters at each echelon, such as forecasting constants, lead time, batch size, capacity constraints, and times to adjust errors in the inventory and work in progress. The relationship between design parameters is causal, meaning that it is explicitly recognized that changing the value of one parameter may lead to changes in the effects of another parameter. Previous studies of the effects of supply chain parameter values reported the results of changing the value of one, or at most two, parameters at a time. The '*one-at-a-time*' approach reveals the effect of one parameter when combined with a particular combination of values for the other parameters, but does not provide the information for calculating the effects of the parameter when combined with any other values for the other parameters, i.e. interactions. A more appropriate methodology is *Taguchi's Orthogonal Arrays* technique in which levels of each factor are systematically varied and all possible combinations of factor levels (parameter values) are considered. Furthermore, it explores the non-linearities, the main effects of the parameters, the severity of interactions among these parameters, and finally the best combination of parameter values in respect of the aspect of performance being analyzed.

Impacts of forecasting methods on the bullwhip effect in an *order-up-to level* (OUT) supply chain have been studied by several researchers (Dejonckheere et al, 2003; Alwan et al, 2003; Zhang, 2004; Sun and Ren, 2005; Hosoda and Disney, 2006; Luong, 2007). Previous research into order-up-to level stock replenishment policy focused on determining the impact of forecasting methods on the bullwhip effect by using statistical approaches (Lee et al 1997a, 2000; Chen et al 2000a, b), but Hosoda and Disney (2006, a) point out that "the statistical approaches become unmanageable when net inventory variances are considered as the expressions for the covariance between the states of the system are very complex". Simulation is applied to this analysis in this thesis, so that these intractable expressions between order rate and inventory variances are avoided and the impact of the exponential smoothing (ES) and the minimum mean squared error (MMSE) forecasting techniques on both order and inventory variations can be investigated.

It has been shown that the simple OUT replenishment policy always results in the bullwhip effect (Dejonckheere et al, 2003), (Hosoda and Disney, 2006, b). Therefore, the simple OUT policy is modified in this thesis by adding a proportional controller into the inventory feedback loop. The impact of the proportional controller, in this modified OUT policy, on the demand amplification and inventory variances is analyzed. The modified OUT replenishment rule dampens the variability in the orders to the upstream echelon but this comes at the price of increased inventory variances at the retailer's level. It is found that by fine tuning of the proportional controller, the order pattern can be smoothed to a considerable extent without affecting the inventory variances.

1.2 Research Objectives

The research aim of this thesis is related to the issue of supply chain modeling and formulation of different policies to minimize the bullwhip effect. The aim drives the formation of the research objectives which shape the methodology and the approach that is needed to conduct the research and to ensure that the thesis provides a good quality contribution to the industrial and academic knowledge. The analysis section of this thesis (Chapters 4-7) is comprised of four chapters and each chapter has different objectives.

➢ **Chapter 4**: To develop a multi-echelon simulation model based on the APVIOBPCS production and inventory control system model using iThink software.

- To simulate the effect of different design parameters on the dynamic responses of the inventory and order rates at the different echelon of the supply chain.

- To carry out a sensitivity analysis of the effects of the chain's parameters on the responses of the system and to explore the best parameter settings for multi-echelon supply chains in respect of demand amplification.

➢ **Chapter 5**: To extend the model by adding batch ordering across each echelon of the supply chain.

- To investigate the impact of a range of batch sizes on demand amplification and to analyze the value of information sharing in a batched model.
- To quantitatively measure the impact of supply chain design parameters on the bullwhip effect, to explore the interaction among these design parameters, and to evolve the best possible values of these parameters for mitigating the bullwhip effect.

➢ **Chapter 6**: To simulate the APIOBPCS model under more realistic assumptions by adding capacity constraints at each echelon.

- To explore the stability boundaries of the multi-echelon supply chain under different capacity constraints.
- To evolve policies to minimize the total backlog bullwhip effect of the supply chain.

➢ **Chapter 7**: To investigate the impact of different forecasting techniques on the order rate and the inventory variance amplification ratios in a simple order-up-to level supply chain.

- To extend the simple order-up-to level supply chain by adding a proportional controller in the inventory feedback loop and to analyze the impact of the proportional controller on the demand amplification and inventory variances.
- To analyze the effects of the parameter values for the proportional controller, the lead time, and the demand autocorrelation on the bullwhip effect and inventory variances.

1.3 Research Contributions

Overall, this research brings a number of benefits to both academia and industry.

Academia: In this thesis a "gap analysis" is carried out in respect of the modeling and control of demand amplification in supply chains. Through extensive literature review, gaps in theory are explicitly stated in each chapter and a methodology is presented to fill these gaps. The outcome of this research will enable researchers and students to identify further research opportunities based on the findings of this research.

Industry: This research is useful for supply chain operations managers to understand the impact of design parameters on the stability boundaries of the multi-echelon supply chain. Manufacturing companies can reduce demand amplification by carefully selecting order batch sizes and sales (demand) forecasting techniques. The service level of the multi-echelon supply chains can be greatly improved by fixing the various levels of capacity constraints and safety stock levels at different echelons. Furthermore, most of the previous research in supply chain operations involved mathematical techniques, which can require an academically advanced understanding of mathematics that most supply chain operations managers do not have (Agaran et al, 2007). In contrast, the use of system dynamics simulation methods can help practitioners to better understand the basic phenomena and to examine the effects of production and inventory control system parameters.

1.4 Thesis Contents Overview

This section briefly describes the content and structure of the research.

Chapter 1 begins with the description of the research background followed by research needs, aims and objectives, research benefits, and thesis organization.

Chapter 2 reviews the evolution in supply chain definitions and the practice of supply chain management. Discussion in this chapter covers a number of important issues involving causes and remedies of the bullwhip effect, supply chain modeling techniques, and the two commonly applied supply chain models in the literature.

Chapter 3 presents the details of the research methodology and tools applied in this thesis. The discussion includes justification of the research methodology employed, explanation of the research design, and description of system dynamics and Taguchi Design of Experiments.

Chapter 4 presents the iThink model of a four-tier multi-echelon supply chain based on beer game model. The impact of this model's design parameters on the response of the actual inventory and order rate at each echelon is simulated. Using Taguchi's orthogonal arrays technique, the effects of the design parameters are analyzed and the best setting of the design parameters in the context of the dynamic response is examined.

Chapter 5 investigates the impact of batch ordering on demand amplification. Another discussion area in Chapter 5 concerns the quantification of the effect of the four-tier supply chains design parameters on the bullwhip effect, the interactions among these parameters is explored and the 'best' parameter settings for mitigating the impact of demand amplification are identified.

Chapter 6 deals with the capacity constraints. The stability boundaries of the capacity constrained multi-echelon supply chain are explored and the impact of different level of safety stock on the service level of the model under different capacity levels is investigated. Taguchi's signal-to-noise ratio is applied to minimize the total backlog in the supply chain.

Chapter 7 discusses the role of exponential smoothing and minimum mean squared error forecasting and their effect on demand amplification and the net inventory ratio. Another discussion area involves the modification of the order-up-to level policy to reduce the net variance ratio.

Chapter 8 draws the conclusions of the research and proposes future work.

The conference papers that have been presented in the course of conducting this research are included in the Appendix.

Chapter 2: Literature Review

2.1. Supply Chain Management

The literature on the subjects associated with this research is broad. In this thesis every chapter has its own contribution; the related literature and gaps in supply chain theory are explained in each chapter. However, an initial literature review is presented in this chapter on the issues related to supply chain dynamics, supply chain models, and modeling techniques commonly applied to production and inventory control systems.

A supply chain is a network of facilities that together produce raw materials and transform them into intermediate goods and then final products that are delivered to the end customers. A supply chain incorporates procurement, manufacturing, and distribution functions, with activities covering local, regional, and increasingly global levels. Supply chain management is important to ensure that operations in the supply chain are smoothly coordinated, integrated, and synchronised. The objective of supply chain management is to maintain the desired customer service level while keeping costs low for procurement, production, and inventory. A supply chain can be composed of many functional levels called echelons. Each echelon can have numerous facilities. The number of echelons, the operational policies at different echelons, information flow among these echelons and supply chain uncertainties, all contribute to the complexity of a supply chain. Examples of supply chain uncertainties include demand fluctuations and lead time variation.

A review of the literature shows that there are many definitions of supply chain management. Table 2.1 provides definitions of supply chain management provided by selected authors.

Author(s)	Definitions
Lamber et al. (1998),p.1	"SCM is the integration of business processes from end user through original suppliers that provide product, services, and information that add value for customers and other stakeholders".
Menter et al. (2001),p.18	"SCM is the systemic, strategic coordination of the traditional business functions and the tactics across [these] business functions within a particular company and across business with the supply chain for the purpose of improving the long term performance of the individual companies and the supply chain as a whole".
Stadler (2002),p.9	"SCM is the task of integrating organizational units along a supply chain and coordinating material, information, and financial flows in order to fulfill (ultimate) customer demands with the aim of improving competitiveness of a supply chain".
Chen & Pluraj (2004),p.147	"SCM, as we envision, is a novel management philosophy that recognizes that individual businesses no longer compete as solely autonomous units, but rather as supply chains. Therefore, it is an integrated approach to the planning and control of materials, services, and information flows that adds value for customers through collaborative relationships among supply chain members".
Christopher (2005), p.5	"SCM is the management of upstream and downstream relationships with suppliers and customers to deliver superior customer value at less cost to the supply chain as a whole".

Table 2.1. Definitions of Supply Chain Management

2.2 The Bullwhip Effect in Supply Chains

2.2.1 Background

One of the most devastating phenomena in a supply chain is the bullwhip effect, i.e. the amplification of demand variability as it progresses up a supply chain. The bullwhip effect was first observed in industry by Jay Forrester in 1961. Forrester did not use the term "*bullwhip effect*" but named the effect "*Demand Amplification*". In some industries it is also known as the "Whiplash Effect". The term, "bullwhip effect" was first used by Proctor & Gamble and later made popular by Lee et al (1997). Executives of *Proctor and Gamble* observed that even though the demand for nappies was fairly stable over time, the retailers' orders were highly variable. In turn, production orders were even more variable. To explain the effect further, the variance of the orders may be larger than that of sales and distortion tends to increase as one moves upstream in the chain from retailer to manufacturer. Typical amplification ratios of 2:1 have been observed between two echelons (Towill 1992), whilst amplification has been observed up to 20:1 between four echelons (Houlihan 1987). Figure 2.1 illustrates a typical picture of demand amplification across four tiers of a supply chain.

2.2.2. Causes of the Bullwhip Effect

A review of previous research suggests that the causes of the bullwhip effect fall into two categories. The first category focuses on the operational causes of the bullwhip effect and the second category involves behavioral causes of bullwhip effect. Lee et al (1997) identified following four causes of the bullwhip effect: demand signal processing, order batching, price variations and rationing and gaming and these are considered here to fall into the operational category.

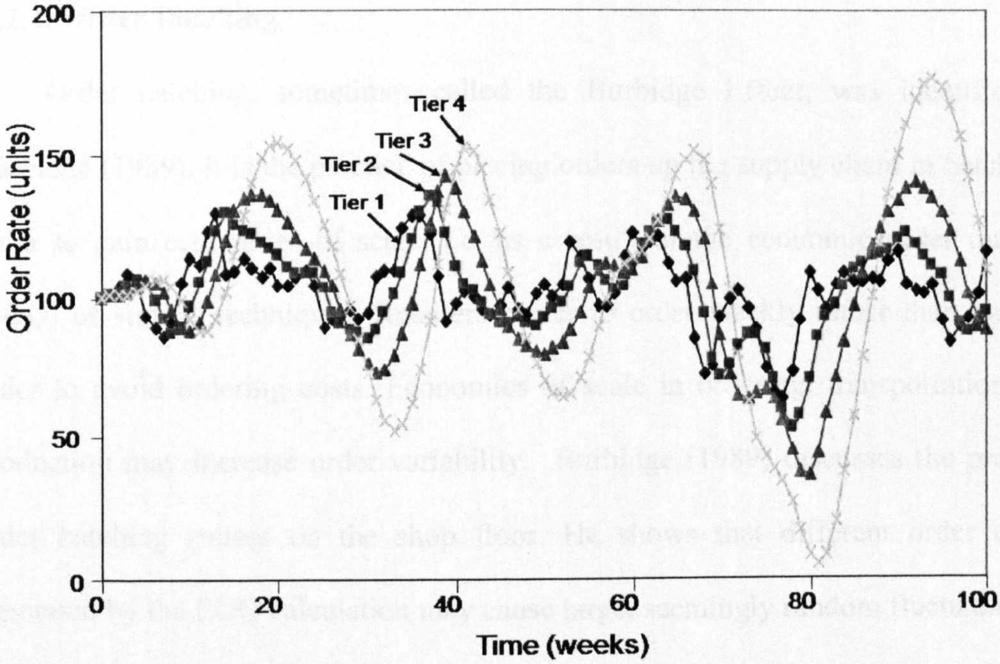


Figure 2.1. Bullwhip Effect in Multi-echelon Supply Chain

2.2.3. Demand Signaling Processing

Demand signal processing is the same mechanism that Forrester (1961) called the inventory replenishment policy. According to Forrester (1961), the way in which decision makers adjust the parameters of inventory replenishment contributes to demand amplification. Forrester highlights that different forecasting techniques tend to accelerate inventory reactions to changes in sales levels. This phenomenon is discussed in Chapter 7. Demand forecasts, target stock levels, safety stock levels and pipeline inventory levels are updated at regular time intervals. The differing rationales for adjusting these parameters create erratic responses. It is possible to design replenishment rules that have a smoothing effect on orders. Forrester (1961) suggests that it is not necessary to recover all of the error or shortfall in the inventory in one time period. Instead, recovery should be spread over a period of time by ordering only a fraction of the inventory deficit each time period.

2.2.4. Order Batching

Order batching, sometimes called the Burbidge Effect, was identified by Burbidge (1989). It is the practice of placing orders up the supply chain in batches in order to gain economies of scale, i.e. as a result of the economic order quantity (EOQ) or similar techniques. Retailers prefer to order weekly rather than daily in order to avoid ordering costs. Economies of scale in ordering, transportation, and production may increase order variability. Burbidge (1989) discusses the problem order batching causes on the shop floor. He shows that different order cycles generated by the EOQ calculation may cause large, seemingly random fluctuations in demand. In order to counteract this problem, Burbidge recommends single cycle flow control in manufacturing systems. In reality, many manufacturing companies place orders with their supplier when they run their material requirement planning (MRP) systems. Since these MRP systems are normally run on a monthly basis, this results in significant batches in the supply chain.

2.2.5. Price Variations

Another major cause of bullwhip effect is price variation. Price variation refers to the practice of offering products at reduced prices to stimulate demand. Customers take advantage of such opportunities and forward buy products, which ultimately causes a temporary surge in demand followed by a temporary trough. Lee et al (1997) recommend that reducing price variations schemes and switching to an "every day low prices" (EDLP) strategy can generate a more level demand and greater supply efficiency.

2.2.6. Rationing and Gaming

Rationing and gaming, also known as the Houlihan effect was identified by Houlihan (1987) who recognised that as shortages or missed deliveries occur in the supply chain, customers tend to overload their orders. This in turn places more demand on the factory, which inevitably leads to more unreliable deliveries. In response, downstream customers increase their safety stocks to meet their desired service level, which further distorts the demand signal. Lee et al. (1997) state that a similar problem also occurs when customers anticipate shortfalls in supply. In this scenario, it is extremely hard to forecast or estimate true demand upstream in the supply chain. Lee et al. (1997) recommend production based on customers' past sales history as a remedy to the gaming problem.

2.2.7. Behavioral Causes of the Bullwhip Effect

Behavioral causes were first considered by Forrester (1961) and further explored by Sterman (1989). The behavioural explanation emphasises the bounded rationality of decision making, particularly when there is the failure to adequately account for feedback effects and time delays. Sterman (1989) argued that bullwhip effect is caused by irrational behavior of participants. Research into behavioural causes of the bullwhip effect shows that managers do not adequately account for time delays, feedback and nonlinearities (Croson and Dhonohue, 2002). Specifically, managers place orders based on the gap between desired inventory and the current inventory level, whilst giving insufficient weight to what is already in the supply line or pipeline. Pipeline underweighting is sufficient to cause the instability observed in both experimental and real supply chains.

2.2.8. Impacts of the Bullwhip Effect

The bullwhip effect has a detrimental impact on the performance of the supply chain. To counteract the bullwhip effect, companies typically increase their buffer inventories in an attempt to smooth production rates and to maintain their desired customer service level. Slack and Lewis (2002) give an introduction to its causes and remedies. Its effects include inaccurate forecasting leading to periods of low capacity utilisation alternating with periods of not having enough capacity, i.e. periods of excessive inventory caused by over production alternating with periods of stock-out caused by under production. This leads to inadequate customer service and high inventory costs

2.2.9. Remedies to the Bullwhip Effect

Many researchers have attempted to mitigate the impact of the bullwhip effect, as it has a highly detrimental impact on the performance of a supply chain. For example, Forrester (1961) pointed out that demand amplification is due to the "system dynamics phenomenon" and can be tackled by reducing delays. Sterman (1989) interprets the phenomenon as a consequence of players' irrational behaviours or misperceptions of feedback through his "beer game". Lee et al. (1997) suggest that the bullwhip effect can be mitigated by information as the sharing of fresh and accurate information on market demand can enable upstream members of the supply chain to reduce the effect. Wickner et al. (1991) present five strategies to smooth supply chain dynamics:

i. fine tuning the existing echelon decision rules;
ii. reducing time delays;
iii. eliminating an echelon by removing the distributor from the supply chain;

iv. improving the individual echelon design rules by taking account of pipeline behaviour;

v. integration of information flows.

2.2.10. Measuring the Bullwhip Effect

Different approaches can be applied to measure the bullwhip effect. Riddalls and Benett (2001) give a qualitative approach to measure the bullwhip effect. They suggest measuring the magnitude of bullwhip effect in two level supply chains by observing the peak order rate of the upper level. This provides a qualitative measure of the bullwhip effect but is not suitable for analytic solutions (Poter and Disney, 2006). Many authors have used statistical measures of the bullwhip effect. For example Chen et al (2000b) measured the bullwhip effect as:

$$\text{Bullwhip}=\frac{\sigma^2 ORATE / \mu ORATE}{\sigma^2 CONS / \mu CONS}=\frac{\sigma^2 ORATE}{\sigma^2 CONS} \qquad (2.1)$$

ORATE is the orders placed on the upstream members of the supply chain. CONS is the actual customer sales faced by the retailer, σ^2 is the unconditional variance of the orders and μ is the unconditional means of the orders. In a two level supply chain, it is normally assumed that unconditional means are identical thus they cancel (Disney and Towill, 2003).

Franso and Wouters (2000) also use a statistical measure of bullwhip effect in the grocery supply chain by dividing the *coefficient of variation of orders placed* by the *coefficient of variation of orders received.* Rather than variance, they used standard deviation ratios as a bullwhip measure:

$$\text{Bullwhip} = C_{out} / C_{in} \tag{2.2}$$

where $$C_{out} = \sigma\,(D_{out}(t, t+T))/\mu(D_{out}(t, t+T)) \tag{2.3}$$

and $$C_{in} = \sigma\,(D_{in}(t, t+T))/\mu(D_{in}(t, t+T)). \tag{2.4}$$

$D_{out}(t, t+T)$ and $D_{in}(t, t+T)$ are the factory orders and completions respectively during the time interval (t, t+T).

2.3. Supply Chain Modeling Approaches

2.3.1 Background

Production and inventory control systems have been studied for more than four decades. Beamon (1998) gives an informative view of supply chain models and modelling techniques. Angerhofer and Angelides (2000) present a taxonomy of research on system dynamics and discuss several techniques and methods applied in supply chain modelling. Min and Zhou (2002) present a literature review of past supply chain modelling efforts and provide guidelines for successful development and implementation of such models. Riddalls et al (2000) divide the supply chain modelling approaches into four broad categories. They point out that no one approach is ideal; all approaches have their advantages and disadvantages. However, simulation models are accurate and offer an holistic, i.e. systems, approach (Riddalls et al., 2000). Because of their ability to view better the whole supply chain rather than individual entities within it. Models can also be used to replicate the system behaviour. The four modeling categories identified by Riddalls et al (2000) are detailed below.

2.3.2. Continuous Time Differential Equation Models

This modelling approach is appropriate for simulation and control theorists. Many tools from (engineering) control theory can be implemented to gain insight into supply chain system dynamics. For example, the Laplace Transform technique is used to solve differential equations and to move between the time and frequency domains. Simon (1952) first used the Laplace Transform technique to study a simple production and inventory control system. System dynamics simulation involving continuous differential equations was pioneered by Forrester (1961). He provides a non-linear multi-echelon supply chain model and subsequently, a detailed insight into supply chain behaviour by using "What if" scenarios. Towill and his colleagues facilitate a greater level of analysis by simplifying the Forrester model into a simple linear system. Towill (1982), John et al (1994) and Riddalls and Bennet (2002) detail studies of various aspects of the *Automatic Pipeline Inventory and Order Based Production Control System* (APIOBPCS) model in the continuous-time domain. Wilson (2007) applies system dynamics simulation in a continuous domain to study the impact of transportation disruption has in the vendor managed inventory (VMI)-APIOBPCS. The advantage of continuous time differential equation models is that complex modes, which are hard to be analysed using analytical methods, can be better explored. Limitations include (Riddalls et al., 2000):

i. differential equations produce a smooth output, which are not suitable for the supply chain modeling;
ii. this approach cannot solve the lot sizing problem in production and inventory control systems.

However, the complexity of multi-echelon supply chains warrants a perspective that considers a supply chain structure and the material flows and information feedback loops inherent to these structures. This is provided by system dynamics simulation (Wilson, 2007)

2.3.3. Discrete Time Difference Equation Models

Discrete time difference equation models involve the use of difference equations and the Z-Transform, a discretized or discrete-time translation of the Laplace Transform. These models have some advantages over the continuous models. For example, they allow the correct modeling of discrete time variables such as weekly order rates and they allow the inclusion of pure time delays in a model as required to model, say, the lead-time or pure-delay caused by a factory operation. The early use of difference equations and the Z-Transform to study production and inventory control systems is reported by Vassian (1955). Popwell and Benney (1987) apply z-Trnasform techniques in order to study materials requirement planning (MRP) systems. Disney and Towill (2002) consider the stability and the robust stability properties of a vendor managed inventory (VMI) supply chain using the Z-Transform. Dejonkckhere et al (2004) investigate the bullwhip effect with the order-up-to stock ordering policy using the Z-Transform. Disney et al (2006) conduct an analysis of production and inventory control systems employing order-up-to level policy in the continuous and discrete domain. They conclude that either domain can be applied because management insights gained from both domains are very similar. White et al (2006) investigate the impact of finite and exponential delays on continuous and discrete VMI-APIOBPCS models. They mention that control theoretic techniques can be used to attain certain performance levels and these design tools can be applied better by using system dynamics simulation. Like continuous differential equation models, these models are also unable to solve batch sizing and sequencing problems.

2.3.4. Discrete Event Simulation Systems

A discrete event simulation is one in which the state of a model changes at only a discrete, but possibly random set of simulated time periods. Discrete event simulation systems involve jobs (raw materials) and resources (buffer inventories). This modelling approach represents individual events and incorporates uncertainties. The structure of these systems can incorporate the stochastic behaviour of a supply chain, which is an important ability in supply chain modelling. Chang and Makatsoris (2001) discuss the requirements for discrete event simulation modeling. Morrice et al (2005) apply discrete event simulation to model the supply chain and the delivery of *Freescale Semiconductor Company*. Semini et al (2006) present a literature review of discrete event simulation modelling in real world manufacturing logistics decision making. Lacking the descriptive language for the formulation of these systems and the absence of the theoretical foundations, these systems have been associated with Monte Carlo Simulation and Black Box techniques.

2.3.5. Operational Research Techniques

Operational research involves mathematical techniques, such as Dynamic Programming, Linear Programming, Queuing Theory, Simulation, and Markov Chains. Chandra (1993) highlights the benefits of using operational research techniques for the solution of batch sizing and the job sequencing problems. These techniques can be used to solve inventory planning, lot sizing, scheduling, and job sequencing problems. However, operational research fails to adequately investigate the dynamic behaviour of the supply chain (Riddalls et al., 2000).

2.4. Production and Inventory Control Systems

2.4.1 Background

The literature review of the production and inventory control systems employed in this research is presented in relevant chapters. Here a brief review of most commonly applied inventory replenishment policies is presented. The purpose of the inventory replenishment policy is to assist the production scheduler to place orders on the factory, providing good smoothing of the actual demand while maintaining the desired customer service level from safety stock. A number of production smoothing rules were developed (Deziel and Ellion, 1965; Simon, 1952); the more recent work involves Dejonckheere et al (2003), Balakrishnan et al (2004), and Dinsey et al (2006).

Much of the management science literature separates the question of production and inventory control. According to Benjaffar et al (2005), a production and inventory system can be treated as independent units when they are decoupled through large stock holding at the manufacturing facility or at subsequent stages of the supply chain. It may also be justified to do this when the inventory and production system belongs to different entities or when transportation lead time is much bigger than the manufacturing lead time. However, in reality both these systems are interconnected and rarely exist as separate entities. A number of different production and inventory control systems for supply chain management have been developed. Axsater and Juntti (1996) presented a review of inventory replenishment policies. Baganha et al (1996) explored the strength and weaknesses of these commonly applied replenishment policies. The most commonly applied replenishment policies are as follows (Watson, 1987).

2.4.2. Continuous Review Inventory Policy

In the continuous review policy, the inventory level is continuously monitored and when it falls below the "reorder level", a fixed quantity is ordered to bring the inventory back to the desired level (Heisig, 2001). Continuous monitoring of stock levels must be feasible to implement this system; is it possible and how expensive is it? The continuous monitoring means that it reacts to surges in demand that cause stock levels to fall rapidly. As it protects against stock-out, it provides a defense when demand is difficult to forecast. It also has the advantage of only ordering stock when necessary, thereby minimizing stock levels and the number of order transactions. It is suitable when there is a fixed cost of ordering as it avoids ordering stock in small quantities when it is not really necessary due to stock levels not being very low, as may happen in the next approach.

2.4.3. Periodic Review Inventory Policy

In a periodic review system stock levels are reviewed at fixed time intervals, and a variable amount of stock is ordered to bring the stock level up to a predetermined target level. An advantage of this approach is that it does not incur the overhead of continuous monitoring, but the subsequent weakness is that it does not react to low stock levels between the review points so there is a risk of stock-out if demand increases. If several stock keeping units (SKUs) use the same reorder cycle, then they can be combined for a single supplier or 'run' of the stock control system, simplifying procedures and reducing costs. Computations of periodic review inventory policy and extensions of such policy are extensively studied by (Glasserman and Tayur, 1996; Roundy and Muckstadt, 2000).

Lee and Wu (2006) have proved that by choosing the appropriate inventory replenishment policy the number of backorders and cost of the inventory can be substantially reduced. In this thesis two different models with a periodic review inventory system are simulated. The reason for choosing the periodic review system is that this is the focus of the literature on production and inventory control system studies. Further, it is an optimal inventory policy where there are variable ordering costs (to make the ordering of small quantities feasible), lost sales are backlogged (so stock-out does not result in lost sales) and holding and shortage costs are proportional (to on-hand inventory or shortages), (Clark and Scarf, 1960; Veinott, 1966). These cost matrices can be used for minimizing the sum of ordering, holding, backlog, and set up cost (Chuang et al, 2004). Federgruen and Zipkin (1986) showed that the periodic review system is also optimal with production capacity constraints. Another reason for choosing the periodic review system is that it provides a benchmark to estimate the desired inventory level for providing a certain service level (Benton, 1991).

2.5. Periodic Review Multi-Echelon Supply Chain Model

One of the most commonly studied periodic review models in the supply chain literature is the *Beer Distribution Game.* This is a simplified but still realistic representation of a multi-echelon supply chain consisting of a retailer, wholesaler, distributor, and factory developed at Massachusetts Institute of Technology in the 1960s. Towill (1982) introduced a greater level of detail into this multi-echelon supply chain by using the *Inventory and Order Based Production Control System*

(IOBPCS) to model each echelon in more detail, applying a basic periodic review algorithm for issuing orders into the supply pipeline, based on current inventory deficit and incoming demand from customers. Edghill et al (1989) extended the model by incorporating variable desired inventory as a function of the demand. Later, a work-in-progress feedback loop was added to the IOBPCS; "Let the production targets be equal to the sum of an exponentially smoothed demand (over Ta time units) plus a fraction (1/ Ti) of the inventory error, plus a fraction (1/ Tw) of the WIP error." This is the "*Automatic Pipeline Inventory and Order Based Production Control System*" (APIOBPCS) (John et al., 1994). Riddalls and Bennett (2002) analysed the impact of pure delay and explored the stability boundaries of the single echelon in the APIOBPCS model. Disney (2002) extended the model into the *Vendor Managed Inventory* (VMI) scenario. Dejonckheere et al (2004) studied the *order-up-to-level* inventory control model and its variants as an important subset of the APIOBPCS. Adjusting the gain of the inventory and the pipeline allows the APIOBPCS to mimic a range of make-to-stock and make–to-order scenarios. This model is particularly powerful as it can represent, by adjusting the design parameter values, a wide range of supply chain strategies such as lean and agile.

Like much system dynamics research, the main portion of this research uses the beer game model since this reflects validated decision rules in a real-world supply chain. Decision rules are validated by proving the existence of amplifications and oscillations in the order rate of the supply chain. Different analytical techniques have been used to investigate the beer game model but none of these are fully satisfactory (White et al, 2006). One of the most commonly applied methodologies to study the various aspects of the beer game model is the control theoretic approach. It is clear that this normally involves linearization through the use of linear models in presenting a view of the whole system. Transfer function analysis, applied in control theory, simplifies the calculation and converts between the frequency and time domains. A transfer function relates the output of a system to its input in the frequency domain using (typically) Laplace transforms, or in discrete form, z-transforms. Transfer function analysis can analyze the model with an order greater than five if all parameters are independent of each other. The order of the system increases with each new parameter and it is extremely difficult to convert the transfer function of greater than fifth order (Holweg et al, 2005). Therefore, we have to resort to numerical approaches or simulation to study the complex supply chains.

Previous studies assume the value of parameters in a supply chain and report modeling results by changing the value of one or two variables at a time. The 'one-at-a-time' approach reveals the effect of one factor with a particular combination of other factors but does not provide the information for calculating the effects of that factor in general with any combination of the other factors. It is important to note that the relationship between design parameters is causal, meaning that it is explicitly recognized that changing the value of one parameter will lead to changes in the effects of changing the values of another variable. Hence, the development of Taguchi's *Orthogonal Arrays* technique in which levels of each factor are systematically varied and all possible combinations of factors are considered. Now a days *Design of Experiments* (DOE) has gained an increased attention among many six sigma practitioners and it is likely that DOE will be a key technique for developing robust product / process in 21st century (Rowland and Antony, 2003). DOE using Taguchi approach can economically satisfy the needs of process design optimization projects in the manufacturing industry by providing maximum information with the minimum number of experiments (Shang et al, 2004). Further, Multi-echelon supply chains consisting of many interaction parameters can better be optimized by *Taguchi's Orthogonal Arrays* technique.

Riddalls and Benett (2001) point out that control theorists are unable to solve the lot sizing problem. Potter and Disney (2006) identify that the impact of order batching on the bullwhip effect has not been clearly explored. They highlight that studying the impact of batch size under stochastic demand in a production APIOBPCS control system using the transfer function analysis applied in control theory is extremely difficult. APIOBPCS is a periodic review system for issuing orders based on incoming demand signals, feed back loops of inventory and pipeline line deficit. These feed forward and feedback loops are in turn affected by control parameters and it is hard to understand the nature of the transfer function analysis involved. Hence, control theorists are unable to study the impact of batch size under stochastic demand process. System dynamics simulation seems an appropriate methodology to investigate the impact of varying batch size on bullwhip effect with a stochastic demand process. Riddalls et al (2002) and White et al (2006) point out that control theorists are dealing with the linearity of that model; there is neither capacity constraints nor order backlog. In obtaining explicit mathematical solutions, linear models are much simpler whilst mathematical analysis is unable to deal with the general solutions to non-linear models. The disadvantage of the system dynamics model with extensive non-linearity is that the general prediction about the outcome of the model cannot be made. In reality a factory's production is always constrained by a capacity limit and sometimes it is not possible to cope with a sudden change in demand. Therefore, studying the model under capacity constraints is necessary to provide a more realistic picture. Further, the standard control theoretic techniques can determine a general picture of response, overshoots, and recovery time in terms of design parameters. These design tools are well established and can be better used by system dynamic soft wares and simulation.

2.6. Demand Forecasting in Periodic Review OUT Model

It has been recognized that demand forecasting, lead times (delays) and ordering policies are among the key causes of the bullwhip effect (Dejonckheere et al (2003). Most supply chains are forecast driven rather than demand driven (Christopher, 1999). Normally they make forecasts based on historical data and use those forecasts to maintain their inventory requirements. The impact of forecasting methods on the bullwhip effect have been studied by several researchers. Dejonckheere et al (2004) quantify the bullwhip effect for order-up-to policies using exponential smoothing, moving average, and demand signaling process. Alwan et al (2003) studies the bullwhip effect in an order-up-to-level (OUT) policy with mean squared forecasting. Both conclude that with that forecasting policy the bullwhip effect can be eliminated or mitigated depending on the correlative structure of the demand process, whether it is negatively correlated, independent and identically distributed (I.I.D), or positively correlated. Zhang (2004) investigates the impact of forecasting methods on the bullwhip effect in a simple order up to level policy with first order autoregressive (AR1) demand process. Findings indicate that moving average (MA), exponential smoothing (ES), and minimum mean squared error (MMSE) forecasting techniques lead to bullwhip effect measures with distinct properties with respect to demand autocorrelation and lead time. Sun et al (2005) makes the comparison of the effects of MA, ES, and MMSE forecasting on the bullwhip effect in an order-up-to level model. Hosoda and Disney (2006) use the transfer function technique and have developed an exact expression for the bullwhip effect and inventory variance using minimum mean squared error forecasting in a three stage supply chain. Luong (2007) develops the bullwhip measure for the AR(1) demand process in a simple order up to level supply chain that uses the MMSE forecasting. He found that the bullwhip effect depends on the value of demand autocorrelation and an upper bound for the demand amplification exists when the lead time increases.

The impact of lead time on the bullwhip effect is investigated by Chen et al. (2000, b), Zhang (2004), Chatfield et al (2004), and Kim et al. (2006). Chatfield et al (2004) analyse the bullwhip effect with stochastic lead time and identify that lead time variability exacerbates variance amplification in the supply chain. Kim et al. (2006) measure the impact of stochastic lead time on bullwhip effects for a k-stage supply chain and find that the bullwhip effect is higher under lead time variability. Most literature studies on lead time show that longer lead times or larger lead time variations have a detrimental effect on supply chain performance, implying that lead time or lead time variability should be minimised.

Replenishment strategies have an impact on the order and net stock variability. Order variability contributes to the bullwhip effect and finally the upstream cost, while variations in net stock level affect the ability to meet a desired service level. Dejonckheere et al (2004) prove that in an order up to level replenishment system, bullwhip is unavoidable with exponential smoothing, moving average, and demand signaling forecasting and propose a general replenishment rule for order smoothing. Balakrishnan et al (2004) emphasized the opportunities to reduce supply chain costs by dampening upstream demand variability. This has led to the creation of new replenishment policies that are able to generate smooth order patterns which in turn can mitigate the demand amplification. In order to control the dynamics of a supply chain, Hosoda and Disney (2006) add a proportional controller in simple order up to level supply chain models with MMSE forecasting. This is named the Generalized OUT policy. Hosoda and Disney (2006) conclude that a two echelon supply chain with this generalized OUT policy can reduce the inventory related cost by 10%. Boute et al (2007) investigate a two level supply chain with I.I.D. customer demand. They propose that decreasing the order variability at the retailer's level incurs the cost of increased variance of the retailer's inventory level. Smoothing the ordering pattern mitigates the bullwhip effect and results in shorter and less variable replenishment lead time, which in turn can benefit the retailer.

Previous research has focused on determining the impact of forecasting methods on the bullwhip effect. However, as pointed out by Hosoda and Disney (2006), the statistical approaches become unmanageable and complex when the net inventory variances are considered as expressions for the co variances between the states of the system. While this approach is better suited to the problem, these intractable expressions are completely avoided in this research. The impact of ES and MMSE on both order and inventory variations is investigated in this research. A simple order up to level policy is then modified by adding a proportional controller into the inventory feedback system. The impact of a proportional controller in a modified order up to level policy on the demand amplification and inventory variance will be analyzed in this work. Boute et al (2007) mention that bullwhip reduction comes at the cost of an increased variance of the inventory levels. Luong (2007) finds that the problem of quantifying the bullwhip effect still remains unsolved due to the complex nature of supply chains. In this thesis, the Taguchi Design of Experiments technique is applied to quantify the impact of different supply chain model parameters on the both bullwhip and inventory variance. The aim is to explore the interaction among these parameters and to identify the best values for these factors in order to minimize both order and inventory variances

2.7. Summary

Supply chain now a day is a complex and dynamic system and its performance is a result of interactions among supply chain players, such as manufacturers, suppliers, distributors, retailers, and customers. Interaction between players may produce both negative (damping) and positive (reinforcing) forms of feedback. A devastating phenomenon in supply chain dynamics is the bullwhip effect. The bullwhip effect is costly to upstream echelons of the supply chain, there is a real cost benefit associated with its reduction. The first section of the literature review highlights the various causes, remedies, and the ways to measure the bullwhip effect.

Next, detailed discussion of the supply chain modeling techniques been presented. The advantages and disadvantages of four commonly applied supply chain modeling techniques have been explored. Different analytical techniques have been applied to investigate the various aspects of bullwhip effect in multi-echelon supply chain but none of these is fully satisfactory. The justification of the modeling technique applied in this thesis has been provided in this section.

The last section presents a brief review of most commonly applied inventory replenishment policies. The purpose of the inventory replenishment policy is to assist the production scheduler to place orders on the factory, providing good smoothing of the actual demand while maintaining the desired customer service level from safety stock. The strengths and weaknesses of commonly applied replenishment policies have been discussed. The review of two different periodic review inventory systems applied in this thesis has been carried out.

For the rest of the thesis a “gap analysis” has been carried out. The literature review has been the primary source to identify the problem. Through extensive literature review, gaps in theory are explicitly stated in each chapter and a methodology has been presented to fill these gaps.

CHAPTER 3: Research Approach and Methods

3.1. Introduction

This chapter presents a discussion of the research methods and highlights the overall research structure applied to support the work. It begins with the description of research objectives which provide the foundation on which the research methodology and research design is developed. Following this, a brief justification of the research methods employed is presented. After this, the system dynamics software used in this thesis for the modeling of supply chains is introduced. Next, detailed discussion of the research design which encompasses, system modeling, simulation, experimental design, and analysis is presented. This includes a introduction to Taguchi Design of Experiments and analysis of variance (ANOVA).

3. 2. Research Objectives

Research objectives lead to areas that require investigation in order to develop the research design and choose the research strategy to achieve the research objectives. Van De Ven (2007) argued problem formulation is the first important task in research and plays a crucial role in grounding the subject. It directly affects how theory building, research design, and problem solving techniques are performed. Bryman and Bell (2007) summarized criteria for evaluating research objectives. Research objectives should be clear, researchable, connected with established theory and research, and have the potential for making a contribution to knowledge.

As discussed earlier (see Section 1.2), there are five key objectives which provide a basis for this research. The overall aim of this research is the investigation of the bullwhip effect in a multi-echelon supply chain model. This objective is accomplished by extending the existing supply chain model, by investigating the different causes of the bullwhip effect, and finally by formulating new policies to mitigate this effect

3.3. Research Approach

3.3.1. Introduction

Many different types of research are available, having been designed for many different research areas and applications (Saunders et al. 2003). According to Hussey and Hussey (1997), research can be classified into four different categories. Among these categories, the process of research can be divided into qualitative and quantitative. Qualitative research involves the collection and analysis of non-numerical data in order to get a better understanding of the subject studied (Denzin and Lincoln, 2000). Quantitative research involves collecting and analyzing numerical data and applying statistical tests. The emphasis is on measurement and analysis of causal relationships between variables (Drongelen, 2001). Simulation modeling is a quantitative research technique (Wass and Wells, 1994).

Angerhofer and Angelides (2000) present taxonomy of research on system dynamics and discuss several techniques and methods applied in supply chain modeling. Riddalls et al (2000) divide the supply chain modeling approaches into four broad categories. The advantages and disadvantages of these modeling techniques are discussed in Section 2.3. Different analytical techniques have been used to investigate the multi-echelon supply chain model but none of these is fully satisfactory (White et al, 2006). In this thesis, system dynamics simulation is combined with Taguchi Design of Experiments. A brief introduction and justification of the methodology is presented below.

3.3.2. System Dynamics Simulation

System dynamics is a well known simulation technique capable of modeling feedback loops explicitly and of evaluating the dynamics of complex processes and systems. Supply chains are complex, dynamic systems and their performance is a result of interactions among supply chain players, such as manufacturers, suppliers, distributors, retailers, and customers. Interaction between players may produce both negative (damping) and positive (reinforcing) forms of feedback. One of the most commonly applied methodologies to study the various aspects of the multi-echelon supply chain model is the control theoretic approach. The problem that faces control theorists is that, although they are often able to write differential equations on the dynamic behavior of the model, in many cases these differential equations cannot be integrated. Instead the control theorists resort to a numerical approach, usually with the help of computer simulation (Pidd, 2004).

Simulation is ideal for mapping these complex interactions and for predicting non linear outputs through "What If" analysis. Running "What if" simulations to test certain policies or strategies on complex models can greatly aid the understanding of how the system changes over time. Sterman (2002) states; "*Simulation is essential for effective systems thinking, even when the purpose is insight, even when we are faced with a "mess" rather than a well structured problem*".

Feedback is an important mechanism in system dynamics modeling. Traditionally feedback was generated through experimentation in the real world. In some scenarios, like altering the batch sizes and capacity constraints, real-world experimentation is too slow, too costly, or simply impossible. Hence, a simulation seems an appropriate methodology to study these feedback effects. Furthermore, mathematical and control theoretic approaches can require an academically advanced understanding of mathematics that most supply chain operations managers do not have (Agaran et al, 2007). In contrast, the use of system dynamics simulation methods can help practitioners to better understand the basic phenomenon and to examine the effects of parameters.

3.3.3. Taguchi Design of Experiments

Though useful, simulation only evaluates the effectiveness of a pre-specified condition and does not provide a solution for optimizing a system. Therefore, system dynamics simulation must be coupled with some optimization technique to determine the 'best' combination of system parameter values. To achieve this, the Taguchi Design of Experiments approach is introduced in this thesis.

Taguchi's method standardizes the statistical technique of design of experiments (DOE) and proposes a methodology that can satisfy economically the needs of process design optimization projects in manufacturing industry. In general, it is applicable to any situation that depends on many influencing factors (i.e., variables or parameters), (Roy,2001). When many factors influence an outcome, the best way to study real behavior is when the influences of all factors have an equal opportunity to be present. Taguchi Design of Experiments can better capture such effects. All kinds of industries can utilize DOE. Where there are products and processes, DOE can be applied. Even a service industry can use DOE when a valid model is available. However, manufacturing and production processes can better utilize this technique (Roy, 2001)

Over the last 20 years or so, it has gained increased acceptance in the USA and Europe as an important ingredient for improving process capability, driving down quality costs and improving process yields. Recently, it has gained increased attention from many six sigma practitioners and it is likely that it will be a key technique for developing robust product/process in the 21st century (Rowland and Antony, 2003).

Multi-echelon supply chains consist of many interacting factors at each echelon, such as forecasting constants, lead time, batch size, capacity constraints, and times to adjust errors in the inventory and work in progress (Holweg et al, 2005). The relationship between these parameters is causal; changing the value of one parameter will lead to changes in the effects of the values of another variable. Mathematics becomes unmanageable to deal with this level of complexity. The application of Taguchi's orthogonal arrays technique in which levels of each factor are systematically varied and where a large number of parameters can be optimized with the minimum number of experiments, seems an appropriate methodology (Shang et al, 2004).

Taguchi recommended a three stage process: system design, parameter design, and tolerance design. In this thesis, Taguchi's parameter design technique is applied. Taguchi (1989) argues that parameter design increases system robustness, reduces experimental cost and improves quality. Parameter design creates fractional factorial designs using orthogonal arrays. Anderson (2004) states that changing only one factor at a time cannot detect interaction effect. Fractional factorial design enables the experimenter to investigate the effect of each parameter (main effect), to determine whether parameters interact, and to evolve the robust design (Khumwan and Pichitlamken, 2007). The aim of the robust design technique is to minimize the variance of the response. Orthogonal arrays of parameter levels determine the simulation experiments run to evaluate the relative effects of parameter values on supply chains with the minimum number of experiments. Fractional factorial design can be used to explore the linear and non-linear effects of the design parameters.

Taguchi stresses the importance of studying the variation of the response and has introduced the Signal-to-Noise Ratio (SNR) to facilitate such investigation (Bendell et al, 1989). SNR is the ratio of the mean (signal) to the standard deviation (noise). The Taguchi approach compares the mean squared deviation (MSD) of the performance under different conditions. SNR provides a mechanism to calculate the robustness of a given combination of design parameter values. The details of the Taguchi methods applied here are presented in Section 3.6. Analysis of variance (ANOVA) is used to analyze the data obtained from the experiments designed using orthogonal arrays.

3.4. System Dynamics Software used (iThink)

The particular system dynamics software used in this research is "iThink Analyst". This proprietary software has been developed more for the business community rather than control engineers. Therefore, it should be more suitable for use by operations managers. iThink software is bundled with tools to create models using stocks, converters, flows, and information feedbacks. Once the conceptual model is defined, structuring the computer simulation is straight forward. Important characteristics of iThink are that it facilitates the modeling of continuous and discrete processes and it includes the graphical and tabulated aids to better analyze the outputs of the model. The Euler's method, proposed by the mathematician Leonhard Euler, is a most commonly applied explicit method in the software for numerical integration of ordinary differential equations. In this method, the computed values for flows provide the estimate for the change in corresponding stocks over the interval delta time (DT). In Euler's method as DT gets longer, fewer calculations are made and the integration error is increased. On the other hand, a smaller DT produces accurate results by increasing the number of the calculations.

3.4.1. Tools of iThink Software

Commonly applied tools in the iThink software for the building of system dynamics simulation models are presented in Table 3.1.

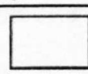
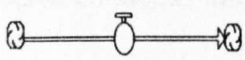
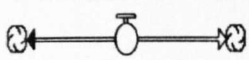
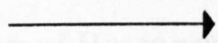
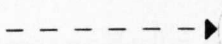
Symbol	Name
	Stock
	Uniflow
	Biflow
	Converter
	Action Connector
	Information Connector

Table 3.1. Symbols used in iThink

i. Stocks (Levels). Stocks are also known as levels and represent the accumulation of both physical and non-physical resources within the system. In the context of this research stocks represent inventories and goods in transit. Stocks have inflow and outflow and therefore will rise and fall.

ii. Flows. Activities continue in dynamic systems and these are represented by dynamic flows between levels. The purpose of flows is to fill and drain accumulations. Flow variables change the stock over time (e.g. factory order rates and completion rates). Inflows are always adding to the stock while outflows are subtracting from the stock. In the model studied, the actual inventory of the production control system is increased by the flow of production and decreased by shipment..

iii. Converter. In iThink a converter converts an input into an output. The converter holds values of constants used in the conversion (e.g. gains) and defines external inputs to the model. The design parameters Ti, Tw, and Ta applied in the supply chain model in this thesis are represented as converters.

iv. Connector. A connector passes information between converters; between stocks and converters; between stocks and flows; and between converters and flows. In the IOBPCS model, a connector is used to connect the converters (Ti, Ta) to the flow (order rate).

3.5. Description of Research Process Steps

A research process/design is used to structure the overall research. It describes a flexible set of guidelines that connect research paradigms to strategies of inquiry, units of analysis and processes of collecting and analyzing data, in ways which are most likely to achieve the research objective (Easterby-Smith, 2002; Denzin and Lincoln, 2000). The particular research methodology employed in this thesis involves system dynamics simulation and Taguchi Design of Experiments. A description of each of the steps involved in this research is provided in this section. Figure 3.1 represents the overall research design of this thesis.

3.5.1 System Modeling

Forrester (1971) argues that focusing on the process of modeling rather than on the results of any particular model speeds up learning and leads to better models, better policies and greater chance of implementation and system improvement. In this thesis, simulation is used as a system dynamics modeling tool. System dynamics models are symbolic models consisting of a combination of diagrams, graphs and equations. This thesis follows the standard steps of modeling techniques indicated by John Sterman (2000) in his book, *Business Dynamics: System Thinking and Modeling for a Complex World* (2000). These standard phases are summarized below.

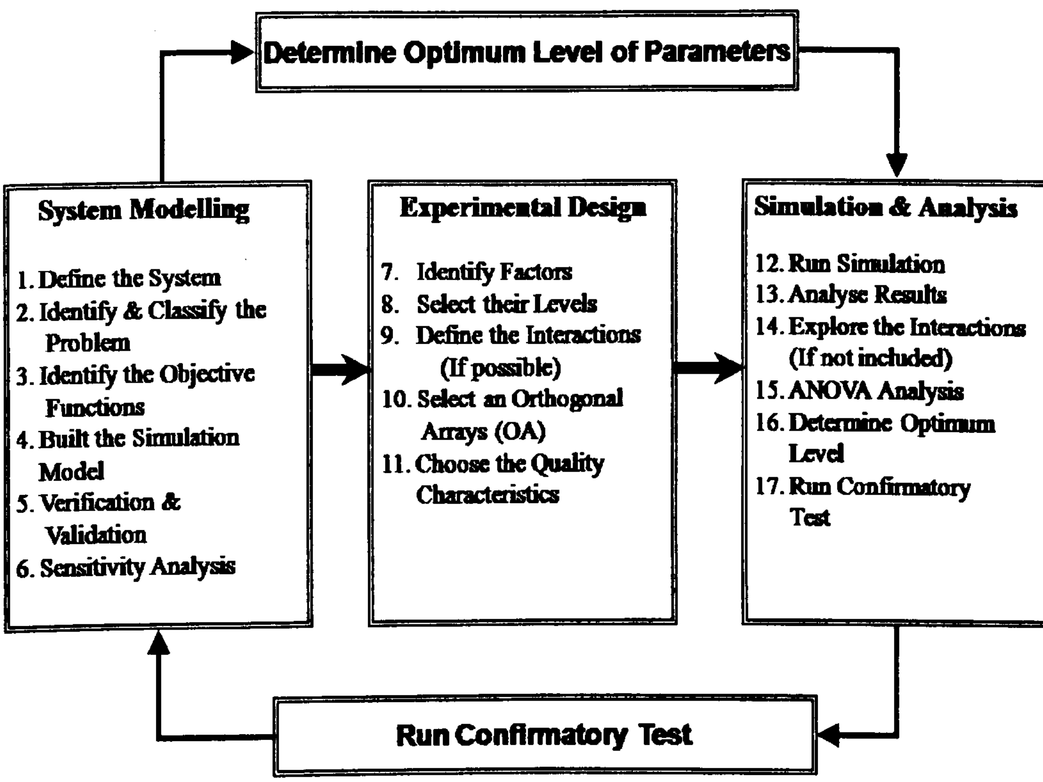


Figure 3.1 Research Design

i. Problem Articulation. A common scientific tool applied in studying problems and solutions is modeling. The model should be built on selected aspects of systems to investigate the specific problem and should not include the whole complexity of a system. Van De Ven (2007) argued that problem formulation is the first important task in research and plays a crucial role in grounding the subject. The literature review has been the primary source to identify the problem. Through extensive literature review, gaps in theory are explicitly stated in each chapter and a methodology is presented to fill these gaps.

ii. Formulating a Dynamic Hypothesis. This step is also known as the "conceptual modeling phase" and involves the development of theory that explains the causes behind the problem. Such theory or hypothesis needs to be converted into a formal simulation model. The following major activities are involved in this step: A problem is examined from the literature review, variables involved in the concerned dynamics are listed and finally a causal diagram is constructed.

The causal loop diagram of the *Inventory and Order Based Production Control System* (IOBPCS) used in this research is shown in Figure 3.2. Causal loop diagrams involve positive loops and negative loops. A positive (i.e. + or **R**) loop is always reinforcing and tends to amplify the state of the system. A negative (i.e. – or **B**) loop resists the change by forcing the system either to fluctuate or to move towards equilibrium. The order rate (ORATE) shows the inflows of the orders to the factory, which is in turn affected by the feed forward flow (**R**) of smoothed sales (SSALES) and the feedback flow (**B**) of error in the inventory (EINV). SSALES and EINV are affected by converters time to adjust error of the inventory (Ti) and time to average sales (Ta). The factory always takes time to produce something so a delay is introduced between the order rate and the completion rate (COMRATE). Once goods are ready these are accumulated in the inventory. Orders are shipped from actual inventory (AINV) and the whole cycle starts again.

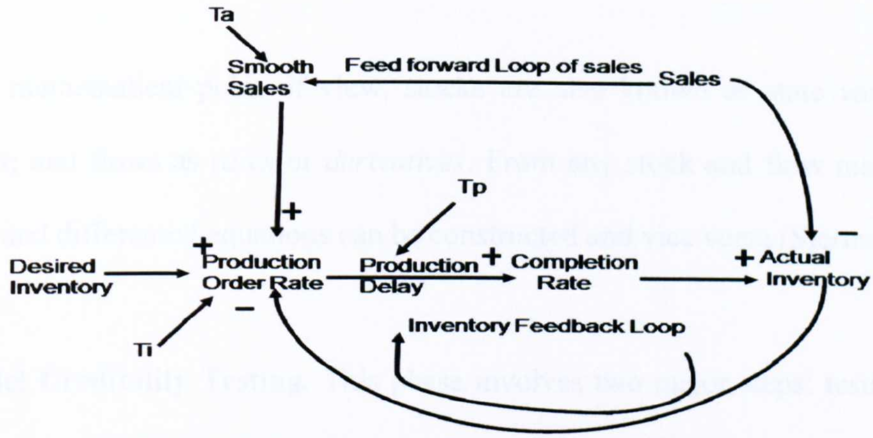


Figure3.2. Causal Loop Diagram of IOBPCS System

iii. Formulating a Simulation Model. The limitation of causal loop diagrams is their inability to capture the stock and flow structure of the systems (Sterman, 2000). Stock and flow diagrams use graphical symbols to distinguish between different types of entities. In this step a formal simulation model is constructed using the iThink software. This phase involves constructing the stock and flow diagram, writing mathematical equations to relate the variables and defining initial values of parameters. The stock and flow diagram of the basic inventory and order based production control system (IOBPCS) studies here is presented in Figure 3.3.

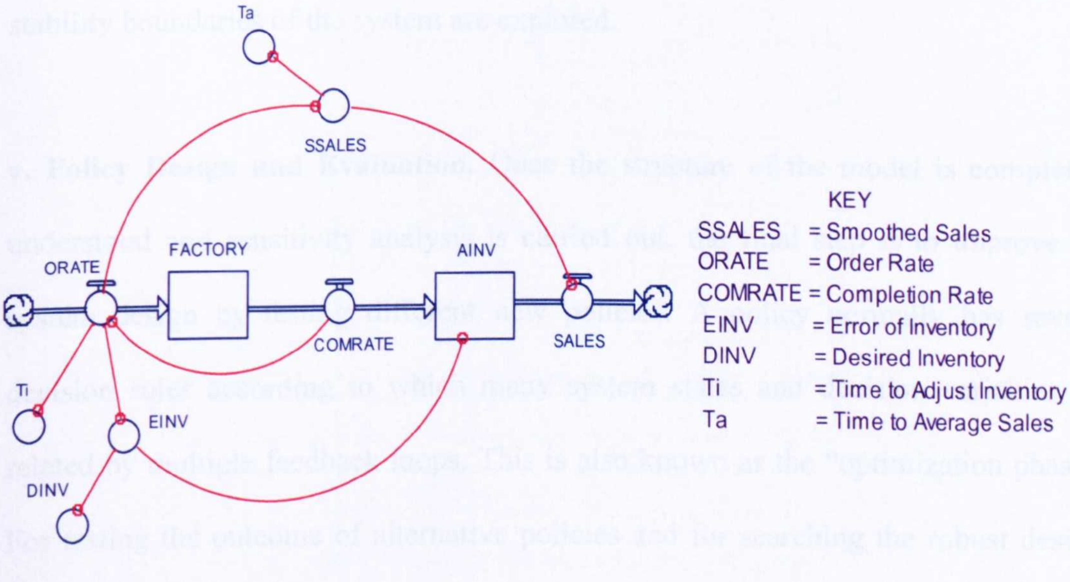


Figure 3.3. Stock and Flow Diagram of IOBPCS

From a mathematical point of view, stocks are also known as state *variables* or *integrals*; and flows as *rates* or *derivatives*. From any stock and flow map, system integral and differential equations can be constructed and vice versa (Sterman, 2000).

iv. Model Credibility Testing. This phase involves two major steps: testing of the model and sensitivity analysis. Testing means whether the structure of the model is the proper description of the real relations between design parameters. Various model testing techniques are available. One of the most commonly applied technique is *Behavior Reproduction* (Sterman, 2000). Plotting the dynamic outputs against real data in a graph representing behavior of the model over time is particularly insightful. In the case of this thesis, these dynamic outputs can be variances in order rate and inventory level. Sensitivity analysis determines the stability boundaries of the system. In Chapter 5, the model is tested and a theory is developed by exploring the impact of batch size on the bullwhip effect. Finally to confirm these findings, sensitivity analysis is carried out by changing the values of design parameters and the stability boundaries of the system are explored.

v. Policy Design and Evaluation. Once the structure of the model is completely understood and sensitivity analysis is carried out, the final step is to improve the system design by testing different new policies. A policy normally has several decision rules according to which many system states and decision variables are related by multiple feedback loops. This is also known as the "optimization phase". For testing the outcome of alternative policies and for searching the robust design, system dynamics simulation must be coupled with an optimization tool. Supply chains consist of many interacting parameters per each echelon and relationship between these parameters is causal. Taguchi Design of Experiments, which can deal with maximum number of parameters with minimum number of experiments and in which level of each factor is systematically varied, is introduced as an optimization tool in this research.

3.6 Taguchi Design of Experiments

Taguchi recommended a three stage process to improve quality: system design, parameter design, and tolerance design. In this research, Taguchi's parameter design technique is applied. This provides a method for creating fractional factorial designs using orthogonal arrays. The outline of the Taguchi methods applied in this research is shown in Figure 3.7. The first two steps are the "brainstorming session" or "planning phase". During this phase the objectives, measurement methods and levels of outer and inner arrays are decided.

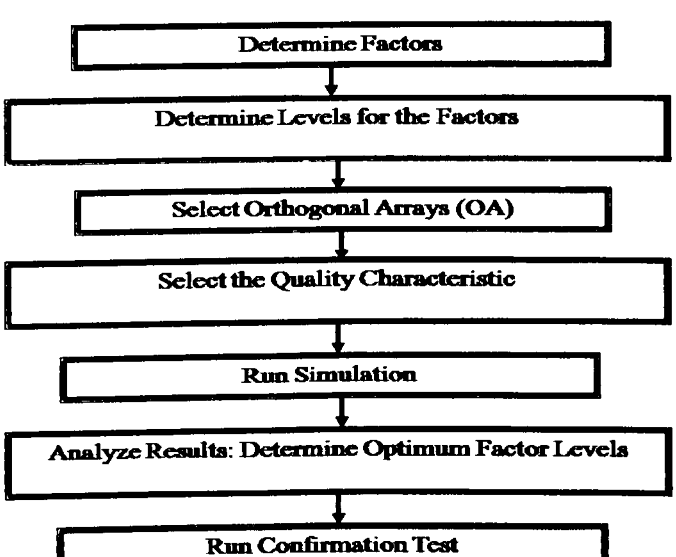


Figure 3.4. Outline of Taguchi Method Applied

3.7 Orthogonal Arrays

The second stage of Taguchi's method applied is the "designing phase". Based on the factors and levels identified, appropriate orthogonal arrays are selected to specify the number of experiments and the manner in which each experiment is conducted. An orthogonal array is a special kind of matrix, which originates from Euler's Latin Square. Orthogonal arrays are written by notation L with a subscript. The subscript indicates the number of combinations of the factors in the experiment. For example, an $L_4(2^3)$ array can be used for three factors at two levels and comprises four rows and hence the four combinations of the factors involved in the study.

3.7.1 Classification of Arrays

In the basic design process, a number of parameters or factors can influence the response of the system. These can be classified into three classes as shown in Figure 3.5 and described below.

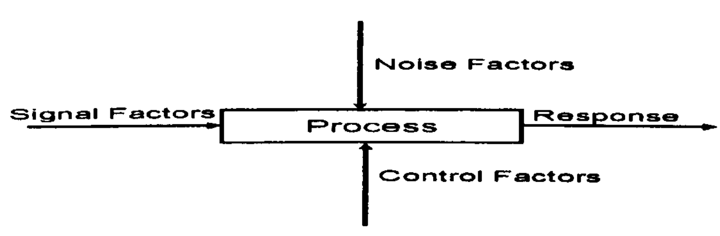


Figure 3.5. Block Diagram of Arrays

i. Control Factors. These form the 'inner arrays' and include those factors that are controllable in real life. In the supply chain model studied, inner arrays are time to adjust inventory and work in progress discrepancies, capacity, and batch size.

ii. Noise Factors. These form the 'outer arrays' and include those factors that are uncontrollable in real life but are controlled during the experiment, examples include sales and lead time. The level of noise factors changes from time to time.

iii. Signal Factors. These factors include those parameters that are set by the experimenter to express the intended value for the response of the product: e.g. temp.

3.7.2 Choice of Orthogonal Arrays

The designing phase of Taguchi's method applied in this thesis involves the choice of orthogonal arrays. The choice of orthogonal array size used in the design of an experiment depends on the total degrees of freedom (DoF) required for the parameters and their interactions. In statistical analysis, DoF is an indication of the amount of information contained in a data set. The DoF of a factor = the number of levels of the factor-1. The DoF of an array = the total of all column DoFs for the array. The DoF of interaction A*B = (DoF of A) x (DoF of B). The columns formed by the horizontal orthogonal arrays are said to be mutually orthogonal, if for any pairs of the columns all combinations of parameter levels occur an equal number of times. The orthogonal arrays must have as many columns as there are factors and interactions involved. Factors and interactions are assigned to array columns via linear graphs. Commonly applied orthogonal arrays with their intended use are presented in Table 3.2.

Array	Intended Use	Levels
$L_4(2^3)$	3 Two Level Factors	
$L_8(2^7)$	7 Two Level Factors	
$L_{12}(2^{11})$	11 Two Level Factors	Two Level Factors
$L_{16}(2^{15})$	15 Two Level Factors	
$L_{32}(2^{31})$	31 Two Level Factors	
$L_9(3^4)$	4 Three Level Factors	
$L_{18}(2^1,3^7)^*$	1 Two Level & 7 Three Level Factors	Three Level Factors
$L_{27}(3^{13})$	13 Three Level Factors	
$L_{16}(4^5)$	5 Four Level Factors	Four Level Factors
$L_{32}(2^1,4^9)^*$	1 Two Level & 9 Four Level Factors	

Table 3.2. Commonly applied arrays and their intended use. *Also known as mixed arrays.

3.7.3. Linear Graphs and Interactions

The multi-echelon supply chain model studied in this research is comprised of seven parameters per echelon. The relationship between these parameters is causal; meaning that changing the value of one parameter will affect the effect of the value of another parameter. To explore the interaction among these parameters, Taguchi's linear graphs and interactions tables are used. Interactions can be explored and can also be included in the experiment. For the interactions to be included in the experiment, Taguchi applied linear graphs and interaction tables to help identify possible combinations of the interaction columns. Linear graphs represent a few possible combinations while the interaction tables provide all possible combination of interaction columns.

A few linear graphs for the commonly applied OA are presented in Figures 3.6a-e. Each circle in the linear graph represents a column within the orthogonal array and an arc represents the interaction between two factors displayed by circles at each end of the arc. DoF for the interaction determines the need for keeping the columns of the array empty. One DoF for the interaction needs one column of the two-level arrays empty and two DoF requires two columns of the three-level arrays empty.

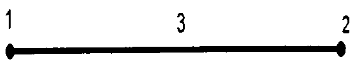


Figure 3.6 a. Linear Graph for an L4 Arrays

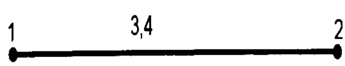


Figure 3.6 b. Linear Graph for an L9 Arrays

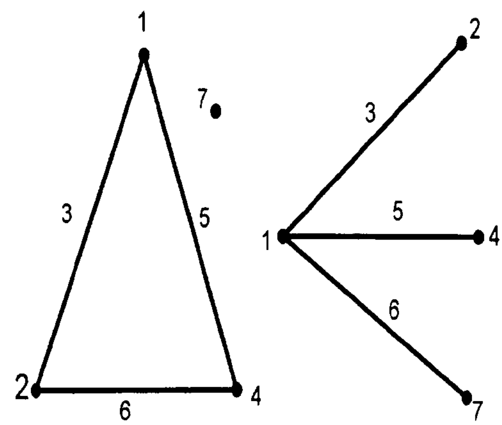


Figure 3.6.c. Linear Graphs for an L8 Arrays

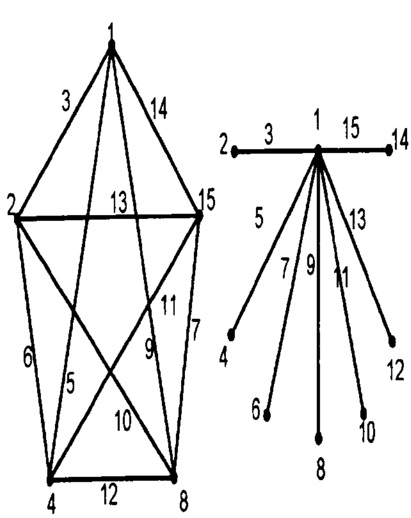


Figure 3.6.d. Linear Graphs for an L16 Arrays

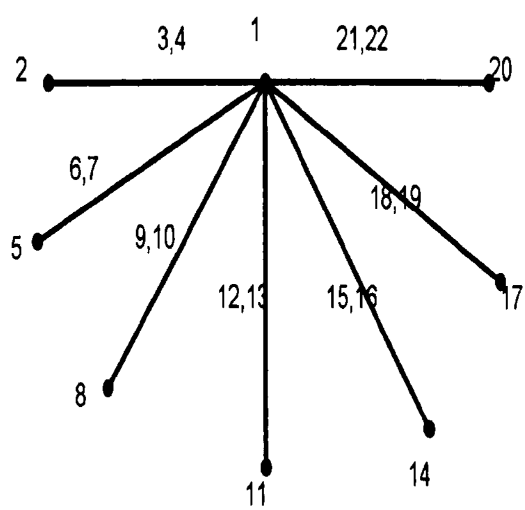


Figure 3.6.e. Linear Graph for an L27 Arrays

3.8. Choice of Quality Characteristics

Once the factors and their levels have been identified and appropriate orthogonal arrays selected, the next step of Taguchi's method is to choose the desired quality characteristics. Taguchi introduced three possible quality characteristics to target; smaller-the-best, nominal-the-best and larger-the-best. This research aims to minimize the bullwhip effect so the quality characteristic of smaller-the-best is selected.

i. Smaller-the-best. This is usually the chosen *Signal to Noise Ratio* (SNR) for characteristics such as minimization of cost, or in this thesis bullwhip reduction. This is used for quality characteristic which can never take negative values and their ideal will be zero and as their value increases performance becomes progressively worse. Equation 2.1 presents the corresponding SNR formula for the quality characteristics of the smaller the best.

$$\text{SNR} = -10 * \text{Log}_{10}\left(\frac{\sum_{i=1} Y_i^2}{n}\right) \qquad (3.1)$$

Where n is the number of observations and Y is the observed data.

ii. Nominal-the-best. This can be used when a specified nominal value is most desired, meaning that neither a smaller nor a larger value is desirable. The SNR for nominal the best is determined by the equation 2.2:

$$\text{SNR} = 10 * \text{Log}_{10}\left(\frac{\text{Mean}^2}{\text{Varaince}}\right) \qquad (3.2)$$

$$\text{Mean} = \frac{\sum_{i=1}^{n} Y_i}{n} \quad \text{And} \quad \text{Varaince} = \frac{\sum_{i=1}^{n} Y_i - \text{Mean}^2}{n-1}$$

iii. Larger-the-best. This is used for quality characteristics that do not take negative values and for which zero is their worst value and is determined by equation 2.3. As their value becomes larger the performance progressively becomes better. When SNR is maximum, the response of the system will be least sensitive to noise factors.

$$S/N = -10 * \text{Log}_{10}\left(\frac{1}{n\sum_{i=1} Y_i^2}\right) \qquad (3.3)$$

3.9. Analysis of Results

In this thesis, experimental results are analyzed to calculate the main effects, interaction effects, ANOVA, and the 'best' values of the parameters.

i. Main effects. The effect of a design parameter on the measured response when the parameter's value is changed from one level to another is known as a "main effect". Main effects are calculated for a particular level of a factor by examining the orthogonal array, the factor assignment, and the experimental results (Roy, 2001). For example, to calculate the average effect of Ti at Level 1, all results of parameter Ti at Level 1 are averaged. Main effect plots are used to depict main effects. When analyzing a factor at three levels, the main effect of the design parameters can be decomposed into linear and non-linear effect as shown in Figure 3.6.

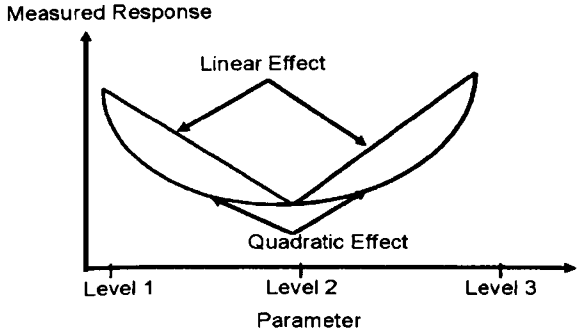


Figure 3.7. Linear & Quadratic Effect

ii. Interaction Effects. If interactions are not included as factors in the OA matrix then interaction effects among parameters are explored. Interaction here refers to factors behaving differently in the presence of other factors such that the trend of influence changes when the levels of the other factors change. Simple but powerful "*interaction graphs*" are used to determine the severity of the interactions between control parameters. If the lines in the graph are parallel there is no interaction between the parameters, whilst non-parallel lines indicate interaction with intersecting lines indicating strong interaction (Antony, 2001). The number of two-factor interactions possible among n factors can be calculated by the formula N=n(n-1)/2. For example, if five factors are considered in the experiment, the number of possible interactions will be 5(5-1)/2=10. The interactions among design parameters of the supply chain model studied are explored in Chapter 5.

iii. Analysis of Variance (ANOVA). The main objective of ANOVA is to find out how much variation each factor causes relative to the total variation observed in the result. The ANOVA procedure applied in this thesis is presented below. The influence of an individual factor is expressed as a fraction (%) of the total variation in the results or measurements. For a set of experimental results, Y1, Y2,...., Yn, the total variation can be calculated by adding deviations of the individual data from the mean value. To assure that all deviations are counted, the individual deviations are squared to make them all positive. So S_T, the total sum of squares is calculated using Equation 2.4

$$S_T = \sum_{i=1}^{N} (Y_i - \overline{Y})^2 \qquad (3.4)$$

This can be reduced to the following form in Equation 2.5.

$$S_T = \sum_{i=1}^{N} Y_i^2 - \frac{T^2}{N} \tag{3.5}$$

where, T^2/N is called the correction factor (C.F) and T is the total of all the results and N is the number of experiments.

Following a similar approach, the variation caused by an individual factor is obtained by an expression called the Factor Sum of Squares. This is calculated by determining the total effect of each level in each factor, by summing the results of each experiment with the factor at the appropriate level. This sum is then squared and divided by the number of experiments that included the factor at that level, as shown in Equation 2.6.

$$S_A = \frac{A_1^2}{N_{A1}} + \frac{A_2^2}{N_{A2}} - C.F \tag{3.6}$$

where, S_A is the sum of squares for factor A, N_{Ai} is the total number of experiments in which level i of factor A is present, and A_i the total of results that include factor A_i. The next step in ANOVA is to calculate the Mean Square or variance (V_A) as shown in Equation 2.7.

$$V_A = \frac{S_A}{f_A} \tag{3.7}$$

Where f_A is the DoF for factor A.

DoF plays an important role in the calculation of confidence intervals and in tests of significance with ANOVA (Roy, 2001, p.211). In statistical analysis of experimental results, the error DoF = Total DoFs – Total of all factors DoFs. If the error DoF is zero, the sum of squares for the error term must also be zero. When both sum of squares and DoF for the error terms are zero, the variance and F-ratios for the error term cannot be calculated. The next step in the ANOVA calculation is to determine the F-Ratios of the factors. F-Ratios are used to see the relative significance of the factors and are calculated using Equation 2.8.

$$F_A = \frac{V_A}{V_e} \tag{3.8}$$

where V_e is the variance for the error term, obtained by calculating the error sum of squares and dividing by the error DoF. With V_e absent, pure sums of squares equal the corresponding sum of squares. Pure sum of squares (S') is determined by Equation 2.9.

$$S'_A = S_A - (V_e * f_e) \tag{3.9}$$

In order to measure the contribution of each factor to the total variation, the percentage influence of each factor is calculated using Equation 2.10.

$$P_A = \frac{S'_A}{S_T} \tag{3.10}$$

The last step in the ANOVA calculation is known as pooling. The process of ignoring a factor once it is deemed insignificant, called pooling is done by combining the influence of the factor with that of the error term. A factor is pooled which has small contribution (Compare S Values) by adding the sum of squares of non-contributing factors. After one or more factors are pooled, ANOVA terms are recalculated and new values for the error terms are established. With the revised error values, pure sums, F-ratios, and the percentage of contribution of each factor can now be recalculated.

iv. Determining the Optimum Values. The final step of the methodology employed involves: determine optimum values and run confirmatory test. Multi-echelon supply chains consisting of many interacting parameters in each echelon are difficult to optimise by direct mathematical techniques. The orthogonal arrays technique seems an appropriate solution. Performance improvement of the system occurs in two areas. First the average of the results will come closer to the target (quality characteristics). The second element of improvement is expected in terms of variation reduction of the distribution of results around the average. Finally, in order to validate the findings a confirmatory test is carried out.

3.10. Summary

This chapter has presented the research methodlogy applied in this thesis. It started with a discussion of research objectives and provided the justification of the research methods used. The chapter then illustrated the research design, the research tools employed, and highlighted the key stages involved in system dynamics modeling ranging from problem articulation to policy design. Next, an introduction to Taguchi Design of Experiments was provided. Finally, the techniques for analysing the results involving main effects and interaction effects and analysis of varaince (ANOVA) were explained.

Chapter 4: The Four Tier Supply Chain Model; Initial Analysis of Effects of Parameter Values

4.1. Introduction

This chapter presents a study of the elements of the four tier supply chain (beer game) model and the initial analysis of the effects of its parameters. Different analytical techniques have been used to investigate the beer game model but none of these is fully satisfactory (White et al, 2006). One of the most commonly applied methodologies to study the various aspects of the beer game model is the control theoretic approach, which focuses on linear modeling and involves the use of the *Laplace or z-Transfer Function* in dealing with the complex differential equations used in modeling the dynamics of the system (Sarimveis et al, 2008). Control strategies can be designed to achieve specific performance levels (e.g reducing the bullwhip effect), but it is difficult to deal with the complex issues such as non-linearities, stochastic behavior, adaptive control and multi-echelon systems related to supply chain modeling (Agaran et al, 2007). However, control engineering techniques are well established and can be used with simulation (White et al, 2006). System dynamic simulation is ideal for mapping complex interactions among design parameters and for studying non-linear outputs through "What If" analysis. Furthermore, control theoretic approaches can require an academically advanced understanding of mathematics that most supply chain operations managers do not have (Agaran et al, 2007). In contrast, the use of system dynamic simulation methods can help supply chain management practitioners to understand better the dynamics of a supply chain and to examine the effects of its parameters' values.

Most of the previous research into the effects of parameter values of production control systems was focused on single echelons (John et all 1994, Riddalls et al 2002), whereas this thesis studies the effects on the dynamic performance of a whole supply chain. Production and inventory control systems seldom exist in isolation, but are connected in series and in parallel to form a complex supply chain. Significant benefits can be gained by doing what is best for the overall supply chain rather than what is best solely for the single echelon. Focusing on the design of a single echelon in isolation without reference to the rest of the supply chain can lead to poor performance overall. Riddalls et al (2000) also pointed out, "*A sequence of locally optimised systems cannot guarantee a global optimum.*" Therefore, the whole supply chain should be taken as a single entity and the best parameter values should be derived with respect to the performance of the whole.

Previous studies of the effects of supply chain parameter values reported the results of changing the value of one, or at most two, parameters at a time. The 'one-at-a-time' approach reveals the effect of one parameter when combined with a particular combination of values for the other parameters, but does not provide the information for calculating the effects of the parameter when combined with any other values for the other parameters, i.e. interactions. It is important to note that the relationship between design parameters is causal, meaning that it is explicitly recognized that changing the value of one parameter may lead to changes in the effects of another parameter. Hence, Taguchi's Orthogonal Arrays technique, in which levels of each factor are systematically varied to understand the effects of a parameter across all possible combinations of values for the other parameters, is appropriate.

Previous studies of supply chain dynamics have focused on deterministic demand patterns. In reality demand is a stochastic process, so it is necessary to study the effects of parameter values with stochastic demand processes. Furthermore, Riddalls et al (2002) have pointed out that no rigorous sensitivity analysis of the design parameters has been carried out on production and inventory control systems. Hence, in this chapter sensitivity analysis of the design parameters on the dynamic response of inventory and order rate has been carried out.

This thesis studies the effect of the parameters of individual production and inventory control systems on the dynamic performance of whole supply chains. It introduces the application of Taguchi Design of Experiments in considering the effects of varying more than one parameter value i.e. interactions, and it considers the response to stochastic demand as well as the dynamic response to deterministic changes in demand.

4.2. Model Description

Since World War II, many researchers have studied production and inventory control systems and models have been developed to investigate various supply chain phenomena. A commonly studied supply chain model is the beer distribution game, which is a simplified but still realistic model with a supply chain consisting of a retailer, a wholesaler, a distributor and a brewery/factory. The earliest description of the game dates back to the work of Forrester (1961) in industrial dynamics. Sterman (1989) developed a multi-echelon beer game and the fundamental control system employed within it has been termed the *Automatic Pipeline Inventory and Order Based Production Control System* (APIOBPCS) (Naim and Towill, 1995). A brief literature review of the model was presented in Section 2.5. John et al (1994) define the *Automatic Pipeline Inventory and Order Based Production Control System*" (APIOBPCS) by, "Let the production targets be equal to the sum of an exponentially smoothed demand (over Ta time units) plus a fraction (1/ Ti) of the inventory error, plus a fraction (1/ Tw) of the WIP error." It is important to note that in APIOBPCS, the desired inventory is assumed constant. By incorporating a variable desired inventory as a function of demand, APIOBPCS can be changed into the *Automatic Pipeline Variable Inventory and Order Based Production Control System* (APVIOBPCS) shown in block diagram form in Figure 4.1. The variable inventory enables the modelling of supply chains where it is necessary to update the "inventory cover" over time (Disney and Towill, 2005). As the block diagram shows, APVIOBPCS has four design parameters n, Ta, Ti and Tw and one system parameter to model the production delay Tp. Where, n is an inventory cover which determines the amount of inventory required to obtain the desired service level. The inclusion of an inventory feedback loop equates to a "make to stock" strategy and the inclusion of the sales feed forward loop equates to a "make to order" strategy. Combining these two is representative of typical practice in industry.

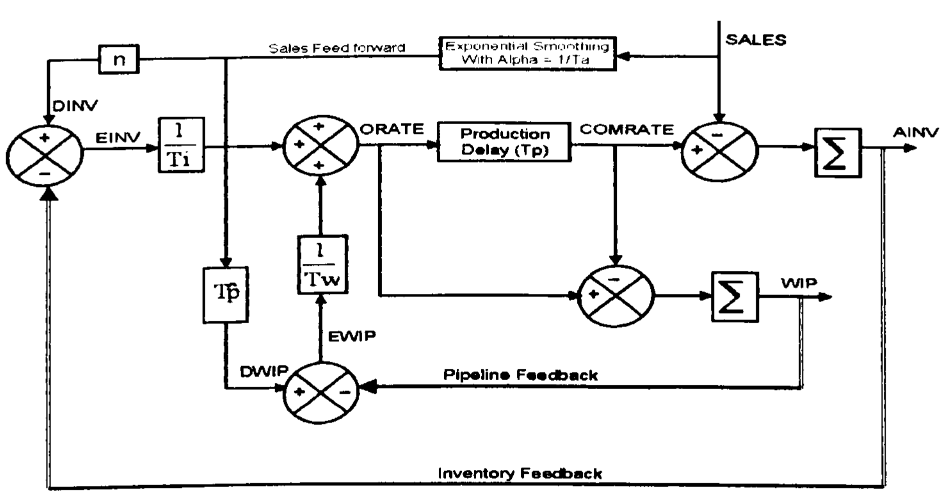


Figure 4.1. Block Diagram of Single Echelon of APVIOBPCS Model

4.2.1. Production Delay (Tp)

In the APVIOBPCS model the process (such as a factory) at the core of a tier is called the production delay and is denoted by Tp; the delay between the placement of the orders and their receipt in the inventory. From a mathematical point of view, there are different types of delays applied in production and inventory control models. The simple pure time delay, i.e. $COMRATE_{t+Tp} = ORATE_t$ is a good approximation of the real world production lead time (Disney et al., 2000) and is easy to implement in simulation. However, mathematical approaches are less amenable to dealing with pure delays as they introduce non-linear behavior (Riddalls and Bennet, 2002). In this thesis the pure time delay is modeled and simulated in iThink.

Figures 4.2.a and 4.2.b show the impact of Tp on the actual inventory and order rate of a single echelon of the supply chain model studied after a step change in demand. Figure 4.2.a shows that smaller lead times reduce the maximum inventory deficit and recovery is much quicker, so by reducing lead times companies can minimize their safety stock requirements. Figure 4.2.b shows that smaller lead times create a smaller overshoot in order rate in response to a pure step change in demand. This means that by decreasing lead times companies can reduce their capacity requirements.

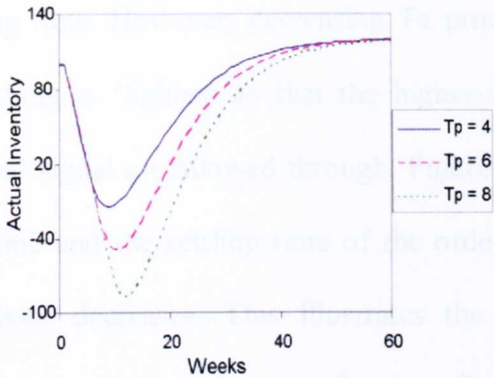


Figure 4.2.a. Impact of Tp on Inventory

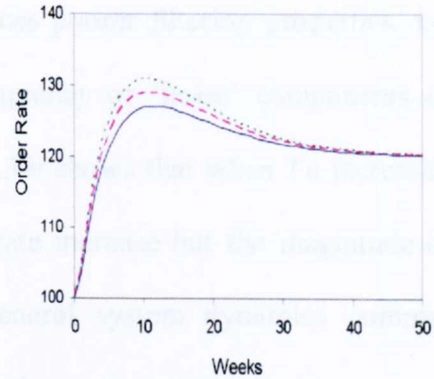


Figure 4.2.b. Impact of Tp on Order Rate

Ti =Tw = 6; Ta = 8

4.2.2. Demand Policy (Ta)

Allowing demand to be used for scheduling without some form of smoothing always results in excessive fluctuations in production rates (Stalk and Haut, 1990). Therefore, demand needs to be smoothed before applying it for scheduling. There are many methods of smoothing the demand. In the APVIOBPCS model simple *Exponential Smoothing* is used. It is the function of previously calculated demand and is weighted towards recent demand values. In iThink the built-in function *SMTH1* calculates the first order exponential smoothed value. In SMTH1, the value of the smoothing constant, denoted as Ta, represents the time to average sales and determines the average age of data in the forecast. The value of Ta determines the degree of smoothing applied to the demand.

$$\mathrm{SSALES}_t = \mathrm{SSALES}_{t-1} + \frac{1}{\mathrm{Ta}}(\mathrm{SALES}_t - \mathrm{SSALES}_{t-1}) \qquad (4.1)$$

The step-response of the inventory in Figure 4.3.a shows that when Ta decreases the response is quicker, displaying a reduced peak deficit, rise time and settling time. However, decreasing Ta produces poorer filtering properties, i.e. the smoothing is 'lighter' so that the higher-frequency or 'noise' components of the demand signal are allowed through. Figure 4.3.b shows that when Ta increases, the rise time and the settling time of the order rate increase but the magnitude of the overshoot decreases. This illustrates the general system dynamics compromise between speed of response and the size of overshoots or over-reactions.

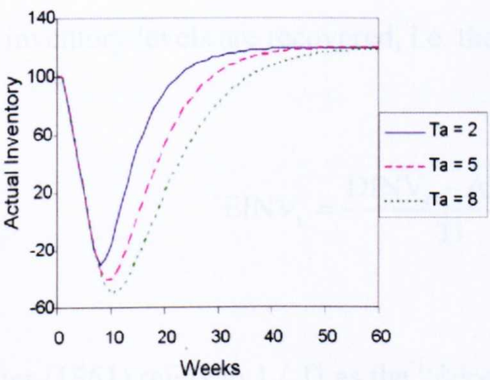


Figure 4.3.a. Impact of Ta on Inventory

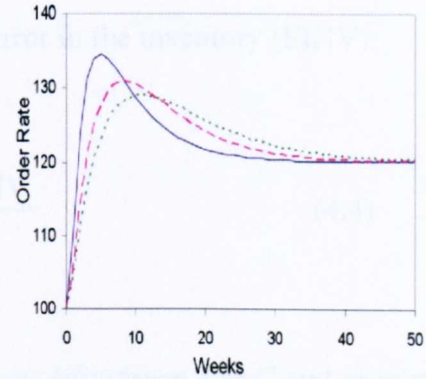


Figure 4.3.b. Impact of Ta on Order Rate

Ti = Tw = 6; Tp = 6

4.2.3. The Inventory Policy (Ti)

The actual inventory levels of the system are the accumulated sum of the difference between the production completion rate and the actual sales. The mathematical equation describing the actual inventory position is:

$$\mathrm{AINV}_t = \mathrm{AINV}_{t-1} + \mathrm{COMRATE}_t - \mathrm{SALES}_t \qquad (4.2)$$

where $\mathrm{COMRATE}_t = \mathrm{ORATE}_{t-Tp}$ An important component to control the production rate in the automatic pipeline variable inventory and production control system is the feedback loop of the error in the inventory. The *Error in the Inventory*

(EINV) is the difference between the *Desired Inventory* (DINV) and the *Actual Inventory* (AINV). In the model presented here, DINV is made adaptive by being set equal to n-weeks of smoothed sales:

$$\mathrm{DINV}_t = \mathrm{SSALES}_t * \mathrm{n} \tag{4.3}$$

In the experiments presented in this thesis n=1. Ti is a divisor applied to the inventory deficit and controls the rate at which discrepancies between the desired and actual inventory levels are recovered, i.e. the error in the inventory (EINV):

$$\mathrm{EINV}_t = \frac{\mathrm{DINV}_t - \mathrm{AINV}_t}{\mathrm{Ti}} \tag{4.4}$$

Forrester (1961) refers to 1 / Ti as the "*Recovery Adjustment Time*" and proposes not to recover the error in the inventory in just one time period. Instead, recovery should be spread over Ti units of time. This is more representative of normal industrial practice where, following a surge in demand, their will be a staged replenishment of the inventory, i.e. production targets should not be set to recover the entire inventory deficit in a single period. The question then arises how much of the inventory discrepancy should be corrected each time period, i.e. what should be the value of Ti? The step responses in Figure 4.4.a show that increasing Ti increases the maximum deficit, the time to rise back to the desired level and the settling time of the actual inventory. Reducing Ti reduces the maximum inventory deficit, although not a great deal, whilst the recovery time, in contrast, is much reduced. The negative aspect of smaller values of Ti is that they can lead to oscillatory behavior; this is seen later in this chapter in the simulation results.

Figure 4.4.b shows that reducing the value of Ti has the typically undesirable effect of increasing the peak overshoot of the order rate, i.e. there is an over-reaction. Lean manufacturing systems, for example, require a leveled demand rather than one with large fluctuations. The magnitudes of the anticipated overshoots of the order rate determine the capacity requirements. If there are to be large peaks in the required order rate, then the capacity requirements will be greatly increased; extra capacity that most of the time will be underutilized. However, rapid recovery of the inventory can be valuable in situations where further increases in demand may cause stock-out and stock-out is highly penalized. So in setting Ti there is a compromise to be made between the speed of the inventory recovery and the amount of capacity required to meet the order rate.

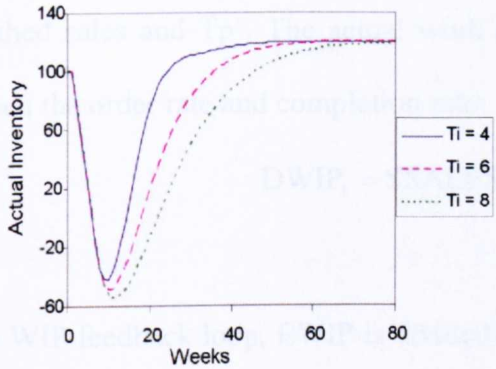


Figure 4.4.a. Impact of Ti on Inventory

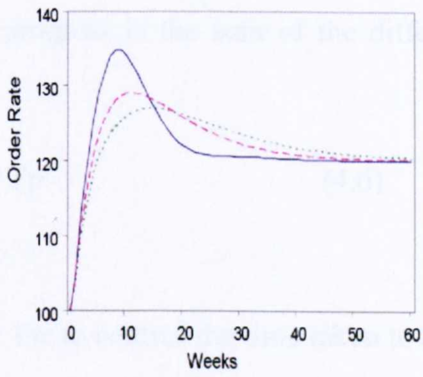


Figure 4.4.b. Impact of Ti on Order Rate

Tw = Tp = 6; Ta = 8

4.2.4. The pipeline policy (Tw)

Sterman (1989) pointed out that poor understanding of the process pipeline (by operations managers), which is the delay between orders being placed and their receipt into the inventory, always disturbs the performance of the system. Hence adding a *Work in Progress* (WIP) feedback loop results in better pipeline control. The *Work in Progress* (WIP) is the accumulation of orders that have been placed on the factory but not yet completed. The main advantage of WIP feedback is that any changes or disturbances, such as machine breakdowns, in the process pipeline are compensated for. In other words, if the pipeline becomes clogged up, the use does not keep turning up the order rate to achieve the desired output. John et al (1994) stated that the incorporation of WIP information into a production control system enables a more stable but faster response. In the model, WIP is simulated by the equation:

$$\mathrm{WIP}_t = \mathrm{WIP}_{t-1} + \mathrm{ORATE}_t - \mathrm{COMRATE}_t \qquad (4.5)$$

The *Error in the Work in Progress* (EWIP) is the difference between the *Desired Work in Progress* (DWIP) and the *Actual* WIP. DWIP is set as the product of smoothed sales and Tp`. The actual work in progress is the sum of the difference between the order rate and completion rate:

$$\mathrm{DWIP}_t = \mathrm{SSALES}_t * \mathrm{Tp}' \qquad (4.6)$$

In the WIP feedback loop, EWIP is divided by Tw to control the time taken to adjust any error in the WIP in the same way and for the same reason that EINV is divided by Ti:

$$\mathrm{EWIP}_t = \frac{\mathrm{DWIP}_t - \mathrm{WIP}_t}{\mathrm{Tw}} \qquad (4.7)$$

Figure 4.5.a shows that Tw has very little effect on the peak deficit in the inventory. However, increasing the value of Tw makes the response faster, reducing both the rise time of the inventory and the time to reach the steady state. Figure 4.5.b shows that increasing Tw increases the magnitude of the overshoot of the order rate

but with little benefit otherwise. So when setting the value of Tw, there is the usual systems dynamics compromise to be made between the speed of reaction and the size of the overshoot, as seen in the speed of recovery of the actual inventory (increased by increasing Tw) and the peak overshoot of the order rate (decreased by decreasing Tw).

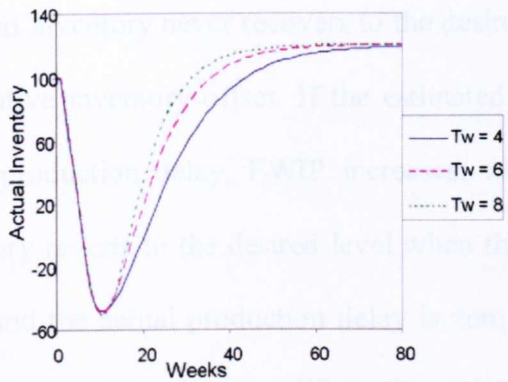


Figure 4.5.a. Impact of Tw on Inventory

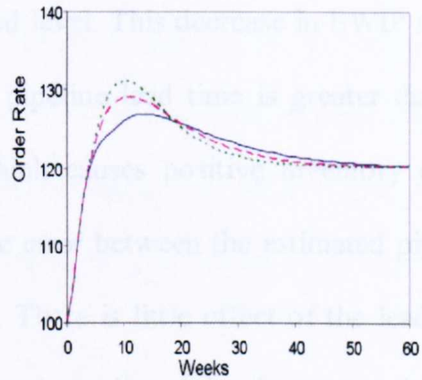


Figure 4.5.b. Impact of Tw on Order Rate

Ti =Tp = 6; Ta=8

4.2.5 Impact of Tp and Tp` on Inventory

In practice the determination of accurate data for WIP is more difficult than for inventories as WIP may be spread all over a factory or other facility whilst inventory is held in a few specific locations, e.g. the goods-out area (Taylor, 1999). APVIOBPCS production and inventory control system requires an estimate of delivery lead time before generating orders. However, with the advent of new technologies such as barcode scanners and RFID, this data acquisition is becoming much easier and more accurate for both. For a stable and robust system, the estimated pipeline delay should always be kept equal to the actual (current) production delay. Failing to match estimated WIP with actual WIP leads to the inventory drift problem (Disney and Towill, 2005). Inventory drift describes the situation where inventory never locks onto the target level after a step change in demand. The main factor in failing to do this is failure in matching the lead time. If the estimated pipeline delay is not equal to the actual production delay then positive or negative inventory offset will occur. Figure 4.6 shows the impact of estimated pipeline delay (Tp`) where actual production delay (Tp) is 6 weeks. If the estimated pipeline delay is less than the actual production delay then the EWIP decreases over time and inventory never recovers to the desired level. This decrease in EWIP results in negative inventory offset. If the estimated pipeline lead time is greater than the actual production delay, EWIP increases, which causes positive inventory offset. Inventory reverts to the desired level when the error between the estimated pipeline delay and the actual production delay is zero. There is little effect of the lead time variations on the order rate. When the estimated pipeline delay is greater then the actual production delay then the magnitude of the order rate overshoot increases and vice versa.

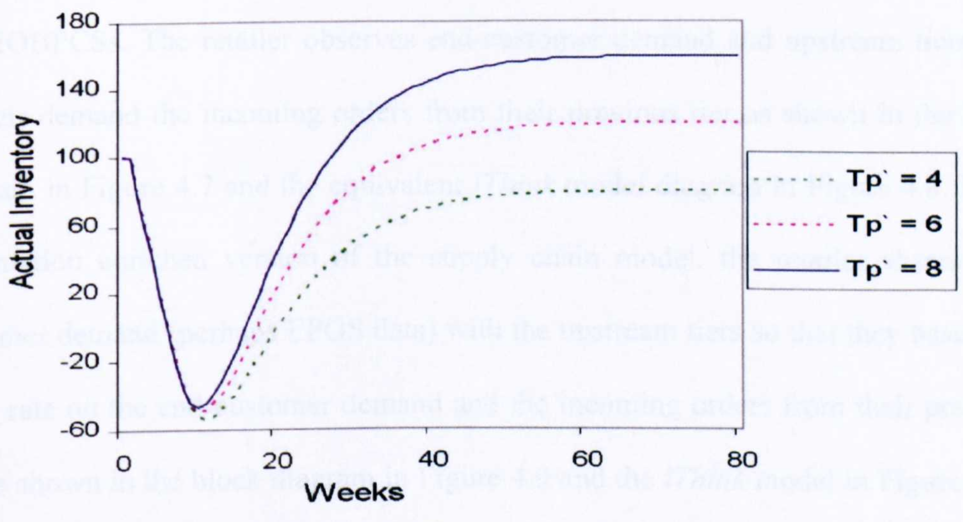


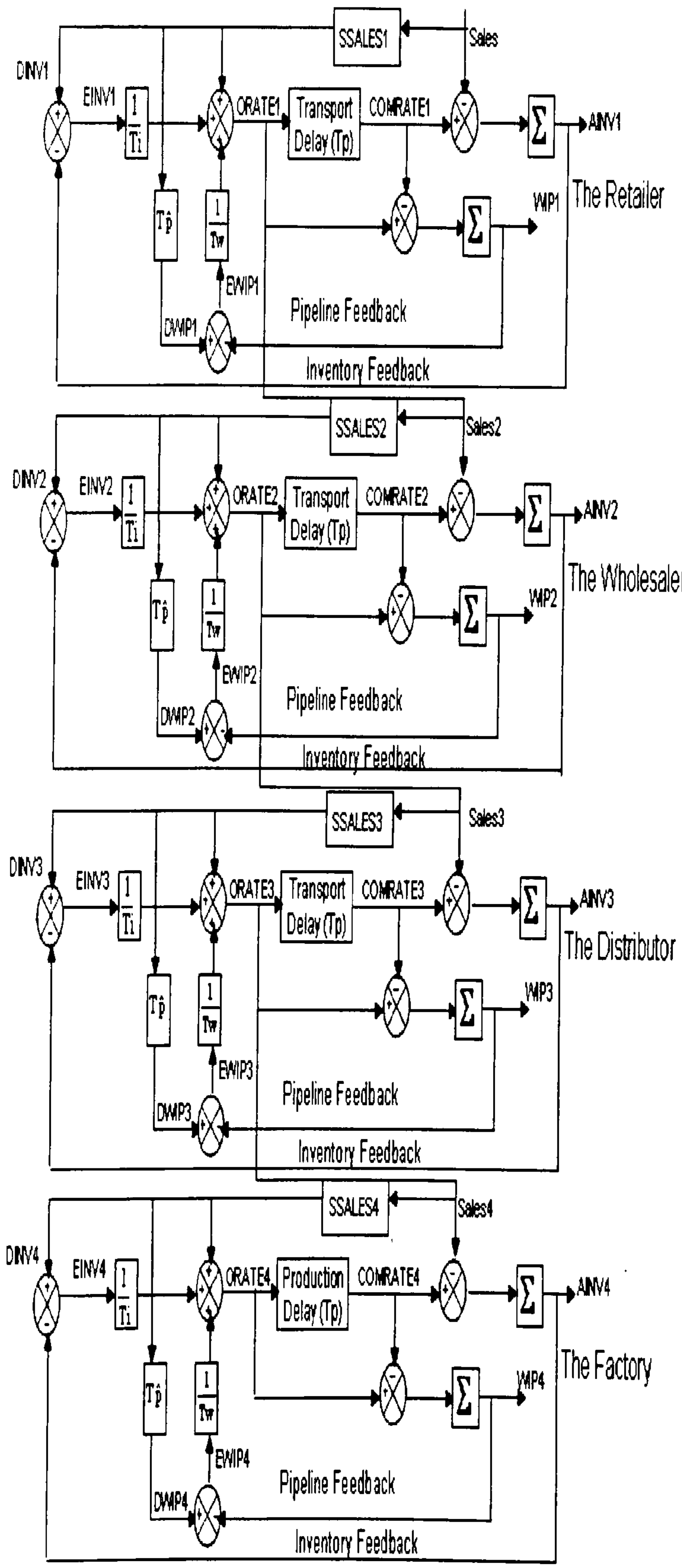
Figure 4.6. Impact of Tp` on Inventory

Ti=Tw=6; Ta=8

4.3 Impact of Information Sharing on the Order Rate and Inventory

In this section, we will show that in a multi echelon supply chain, it is very beneficial to share end-customer demand information throughout the chain. The value of sharing information between echelons (information sharing) has been discussed by many authors, e.g. (Jones et al., 1997), (Lee et al., 2000), (Li et al., 2005) and (Fiala, 2005). The rise of the Internet has made global information sharing easy, low cost and fast. In principle, the information that can be shared includes inventory levels, sales data, demand forecasts, the status of orders, product planning, logistics and production schedules and can be grouped into three types: product information; customer demand information; inventory information (Lee and Wang, 2000).

In this thesis the sharing of customer demand information is first studied by comparing the performance of a supply chain with and without such information sharing. The basic, non-information-sharing supply chain is the four echelons, beer game model without information sharing and is constructed by joining together four APVIOBPCSs. The retailer observes end-customer demand and upstream tiers take as their demand the incoming orders from their previous tier as shown in the block diagram in Figure 4.7 and the equivalent *iThink* model diagram in Figure 4.8. In the information enriched version of the supply chain model, the retailer shares end-customer demand (perhaps EPOS data) with the upstream tiers so that they base their order rate on the end-customer demand and the incoming orders from their previous tier as shown in the block diagram in Figure 4.9 and the *iThink* model in Figure 4.10. In order to lessen the impacts of spikes in customer demand and to avoid ramping production up and down, which offers no benefits, customer demand is smoothed before sharing.



Glossary of Terms

AINV	Actual Inventory
DINV	Desired Inventory
EINV	Error of Inventory
ORATE	Order Rate
COMRATE	Completion Rate
WIP	Work in Progress
DWIP	Desired Work in Progress
EWIP	Error of Work in Progress
SSALES	Smoothed Sales
Ti	Time to Adjust Inventory
Ta	Time to Average Sales, i.e. Exponential Smoothing Parameter
Tw	Time to Adjust Work in Progress
Tp	Actual Manufacturing or Transportation Delay
Tp`	Estimated Pipeline Delay

Figure 4.7. Block Diagram of Multi-Echelon Supply Chain

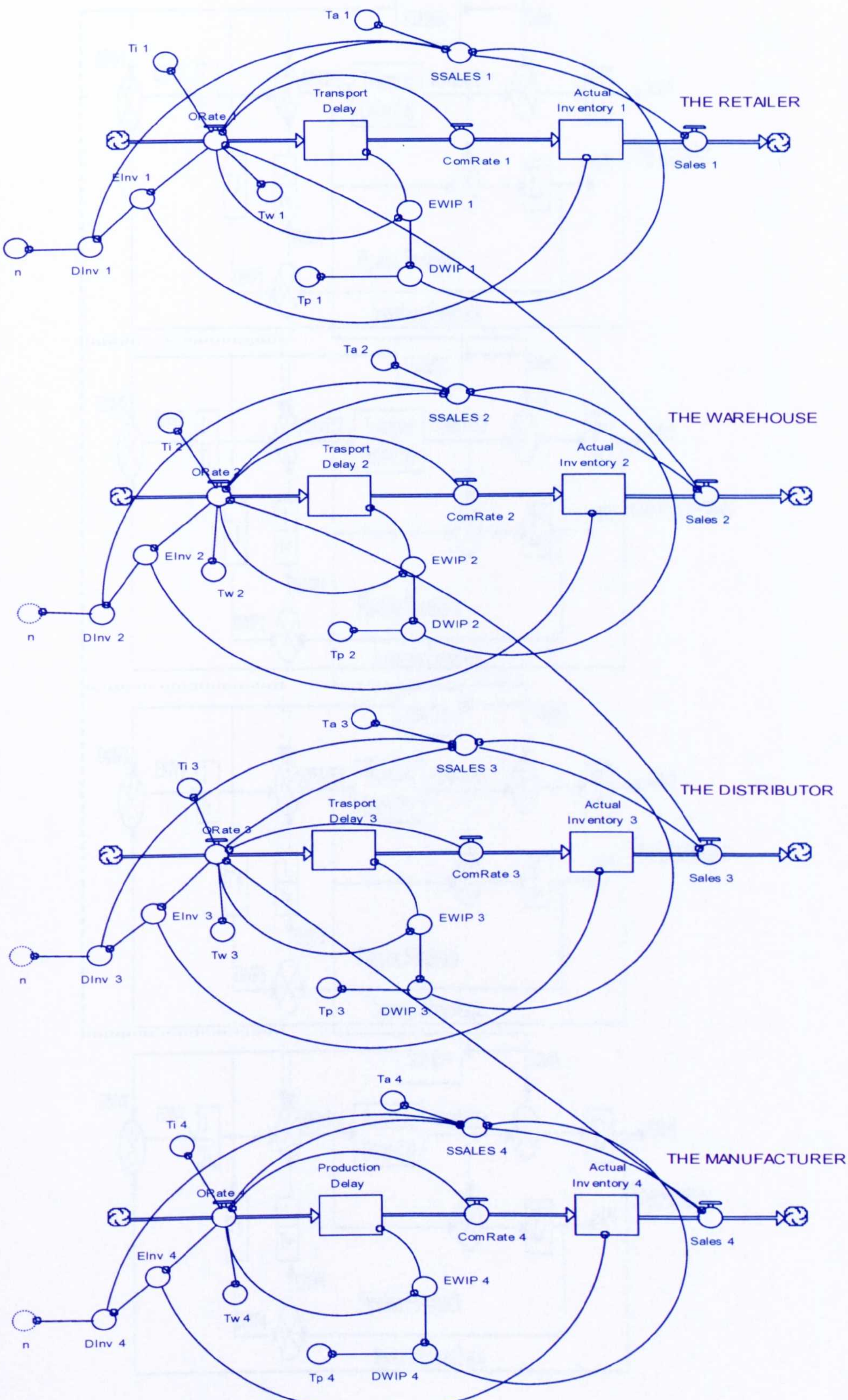


Figure 4.8. iThink Model of Multi-Echelon Supply Chain

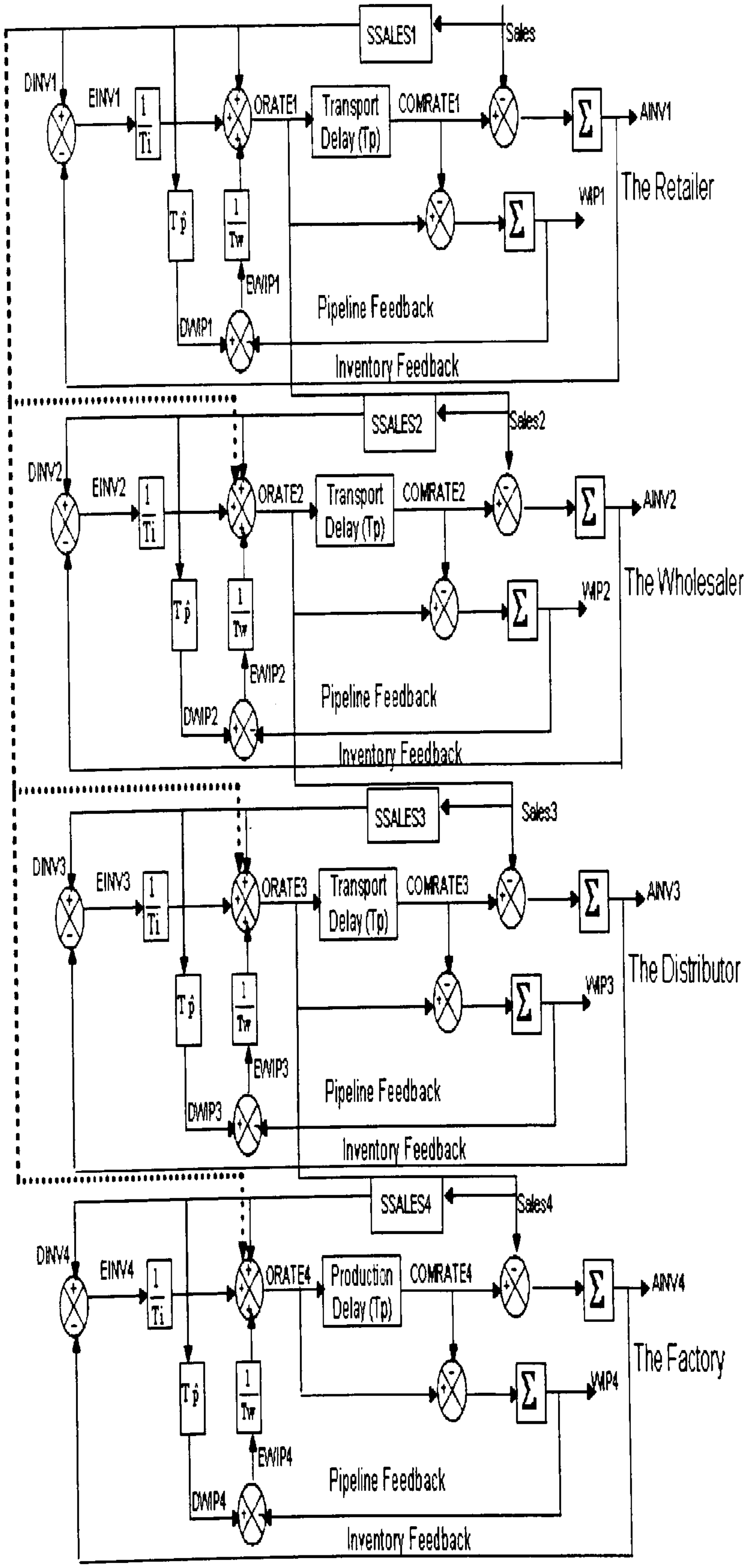


Figure 4.9. Block Diagram of Information Enriched Multi-Echelon Supply Chain

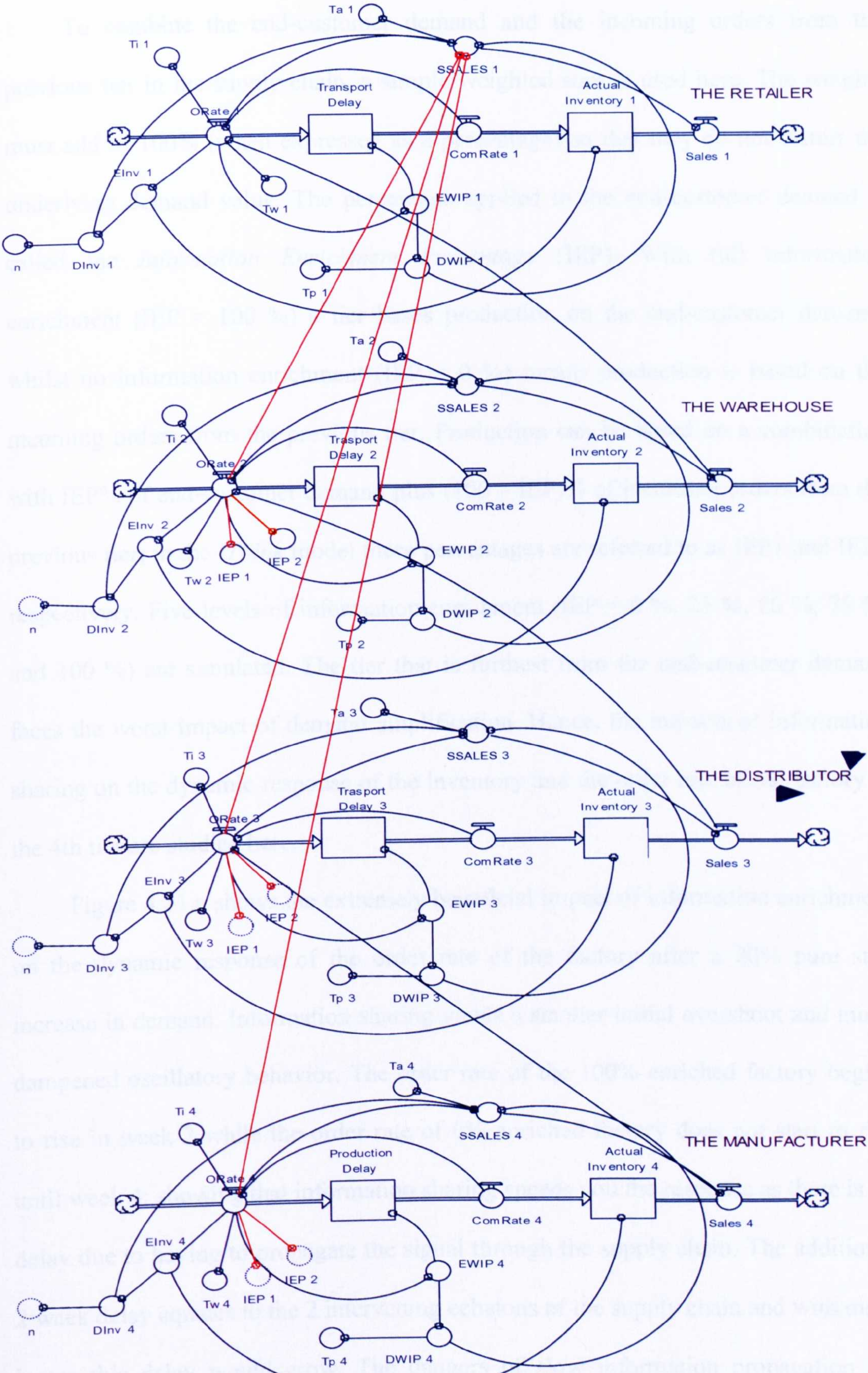


Figure 4.10. iThink Model of Information EnrichedMulti-Echelon Supply Chain

To combine the end-customer demand and the incoming orders from the previous tier in the supply chain, a simple weighted sum is used here. The weights must add to 100% (when expressed as a percentage) so that they do not distort the underlying demand value. The percentage applied to the end-customer demand is called the *Information Enrichment Percentage* (IEP). With full information enrichment (IEP = 100 %) a tier bases production on the end-customer demand, whilst no information enrichment (IEP = 0 %) means production is based on the incoming orders from the previous tier. Production can be based on a combination with IEP% of end-customer demand plus (100 – IEP)% of incoming orders from the previous tier; in the *iThink* model these percentages are referred to as IEP1 and IEP2 respectively. Five levels of information enrichment (IEP = 0 %, 25 %, 50 %, 75 %, and 100 %) are simulated. The tier that is furthest from the end-customer demand faces the worst impact of demand amplification. Hence, the impacts of information sharing on the dynamic response of the inventory and the order rate of the factory at the 4th tier are studied here.

Figure 4.11.a shows the extremely beneficial impact of information enrichment on the dynamic response of the order rate of the factory after a 20% pure step increase in demand. Information sharing yields a smaller initial overshoot and much dampened oscillatory behavior. The order rate of the 100% enriched factory begins to rise in week 2 while the order rate of 0% enriched factory does not start to rise until week 4; showing that information sharing speeds you the response as there is no delay due to having to propagate the signal through the supply chain. The additional 2 week delay equates to the 2 intervening echelons of the supply chain and with more layers this delay would grow. The dangers of slow information propagation are outlined by Stalk and Hout (1990), "*Once information ages, it loses value. The only*

way out of this disjointed supply chain system between companies is to compress information time so that the information circulating through the system is fresh and meaningful".

Figure 4.11.b shows the effect of information sharing on the dynamic response of the inventory of the factory. The initial peak deficit in the inventory is greatly reduced as IEP is increased with 100% IEP reducing the deficit by approximately 30%. There is an even more substantial reduction in the subsequent, overstocking peak of approximately 75%. In essence, the magnitude of the reaction is reduced. However, one downside of this is that the inventory is slower to climb out of the deficit. This longer rise time means that there is a longer period during which there is a backlog in satisfying orders and a higher risk of more stock-out (poor customer service) should the demand rise again. What is seen, once again, is the systems dynamics compromise between the speed of response and the size of overshoots or over-reactions, although in this case the reduction in the size of the overshoot is most dramatic.

In the beer game model, the end-customer demand is distorted by each successive tier in the chain. However, in an information enriched supply chain each tier can base its forecast on the true end-customer demand. The sharing of real customer demand directly removes the problem of distortion and amplification which in turn improves the dynamic performance of the whole supply chain. In the example in Figure 4.11.a, 100% enrichment results in a 55% reduction in the overshoot of the order rate at the factory. This effect on the order rate would be extremely beneficial to a manufacturing business as very large fluctuations in order rate are met by costly over-capacity, buffer stocks or reduced service levels. However, even with information sharing, there is still much room for improving the dynamic performance by tuning the design parameters of the control system, especially Ta and/or Ti.

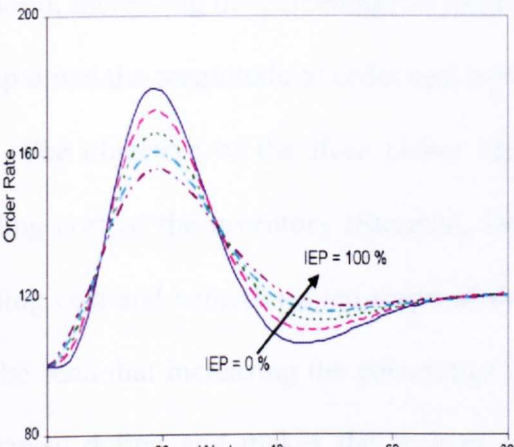


Figure 4.11.a. Impact of Information Sharing on Order Rate

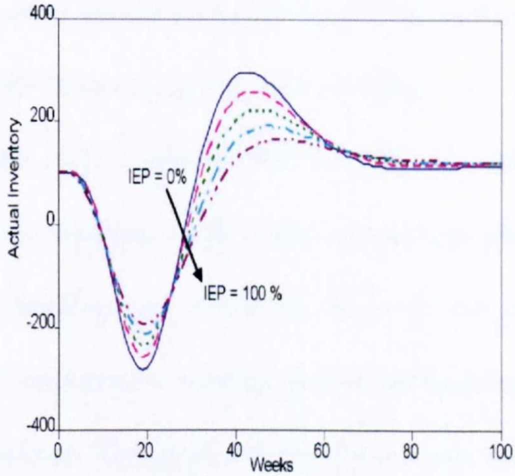


Figure 4.11.b. Impact of Information Sharing on Inventory

Mason-Jones and Towill (1997) also used simulation to study the impact of information sharing on the order rate and stock level of the factory in the APIOBPCS. They found that IEP=75 % provides the best dynamic response. Their argument is that 75% gives a good (best) compromise between reducing the magnitude of peaks and troughs in the response whilst still giving a fast response: the systems dynamics compromise.

In terms of order rate, Figure 4.11.a shows that that as the percentage of enrichment increases the amplification and response time of the order rate decreases. So, it can be concluded that increasing the percentage of information enrichment decreases the bullwhip effect. Hence, in terms of bullwhip effect reduction across the multi-echelon supply chain 100% enrichment should be preferred. The Mason-Jones and Towill (1997) hypothesis is based on a supply chain model with no capacity constraints. It is also reasonable to think that production and distribution are in reality capacity constrained and it may not be possible to increase activity levels to cope with peak demand, even if it is possible to do it; sometimes cost would be so high that it is not an acceptable solution. Overshoot of the order rate determines the capacity requirements. Greater the overshoot the more capacity is needed. In such scenario, increasing the percentage of information enrichment (100 % IEP) to further damp down the magnitude of order rate overshoot seems appropriate solution.

The objective of the *Beer Game Model* is to minimize the backlog and the holding cost of the inventory (Sterman, 1989). Backlog costs twice as much as the holding cost and sometimes ten times of the holding cost. From the figure 4.11.b, it can be seen that increasing the percentage of information sharing decreases the peak inventory deficit and makes the recover quicker. The peak of the deficit and the recovery time determines the back log cost of the supply chain. Further, the maximum deficit of the inventory determines the safety stock requirements of the company. The bigger deficit requires more safety stock to maintain the desired customer service level. 100 % enrichment reduces the peak deficit of the inventory and makes recovery quicker as compared to 75 % enrichment. Hence, in terms of safety stock reduction and the minimization of the backlog cost hundred percent enrichment should be preferred. Information enrichment reduces the surplus inventory level by damping the peaks of the overshoot of the inventory. Surplus inventory is always an excessive stock which adds to the holding cost. For minimizing the holding cost, 100 % enrichment should be the better solution.

The downside of information sharing is that it increases the rise time of the inventory. Rise time determines the stock out period and affects the customer service level. Whilst the large reduction in the peak inventory deficit is a good thing, there is a longer rise time to replenish the inventory up to the desired level, causing a greater period during which there is a risk of stock-out if any other increases in demand or other supply problems occur. In general, the 75% enriched model performs best for the rise time of the inventory as found by Jones et al (1997), but this is not a strict rule that can be applied in every supply chain, because in some situations the damping of the undershoot and overshoot levels and quicker recovery are more important than the rise time.

4.4 Initial Analysis of the Combined Effects of Parameters

4.4.1 Introduction

The previous sections presented a study of the effects of individual parameters of the echelons on the dynamic response of the supply chain. The next step is to investigate the effects of more than one parameter changing and the stability properties of the multi-echelon supply chain; some parameter value combinations will interact to give unstable performance. It is normally believed that better performance can be gained by reducing time delays in the supply chain and this is not disputed here. However, better performance can also be obtained by carefully selecting the values of the design parameters of the echelons and the supply chain, i.e. tuning the control system. This is a low cost and immediately implemented solution as the physical processes are not altered.

4.4.2 Review of Results in the Literature

The two main design objectives for the robust production and inventory control system are good inventory recovery and attenuation of demand rate fluctuation on the ordering rate (Sarimveis et al., 2008). However, these performance objectives can be conflicting. A trade-off between good inventory recovery and fine rejection of random demand disturbances needs to be explored. To do this, the performance measures discussed above coupled with graphical techniques are used to investigate the impact of design parameters on the performance of the system. Sterman (1987) assumed, through his beer game model, that Tw ≥ Ti, because managers always put more emphasis on their inventory levels than the pipeline. Sterman argues this is reasonable since inventory discrepancies are much more immediately apparent to managers than the variances in the pipeline. John et al (1994) found that for a deterministic input in a single echelon of the APIOBPCS model, Ti = Tp, Tw=Ta=2Tp is a 'good' design. This setting was derived using classical control theory and simulation. This combination avoids unnecessary fluctuations in the inventory and order rate whilst the recovery time is not excessively long. Mason-Jones et al. (1997) explored parameter settings for pipeline feedback that ensures good control of material flow in a four echelon supply chain. They found that the setting of the design parameters for inventory, pipeline, and forecasting is directly related to the production or process lead time. They found that Ti = Tp = Tw and Ta = 2 Tp are the best settings for the four echelon beer game model. Disney et al. (1997) used Laplace-transform transfer-functions and simulation and in order to achieve a trade-off between controlling the bullwhip effect and inventory variances, they proposed that Ti = 4, Tw = 15, Ta = 8 is a good design. Riddalls and Bennett (2002) studied the stability boundaries of a single echelon of the APIOBPCS with a pure time delay to model the production delay. Most notably, they found that the ratio of Ti to Tw plays the most important role in determining stability; for good dynamic behaviour (swift response, no overshoot, small inventory discrepancy, non-oscillatory behaviour) systems with Ti = Tw behave best and are most stable, i.e. furthest from instability. This finding confirmed the similar earlier finding of

Sterman (1989). Riddalls and Bennett concluded that, "it is important to make inventory and WIP adjustments in similar proportions, otherwise one will overcorrect for the other, leading to oscillations." They showed how small increases in Tw, relative to Ti result in much poorer responses in the sense of greater oscillations. They also emphasised that larger values of Ti are undesirable as they lead to slower responses and larger inventory depletion.

4.4.3 Dimensions of the Step Response

Before proceeding to present the initial simulation results of the response of the system to a step change in demand, consideration needs to be given to the features of the step response that are to be studied.

The Inventory Response

To measure performance in respect of controlling or recovering the inventory levels in response to changes in demand, the following inventory impact dimensions are used here (illustrated in Figure 4.12.a):

i. Maximum Inventory Deficit. Following a step increase in demand there is always an initial drop in the inventory level which is called the 'peak or maximum inventory deficit'. It reflects the ability of the echelon to satisfy orders through safety stock and is a fundamentally important measure of performance.

ii. The duration of deficit. After an initial drop in the inventory level due to a step increase in demand, the inventory always takes time to return to the desired level. This is called the duration of deficit and is associated with the stock out period. During periods of deficit customers are not being supplied immediately from stock so that customer service levels are reduced. When the response of the inventory is oscillatory, the first deficit period is used for the measurement.

iii. Maximum surplus inventory. Following the above deficit there may be an over-reaction in the recovery. The first peak or maximum surplus is measured as the difference between the peak of the actual inventory and the desired level. It may be expressed as a percentage of the desired level.

iv. Settling time. The time to recover is the measure of the time when the inventory level settles back at the desired level. Due to the mathematics of the supply chain model it takes a protracted time for the inventory level to settle down to exactly the desired value (error = 0). As a consequence, a more meaningful measure is the time for the inventory level to settle within a small percentage of the desired value e.g. $\pm$ 1 % to $\pm$ 5 %. Like Rice et al (2005), in this thesis the $\pm$ 3 % (compromise) criterion is used.

v. Integral of Time multiplied by Absolute Error (ITAE). The *ITAE* is a standard, widely used measure in (Engineering) Control Theory and System Dynamics. It is the integral of (absolute area underneath) the inventory response multiplied by time and was originally developed by Graham and Lathrope (1953). It penalizes both over and under stocking equally and the time weighting factor penalizes errors of long duration. *ITAE* is a measure of the total fluctuation in the inventory response and therefore the amount of inventory that needs to be held in order to cope with step increases in demand. A smaller value of *ITAE* implies that less buffer stock is required and vice versa. Hence *ITAE* can be considered as a 'surrogate' for an inventory cost metric and is a useful measure of the inventory recovery (Disney and Towill, 2002). The principle is that the smaller the *ITAE* value the better. In discrete form, ITAE is calculated as follows:

$$\text{ITAE}_{\text{AINV}} = \sum_{n=1}^{\infty} n \left| E_n \right| \qquad (4.8)$$

where n is the time period and E_n is the error in the inventory at time n, measured as the difference between the actual inventory level and the desired inventory level.

The simpler *Integral of Absolute Error* (IAE) could be used without the time weighting (n), but it is generally viewed as being inferior to the ITAE which gives greater weighting to the errors occurring longer after the initial change in demand, thereby highlighting responses with a protracted settling time or extended oscillatory behavior as well as those with large initial peaks or troughs.

The Order Rate Response

To measure performance in respect of controlling or recovering the order rate in response to changes in demand, the following order rate impact dimensions are used in this research (illustrated in Figure 4.12.b):

i. Rise time. This is the time to reach the desired order rate for the first time following a change in demand and is a measure of the 'speed' of the response. However, this may be followed by a large overshoot and possibly oscillatory behaviour during a settling period. Whilst faster rise times may be desirable, they produce undesirable, larger overshoots and oscillatory behavior, so the usual systems dynamics compromise is required.

ii. Peak time. This is the time at which the step response reaches its first maximum peak value and is related to the rise time.

iii. Peak order rate. This is the magnitude of the maximum or peak order rate seen in the response to a step change in demand. The maximum order rate determines the maximum capacity required and the maximum 'stress' placed on the system. It also indicates how 'dynamic' the capacity must be in satisfying the order rate. Large peaks in the order rate are the manifestation of demand amplification.

iv. Settling Time. As for the inventory level, the ± 3 % criteria are applied.

v. ITAE. This is as described for the inventory level. Generally, factories and other echelons want a smooth order rate that achieves its steady state as soon as possible without too much overshooting and oscillation so that they can plan and utilize capacity more effectively. In general, the smaller the ITAE the better the response in this respect.

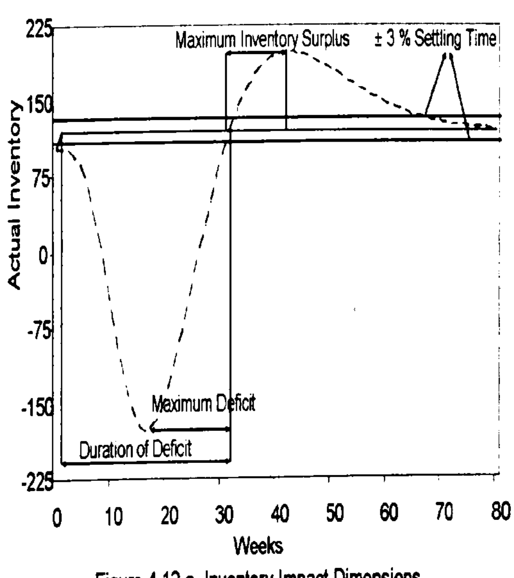


Figure 4.12.a. Inventory Impact Dimensions

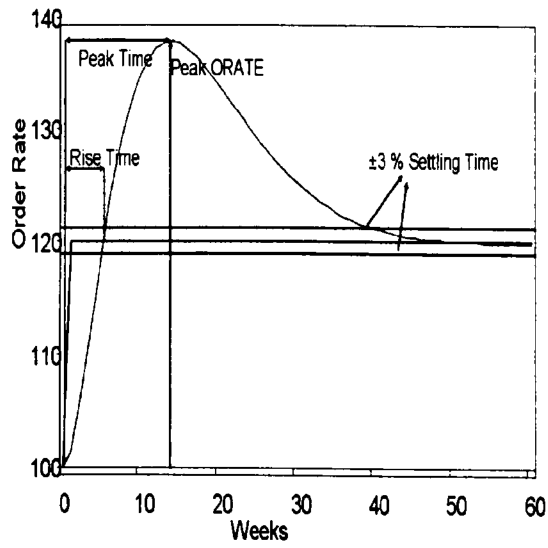


Figure 4.12.b. Order Rate Impact Dimensions

4.4.4 The Step Response Experiments

Previous studies of the effects of supply chain parameters reported the results of changing the value of one or at most two variables at a time. In this thesis, Taguchi Design of Experiments is introduced to analyze a range of parameter values and their interactions, but without having to run an experiment for every combination. This form of analysis is introduced in the following Chapter 5, where Taguchi Design of Experiments and analysis of variance techniques are applied to many sampled responses measured using a single measure of the bullwhip effect. This becomes a somewhat abstract form of analysis in which the actual time-domain response curves are not studied directly 'by eye'. In general, there are too many complex responses for the human brain to analyze without consolidating measures, such as the bullwhip measure, and a systematic method of analysis, such as Taguchi Design of Experiments and analysis of variance. However, the remainder of this chapter does perform a more direct and rudimentary analysis of the effects on the dynamic performance of the 4th tier of the supply chain (as in the previous section) of changing more than one parameter value to gain a direct, 'visual' understanding of what is happening to the responses before proceeding to the more abstract and consolidated perspective seen in Chapter 5.

There are countless potential combinations of meaningful parameter values and this is why Taguchi Design of Experiments is introduced in Chapter 5. In the preliminary analysis presented here, orthogonal arrays of parameter values of the form used in Taguchi Design of Experiments are used to select a representative sample of parameter value combinations, to explore the stability boundaries of the supply chain at the 'worst-case' tier, the 4th tier.

Three factors are considered, Ti, Tw and Ta at four levels as defined in Table 4.1. The appropriate orthogonal arrays of experiments are the L_{16} arrays in Table 4.2 where the columns are mutually orthogonal.

Factors	*Level 1*	*Level 2*	*Level 3*	*Level 4*
Ti	4	6	8	10
Tw	4	6	8	10
Ta	2	4	8	12

Table 4.1. Parameters and their Levels

Experimental Run	*Ti*	*Tw*	*Ta*
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	3
6	2	2	4
7	2	3	1
8	2	4	2
9	3	1	1
10	3	2	2
11	3	3	3
12	3	4	4
13	4	1	4
14	4	2	3
15	4	3	1
16	4	4	2

Table 4.2. L16 Arrays

The test signal is a 20 % step increase in demand from 100 to 120 per week and the simulation is run for 100 weeks as this is enough to capture most of the steady-state responses. Those that go beyond this are simply regarded as 'very long' and unacceptable (well into the region of unacceptable parameter values), although care is taken to check that they do indeed settle on target. A deterministic step input evaluates the system's ability to cope with sudden but maintained change. The response to a step change in demand is of importance not only because it gives a shock to the system but additionally it is an input that is easily visualized and reveals the basic dynamic characteristics of the system (Bonney et al., 1994), (John et al., 1994).

The order rate and inventory step responses for the sixteen different combinations of design parameters are given in Figures 4.13 a-d and Table 4.3. The responses have been divided into two distinct groups. The first group (Figures 4.13 a-b) comprises responses that are clearly stable, without highly oscillatory behavior or large peak overshoots that could be described as over-reaction. The second group does display this excessive over- reaction in its peak responses and possibly oscillatory behavior, i.e. the responses are tending towards instability and are certainly unacceptable for the management of the inventory and production control system.

	Impact on AINV					Impact on ORATE				
Run	Maximum Deficit	Duration of Deficit	Maximum Surplus Inventory	Settling Time	ITAE	Maximum Orate	Rise Time	Peak Orate Time	Settling Time	ITAE
Expt1 – Tier1	-40	28	0	28	10360	144	2	5	14	940
Expt1 – Tier2	-153	14	62	35	24283	192	2	6	23	2493
Expt1 – Tier3	-356	14	280	45	63396	288	3	7	26	7115
Expt1 – Tier4	-763	14	860	45	171502	474	3	8	36	20522
Expt2 – Tier1	-43	20	15	29	14970	140	4	7	16	1786
Expt2 – Tier2	-156	18	150	52	59545	178	4	10	37	7826
Expt2 – Tier3	-374	18	500	67	222987	248	5	12	53	30029
Expt2 – Tier4	-767	18	1375	90	781545	376	6	13	76	106813
Expt3 – Tier1	-50	22	10	42	22136	140	5	9	22	2707
Expt3 – Tier2	-160	20	160	69	90506	172	6	12	45	12760
Expt3 – Tier3	-371	21	535	>100	356765	230	7	15	78	51238
Expt3 – Tier4	-915	24	1375	>100	1283498	337	8	17	>100	185886
Expt4 – Tier1	-50	47	0	47	31548	140	6	10	33	3832
Expt4 – Tier2	-168	22	148	82	127936	170	7	14	65	19928
Expt4 – Tier3	-365	24	508	>100	538975	225	8	17	>100	84602
Expt4 – Tier4	-1040	25	1320	>100	2028719	350	9	19	>100	318166
Expt5 – Tier1	-48	61	0	60	69500	127	5	13	29	3569
Expt5 – Tier2	-86	40	13	80	95324	136	6	16	37	4947
Expt5 – Tier3	-140	37	50	85	166023	147	7	18	40	8505
Expt5 – Tier4	-210	37	112	85	277650	163	8	20	73	14038
Expt6 – Tier1	-60	69	0	57	81080	127	5	12	30	4106
Expt6 – Tier2	-111	43	14	89	110351	137	7	17	38	5772
Expt6 – Tier3	-175	39	56	90	201364	150	9	20	42	10456
Expt6 – Tier4	-262	39	132	90	343597	168	11	24	76	17862
Expt7 – Tier1	-40	25	0	25	12849	136	3	6	15	1211
Expt7 – Tier2	-122	17	70	35	34866	165	4	7	29	3534
Expt7 – Tier3	-293	17	250	49	96320	217	4	8	39	10111
Expt7 – Tier4	-580	17	674	62	259578	310	4	9	46	27823
Expt8 – Tier1	-39	24	7	33	18900	136	4	8	18	1872
Expt8 – Tier2	-140	22	105	51	61273	164	5	11	35	6460
Expt8 – Tier3	-300	22	300	67	189417	209	6	13	50	20262
Expt8 – Tier4	-560	22	845	84	550315	285	7	15	69	59596

Table 4.3. Simulation Results of L16 Arrays-Continued on next page :-

Run	Impact on AINV					Impact on ORATE				
	Maximum Deficit	*Duration of Deficit*	*Maximum Surplus Inventory*	*Settling Time*	*ITAE*	*Maximum Orate*	*Rise Time*	*Peak Orate Time*	*Settling Time*	*ITAE*
Expt 9 – Tier 1	-30	68	0	68	46249	136	3	4	16	2218
Expt 9 – Tier 2	-100	50	0	44	35942	164	3	5	26	1840
Expt 9 – Tier 3	-200	30	10	70	44828	209	4	6	26	4306
Expt 9 – Tier 4	-360	30	100	72	74633	290	4	7	38	11671
Expt 10 – Tier 1	-50	53	0	53	43433	130	4	8	21	2503
Expt 10 – Tier 2	-100	32	10	67	53828	142	5	9	28	3178
Expt 10 – Tier 3	-175	27	50	70	95632	160	6	11	28	5695
Expt 10 – Tier 4	-280	25	120	71	167492	185	7	13	54	9938
Expt 11 – Tier 1	-55	67	0	67	61868	128	6	11	27	3486
Expt 11 – Tier 2	-110	37	21	79	99030	140	8	16	35	5885
Expt 11 – Tier 3	-180	35	80	79	187081	155	9	19	61	10658
Expt 11 – Tier 4	-280	35	180	>100	345900	178	10	21	70	19562
Expt 12 – Tier 1	-70	70	0	70	90064	128	7	14	30	4525
Expt 12 – Tier 2	-125	44	17	93	130385	138	9	19	42	6780
Expt 12 – Tier 3	-193	41	68	93	245745	152	11	23	50	12749
Expt 12 – Tier 4	-286	41	158	>100	427982	170	13	26	80	22343
Expt 13 – Tier 1	-81		0	>100	262092	125	11	20	37	8061
Expt 13 – Tier 2	-107	84	7	>100	286822	130	13	26	62	9526
Expt 13 – Tier 3	-141	74	31	>100	393447	135	16	31	73	12446
Expt 13 – Tier 4	-182	72	67	>100	552944	142	19	40	80	16673
Expt 14 – Tier 1	-60	90	0	84	117386	126	6	17	30	4916
Expt 14 – Tier 2	-91	55	10	96	139211	133	8	20	44	5987
Expt 14 – Tier 3	-137	48	38	>100	232172	142	10	23	49	9688
Expt 14 – Tier 4	-194	46	85	>100	374937	153	12	26	52	15479
Expt 15 – Tier 1	-30	65	0	54	36575	132	2	5	17	2062
Expt 15 – Tier 2	-89	34	4	54	35265	149	3	6	23	2002
Expt 15 – Tier 3	-177	22	26	65	56745	173	3	7	23	3272
Expt 15 – Tier 4	-305	19	75	65	93825	211	3	8	42	5449
Expt 16 – Tier 1	-41	65	0	52	44183	130	4	8	22	2615
Expt 16 – Tier 2	-97	32	15	68	61894	142	5	10	28	3747
Expt 16 – Tier 3	-176	28	64	68	115830	160	6	12	46	7044
Expt 16 – Tier 4	-287	28	157	93	213212	186	7	14	75	13018

Table 4.3 (continued) Simulation Results of L16 Arrays

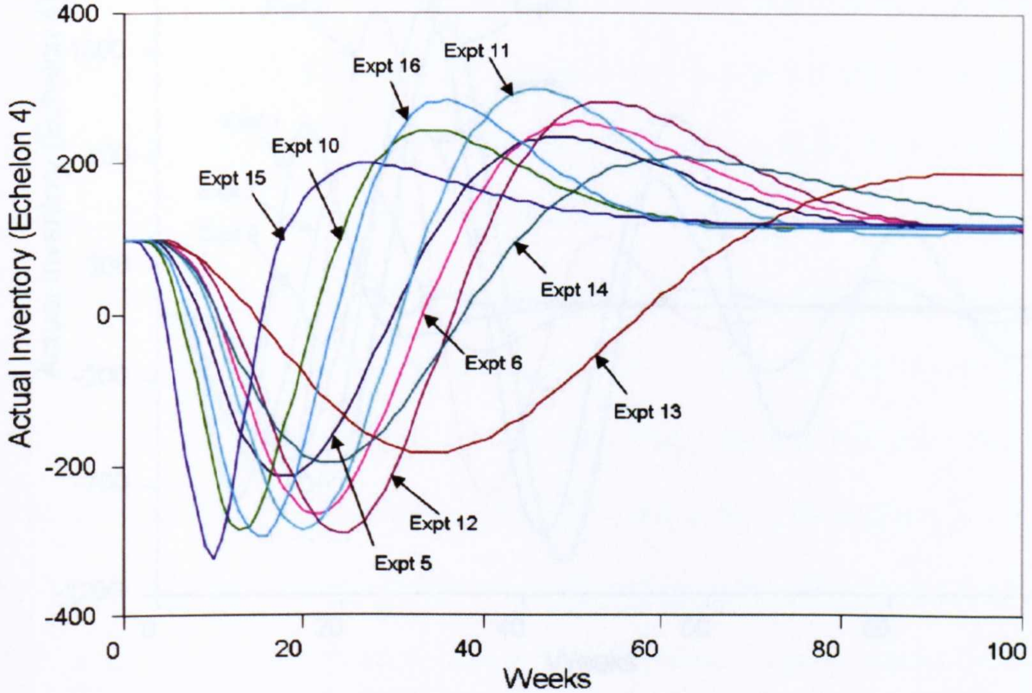


Figure 4.13.a. Impact of Parameters on the Response of Actual Inventory

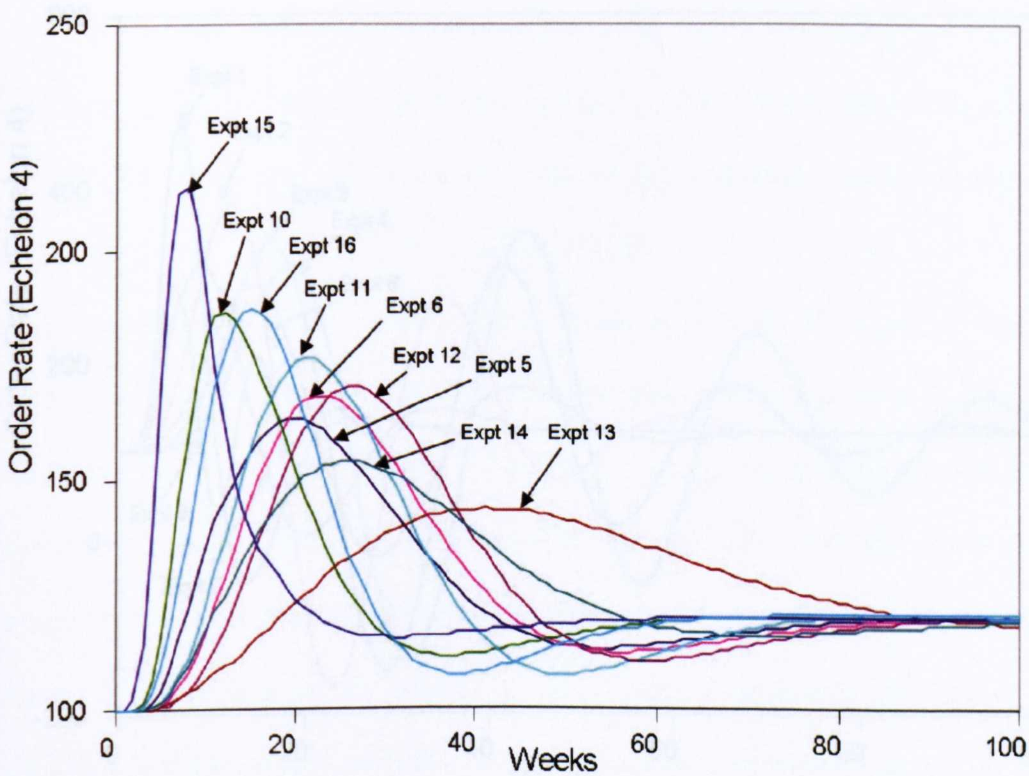


Figure 4.13.b. Impact of Parameters on the Response of Order Rate

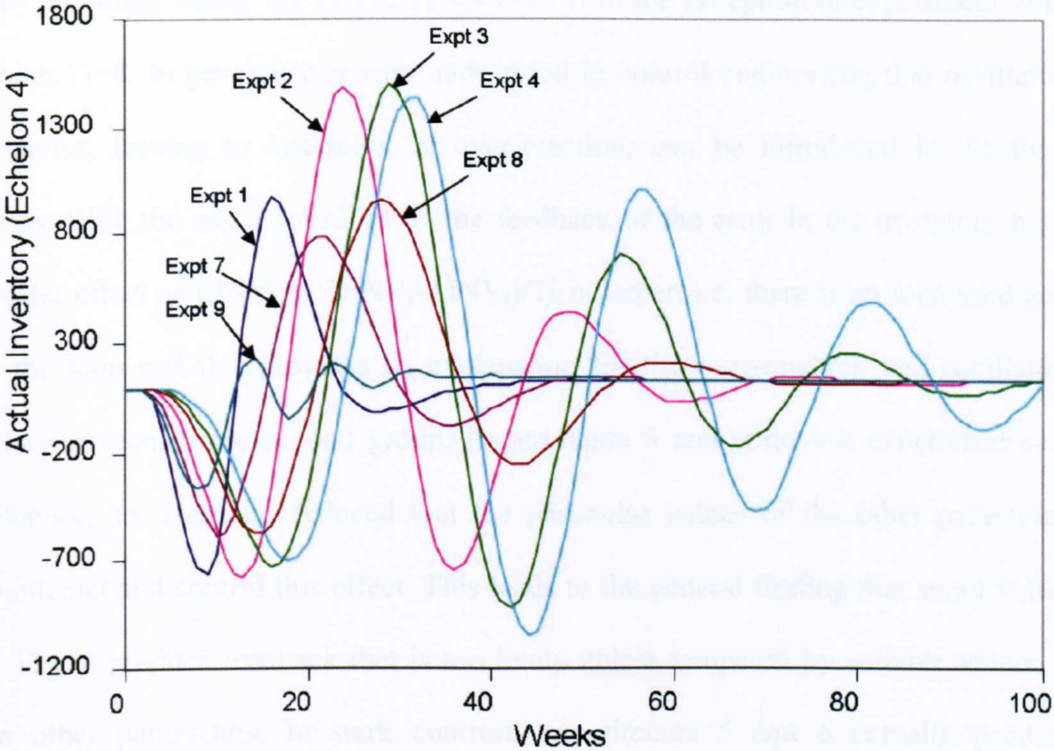


Figure 4.13.c. Impact of Parameters on the Response of Actual Inventory

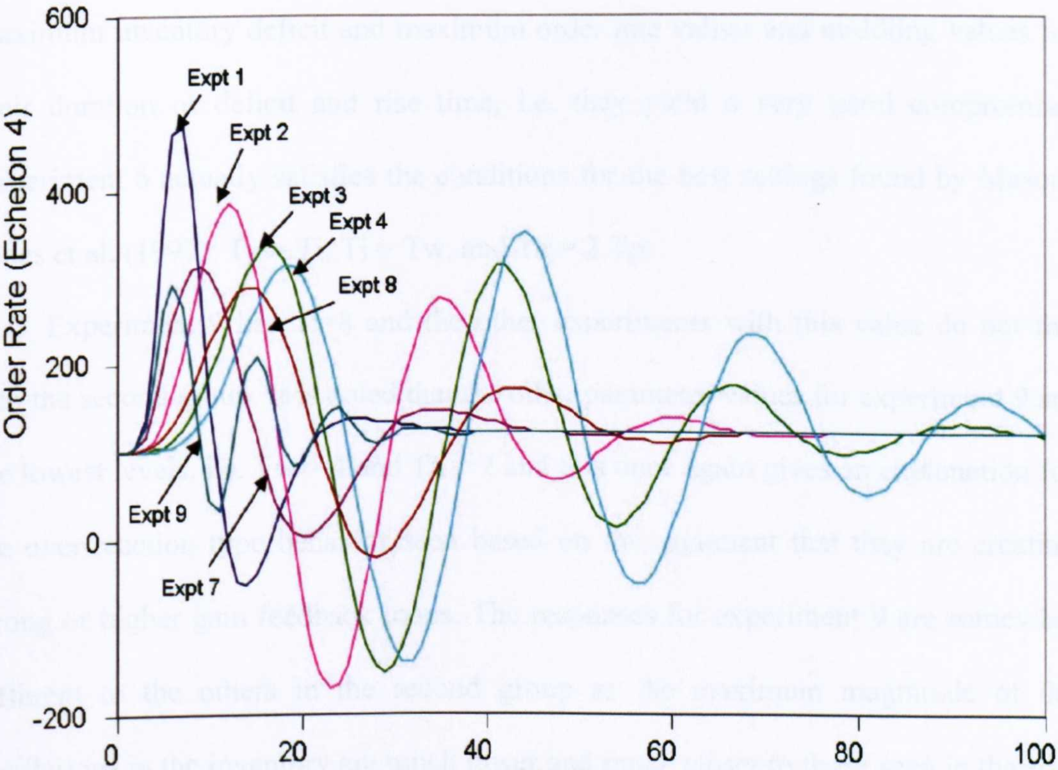


Figure 4.13.d. Impact of Parameters on the Response of Order Rate

The second group comprises experiments 1-4 and 7-9 and Table 4.2 shows that they use small values for Ti, i.e. Ti = 4 or 6, with the exception of experiment 9 for which Ti=8. In general, it is well understood in control engineering that oscillatory behavior, leading to instability or over-reaction, can be introduced by feedback loops. With the small values of Ti the feedback of the error in the inventory has a greater effect as $EINV_t = (DINV_t - AINV_t)/Ti$ is larger, i.e. there is an increased gain in the loop and this provides an explanation for the over-reaction and oscillatory behavior seen in the second group. Experiments 5 and 6 do not experience such behavior, so it can be deduced that the particular values of the other parameters counteract and control this effect. This leads to the general finding that small values of Ti can produce feedback that is too lively unless tempered by suitable values of the other parameters. In stark contrast, experiments 5 and 6 actually produce particularly good results with relatively small ITAE values, two of the smaller maximum inventory deficit and maximum order rate values and middling values for their duration of deficit and rise time, i.e. they yield a very good compromise. Experiment 6 actually satisfies the conditions for the best settings found by Mason-Jones et al. (1997); Tp = Ti, Ti = Tw, and Ta = 2 Tp.

Experiment 9 has Ti=8 and the other experiments with this value do not fall into the second group. It is noted that the other parameter values for experiment 9 are the lowest levels, i.e. Tw = 4 and Ta = 2 and this once again gives an explanation for the over-reaction type behavior seen based on the argument that they are creating strong or higher gain feedback loops. The responses for experiment 9 are somewhat different to the others in the second group as the maximum magnitude of the oscillations in the inventory are much lower and much closer to those seen in the first group. The oscillatory behavior aside, experiment 9 yields one of the best step responses overall with Table 4.3 showing that across all 16 experiments it has the best (smallest) ITAE for the inventory, the 3rd best ITAE for the order rate and relatively very short rise time and duration of deficit.

The first group of responses displays much lower ITAE values and maxima in their responses, and less behavior of an oscillatory nature, in other words, smaller over-reaction and therefore tendency towards stability. However, experiment 13 can be viewed as going too far in this direction, resulting in too slow a response with an extremely long duration of deficit and a very late peak order rate time. Experiment 14 is also wandering out in this direction. In general, with the exception of the slower experiment 13 and perhaps 14, the first group of experiments, plus possibly experiment 9 from the second group, is beginning to define the boundaries of acceptable and highly stable performance and therefore the region of acceptable control system parameters. The question of experiment 9's inclusion is considered later when studying the stochastic response.

Experiments 5 and 6 illustrate the general systems dynamics or engineering principle that high feedback gain systems can soon move from good fast behavior towards instability with changes in parameter values i.e. there is high sensitivity. On the other hand, slower systems produce more robustly stable responses but at the cost of tending towards being too slow, as seen in experiments 13 and 14, which endorse the finding of Riddalls and Bennett (2002) that larger values of Ti are undesirable as they lead to slower responses and larger inventory depletion.

According to the ITAE criteria, experiments 15, 9 and 10 are the best in that order. Experiment 15 has the lowest ITAE for the order rate and the 2nd lowest for the inventory. Figure 4.13.a shows that experiment 15 does indeed have one of the best inventory responses as it is very fast but without excessive overshoots compared to the rest of the first group. However, Figure 4.13.b shows that the order rate, although fast to rise and return close to the target, has a relatively large peak overshoot. This very large peak would be most undesirable in a typical real-world production control situation. Much better order rate responses are clearly achieved in experiment 5, which still has a relatively low ITAE, but only the 5th lowest. It could be argued that experiments 10 and 16 give the best compromise as they lie between 5 and 15. Generally, the results demonstrate that ITAE must not be used on its own in selecting parameter values for a production control system. Large, but not excessive, peak overshoots are not typically so undesirable in electrical and electro-mechanical engineering and the usual world of 'hard systems' control engineering, from where ITAE has been adopted as a measure of performance. This is a most notable difference between the requirements of production control and typical hard-systems control. Lean manufacturing and the efficient utilization of expensive manufacturing resources is predicated on demand leveling rather than the large peaks in control signals seen in the control of electro-mechanical systems with, possibly, high levels of inertia. Human beings cannot produce twice as much immediately, whereas an electrical motor can be expected to respond to large increases in electric current.

The finding of Riddalls and Bennett (2002) that Ti = Tw produces the best, or at least 'good' responses is partially borne out here. When Ti=Tw=4, i.e. small, the response is of the unsatisfactory type in the second group (experiment 1). However, for larger values the Ti = Tw condition does produce good results (experiments 6, 11, 16) in respect of all the measures. Looking at the results it is primarily when Ti is small that the system over-reacts and tends towards instability (see experiments 1-4 and 7-8). In contrast, when Tw is small the other parameters are more able to compensate (see experiments 5 and 13). So a rider should be added to the original finding that Ti = Tw produces good results provided that this is not over-ridden by too much gain in the inventory feedback loop, i.e. provided that 1/Ti is not too large, resulting in over-reaction tending towards instability.

4.4.5 Response to Stochastic SALES

A production control system must respond quickly to real, deterministic change whilst not over-reacting to the stochastic components of demand. This is a standard control system paradox. If one considers the exponential smoothing, the noise or high-frequency component of demand is increasingly filtered out by decreasing α (increasing Ta) but the smoother will be slower to respond to real, deterministic change such as a pure step change in demand. If the smoother is made to respond faster by increasing α (decreasing Ta) then the noise will not be so heavily smoothed.

To study the effects of the parameter values on the response to stochastic demand, a customer demand that is a normally distributed, stationary stochastic I.I.D. process with a known mean, μ, and variance σ^2 is simulated. It is assumed that σ is significantly smaller than μ, so that the probability of negative demand is negligible (Lee et al., 1997). In the experiments conducted here μ=100/week and σ^2 =20. The results are the average of 30 simulation runs of the model, each of 300 weeks.

The APVIOBPCS parameter values are the same as those used in the step response experiments, giving a further 16 experiments.

Selecting a best parameter setting for a stochastic SALES pattern is difficult and unreliable (Mason-Jones et al., 1997); what is best in respect of the step response or other deterministic change in demand is not necessarily the best in respect of the response to stochastic changes in demand. As mentioned before, production-distribution systems need a fairly level demand in order to minimize capacity requirements, fully utilize the available capacity and to be able to plan effectively etc. Therefore, it is the variance of the order rate and inventory responses that are measured in the experiments and presented in Table 4.4. Figures 4.14.a-b illustrate the two worst and the two best stochastic responses from the 16 experiments. They shows very clearly the enormous difference in performance caused by changing the parameter values.

Experimental Run	Order Rate Variance		Actual Inventory Variance	
	Tier 1	Tier 4	Tier 1	Tier 4
1	1218	89711	5076	711085
2	515	68609	6052	1417288
3	318	53267	5463	1269797
4	266	70398	6337	1572570
5	170	369	3683	16577
6	116	412	4066	21658
7	665	17961	4881	318041
8	326	14733	4957	343654
9	953	42730	4089	149736
10	270	1147	3959	31919
11	134	622	3744	25398
12	100	610	4078	26710
13	76	67	3356	6582
14	104	206	3605	9918
15	507	3609	3830	49893
16	208	1137	3957	31910

Table 4.4. Results of L16 Arrays

Table 4.4 shows the marked variation in the variances at Tier 4 (Tier 1 is discussed later) across the 16 experiments and, as one might expect, the highest variances are recorded by the second group of experiments i.e. for parameter values that lead to over-reaction tending towards instability. The variances are extremely large, both in absolute terms and when compared with the results obtained by the first group. This leads to the conclusion that the second group simply defines an unacceptable region of parameter values. It should be noted that whilst experiment 9 gave a good ITAE result for the step response and might have been placed in the first group of responses in respect of being acceptable, experiment 9 clearly gives a poor stochastic response and so rests firmly in the second group, although it is still much better than the others in the group.

Within the first group, the ranking of the results, starting with the best or lowest variance is 13, 14, 5, 6, 12, 11, 16, 10, 15. As experiments 13 and 14 produced a very slow step response, too slow indeed, the low variance in the stochastic response is to be expected. However, as the step response was clearly too slow, the corresponding parameter values are not acceptable even though they produce the 'best' suppression of stochastic demand i.e. this setting is too resistant to change, it exhibits too much inertia. Turning to the next two experiments 5 and 6, these produced particularly good results for the step response also, so that overall they appear to represent a very good set of parameter values, and arguably the best. Significantly, experiment 6 satisfies the previously discussed condition Ti = Tw, whilst experiment 5, which has the slightly better results, is close to this condition suggesting that the condition should be Ti≈Tw rather than the more strict condition. Riddalls and Bennett (2002) did allude to this in defining the condition that does not lead to oscillation.

Experiment 6 also satisfies the narrower condition Ti = Tw = Tp and Ta = 2Tp reported by Mason-Jones at al. (1997) as the condition that gives the best results.

It is noted that a fundamental purpose of Ta and the exponential smoothing of SALES is to protect the system from stochastic variation and sudden sharp increases in demand, with the largest value producing the 'heaviest' smoothing. The largest value is Ta=12 as used in experiments 4, 6, 12 and 13. Experiment 13 does indeed produce the smallest variance and experiments 6 and 12 also produce very small variances. However, it is noted that experiment 4 (smallest Ti) produces by far the largest variance and this is extremely large, demonstrating the importance of the other parameters in determining the stochastic response, for example, sales smoothing does not compensate for high gain in the inventory feedback (small Ti).

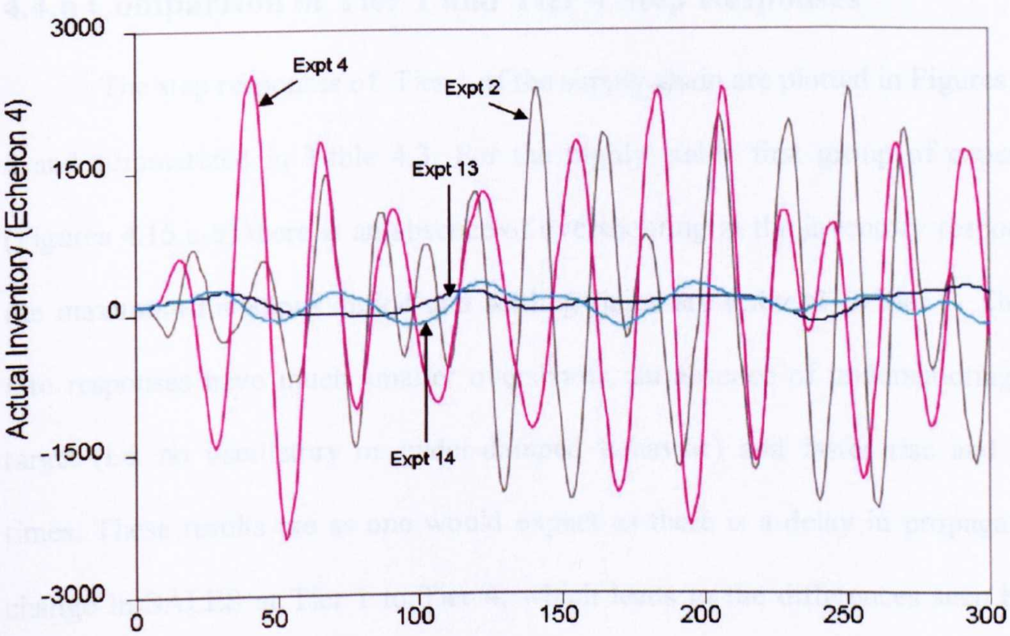


Figure 4.14.a. Stochastic response of AINV 4

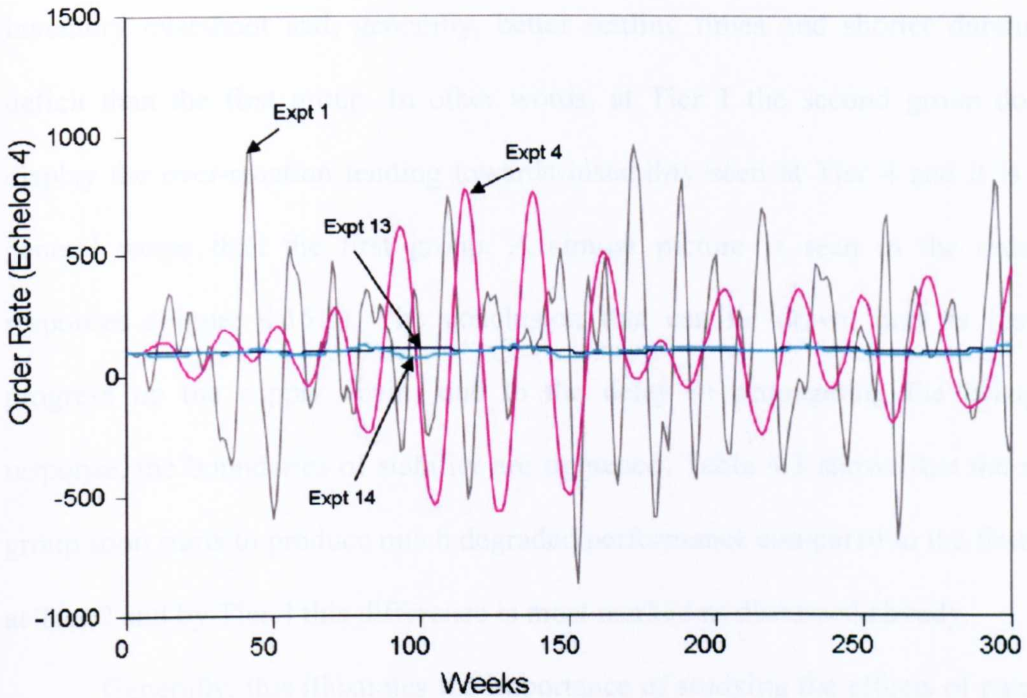


Figure 4.14.b. Stochastic response of ORATE 4

4.4.6 Comparison of Tier 1 and Tier 4 Step Responses

The step responses of Tier 1 of the supply chain are plotted in Figures 4.15.a-d and summarized in Table 4.3. For the highly stable first group of experiments (Figures 4.15.a-b) there is an absence of overshooting in the inventory response and the maximum inventory deficit and settling times are reduced at Tier 1. The order rate responses have much smaller overshoots, an absence of undershooting of the target (i.e. no oscillatory or under-damped behavior) and faster rise and settling times. These results are as one would expect as there is a delay in propagating the change in SALES at Tier 1 to Tier 4, which leads to the differences seen between Tier 1 and Tier 4 where the magnitude of the swings in the responses are amplified and the responses are much slower.

The second group's inventory responses at Tier 1 (Figure 4.15.c) have maximum deficits that are comparable to those of group one, very small or no inventory overshoot and, generally, better settling times and shorter durations of deficit than the first group. In other words, at Tier 1 the second group does not display the over-reaction tending towards instability seen at Tier 4 and it is not in general worse than the first group. A similar picture is seen in the order rate responses (Figure 4.15.d). The conclusion that can be drawn here is that with progress up the supply chain, due to the delay in propagating the changes in response, the boundaries of stability are tightened. Table 4.3 shows that the second group soon starts to produce much degraded performance compared to the first group at Tier 2 and by Tier 4 this difference is most marked as discussed already.

Generally, this illustrates the importance of studying the effects of parameter values on the whole supply chain and not just a single business entity, as there is a tightening or shrinking of the region of acceptable parameter values to control demand amplification. In the example presented here the second group of unsuitable parameters is not evident in the single entity analysis, i.e. the analysis at Tier 1.

Table 4.4 shows that whilst the second group of experiments still produces the worst response to stochastic SALES (largest variances) at Tier 1, the difference is far less marked than at Tier 4. The highly non-linear and substantial growth in variance up the supply chain to Tier 4 demonstrates the severe demand amplification caused by the second group of parameter values. This non-linearity draws the performance of the two groups apart so that there is a big gap between the two, especially in respect of the order rate variance.

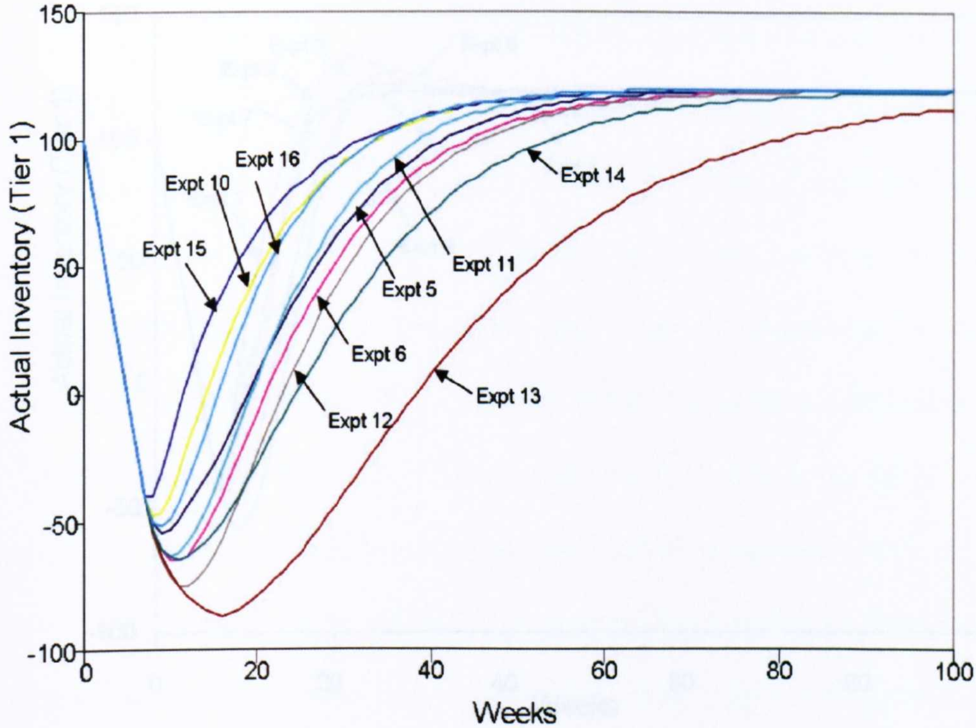


Figure 4.15.a. Impact of Parameters on the Response of Actual Inventory

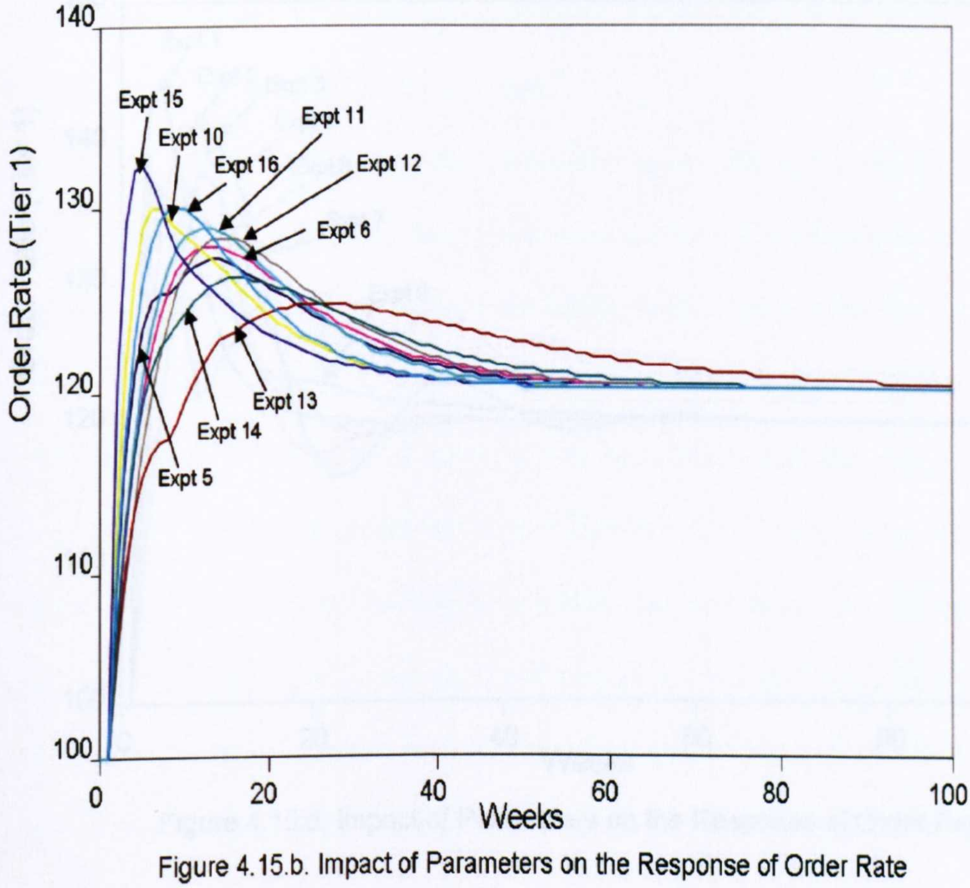


Figure 4.15.b. Impact of Parameters on the Response of Order Rate

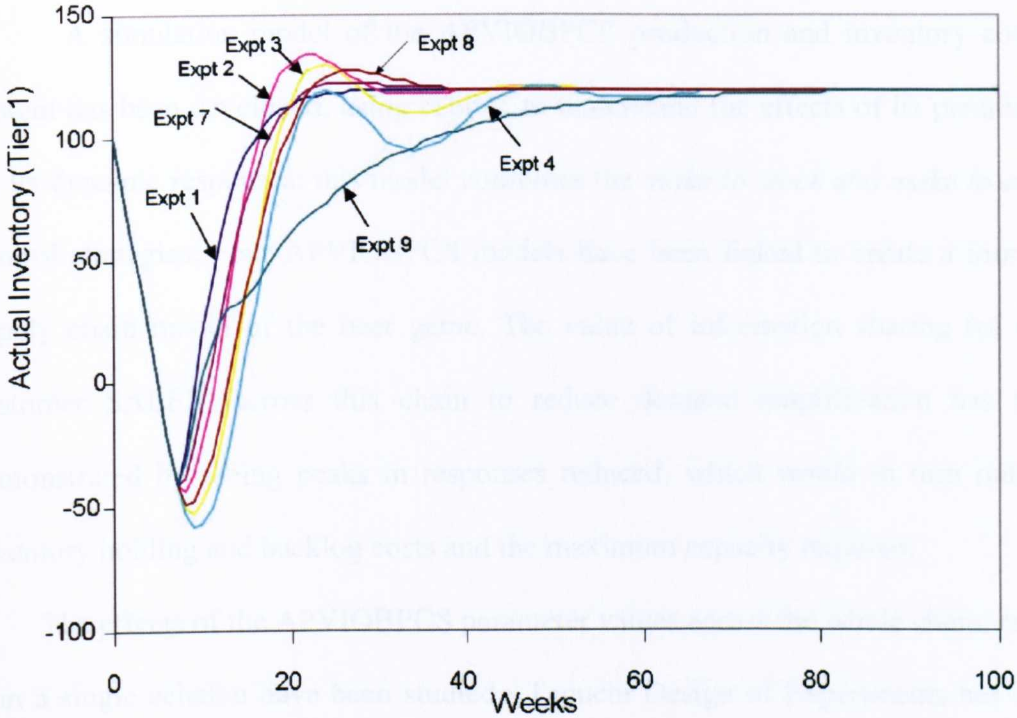


Figure 4.15.c. Impact of Parameters on the Response of Actual Inventory

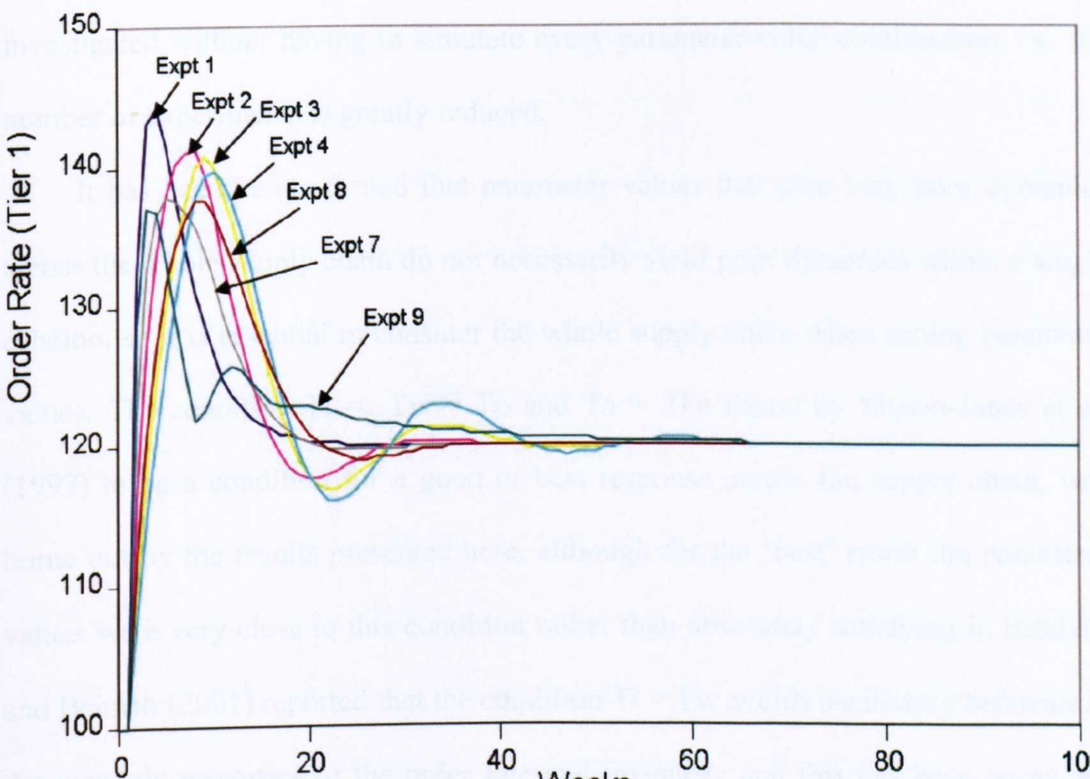


Figure 4.15.d. Impact of Parameters on the Response of Order Rate

4.5 Summary of Findings including a Qualitative Perspective

A simulation model of the APVIOBPCS production and inventory control system has been developed, using iThink, to understand the effects of its parameters on its dynamic responses; this model combines the *make to stock* and *make to order* control strategies. Four APVIOBPCS models have been linked to create a four-tier supply chain model of the beer game. The value of information sharing (of end-customer SALES) across this chain to reduce demand amplification has been demonstrated by seeing peaks in responses reduced, which would in turn reduces inventory holding and backlog costs and the maximum capacity required.

The effects of the APVIOBPCS parameter values across the whole chain, rather than a single echelon have been studied. Taguchi Design of Experiments has been used to derive a sample that is representative of the parameter-value space being investigated without having to simulate every parameter-value combination, i.e. the number of experiments is greatly reduced.

It has been demonstrated that parameter values that give very poor dynamics across the whole supply chain do not necessarily yield poor dynamics within a single echelon, so it is essential to consider the whole supply chain when setting parameter values. The condition Ti = Tw = Tp and Ta = 2Tp found by Mason-Jones et al. (1997) to be a condition for a good or best response across the supply chain, was borne out by the results presented here, although for the 'best' result the parameter values were very close to this condition rather than absolutely satisfying it. Riddalls and Bennett (2001) reported that the condition Ti = Tw avoids oscillatory behavior in the dynamic responses of the order rate and inventory and this has been borne out here, except when Ti = Tw is very small (4 in the experiment here) in which case the over-lively inventory feedback, due to the small Ti, caused very large oscillations and, indeed, the worst response; this means that the Ti = Tw condition is subject to Ti not being very small. It has been noted also that a large Ti can produce too slow a response, again confirming the findings of Riddalls and Bennett (2001). The close agreement between the findings of Riddalls and Bennett (2001) and Mason-Jones et al. (1997) provides a degree of verification of the iThink simulation model implemented here.

As in human endeavour in general, in selecting parameter values for the APVIOBPCS supply chain there is a choice between safe and stable without over-reacting but with the danger of becoming too slow to react to real change, i.e. too cautious, versus fast to react to real change (as opposed to noise) in a stable manner but with the danger of over-reacting and moving towards instability. This is seen in the dynamic responses seen here. Generally, a small Ti leads to over-reaction tending towards instability. However, within the range of experiments with a small Ti, two produce the very best results; fast but without load overshoots. Similarly, within the range of experiments with a larger Ti that yield more stable responses, there are two experiments that produce very slow responses that would typically be unacceptable in practice. So two groups of 'good' or 'stable' response have been seen. One of these groups is within the area of fast responses and one is within the area of slow and very stable responses.

Consider a Ferrari motor car versus a standard family saloon. The former is most likely to win a race, but without a good driver and careful control it is also the most likely to crash and kill. The standard family saloon may not win the race, but it is the most likely to arrive safely. The choice may depend upon the quality of the driver and the route to be taken (the demand). In this respect, with careful management parameter values associated with experiments 5 and 6 may be adopted to give good results, but if one cannot safeguard against or afford to risk falling towards instability, then one might take the safer option of using the other parameter values of the other first group of experiments. However, in this case one must safeguard against the danger of slipping into too slow a response as seen in experiments 13 and 14.

Endorsed by the stochastic response results, it is clear that the two groups of responses identified here begin to define the regions of acceptable and unacceptable parameter values, particularly in respect of their closeness to instability. The value of the ITAE gives a rough-cut between the two groups, although experiment 9 had a very good ITAE but poor stochastic demand response. So the use of ITAE needs to be tempered by consideration of the stochastic response. Furthermore, as experiment 15 had the lowest ITAE but a noticeably large original overshoot in the order rate step response, interpretation of the ITAE must also be tempered by the detailed features of the dynamic responses; with specific applications/situations determining which are the most important features and their desired characteristics, e.g. will the situation tolerate large overshoots to achieve rapid rise times?

The specific results obtained here are those for the specific values of Tp and n. However, the general, qualitative findings can be carried forward into production control in general. In particular, there are clear regions of good and bad parameter values resulting in either high stability or closeness to instability. Within the stable area there are pockets of too much inertia (slow responses) whilst within the more unstable area there are pockets of very good, stable, fast response. Supply chains should be positioned accordingly to meet the conditions within which they are operating.

Chapter 5: Analysis of the Bullwhip Effect with Order Batching

5.1. Introduction

Order batching is well recognized as a major cause of the bullwhip effect, e.g. (Lee et al., 1997). However, there has been little detailed research into precisely how batch size contributes to the level of demand amplification. Finding the optimal solution to batching is not easy since it is directly related to inventory holding and backlog costs. In many production-distribution systems materials move from one echelon to another in fixed lot sizes. For example, a retailer might order a full truck or container load from the wholesaler to qualify for a quantity discount and to optimize transport costs by fully utilizing the fixed-cost truck or container. When the batch size of purchased goods is outside of the control of a manufacturer, the production control objective is to set the other control parameters to mitigate any amplification effects. For a manufacturer, significant economies of scale can be achieved by producing in large batches, but the resultant large inventories will increase the stock holding costs. The inventory manager, however, always favors policies which meet the forecasted demand with minimal inventory. The rapprochement of these conflicting objectives is a fundamental aim of inventory management theory.

It is generally advocated that batch size should be reduced as much as possible (Burbidge, 1981), but there has been limited detailed investigation into the impact of batch size on demand amplification, which raises the question, "Does this hold totally true in respect of minimizing demand amplification?". This chapter addresses this gap in the research by introducing batching into the 4-tier supply chain model and then conducting simulation experiments to understand: the impact of batch sizes on the bullwhip effect under deterministic and stochastic demand processes; the impact of information sharing across wide ranges of batch sizes; the impact of design parameters on the bullwhip effect (which is measured quantitatively) and the severity of the interaction among these parameters when there is batching; finally, the best values of design parameters for mitigating the bullwhip effect when there is batching are explored.

The bullwhip effect is the observed amplification of the demand variability as it moves up a supply chain. Its causes, effects, and remedies are discussed in the literature review section. Order batching is one of the key causes of the bullwhip effect identified by Lee et al (1997) and Riddalls and Bennett (2001). It refers to the phenomenon of placing orders to upstream echelons in batches. Burbridge (1981) emphasized the need to reduce the batch size as much as possible. Technical or economical problems may not allow the implementation of smaller batch sizes. There is a clear and crucial need to fully understand the impact of varying the batch size on demand amplification across multi-echelon supply chains in order to enable operations managers to make better decisions around batching.

Batching is a clustering of items for purchasing, transportation or manufacturing processes and is also known as *Lot Sizing*. It is a mechanism that induces time-phased production that is usually non-synchronized with the actual demand. In this way, batching results in excessive inventory or backorders. The reasons for batch ordering include the *Economic Order Quantity* (EOQ), *Periodic Inventory Review* and *Transportation Economies*. Batching is also related to *Economic Batch Quantity* (EBQ) where it is beneficial economically for a company to produce large batches since it can reduce the number of facility set-ups and improve manufacturing efficiency. Companies prefer to order in batches to gain economies of scale. Long process set-up times are a major cause of large production batches within factories with the corollary being that rapid changeovers are required to reduce batch sizes. These large batch sizes can lead to large fluctuations in inventory levels as first a large batch is produced, far in excess of current demand, so that the inventory levels rise to high levels only to be reduced until they reach a reorder point, at which point a new large batch enters the inventory. Furthermore, batching amplifies the demand as it passes up a supply chain as the real demand is rounded-up to hole batch sizes for production processes and ordering from suppliers, and this rounding-up stacks-up along the supply chain when different batch sizes are used. For example, demand for a product may be 10 units, the production batch size may be 100 and an outsourced component used in the product (one component per product) may have an order batch size of 40. The initial demand of 10 is amplified to 100 in the factory, which results in a further amplified order for 3x40=120 components, assuming there are no components in stock already. This amplification can continue unabated up the supply chain. For example, if the component supplier ordered sub-components in batches of 50, the demand signal would jump to 150.

5.2. Literature Review

Cachon (1999) has studied the impact of order batching in a two level supply chain with a single supplier and many retailers. The study suggests that the bullwhip effect at the supplier's level can be reduced by balancing the orders of the retailers, a longer order interval time, and smaller batch sizes. Balancing the retailers' orders means that instead of placing the orders at the same time, each retailer should place orders at a different time because the bullwhip effect at the supplier's level is maximized when all retailers place orders in a synchronized manner. Riddalls and

Bennett (2001) studied the impact of batch production cost on the bullwhip effect. They proposed measuring the magnitude of the bullwhip effect in a two-tier supply chain by observing the peak order rate of the upper level (the supplier). They found that the relationship between batch size and demand amplification is non-linear and depends on the remainder of the quotient of average demand and batch size. The limitation of their findings is that there is always an initial increase (overshoot) in the order rate after a step change in demand. Hence, such assessment of the peak of the order rate as a measure of the bullwhip effect is not an accurate, quantitative measure of demand amplification.

Holland and Sodhi (2004) studied a two-tier supply chain model in which the retailer is bound to order in integer multiples of the batch size. Both retailer and manufacturer follow a periodic review and order-up-to level replenishment policy. Simulation was run for five different batch sizes and statistical analysis was carried out to quantitatively measure the impact on the bullwhip effect of batch size across each echelon. They found that the bullwhip effect across each echelon of the supply chain was proportional to the square of the batch size. Potter and Disney (2006) continued the work of Holland and Sodhi by considering the impact of a full range of batch sizes on demand amplification in a single echelon of APVIOBPCS. They found that the bullwhip effect from batching can be reduced if the average demand is an integer multiple of the batch size.

It has been recognized generally that the bullwhip effect can be minimized by reducing the batch size as much as possible, but there has been little study of the impact of batch size across a multi-echelon supply chain. Riddalls and Benett (2001) pointed out that control theorists are unable to solve the lot sizing problem. Potter and Disney (2006) mentioned that the impact of order batching on bullwhip has not been clearly explored. They pointed out that studying the impact of batch size on the APVIOBPCS, under a stochastic demand process, using the transform techniques of control theory is extremely challenging. System dynamics simulation then seems an appropriate methodology to investigate the impact of varying batch size on the bullwhip effect with a stochastic demand process. The value of information sharing as a remedy to reduce the bullwhip effect has been widely recognized. However, whilst some studies have analyzed the value of information sharing in capacitated supply chains, there has been little research into the value of information sharing when there is order batching; this chapter addresses this gap.

Previous studies have identified several possible causes of the bullwhip effect but little attention has been given to measuring quantitatively the impact of these causes on the bullwhip effect (Paik et al., 2007). Luong (2007) also pointed out that the problem of quantifying the bullwhip effect still remains unsolved due to the complex nature of supply chains. Furthermore, the severity of the interaction among the design parameters involved in the APVIOBPCS needs to be explored further than the initial study in the previous chapter. Taguchi Design of Experiments (Orthogonal Arrays) is applied here in analyzing the effects of the design parameters on demand amplification and the interactions among the parameters, and identifying the best combinations of parameter values for mitigating the impact of demand amplification.

5.3. Measure of the Bullwhip Effect

Different approaches can be taken to measuring the bullwhip effect and these were discussed in Chapter 2. Adopted here is the common approach of dividing the coefficient of variation of orders placed by the coefficient of variation of orders received (Chen et al, 2000). The coefficient of variation is defined as the ratio of the variance of the output (ORATE) to the variance of the input (Sales) as shown in Equation 5.1. Following the practice of other authors, in order to make calculations simple for both deterministic and stochastic demand processes, only the variance of the output needs to be calculated.

$$\text{Bullwhip} = \frac{\text{Var(Orate)}}{\text{Var(Sales)}} \qquad (5.1)$$

5.4. Supply Chain Model with Order Batching

5.4.1. The Batching Equation

The supply chain model used in this thesis is extended by introducing batch ordering across each APVIOBPCS echelon. Batching is introduced by the ROUND function in the iThink software package. The round function rounds values up to the next integer value. So to convert an ORATE to batches of size (BS), the following formula is used:

$$\text{Number of batches} = \text{ROUND (ORATE / BS)} \qquad (5.2)$$

and the new ORATE is then:

$$\text{Batched ORATE} = \text{Number of batches x BS.} \qquad (5.3)$$

Unless stated otherwise, the APVIOBPCS parameter values applied in this chapter are Ti = Tw = Tp = 6, and Ta = 2Tp = 12, i.e. a 'good' set of values in accord with the findings of the previous chapter and Mason-Jones et al. (1997).

5.4.2. Initial Simulation of Step Response

In the initial analysis, the step response is simulated for small, medium and large batch sizes. The test SALES pattern is a pure step increase of 20% from 2000 to 2400 per week. The results are observed first at the retailer, i.e. Tier 1 of the supply chain, in Figures 5.1.a-5.1.d which show that batch size has a major impact on the response. Figure 5.1.d presents the worst case scenario across the four figures. This is because it presents results for batch sizes for which demand is not an integer multiple of the batch size. For these batch sizes the order rate to can never settle on the new demand level of 2400. Instead, they will oscillate around this level ad infinitum. Figures 5.1.a-c present the results for batch sizes for which demand is an integer multiple of the batch size. The larger of these batch sizes force a quicker rise time as the initial orders are rounded up. However, medium and larger batch sizes produce large spikes along the response, except when they equal half or the whole of the new demand when the order rate locks directly onto the desired level.

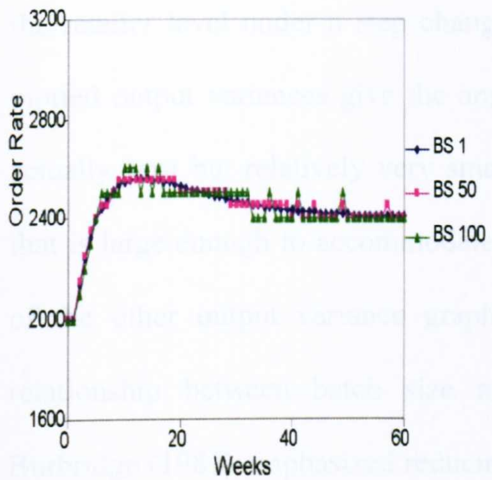


Figure 5.1.a. Impact of Smaller Batch Sizes on the Order Rate

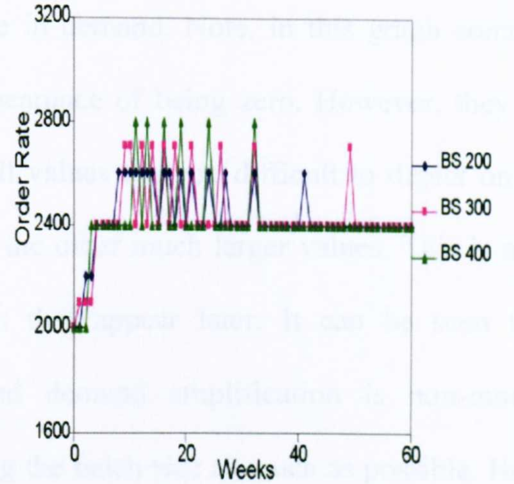


Figure 5.1.b. Impact of Medium Batch Sizes on the Order Rate

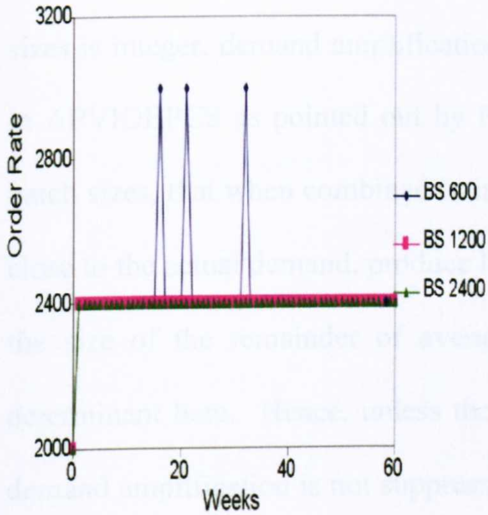


Figure 5.1.c. Impact of Larger Batch Sizes on the Order Rate

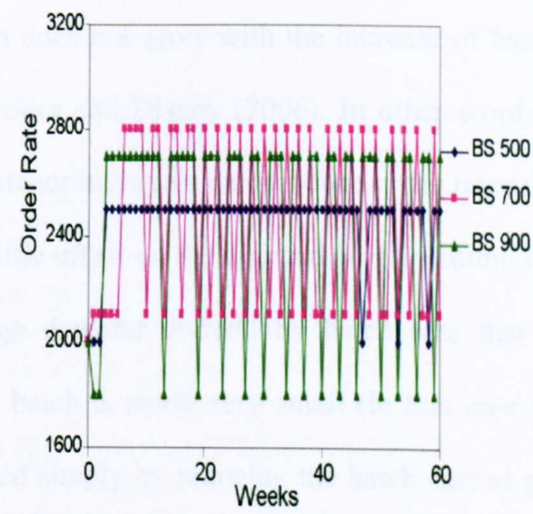


Figure 5.1.d. Impact of Non Integer Batch Sizes on the Order Rate

5.4.3. Impact of Batch size on Bullwhip Effect

Figure 5.2 shows the impact of the various batch sizes on the bullwhip effect at the retailer level under a step change in demand. Note, in this graph some of the plotted output variances give the appearance of being zero. However, they are not actually zero but relatively very small values that are difficult to depict on a scale that is large enough to accommodate the other much larger values. This is also true of the other output variance graphs that appear later. It can be seen that the relationship between batch size and demand amplification is non-monotonic. Burbridge (1981) emphasized reducing the batch size as much as possible. However, when the quotient of the average demand and batch size (average demand / batch size) is integer, demand amplification does not grow with the increase of batch size in APVIOBPCS as pointed out by Potter and Disney (2006). In other words, large batch sizes, that when combined in integer multiples can produce order rates that are close to the actual demand, produce little effect on the demand amplification, i.e. it is the size of the remainder of average demand divided by batch size that is the determinant here. Hence, unless the batch is made very small (in this case < 400) demand amplification is not suppressed simply by reducing the batch size as pointed out by Burbidge, rather it can be controlled by a judicious mix of decreases in batch size and adjusting the batch size so that the average demand is an integer multiple of it, i.e. the remainder of demand/batch size is zero or close to zero. However, it is noted that use of a large batch size placed at one of the local minima amplification points has the danger that changes in average demand can lead to large increases in amplification unless the batch size is adaptive, i.e. there is high sensitivity.

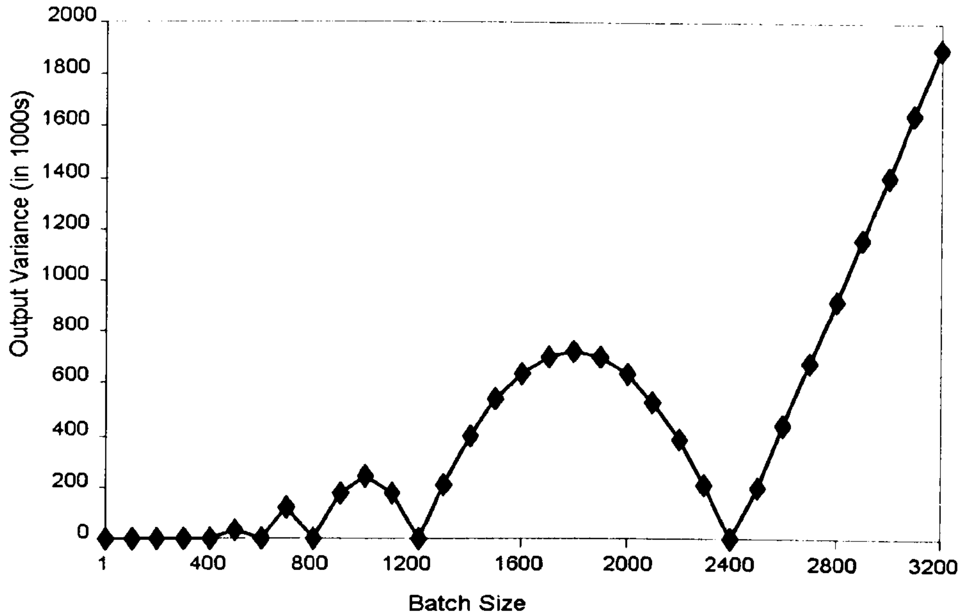


Figure 5.2. Impact of Batch Size on Bullwhip Effect for Step Demand

5.4.4. Stochastic Demand Process

Potter and Disney (2006) reported that studying the impact of batch size under a stochastic demand process in APVIOBPCS is extremely difficult using a control theoretic approach of Laplace and Z-transforms. APVIOBPCS is a periodic review system for issuing orders based on incoming demand signals and feedback loops of inventory and pipeline deficit. These feed-forward and feedback loops are in turn affected by control parameters and it is hard to understand the nature of the transformation involved. Hence, control theorists have been unable to study the impact of batch size under a stochastic demand process, so the system dynamics simulation approach seems an appropriate methodology for the investigation.

As in the previous chapter, to simulate a stochastic customer demand, SALES follows a normally distributed, stationary stochastic I.I.D. process with a known mean, μ, and variance σ^2. As before, it is assumed that σ is significantly smaller than μ, so that the probability of negative demand is negligible (Lee et al., 1997). A normally distributed stochastic demand pattern with a known mean of 2000/week and standard deviation of 400 is simulated and the results are the average of 50 runs of the model, each of 500 weeks length.

It can be seen from Figure 5.3 that the pattern, rather than the amplitude, of the impact of batch size on the demand amplification is the same as seen in Figure 5.2 for the step change in SALES. Again it is found that the output variance (bullwhip effect) decreases to a local minimum as the quotient of average demand and batch size approaches an integer value.

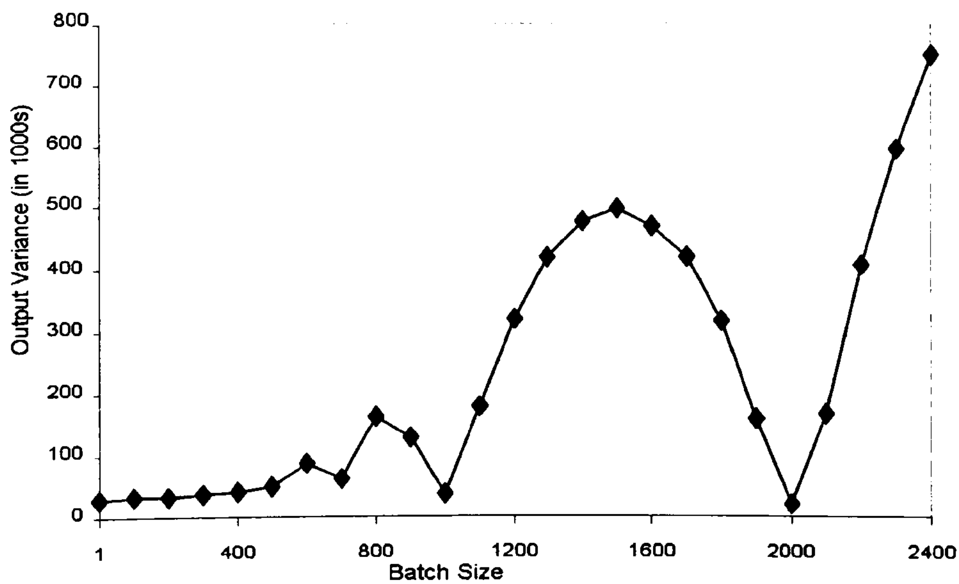


Figure 5.3. Impact of Batch Size on Bullwhip Effect for Stochastic Demand

Clearly, reducing demand amplification due to batching is not just about getting as close as possible to a batch size of one, it is also about how close demand is to an integer multiple of the batch size. Figures 5.2 and 5.3 show that when the quotient of batch size and average demand is not integer, increasing the batch size increases the gap between the minimum variance points and the magnitude of the peak demand amplification between these points. Consequently, fairly small changes in large batch sizes can cause big changes in demand amplification.

If operations managers with large batch sizes monitor trends in average demand, it may be possible to monitor and anticipate movement up the curve of the output variance, i.e. to forecast high amplification, and subsequently plan to change the batch size to reduce this. If the batch size is changed so that there is an integer multiple of it that matches demand, the bullwhip effect is minimized.

If the batch size is increased beyond the average demand then the output variance, i.e. the bullwhip effect, increases rapidly and linearly. A corollary to this is that if the demand starts to decrease below the batch size then the bullwhip effect will grow rapidly. Again, the operations manager should monitor for this condition.

5.5. Impact of Information Sharing with respect to Batch Size

The impact of information sharing on the bullwhip effect has been discussed by many authors and they have revealed the value of information sharing, see for example (Lee et al., 2000), (Ge et al., 2004) and (Lee et al., 2004). Some authors, such as (Chen, 1998), (Moinzadeh, 2002) and (Li et al., 2005), argue that the value of information sharing depends on the particular parameter values used within the supply chain model. Graves (1999) argued that information sharing has no value for the supply chain. Graves studied an adaptive periodic review inventory policy, where the end-customer demand is an integrated moving average process, and found that when upstream echelons know the exact parameters of the demand process then information sharing has no value. Whilst information sharing is frequently cited as being the key to reducing demand amplification, there has been little research toinvestigate the value of information sharing in a batched model although batching is acknowledged as a major cause of amplification.

The phenomenon of demand amplification can be seen clearly in Figure 5.4, which shows the output variance of the step response for Tier 1 and Tier 4 with 0% and 100% IEP.

Figure 5.4 shows that in percentage terms the increase in demand amplification between tiers1 and 4 is greatest with the smaller batch sizes, i.e. a large batch size may cause a large output variance at tier 1, but then this output variance does not increase so much in percentage terms, as it passes up the supply chain. So whilst the drive in manufacturing might be to reduce batch sizes, this will lead to greater demand amplification in percentage terms at upstream of supply chain. It is further noted that the value of information sharing is greatest for the smaller batch sizes, as there is a much greater improvement in the amplification ratio when IEP is changed from 0% to 100%; where amplification ratio is the ratio of the output variances of Tier 4 and Tier 1.

In the literature, a typical amplification ratio observed between two echelons is 2:1 (Towill, 1992) and between four echelons is 20:1 (Houlihan, 1987). In Figure 5.4, for batch sizes less than 400 an amplification ratio of the order of 20:1 is indeed seen between Tier 4 with IEP=0% (no information sharing) and Tier 1. However, this ratio is far less for the larger batch sizes.

The amplification ratio can be reduced to the order of 8:1 for the smaller batch sizes through full information sharing, i.e. IEP=100% and this agrees with the findings of (Chen et al., 2000) and (Chatfield et al., 2004). For the larger batch sizes, whilst the amplification ratio is less, making demand amplification arguably a less significant problem, the use of information sharing can almost eliminate any significant demand amplification. There is a dilemma here because information sharing will have a cost associated with its implementation, and whilst it may deal with the problem of demand amplification very well, the problem is primarily caused at Tier 1 with very large batch sizes for the supply chain studied here. In contrast, information sharing is clearly of great value when the batch size is smaller. So, with the increasing drive to reduce batch sizes, there is an increasing justification for adopting and investing in information sharing.

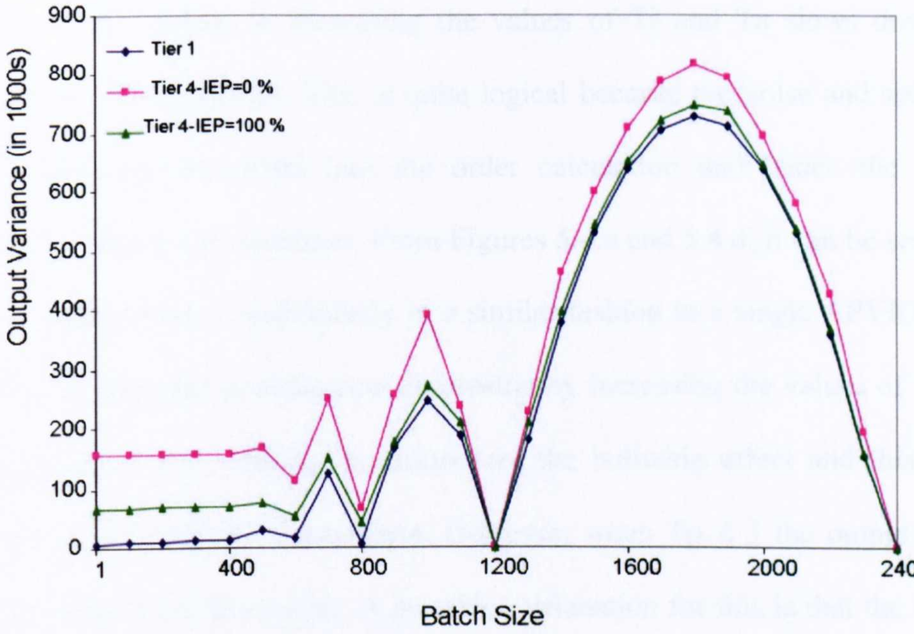


Figure 5.4. Impact of Information Sharing on Batch Size

5.6. Sensitivity Analysis

System dynamics approaches typically involve four stages: model identification, verification, model testing, and policy design (Sterman, 2000). The purpose of model testing is to increase confidence in the model, leading to the acceptance of underlying dynamic results. Among the various model testing procedures, one commonly applied technique in system dynamics simulation is sensitivity analysis, which investigates the robustness of the model and determines the stability boundaries of the system. The above simulation results are based on a specific set of design parameters, i.e. Ti = Tp = Tw = 6, Ta = 2Tp =12. There is the possibility that these results are particular to this combination of design parameters. Therefore, sensitivity analysis is carried out by changing the values of design parameters associated with the model in order to validate the above findings and to explore the stability and critical stability boundaries of the system.

The simulation results of the sensitivity analysis are presented in Figures 5.5.a-d. As mentioned in Chapter 4, increasing the values of Ti and Ta slows down the response of the APVIOBPCS. This is quite logical because the noise and spikes in demand signals are smoothed into the order calculation and hence the output variance of the order rate decreases. From Figures 5.4.a and 5.4.d, it can be seen that the supply chain behaves qualitatively in a similar fashion to a single APVIOBPCS model with the demand amplification decreasing by increasing the values of Ti and Ta. It is observed that reducing Tp minimizes the bullwhip effect and this result verifies the time compression paradigm. However, when Tp ≤ 3 the output of the farthest echelons starts decreasing. A possible explanation for this is that the system touches the stability boundaries. There is little effect of the Tw. Smaller values of Tw damp the peaks in the response of the ORATE providing an opportunity to reduce the demand amplification although the settling time is increased.

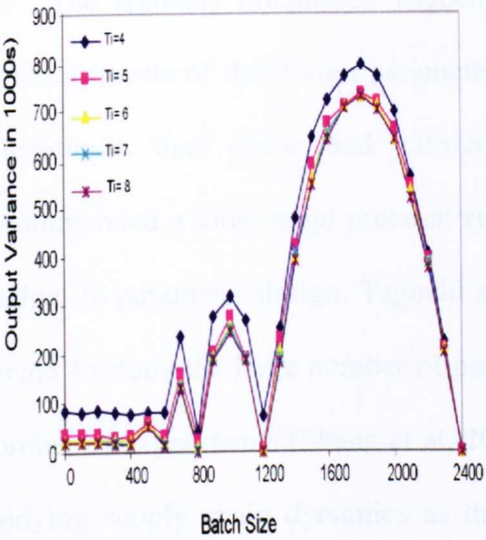


Figure 5.5.a. Impact of Ti on Bullwhip Effect

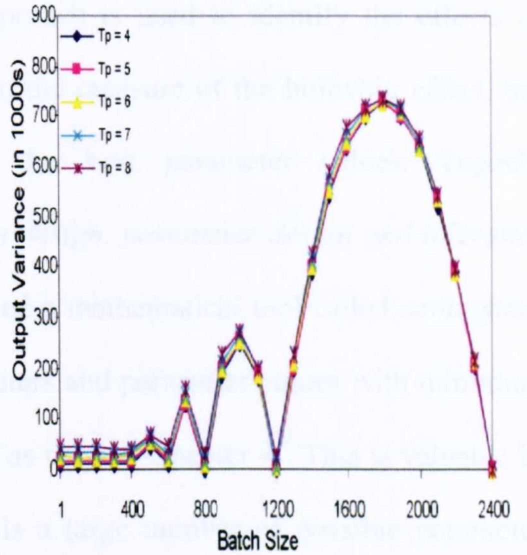


Figure 5.5.b. Impact of Tp on Bullwhip Effect

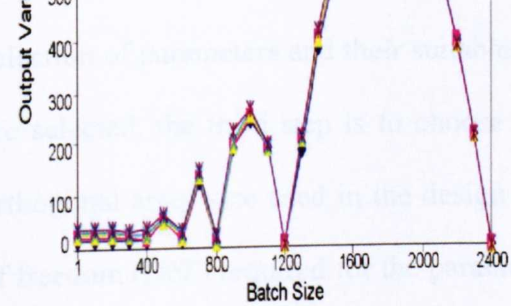


Figure 5.5.c. Impact of Tw on Bullwhip Effect

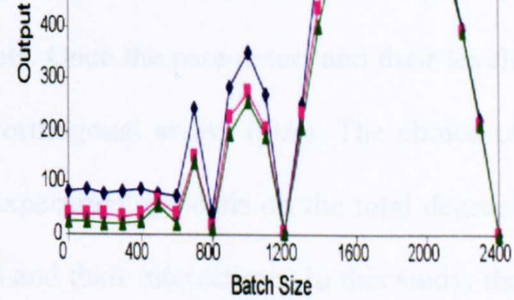


Figure 5.5.d. Impact of Ta on Bullwhip Effect

5.7. Statistical Analysis using Taguchi Design of Experiments

5.7.1. Introduction

The arguably ubiquitous Taguchi approach is used to identify the effects of different levels of the design parameters on the measure of the bullwhip effect, the interactions that occur and ultimately the best parameter values. Taguchi recommended a three stage process: *system design, parameter design and tolerance design.* In parameter design, Taguchi applied a mathematical tool called *orthogonal arrays* to study the large number of parameters and parameter values with minimum number of experiments (Shang et al, 2004) as used in Chapter 4. This is valuable in studying supply chain dynamics as there is a large number of possible parameter value combinations

The first step in parameter design is the selection of quality characteristics. There are three types of quality characteristics in Taguchi methods; smaller-the-better, larger-the-better, and nominal-the-best. The purpose of this research is to minimize demand amplification by exploring the best parameter levels, therefore the smaller-the-better quality characteristic is applied in this study. The next step is the selection of parameters and their suitable levels. Once the parameters and their levels are selected, the third step is to choose the orthogonal arrays (OA). The choice of orthogonal array size used in the design of experiment depends on the total degrees of freedom (DoF) required for the parameters and their interactions. In this study, the DoF for six control factors, each with three levels is 6 x (3-1) +1= 13. The L_{18} orthogonal arrays, which can be used for one two-level factors and up-to seven three-level factors, is appropriate for this study.

Table 5.2 that defines, for each experiment, the level of each factor or parameter to be used. In this array, the columns are mutually orthogonal. That is, for any pairs of columns, all combinations of parameter levels occur an equal number of times. The factor levels used in the experiments reported here are given in Table 5.1. Levels of the design parameters are chosen such that the stability boundary of the system is not disturbed as explored in Chapter 4. The positive point of a three level experiment is that it decomposes the main effect into linear and quadratic effects which allows non-linear effects caused by the design parameters to be taken into consideration. A normally distributed, stochastic demand pattern with a known mean of 1000 and standard deviation of 300 units per period is considered. Like Chatfield et al (2004), simulation results are the average of the 30 runs of the model, each of 500 weeks length.

Factors	Level 1	Level 2	Level 3
Production / Pipeline Delay (Tp)	4	6	8
Information Enrichment Percentage (IEP)	0 %	50 %	100 %
Time to adjust Inventory (Ti)	6	8	10
Time to adjust Work in Progress (Tw)	6	8	10
Smoothing Constant (Ta)	6	9	12
Batch Size (BS)	100	200	300

Table 5.1. Factors and their Levels

Experimental Run	Tp	IEP	Ti	Tw	Ta	BS
1	1	1	1	1	1	1
2	1	2	2	2	2	2
3	1	3	3	3	3	3
4	2	1	1	2	2	3
5	2	2	2	3	3	1
6	2	3	3	1	1	2
7	3	1	2	1	3	2
8	3	2	3	2	1	3
9	3	3	1	3	2	1
10	1	1	3	3	2	2
11	1	2	1	1	3	3
12	1	3	2	2	1	1
13	2	1	2	3	1	3
14	2	2	3	1	2	1
15	2	3	1	2	3	2
16	3	1	3	2	3	1
17	3	2	1	3	1	2
18	3	3	2	1	2	3

Table 5.2. Inner Arrays (L18)

To analyze the results of experiments designed with orthogonal arrays many approaches have been used (Tsai, 2002). One commonly used approach involves graphing the effects and the interactions among the parameters and visually identifying the significant factors and interactions (Vlachogiannis and Roy, 2005). This technique involves the 'average values' and is used in this study. The analysis of the results obtained here with the L_{18} arrays is given in the following sections

5.7.2. Calculation of Main Effects

The effect of a design parameter on the measured response when the parameter's value is changed from one level to another is known as a '*main effect*' and is calculated for a particular level of a factor by examining the orthogonal array, the factor assignment, and the experimental results (Roy, 2001). For example, to calculate the average effect of information sharing (IEP) at Level 1, all results of IEP at Level 1 are averaged and so on. Figure 5.6 illustrates the sensitivity of the bullwhip effect measurement to changes in the parameter values across the experimental values in Table 5.1. Figure 5.6 shows that the bullwhip effect measurement is most sensitive to Ti, whilst IEP is the next most significant factor. Smaller values of Ti produce over-reaction and oscillatory behavior which results in higher production costs, higher inventory costs and poor customer service levels as explained in Chapter 4. Forrester (1961) also proposed not to recover the "*error of inventory position*" in one time period. Instead, recovery should be spread over time by ordering only a fraction of the inventory deficit. Suitable values of Ti not only ensure stability but also determine the capacity requirements; with larger values of Ti less capacity is required to satisfy an increase in demand.

Information sharing has been proposed as a remedy to the bullwhip effect and increasing the information enrichment percentage to 100% reduces the bullwhip measure used here. Smaller Ta values are highly responsive to recent changes in underlying demand pattern, amplifying the demand, whilst larger values produce smooth ordering. Increasing Ta increases the damping effect of the exponential smoother, so it is not surprising that it also reduces the bullwhip effect. It is observed that reducing Tp minimizes the bullwhip effect and this result verifies the time compression paradigm and the importance of compressing Tp (production lead time) to reduce demand amplification.

Again it can be seen that when the quotient of the average demand and batch size (average demand / batch size) is integer, demand amplification does not grow with the increase of batch size. Figure 5.6 shows a very little effect on the bullwhip measure when batch size is varied from level 1 to level 2. This difference can be due to either the random demand pattern or the error observed in the ANOVA calculation. A substantial increase in demand amplification is observed when batch size increases from level two to level three, which does not satisfy the criterion that demand is an integer multiple of it. The least sensitivity is seen with Tw. Larger values of Tw increase the peak overshoot of the order rate but decrease the recovery time. On the other hand, smaller values of Tw dampen the peaks in the response of the order rate, but increase the settling time. However, smaller Tw values provide an opportunity to reduce the demand amplification as explained already in Chapter 4.

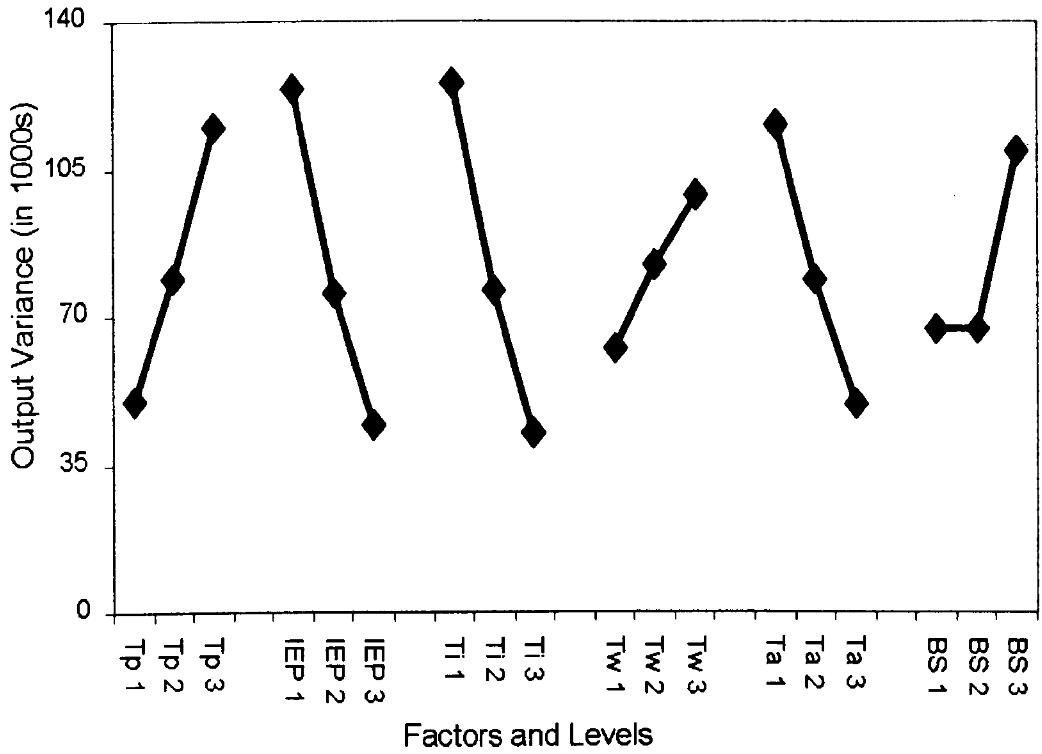


Figure 5.6. Plot of Main Effect Response

5.7.3. Calculation of Interaction Effects

The next step is to explore the interactions among the parameters. Interaction here refers to particular parameter values behaving differently in the presence of particular values of the other parameters, i.e. the trend of influence changes when the levels of the other factors change. The number of two factor interactions possible among N factors is N(N-1)/2 (Roy, 2001). In this experiment of six factors, the number of possible interactions is 6(6-1)/2 = 15. Simple but powerful "*Interaction Graphs*" (Figures 5.7.a-5.7.h) are used to determine the severity of the interactions between control parameters. If the lines in the graph are parallel there is no interaction between the parameters, whilst non-parallel lines indicate interaction with intersecting lines indicating strong interaction (Antony, 2001).

Eight important interactions are observed in this analysis. Interaction plots are obtained by graphing the combined effects of the pairs of the factors studied. So, to test for the presence of interaction between IEP and Ta, the average effects of IEP1 with Ta1, IEP1 with Ta2, IEP1 with Ta3, IEP2 with Ta1, IEP2 with Ta2, IEP2 with Ta3, IEP3 with Ta1, IEP3 with Ta2 and IEP3 with Ta3 need to be calculated. For example, the average effect of IEP1 with Ta1 is obtained by averaging the results of experimental runs which contain both IEP1 and Ta1. The "*severity of the interaction*" (SI) determines the presence of the strongest and weakest interactions. The SI values for the experiments conducted here are given in Table 5.3.

Serial No	Interacting factor pairs	Severity index SI (%)	Best factor levels
1	IEP * BS	65	3, 3
2	Ta * BS	58	3,3
3	IEP * Ta	50	3,3
4	IEP * Ti	48	3,3
5	Tp * Tw	35	2,1
6	Ti * Ta	31	1,1
7	Ti * BS	27	3,2
8	Tp * IEP	12	1,3

Table 5.3. Severity of interaction between the factors

Table 5.3 and Figure 5.7.a show that the strongest interaction is between IEP and BS, i.e. information sharing and batch size. The beneficial impact of information sharing on the demand amplification varies with or is dependent upon the batch size. This phenomenon has been discussed already in this chapter. The next strongest interaction occurs between batch size and Ta. Increasing the value of Ta reduces the sensitivity of demand amplification to batch size. Put another way, when Ta is small, larger batch sizes result in a large increase in demand amplification, whereas with the smallest batch size the smallest and largest Ta values produce similar levels of amplification. The increase in amplification with batch size does not contradict the earlier result that the amplification ratio decreases with very large batch sizes. The range being considered in this section is all within the lower range of batch values considered earlier i.e. <400.

The third strongest interaction is observed between IEP and Ta; the value of information sharing is affected significantly by the forecasting error generated due to inaccurate forecasts. Without information sharing the demand amplification increases considerably as Ta is reduced, and then the smaller Ta (with the much higher amplification to start with) benefits most from information sharing, indeed it benefits considerably.

There is a strong interaction between IEP and Ti. The value of 100% IEP, i.e. the percentage improvement in the output variance, increases as Ti decreases. Chapter 4 has already shown that smaller Ti values cause over-reaction and oscillatory behavior, taking the dynamic responses towards instability. Information sharing can help to control these effects which are a form of demand amplification, so the smallest Ti benefits most from information sharing.

The next strongest interaction is observed between Tw and Tp, smaller values of Tp and Tw create less overshoot in the order rate. When the lead time is larger, decreasing the value of Tw can dampen down the magnitude of the overshoot of the order rate.

The sixth strongest interaction is between Ti and Ta. Smaller values of both Ti and Ta are highly responsive to recent changes in underlying demand pattern while larger values produce smooth ordering.

Another important interaction is observed between Ti and batch size. The batch sizes simulated here produce almost the same amplification for high Ti.

The least significant interaction observed is between IEP and Tp. Information sharing has more value when the production or distribution lead time is small. All other interactions have an SI less than 10 %

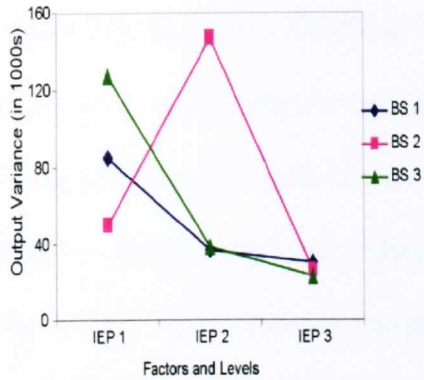


Figure 5.7.a. Interaction between IEP and Batch Size

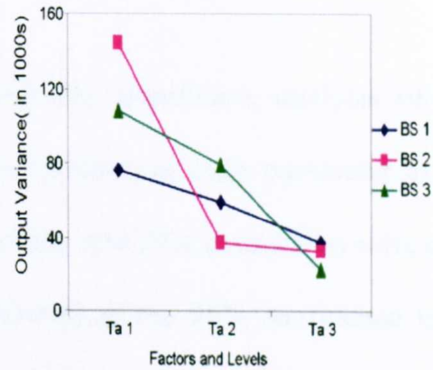


Figure 5.7.b. Interaction between Ta and Batch Size

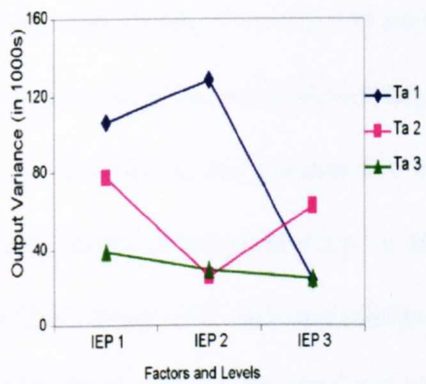


Figure 5.7.c. Interaction between IEP and Ta

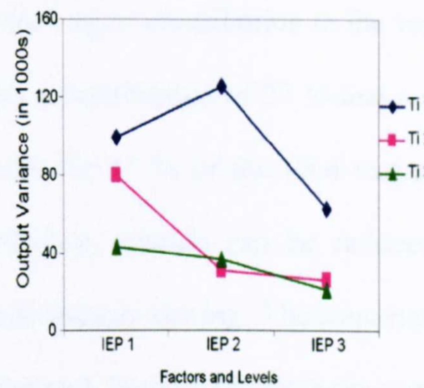


Figure 5.7.d. Interaction between IEP and Ti

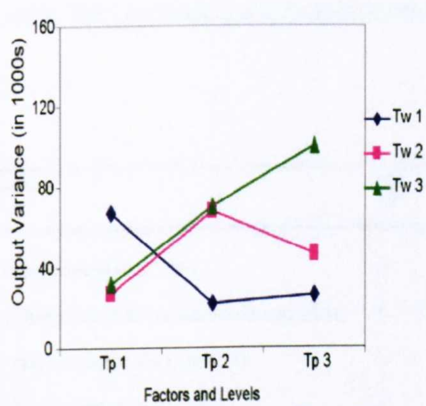


Figure 5.7.e. Interaction between Tp and Tw

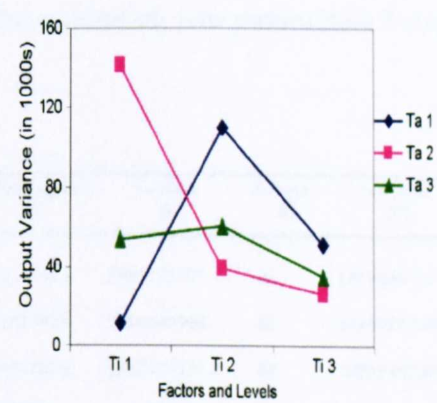


Figure 5.7.f. Interaction between Ti and Ta

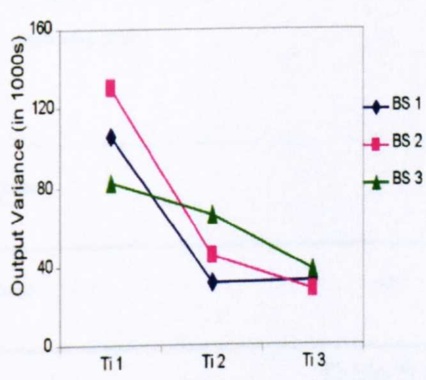


Figure 5.7.g. Interaction between Ti and Batch Size

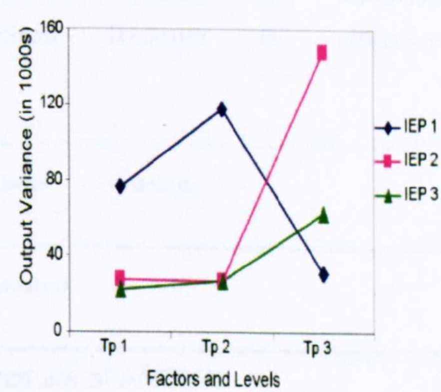


Figure 5.7.h. Interaction between Tp and IEP

5.7.4. Analysis of Variance (ANOVA)

To discover which effects are statistically significant, analysis of variance (ANOVA) is performed to quantify the contribution of each parameter to the total variation in the experimental data. Details of the ANOVA calculation were discussed in Chapter 3. The ANOVA tests are performed at the 95% confidence level. The ANOVA results in Table 5.4 show that all the factors involved in this study are statistically significant. However, Ti makes the largest contribution to the variation in the measurement of the bullwhip effect, with a contribution of 27 % and next is IEP at 24%, so that these two parameters account for 51 % of the total variance. This means that demand amplification at the farthest echelon can be reduced greatly through fine tuning of Ti and introducing information sharing. The importance of Ti agrees with the initial results obtained in Chapter 4. Ta and Tp also have a substantial impact with the percentage contribution of the remaining two parameters being much smaller.

Factors	DOF (f)	Sum of Squares (S)	Variance (V)	F-Ratio (F)	Pure Sum (S')	Percent P (%)
1.Production Delay (Tp)	2	13011567414	6505783707	42	12698467090	16
2. Information Enrichment Percentage (IEP)	2	19221327927	9610663964	61	18908227603	24
3. Time to Adjust Inventory (Ti)	2	21244542625	10622271313	68	20931442301	27
4.Time to Adjust WIP (Tw)	2	4063123195	2031561598	13	3750022871	5
5.Smoothing Constant (Ta)	2	13368420236	6684210118	43	13055319912	17
6. Batch Size (BS)	2	7156758303	3578379152	23	6843657979	9
Error	5	782750809	156550162			2
Total	17	78848490509				100 %

Table 5.4. Results of ANOVA

5.7.5. Determining the Optimum Values

It should be noted that Tp, the production lead time, is not strictly speaking a control system design parameter to be optimized at will. It is instead a parameter of the system under control although a company could chose to reduce Tp through investment in resources and improved operations management. Nevertheless, Tp is included in this analysis so that its effect can be understood along with the interactions it has with the control parameters.

Little research has been carried out to identify 'optimal' or 'good practice' values and relationships among the different design parameters of supply chains. Supply chains consisting of many interacting factors are difficult to optimize by control theoretic techniques (Holweg et al, 2005). Therefore Taguchi's Orthogonal Arrays technique is introduced to identify the optimum relationship among the design parameters. The best parameter levels within the range of values considered here are given in Table 5.5; this is in the context of minimizing the chosen measure of the bullwhip effect. It is found that use of the largest Ti and Ta can control excessively large fluctuations in the order rate by damping the reaction to errors in the inventory. According to the measure chosen here 100% information enrichment is preferred. This is contrary to the result of Mason-Jones et al. (1997). It is found that Tp should be made as small as possible, which verifies the value of the time compression paradigm for reducing the bullwhip effect. It is found that the bullwhip effect does not increase when the batch size is set so that average demand is an integer multiple of it. In this study, levels 1 and 2 of batch size satisfy this criterion and very little increase in demand amplification is observed when batch size changes from level 1 to level 2 as shown in Figure 5.6. This difference can be attributed to the error observed in the ANOVA. Both these levels are optimum for mitigating the bullwhip effect. The smaller value of Tw damps down the magnification in the order rate and can be used as a remedy for the bullwhip effect.

However, it must be noted that the 'best' set of parameters with respect to demand amplification, as measured by the output variance, is not necessarily the best set of parameters overall. As seen in Chapter 4, there are compromises to be made between conflicting characteristics of the dynamic responses. So, the set of parameter values presented here is not being portrayed as definitively the best set, but rather a demonstration of what might be done in a specific application using Taguchi Design of Experiments. It also gives a summary guide to how demand amplification can be reduced using parameter settings.

Factor	Level	Level Description
Production Delay (Tp)	1	4
Information Enrichment Percentage (IEP)	3	100 %
Time to Adjust Inventory (TI)	3	10
Time to Adjust WIP (Tw)	1	4
Smoothing Factor (Ta)	3	12
Batch Size (BS)	1	100

Table 5.5. Factors at Optimal Condition

5.8. Summary

i. Previous studies paid little attention to measuring the impact of causes of the bullwhip effect and although information sharing is cited as the key to reducing this effect, there has been little research into the value of information sharing in a batched model although batching is acknowledged as a major cause of amplification. This chapter has addressed these gaps by analyzing the effects of the design parameters, and their interactions, in the APVIOBPCS-based supply chain model with batch ordering. This analysis has gone beyond the rudimentary study in Chapter 4 by applying Taguchi Design of Experiments and ANOVA.

ii. It has been seen that the relationship between batch size and demand amplification is non-monotonic. Although Burbridge (1981) emphasized reducing the batch size, the results presented here show that when the quotient of the average demand and batch size is integer, demand amplification does not grow with increases in batch size. Large batch sizes, that when combined in integer multiples can produce order rates that are close to the actual demand, produce little demand amplification, i.e. it is the size of the remainder of the quotient that is the determinant. Unless the batch is made very small, demand amplification is not suppressed simply by reducing the batch size, rather it can be controlled by a judicious mix of decreases in batch size and adjusting the batch size so that the remainder of demand/batch size is zero or close to zero. However, it is noted that use of a large batch size placed at one of the local minima amplification points has the danger that changes in average demand can lead to large increases in amplification, i.e. there is high sensitivity.

iii. It has been proposed that if operations managers with large batch sizes monitor trends in average demand, they could anticipate movements up the curve of the output variance, i.e. high amplification, and subsequently plan to adjust the batch size to reduce this.

iv. If the batch size is increased beyond the average demand then the output variance, i.e. the bullwhip effect, increases rapidly and linearly. A corollary to this is that if the demand starts to decrease below the batch size then the bullwhip effect will grow rapidly. Again, operations managers could monitor for this condition.

v. In percentage terms, the increase in demand amplification between tiers 1 and 4 is greatest with the smaller batch sizes, i.e. a large batch size may cause a large output variance at Tier 1, but this output variance does not increase much in percentage terms, as it passes up the supply chain. So the ubiquitous drive to reduce batch sizes in manufacturing can lead to greater demand amplification in percentage terms. It is further noted that the value of information sharing is greatest for smaller batch sizes, for which there is a much greater improvement in the amplification ratio when IEP changes from 0% to 100%.

vi. Whilst the amplification ratio beyond Tier 1 is much less for large batch sizes, making it a less significant problem, information sharing can almost eliminate any significant demand amplification. There is a dilemma here because information sharing will have a cost associated with its implementation, and whilst it may deal with the problem of demand amplification very well, the problem is primarily caused at Tier 1 with very large batch sizes. In contrast, information sharing is clearly of great value when the batch size is smaller. So, with the increasing drive to reduce batch sizes, there is an increasing justification for adopting and investing in information sharing.

vii. The sensitivity of the bullwhip effect to parameters of the APVIOBPCS has been analyzed. The bullwhip is sensitive to all of them. The degree of sensitivity to each parameter has been considered. Some rationale for the degrees of sensitivity seen has been given by considering the effects of the parameters on the dynamic responses of the APVIOBPCS determined in Chapter 4.

viii. The interactions between parameters in respect of their effect on demand amplification has been analyzed. The strongest interaction is seen in the beneficial impact of information sharing on demand amplification being dependent upon the batch size. The next strongest interaction is seen in increased values of Ta reducing the sensitivity of demand amplification to batch size. The third strongest interaction is observed between IEP and Ta, i.e. the value of information sharing is affected significantly by the forecasting error. Without information sharing, demand amplification increases considerably as Ta is reduced, and then the smaller Ta (with the much higher amplification to start with) benefits most from information sharing, indeed it benefits considerably. There is a strong interaction between IEP and Ti; decreasing Ti causes over-reaction and oscillatory behavior, as seen Chapter 4, so the benefit of 100% information sharing increases.

ix. The ANOVA shows that Ti (27%) and IEP (24%) make the largest contribution to the variance of the bullwhip effect with their combined contribution being 51%. This means that demand amplification at the farthest echelon can be reduced greatly through fine tuning of Ti and introducing information sharing. The importance of Ti agrees with the initial results obtained in Chapter 4. Ta (17%) and Tp (16%) also make a substantial contribution.

x. Future work should investigate the cost implications of order batching in multi-echelon supply chains. This research has focused on the periodic review inventory control system, the continuous review inventory control system should be considered in future work.

Chapter 6: Analysis of Capacity Constraints on the Backlog Bullwhip Effect

6.1. Introduction

Most of the previous studies involving the APIOBPCS model are based on unconstrained capacity. However, it is more reasonable to think that production and distribution are in reality capacity constrained so that it may not be possible to increase activity levels to cope with peak demand. Even if it is possible, the cost may be so high that it is not an acceptable solution.

A discussed previously, one of the most commonly applied methodologies to study the various aspects of the APIOBPCS model is the control theoretic technique. It is clear that these control theoretic models are linear whilst presenting a view of the whole system. Riddalls et al (2002) and White et al (2006) pointed out that control theorists are dealing with the linearity of the model as there are no capacity constraints. Hence, in this chapter model is extended by adding capacity constraints across each echelon of APIOBPCS.

Linear models can work adequately in physical science but fail to represent the essential characteristics of industrial processes (Forrester, 1961). In obtaining explicit mathematical solutions, linear models are much simpler while mathematical analysis is unable to deal with the general solutions to non-linear models. The reason is that the inclusion of non-linearities, such as capacity constraints, creates an infinite number of solutions that can only be solved through simulation or numerical techniques (Holweg and Disney, 2005). In non-linear systems, cause–effect relationships between variables are not proportional. Small variations in customer demand at Tier1 (the retailer) can cause disproportionate oscillations and fluctuations in the order rate of the farthest tier (the factory). The dynamic behavior of the non-linear supply chain can best be explored by simulation.

This chapter addresses the gap in the research by introducing capacity constraints at each echelon of the APIOBPCS-based supply chain simulation model. Capacity constrains the ability of the factory to process goods by imposing an upper limit on production capability and thereby determines the service level. Introducing capacity constraints at each echelon of the supply chain may lead to an increasingly large orders backlog. This backlog not only affects the customer service level but also the stability of the supply chain. The variance in each echelon's backlog increases as one proceeds up the supply chain and this effect is referred as the "*backlog bullwhip effect*" (Anderson et al., 2005).

A multi-echelon production and inventory control system is said to be stable if, on average, it can produce finished goods at the required rate (Glasserman and Tayur, 1994). By introducing different levels of capacity constraints across each echelon of the APIOBPCS-based supply chain model, the stability boundaries of the system are explored. A heavily backlogged system is said to be unstable. In this thesis, Taguchi's "signal to noise ratio" is applied to evaluate policies that minimize backlog bullwhip effect across multi-echelon supply chain.

The remainder of this chapter is organized as follows. Section 2 presents the literature review. Section 3 explains the extended model. Section 4 describes the initial analysis of the effects of the capacity constraints on the dynamic response of the inventory and order rate, and explores the stability boundaries of the capacitated multi-echelon supply chain. Section 5 considers the conditions under which information sharing is most valuable in the capacity constrained multi-echelon supply chain. Section 6 applies Taguchi Design of Experiments to evolve the policies that minimize the total backlog variances of the multi-echelon supply chain and Section 7 presents a summary.

6.2 Literature Review

Capacity can be defined as the maximum level of value-added activity over a period of time that a process can achieve under normal operating conditions (Slack et al, 2004). Capacity constraints have an unambiguous connection with the capability to respond to changes in demand and with the replenishment lead time. Many studies employ supply chain models that ignore capacity constraints (Anderson et al, 2005). Ballou (1992) indicated that, when more than two echelons are involved, managing the inventory throughout the entire chain becomes too complex for mathematical analysis and is usually carried out with the help of computer simulation. The complexity of multi-echelon supply chains, warrants a perspective that considers the supply chain structure, non-linearities, and feedback, which is provided by system dynamics modeling (Wilson, 2007). However, to take full advantage of simulation, an appropriate simulation modeling tool is required (Chatfield et al, 2004) such as iThink, which is used throughout this thesis and for the modeling of a capacitated multi-echelon supply chain in particular in this chapter

Capacity influences the ability of the production facility to meet customer orders, but also impacts the cost efficiency through plant and equipment utilization. Some research suggests that firms should provide enough additional capacity to enable a rapid response while other research argues that excess capacity may be detrimental to supply chain performance. Hopp and Spearmann (1996) describe the non-linear impact that capacity has on manufacturing cycle time in a single facility manufacturing operation. Their findings show that tight capacity is often detrimental to system performance. Helo (2000) deals with demand amplification and the trade-off between capacity constraints and lead time. It is found that capacity constraints determine the response of the system, and the responsiveness of the supply chain to varying demand can be increased by increasing capacity levels. Biller et al. (2002) study capacity relative to flexibility and evaluate its impact on the overall supply chain performance. Interestingly, their result somewhat contradicts earlier research in suggesting that adding effective capacity through flexibility increases observed variability in orders along with its associated cost. Wu and Meixell (2005) obtain similar results in their study of integration in supply chains and show that limited capacity has a smoothing effect on the bullwhip effect in supply chains.

In multi-echelon supply chains, it is extremely difficult to decide how much safety stock should be held at each echelon in order to minimize inventory costs and provide a high level of customer service. Capacity constraints have an unambiguous connection with the capability to respond to changes in demand, with safety stock levels (raw materials or finished products), and with the replenishment lead time. Greater product variety, shorter life cycles, and technological changes have made the use of buffering inventories difficult. Graves and Willems (2000) studied a periodic review multi-echelon supply chain. An optimization algorithm was developed for determining the minimum safety stocks at different echelons in order to achieve the desired service level. A limitation of their work is that there are no capacity constraints. When demand forecasts are not accurate and there are capacity constraints, maintaining safety stocks will be difficult since all capacity is being used to fill orders (Kempf, 2004). The inventory variances also determine the safety stock requirements and affect the inventory holding cost (Anderson et al, 2005).

6.3 The Extended Model

The supply chain model developed in this thesis is extended by adding capacity constraints across each echelon of APIOBPCS. The limitations of capacity constraints can be applied on either the order rate or the completion rate. According to Evans and Naim (1994), constraining the order rate being placed on the production facility appears to be the realistic placement within the system and therefore offers more insight into the effect of capacity constraints. The block diagram of a single echelon of the extended model is presented in Figure 6.1. It is important to note that the desired inventory level is now kept fixed, rather than being a multiple of smoothed Sales, i.e. the model is based on APIOBPCS rather than APVIOBPCS. The reason for this is to better explore the impact of different levels of safety stock and capacity constraints on the backlog bullwhip effect. The order rate (ORATE) is constrained, which gives the new 'actual' order rate (AORATE)

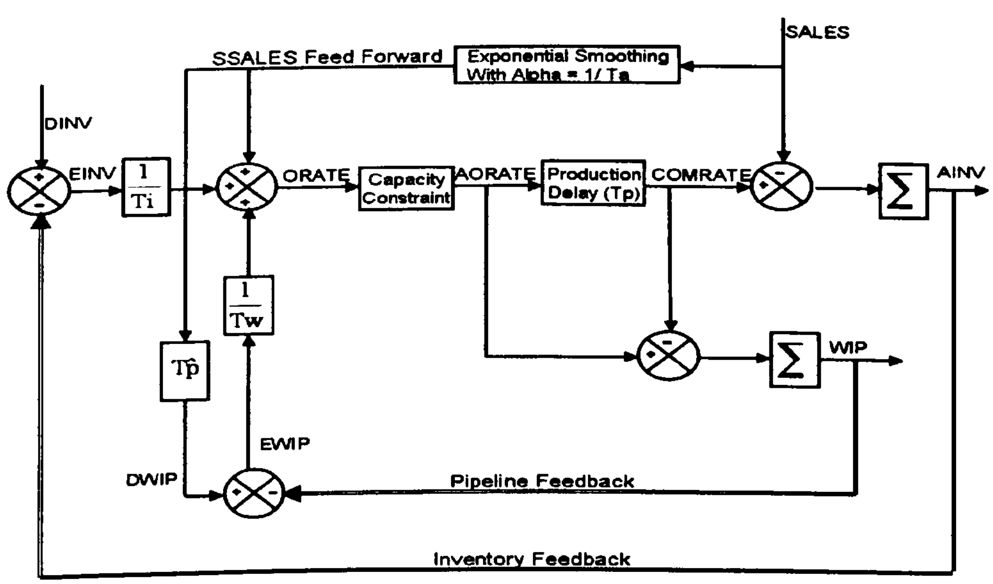


Figure 6.1. Block Diagram of Single Echelon of Capacitated APIOBPCS Model

6.4 The Stability Boundaries of the Multi-Echelon Capacitated Supply Chain

The stability of each echelon can be ensured through the related echelon's 'shortfalls', also known as backlogs, which are measured by the shortfall in the actual inventory. The model is simulated for various levels of capacity 'tightness', is defined by the total capacity divided by the average demand. Like Zhao et al., (2002) and Byrne and Heavey, (2006), three levels of capacity tightness are simulated: Low (1.33), Medium (1.18), and High (1.05). These levels correspond to the utilization of resources of 75%, 85%, and 95% respectively. A deterministic step increase in Sales of 20% from 100 to 120/week is initially applied in the simulation to evaluate the system's ability to cope with sudden but maintained change. The responses of the actual inventory and order rate at each echelon are then analysed. The following set of 'good' parameter values is used as before Ti = Tw = Tp = 6, Ta = 2Tp. DINV is set to 100

Figures 6.2.a to 6.2.h show the response of the actual inventory and order rates of the multi-echelon supply chain under the three levels of capacity. Figures 6.2.a and 6.2.b show the responses without capacity constraints; the bullwhip effect is clearly seen as the size of overshoots and undershoots grows up the chain. The introduction of capacity constraints in the other Figures produces a drastic change in the responses, revealing the 'time-axis' sensitivity of the model. It can be seen that the recovery time increases with the increase of capacity constraints as shown by Helo (2000). The negative effects of the tightest capacity constraints are clearly visible in the inventory and order rate at Tier 4 (Figures 6.2.c and 6.2.d). It can be seen that the manufacturer experiences capacity shortfall and would not be able to catch up for 128 weeks.

Capacity shortfall is the measure of the order quantity that exceeds the available capacity. Designing in capacity shortfall, i.e. tight capacity constraints, is called the "trailing capacity strategy", where capacity lags the demand and therefore capacity is fully utilized (Vlachos et al, 2007). Glasserman and Tayur (1994) analyzed the stability boundary of multi-echelon capacitated supply chain with a periodic review inventory policy. A multi-echelon production and inventory control system is said to be stable if, on average, it can produce finished goods at the required rate. Glasserman and Tayur showed that their system is stable as long as the mean demand per period is smaller than the production capacity at each echelon in each period. Figure 6.2.d shows that the actual inventory level is not able to catch up for 128 weeks when capacity over mean demand is 1.05, i.e. capacity is tightly constrained. A backlog of unfilled orders thereupon develops at the factory. If the manufacturer adapts a level production/capacity plan, which involves running the operation at a uniformly high level of capacity availability (Slack et al, 2004), the inventory level would not be able to recover after two and half years. This shortfall of the inventory for two and half years for a 20% step change in demand makes the system effectively unstable.

The primary means for buffering against uncertain demand is inventory. The use of buffer inventories is increasingly difficult because of greater product variety and short technological life cycles (Helo, 2000). Increased capacity is an effective alternative to inventory in buffering against demand variability and the use of protective capacity can substantially reduce the buffer inventories. To counter the backlog effect due to limited capacity, it may be worth the manufacturer either decreasing the production delay or investing in extra capacity above the average order quantity. Such extra capacity can also provide safety capacity if there is another increase in demand. When order volatility increases, the shortfall of the actual capacity will increase, but an investment in safety capacity can greatly reduce this capacity shortfall (Van Mieghem, 2006).

Capacity constrains the ability of an echelon to process goods. Increasing capacity results in a 'squeezed' behavior. As capacity increases, inventory is quicker in recovery but under-damping is observed before locking on to the desired level. Figures 6.2.e and 6.2.f show the response of the order rate and actual inventory of the multi-echelon supply chain with medium capacity constraints. It is evident that the stock level of the capacitated manufacturer will recover after 55 weeks. When the factory has medium constraints, the appropriate manufacturing strategy would be 'matching capacity strategy', meaning an attempt is made to change demand to fit the capacity availability (Vlachos et al, 2007). The objective is to transfer customer demand from peak periods to quiet periods. During the periods of low demand, the available capacity can be fully utilized to produce the buffer stock for the peak demand periods.

"An appropriate balance between capacity and demand can generate high profits and satisfied customers, whereas getting the balance 'wrong' can be potentially disastrous." (Slack et al, 2004). There is a threshold value, beyond which capacity constraints do not alter the response of the actual inventory and order rate of the four echelons. In Figures 5.2.g and 5.2.h the supply chain with low capacity constraints behaves in a similar fashion to the unconstrained chain. The factory (farthest echelon) should be confident in dealing with the 20% increase in demand, with a capacity level of 1.33 over the mean demand. This situation has been named the "leading capacity strategy", where the manufacturer can use excess capacity to absorb sudden increases in demand (Vlachos et al, 2007). In this scenario, the appropriate strategy for the manufacturer would be the 'chase demand plan' by which a manufacturer attempts to match capacity closely to the varying levels of forecast demand and would require a level of physical capacity, which would only be used occasionally (Slack et al, 2004) A chase demand strategy minimizes or eliminates the finished goods inventory.

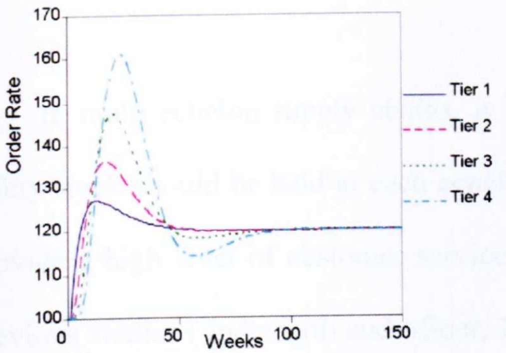


Figure 6.2.a. Response of the Un-capacitated Order Rate

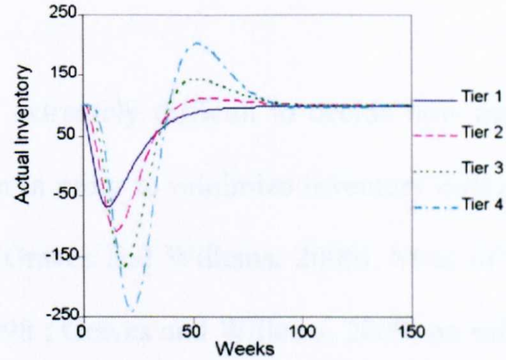


Figure 6.2.b. Response of the Un-capacitated Actual Inventory

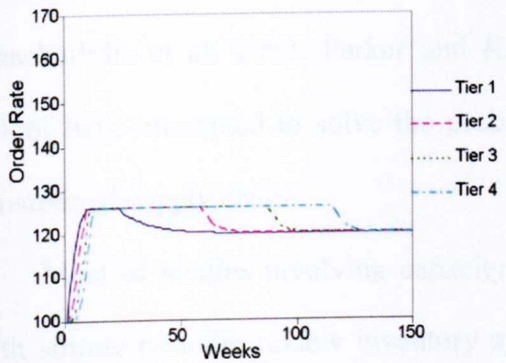


Figure 6.2.c. Impact of Capacity Constraints (High) on Order Rate

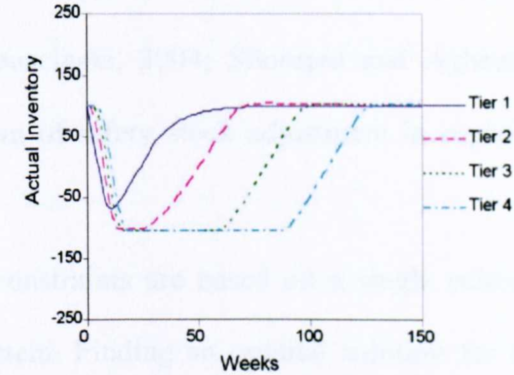


Figure 6.2.d. Impact of Capacity Constraints (High) on Actual Inventory

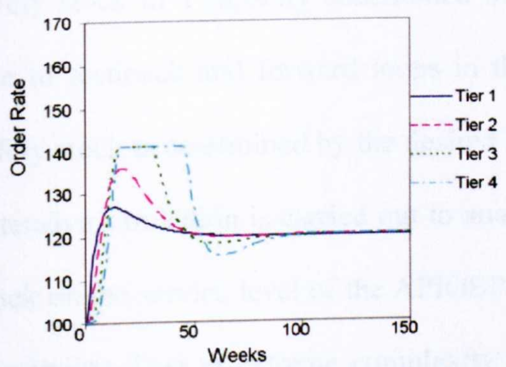


Figure 6.2.e. Impact of Capacity Constraints (Medium) on Order Rate

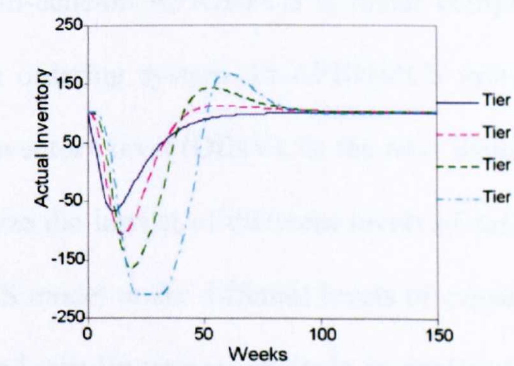


Figure 6.2.f. Impact of Capacity Constraints (Medium) on Actual Inventory

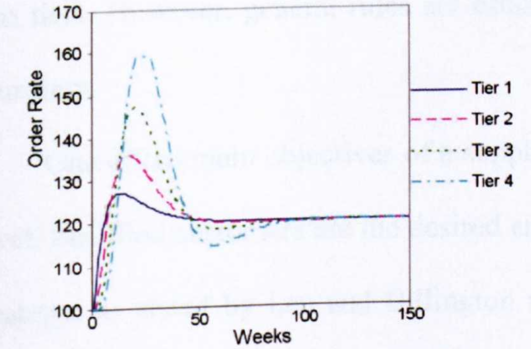


Figure 6.2.g. Impact of Capacity Constraints (Low) on Order Rate

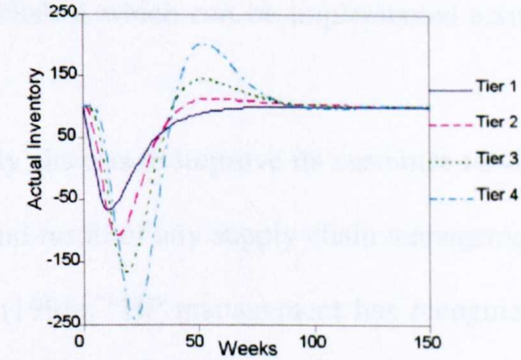


Figure 6.2.h. Impact of Capacity Constraints (Low) on Actual Inventory

6.5 Determination of Optimal Safety Stock Levels

In multi-echelon supply chains, it is extremely difficult to decide how much safety stock should be held at each echelon in order to minimize inventory cost and provide a high level of customer service (Graves and Willems, 2000). Most of the previous studies (Inderfurth and Miner, 1998 ; Graves and Willems, 2000) on safety stock location are based on systems without capacity constraints. Few researchers (Paschailidis et al, 2002; Parker and Kapuscinski, 2004; Sitompul and Aghezzaf ,2006) have attempted to solve the problem of safety stock adjustment in capacity constrained supply chain.

Most of studies involving capacity constraints are based on a single echelon with simple periodic review inventory system. Finding an optimal solution for the safety stock in a capacity constrained multi-echelon APIOBPCS is rather complex due to feedback and forward loops in the ordering system. In APIOBPCS system safety stock is determined by the desired inventory level (DINV). In the next section, extensive simulation is carried out to analyze the impact of different levels of safety stock on the service level of the APIOBPCS model under different levels of capacity constraints. Due to extreme complexity and non-linearities, analysis is confined to two tiers. However, general rules are established which can be implemented across four tiers.

One of the main objectives of a supply chain is to improve its customer service level. Satisfied customers are the desired end result of any supply chain management strategy; as stated by Lee and Billington (1995), "HP management has recognized that its performance filling orders will cause it to win or loose the battle". Capacity tightness as well as safety stock levels determine the customer service level of the supply chain. A useful customer service metric is "fill rate" (Zipkin, 2000), is a fraction of the demand that is satisfied from the available safety stock. Fill rate is a popular metric in industry (Disey et al, 2006) and is applied in the analysis presented here. In APIOBPCS, the service level (fill rate) of one tier is calculated by the percentage of the previous tier's orders satisfied through the available inventory of the former tier.

Three levels of capacity constraints (Low, Medium, and High) are applied in the simulation experiment here, as before in Section 6.4. The safety stock level is a constant times the average sales (Ng et al, 2002). Simulation is run for 500 periods and each run is simulated ten times. Like Zhao et al (2002), the average fill rate is calculated by averaging the results of 10 runs of the simulation model. For each experiment, the safety stock levels are increased gradually such that 100% service level is achieved at both tiers. A normally distributed demand with mean (μ = 100/weeks) and standard deviation (σ = 20) is used. The 'good' set of system parameters used before is used here, i.e. Ti = Tw = Tp, Ta = 2Tp.

Mapes (1992) simulated the effect of capacity constraints on safety stock in a single echelon of a periodic review inventory control system and the results indicated that increasing the safety stock level increases the customer service level. Table 6.1 also shows that increasing the safety stock of both tiers increases the percentage of the fill rate. The zero safety stock level will provide the lowest service level and the maximum safety stock will result in the highest service level. It can be said that the relationship between service level and safety stock is "monotonic", as found by Korevaar (2007) also. However, there is a threshold beyond which increasing the safety stock has very little impact on the service level as shown in Table 6.1. In capacity constrained supply chains the service level also depends on the capacity tightness.

The use of buffer inventories to protect against varying market demand is increasingly difficult due to greater product variety and shorter technological life cycles (Helo, 2000). Table 6.1 shows that capacity is an effective alternative to safety stock in achieving a higher customer service level. Increasing capacity can substantially reduce the level of safety stock required. When a firm decides to increase its service level, capacity and/or buffer stocks should be increased, with the choice depending on the nature of the product. For example, increasing capacity is a better solution for agile manufacturing. Increasing the safety stock in high-tech or other industries where the product life cycle is short poses potential dangers of obsolescence.

Sitompul and Aghezzaf (2006) showed that safety stock levels in capacity constrained supply chains must be high to achieve the desired service level as compared to non constrained supply chains. However, the amount of safety stock required to achieve the desired service level depends on the capacity constraints. Highly capacity-constrained systems require larger safety stocks and vice versa. In the highly capacity constrained supply chain simulated here a 100 % fill rate can be achieved by fixing the safety stock level at 4.25 and 5.75 times average sales at Tier 1 and Tier 2 respectively as shown in Table 6.1. With the low capacity-constrained system, the optimal levels of the safety stock should be set at 3 and 4 times average sales at Tier 1 and Tier 2 respectively.

Safety Stock (DINV)	High Capacity Constraints Tier 1	Tier 2	Medium Capacity Constraints Tier 1	Tier 2	Low Capacity Constraints Tier 1	Tier 2
1 * Sales	33	18	45	32	56	44
1.25 * Sales	38	22	50	37	61	49
1.5 * Sales	42	27	56	41	66	55
1.75 * Sales	46	31	61	46	73	60
2 * Sales	51	36	66	51	78	64
2.25 * Sales	56	39	71	57	84	65
2.5 * Sales	62	43	77	62	90	71
2.75 * Sales	67	46	83	66	96	77
3 * Sales	72	51	89	72	100	82
3.25 * Sales	78	56	95	77	100	88
3.5 * Sales	83	59	100	81	100	93
3.75 * Sales	87	64	100	85	100	97
4 * Sales	92	69	100	90	100	100
4.25 * Sales	97	73	100	94	100	100
4.5 * Sales	100	78	100	98	100	100
4.75 * Sales	100	84	100	100	100	100
5 * Sales	100	89	100	100	100	100
5.25 * Sales	100	93	100	100	100	100
5.5 * Sales	100	98	100	100	100	100
5.75 * Sales	100	100	100	100	100	100
6 * Sales	100	100	100	100	100	100

Table 6.1. Impact of Safety Stock and Capacity Constraints on Fill Rate (%)

6.6 Backlog Bullwhip Effect in a Multi-Echelon Supply Chain

Capacity constraints the ability of an echelon to produce so that it is a determinant of the service level. The backlog variance directly impacts the customer service level and hence is costly, while inventory variances determine the safety stock requirements and affect the inventory holding cost (Boute et al, 2007). The stability of each echelon can be ensured through the related echelon's shortfalls. Shortfalls, also known as backlogs, are measured by the shortfall of actual inventory of each echelon. Variance in the backlog is known as the "*backlog bullwhip effect*" (Anderson et al, 2005).

In a simple production and inventory control system, the order backlog is calculated when the production capacity reaches saturation. In APIOBPCS, production is controlled by the feed-forward loop of smoothed sales and the feedback loops of error in the inventory and error in the WIP. The backlog is recorded through a reduction in actual inventory level. Recording unfilled orders due to production saturation and maintaining a new feedback loop of the production order backlog, when the factory is operating at capacity within the APIOBPCS, leads to the double accounting phenomenon (Evans and Naim, 1994). Only one level should be recorded due to saturation either at the production or inventory control level, but not both. Here, backlog is recorded through the shortfall of the inventory.

In the next set of experiments conducted here, different levels of design parameters, capacity constraints, and safety stock levels are introduced across each tier of the APIOBPCS model. The objective is to minimize the backlog bullwhip effect across the multi-echelon supply chain by evolving appropriate values of design parameters, safety stock and capacity levels at each tier. Analysis is limited to two tiers of APIOBPCS model. To deal with this level of complexity and nonlinearity, Taguchi Design of Experiments is applied.

6.7 Taguchi Design of Experiments

Capacity and inventory planning can reduce the supply chain cost (Chao et el, 2008). Determining the safety stock placement at different echelons to achieve the desired level is extremely complex when production and distribution have capacity constraints (Sitompul and Aghezzaf, 2006). An important question in supply chain management is how to co-ordinate inventories and capacities in multi-echelon supply chains under stochastic demand processes, while providing a high level of customer service. To answer this question, Taguchi Design of Experiments is applied to evolve the optimum values of capacity, safety stock, and design parameters for two tiers of APIOBPCS.

The objective of the supply chain is to provide high service levels coupled with minimizing the backlog variances with minimum safety stock levels and capacity. One possibility is that each echelon independently determines its own safety stock and capacity levels. In reality, supply chains never exist in isolation, rather they act (or should act) in unity and local optima cannot guarantee global optima. Supply chains should be run as a single entity and policies should be derived to aim for global optima. Hence, different sets of deign parameters, stock levels and capacity levels are introduced across both tiers of the supply chain with the aim of minimizing the total backlog bullwhip effect, where the total backlog bullwhip is the sum of the backlogs at both tiers.

6.7.1 Inner Arrays

As explained in Chapter 3, the first step in parameter design is the selection of quality characteristics. The purpose of this research is to minimize total backlog bullwhip effect in the two tier APIOBPCS model by exploring the best factor or parameter levels, therefore the 'smaller-the-better' quality characteristic is applied here. The next step is to select the factors and their levels.

The supply chain model produced has five interacting inner arrays per tier; Time to adjust inventory (Ti), time to adjust work-in-progress (Tw), time to averaging sales (Ta), safety stock (DINV), and capacity constraints (Cap). The best value of design parameters (Ti, Tw, and Ta) for the stable response has been demonstrated in Chapter 4. The condition Ti = Tw = found by Mason-Jones et al (1997) and Riddalls and Bennett (2001) to be a condition for a good or best response across the supply chain, was also borne out by the results presented in Chapter 4. Hence, the condition Ti = Tw is applied in this analysis such that changing the value of Ti will also apply the same value to Tw. The three levels of Ti and Ta, DINV, and capacity considered at each tier are shown in Table 6.2. In the experiments, three different levels of safety stock are examined for both tiers. The stock levels selected are identified by analysis of the simulation results in Table 6.1. It is important to note that the above stock levels for Tier 1 and Tier 2 were selected for certain sets of design parameters. In this analysis these stock levels are rounded to the nearest integer values.

After the factors and their relevant levels are selected, the next step is to choose appropriate orthogonal arrays (OA). The choice of orthogonal array size used in the design of experiments depends on the total degrees of freedom (DoF) required for the parameters and their interactions. In this study, the DoF for 8 control factors (inner arrays), each with three levels is 8 x (3-1) +1= 17. The L_{27} orthogonal arrays, which can be used for five to thirteen three-level factors, is the appropriate selection for the inner arrays.

6.7.2 Outer Arrays

Outer arrays, also known as 'noise factors', involve those parameters that are uncontrollable in real life but are controlled during the experiment. In this study, two outer arrays are considered; sales and lead time. In APIOBPCS, the lead time is normally assumed to be constant. Whilst lead time is not a control system design variable (i.e. an inner arrays factor) it is possible that it may vary or a business may invest in lead time reduction. Therefore, the effect of lead time should be investigated so two lead time values are included in the outer arrays. A normally distributed demand with a mean (μ, 100) and standard deviation (σ) is considered. The following two levels of coefficient of variation (CV) of demand are considered in the outer arrays; (0.2, 0.4). The outer arrays are given in Table 6.3.

Factors	Level 1	Level 2	Level 3
Safety Stock (DINV1) Tier 1	3 * Sales	4 *Sales	5 * Sales
Safety Stock (DINV2)Tier 2	4 * Sales	5 * Sales	6 * Sales
Capacity Constraints (Cap1)Tier 1	High	Medium	Low
Capacity Constraints (Cap2) Tier 2	High	Medium	Low
Time to Adjust Inventory (Ti1) Tier 1	4	6	8
Time to Adjust Inventory (Ti2) Tier 2	4	6	8
Time to Average Sales (Ta1) Tier 1	6	9	12
Time to Average Sales (Ta2) Tier 2	6	9	12

Table 6.2. Inner Arrays

Factors	Level 1	Level 2
Demand (Sales)	100 (CV=0.2)	100 (CV=0.4)
Lead Time (Tp)	4	6

Table 6.3. Outer Arrays

Experimental Run	Safety Stock 1	Safety Stock 2	Capacity 1	Capacity 2	Tl 1	Tl 2	Ta 1	Ta 2
1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2
3	1	1	1	1	3	3	3	3
4	1	2	2	2	1	1	1	2
5	1	2	2	2	2	2	2	3
6	1	2	2	2	3	3	3	1
7	1	3	3	3	1	1	1	3
8	1	3	3	3	2	2	2	1
9	1	3	3	3	3	3	3	2
10	2	1	2	3	1	2	3	1
11	2	1	2	3	2	3	1	2
12	2	1	2	3	3	1	2	3
13	2	2	3	1	1	2	3	2
14	2	2	3	1	2	3	1	3
15	2	2	3	1	3	1	2	1
16	2	3	1	2	1	2	3	3
17	2	3	1	2	2	3	1	1
18	2	3	1	2	3	1	2	2
19	3	1	3	2	1	3	2	1
20	3	1	3	2	2	1	3	2
21	3	1	3	2	3	2	1	3
22	3	2	1	3	1	3	2	2
23	3	2	1	3	2	1	3	3
24	3	2	1	3	3	2	1	1
25	3	3	2	1	1	3	2	3
26	3	3	2	1	2	1	3	1
27	3	3	2	1	3	2	1	2

Table 6.4. $L_{27}(3^{13})$ Orthogonal Arrays for Controllable Factors

Experimental Run	Demand	Lead Time
1	1	1
2	1	2
3	2	1
4	2	2

Table 6.5. $L_4(2^3)$ Orthogonal Arrays for Noise Factors

6.7.3 Analysis of Results

A statistical measure called the '*Signal-to-Noise Ratio*' (SNR) proposed by Taguchi is applied for measuring the functional performance of the system by making it insensitive to the effect of noise (Lu and Antony, 2002). The details of SNR were presented in Chapter 3. The end result is "robust design" that is less sensitive to noise factors. It is measured in decibels by using the following formula (Roy, 2001);

$$SNR = -10\text{Log}_{10}(\text{MSD}) \qquad (6.1)$$

where MSD is the measure of mean squared deviation in the performance. Since in every design less noise, relative to the size of the signal, is required, the larger the SNR the greater the performance. For the quality characteristic of 'smaller-the-better', the corresponding MSD formula is:

$$\text{MSD} = \frac{1}{n}\sum_{i=1}^{n} Y_i^2 \qquad (6.2)$$

where: n = number of test results

Y_i = *i* th observed response value

6.7.4. Calculation of Main Effect

The effect of a design parameter on the measured response, when the parameter's value is changed from one level to another, is known as a '*main effect*' and is calculated for a particular level of a factor by examining the orthogonal array, the factor assignment, and the experimental results (Roy, 2001). Details of the calculation of main effects are presented in Chapter 5. Simulation results are the average of the 30 runs of the model, each of 500 weeks length.

Figure 6.3 shows that the total backlog bullwhip effect measurement is most sensitive to capacity tightness at Tier 2. When the order rate at Tier 2 saturates due to capacity constraints, a backlog of unfilled orders thereupon develops at that Tier. In this situation, the down stream tiers are prone to over ordering which further magnifies the demand and backlog. This backlog is regenerative (more orders cause a larger backlog and more delays and more ordering ahead) causing a larger backlog of orders (Forrester, 1961). This phenomenon can be referred to the "*Reverse Bullwhip Effect*" as shown by Rong et al (2008). The saturation at Tier 2, due to capacity constraints, results in a reverse bullwhip effect which further amplifies the backlogs at both tiers. Hence, it can be said that capacity constraints at the farthest tier are very important for controlling the total backlog of the model.

Previous research has indicated that the bullwhip effect has detrimental impacts on the upstream tiers, while Xu et al (2007) have shown that the bullwhip effect impacts the performance of the whole supply chain. It has been suggested that significant benefits can be achieved by 'strategic alliance' among supply chain partners. When production and distribution have capacity constraints then the reverse bullwhip effect deteriorates the performance of the whole supply chain.

The total backlog bullwhip effect is next most sensitive to capacity tightness at Tier 1. Figure 6.3 shows that capacity constraints at Tier 1 have a highly non-linear impact. This means that choosing an appropriate capacity level at Tier 1 is very critical. Capacity tightness at the Tier 1 determines the magnitude of the order rate and hence the safety stock level of Tier 2. Low and high capacity tightness at Tier 1 produces highly erratic ordering patterns which significantly increase the total variations of the backlog, while retailer working with medium capacity constraints produces smooth ordering pattern. This smoothing of the orders minimizes the inventory variations at Tier 2 and hence reduces the variations of the total backlog.

Figure 6.3 shows sensitivity of the SN Ratio to safety stock at Tier 1 and Tier 2. It can be seen that safety stock levels at both tiers have a substantial impact on the total backlog of the model. It is normally assumed that increasing the safety stock at a particular level will decrease its backlog. While, Anderson et al (2005) have shown that policies for minimizing backlog variations at Tier 1 and Tier 2 will both, in general, differ from that which will minimize the total variations of the backlog. Figure 6.3 shows that when production and distribution have capacity constraints then increasing the safety stock from the desired level increases the total variations of backlog. This is quite logical since larger safety stock levels result in larger inventory variations. When Tier 2 is working at saturation due to capacity tightness then sometimes it may not be able to cope with the larger inventory variations (large fluctuations in order rate) of the Tier 1. This situation again results in the reverse bullwhip effect. Hence, the determination of optimal safety stock levels in capacity constrained supply chains play s crucial role in mitigating the total backlog bullwhip effect. .

It has been shown in Chapter 5 that Ti is the most significant factor for the bullwhip effect in APVIOBPCS with batch ordering. However, in the capacity constrained supply chain simulated here the impact of Ti to backlog bullwhip effect is much smaller. Indeed, Table 6.6 shows the small contribution of Ti and Ta to the variance of the backlog.

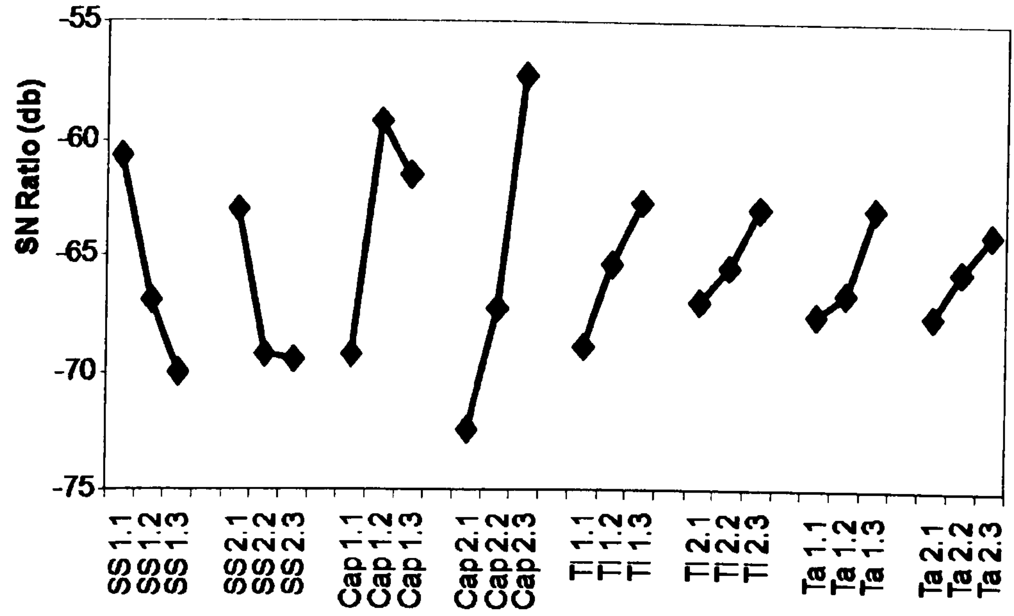


Figure 6.3. Plot of Main Effect Response

Where,

SS x.y = Safety stock Tier x, factor level y (see Table 6.2)

Cap x.y = Capacity Tier x, factor level y (see Table 6.2)

Ti x.y = Time to adjust inventory Tier x, factor level y (see Table 6.2)

Ta x.y = Time to average sales Tier x, factor level y (see Table 6.2)

6.7.5. Analysis of Variance (ANOVA)

To discover which effects are statistically significant, analysis of variance (ANOVA) is performed to quantify the contribution of each parameter to the total variation in the experimental data. Details of the ANOVA calculation were given in Chapter 3. The ANOVA tests are performed at the 97 % confidence level. The ANOVA results in Table 6.6 show that all the factors involved in this study are statistically significant. However, capacity constraints at Tier 2 makes the largest contribution to the variation in the measurement of the backlog bullwhip effect, with a contribution of 40 % and next is capacity constraints at Tier 1 with 20%, so that these two parameters account for 60 % of the total variance. This means that total backlog bullwhip effect can be reduced greatly through adjusting the capacity levels. The safety stocks levels accounts far less of the backlog bullwhip effect than does the capacity constraints, but their contribution is still significant unlike the much lower contribution of the design parameters Ti and Ta.

Factors	DOF (f)	Sum of Squares (S)	Variance (V)	F-Ratio (F)	Pure Sum (S')	Percent P (%)
1.Safety Stock-Tier 1	2	384	192	40	374	14
2.Safety Stock-Tier 2	2	205	103	21	195	8
3.Capacity Constraints-Tier 1	2	552	276	78	543	20
4.Capacity Constraints-Tier 2	2	1062	531	111	1052	40
5.Time to Adjust Inventory-Tier 1	2	179	89	19	169	6
6.Time to Adjust Inventory-Tier 2	2	106	53	11	97	4
7.Time to Average Sales-Tier 1	2	105	53	11	96	4
8.Time to Average Sales-Tier 2	2	52	26	5	53	2
Error	10	48	5			2
Total	26	2693				100 %

Table 6.6. Results of ANOVA

6.7.6. Determining the Optimal Values

Little research has been carried out to identify 'optimal' values of the safety stock and capacity constraints across multi-echelon supply chains. Determining the optimal values of safety stock at different echelons to achieve the desired level is extremely complex when production and distribution have capacity constraints (Van Houtum et al,1996; Sitompul and Aghezzaf ,2006). Analysis in this section fills this gap and offers insight to develop a trade-off between capacity and safety stock at different echelons, which will enable production managers to take better decisions about their capacity and safety stocks.

The best parameter levels within the range of values considered here are given in Table 6.7; this is in the context of minimizing the chosen measure of the backlog bullwhip effect.

According to the measure chosen here medium capacity constraints at Tier 1 and Low capacity constraints at Tier 2 should be preferred. Medium capacity constraints at Tier 1 produces smooth ordering and low capacity constraints at the farthest tier absorbs the magnitude of the backlog from previous tiers. This supports what Parker et al (2004) have shown that Tier 1 must have lower capacity than Tier 2.

Parker et al (2004) have demonstrated optimal policies for capacity constrained order-up-to-level production inventory control system. It has been shown that the optimal safety stock level of Tier 1 is constrained by its capacity and the safety stock level of Tier 2 while the optimal safety stock level of Tier 2 is constrained by the capacity tightness of Tier 1. It is important to note that the safety stock level of Tier 2 should be higher than the safety stock level of Tier 1 otherwise the system will face the 'induced penalty cost'; Tier 1 accrues induced cost for limiting the ability of Tier 2 to reach a desired safety stock level as a result of the capacity limitation of Tier 1, while Tier 2 accrues induced cost for potentially not fulfilling the demand of Tier 1.

Values of Ti and Ta not only ensure stability but also determine the capacity requirements of the system. Increasing Ti can control excessively large fluctuations in the order rate by damping the reaction to errors in the inventory. The results presented in Table 6.7 show that the largest values of Ti and Ta can perform better for the chosen measure of performance. The results in Table 6.7 show different parameters values at different tiers, this supports what Anderson et al (2005) found, that pursuing the same policies at all tiers increases the backlog of the model.

Factors	Level	Level Description
Safety Stock-Tier 1	1	3*Sales
Safety Stock-Tier 2	1	4*Sales
Capacity Constraints-Tier 1	2	1.18
Capacity Constraints-Tier 2	3	1.33
Time to Adjust Inventory-Tier 1	3	8
Time to Adjust Inventory-Tier 2	3	8
Time to Average Sales-Tier 1	3	12
Time to Average Sales-Tier 2	3	12

Table 6.7. Factors at Optimal Condition

6.8 Summary

i. Previous studies involving the APIOBPCS model are based on unconstrained capacity. One of the most important methodologies to investigate various aspects of APIOBPCS model is control theoretic techniques. As pointed out by Riddalls et al (2002) and White et al (2006), control theorists are dealing with the linearity of the model and there are no capacity constraints. This chapter has addressed this gap by introducing capacity constraints at different echelons of the APIOBPCS model.

ii. The stability boundaries of a multi-echelon supply chain with capacity constraints have been explored. Inventory shortfall determines the stability boundaries of the capacity constraint supply chain. The system may experience immense backorders if capacity constraints are not dealt with effectively. It has been seen that tight capacity constraints (e.g. capacity / mean demand = 1.05) result in high inventory shortfalls at the upstream tiers. When capacity tightness is not so tight (capacity / mean demand = 1.3) then the system behavior approaches that of the APIOBPCS without capacity constraints.

iii. It has been seen that safety stock and capacity constraints determine the service level of the supply chain. When capacity constraints are very tight then larger safety stocks are required to achieve the desired service level and vice versa.

iv. Increasing the safety increases the service level of a tier. However, there is, of course, a threshold beyond which increasing the safety stock does not increase the service level any more.

v. It has been shown that when the order rate of the farthest tier saturates due to capacity constraints then over ordering by the previous tiers magnifies the total backlog of the supply chain. This phenomenon has been termed the "reverse bullwhip effect". Hence, a more cautious approach toward the ordering pattern is required by downstream tiers when production and distribution have capacity constraints.

vi. The sensitivity of the backlog bullwhip effect to the capacity, the safety stock, and the design parameters of APIOBPCS has been explored. The degree of sensitivity to capacity constraints has been found to be very significant, especially the capacity constraints at the farthest tier, which contribute 40% to the total backlog variance This shows the importance of the capacity constraints of the farthest tier.

vii. An interesting finding is that the sensitivity of the backlog variances to the design parameters in the capacity constrained supply chain is very low. While, in the previous chapters it has been seen that bullwhip effect is most sensitive to Ti when there are no capacity constraints.

viii. It has been found that smooth ordering by Tier 1 can be achieved when Tier 1 has medium capacity constraints and low safety stocks. This smooth ordering reduces the total backlog variations of the supply chain. Increasing the value of Ti and Ta stabilizes the system and less capacity is required to meet the desired service level.

ix. Future work should investigate the impact of flexible capacity on stability, lead time, and the service level of the model. Another important dimension for further work is the total cost implications of capacity constraints and safety stocks in multi-echelon supply chain.

Chapter 7: Impact of Forecasting Methods and Replenishment Rules on Net Variance Ratio in Order-up-to Level Policy

7.1 Introduction

The literature review in Chapter 2 discussed that demand forecasting, lead times (delays) and ordering policies are among the key causes of the bullwhip effect. Hence, in this chapter the analysis of the bullwhip effect and inventory variances induced by different forecasting techniques and replenishment rules is presented. A basic order-up-to level replenishment rule is studied where the retailer reviews the inventory position periodically and places a replenishment order to the manufacture. The end customer demand faced by the retailer is a first order autoregressive process, denoted AR (1). Like other authors, AR (1) process is used to obtain some basic managerial insights rather than more complex AR (n) processes. The retailer's ordering pattern and inventory policies have a direct impact on the production of the upstream echelon. The upstream echelon prefers a smooth ordering pattern by the retailer. However, smoothing of the orders comes at the price of increased inventory variances at the retailer's level. Different forecasting techniques and replenishment policies are analyzed to develop a trade-off between the order and inventory variances of the retailer under a varying demand process.

The contribution of this chapter is three fold. First, the impact of exponential smoothing (ES) and minimum mean squared error (MMSE) forecasting techniques on the bullwhip effect is observed. Secondly, previous research into the order-up-to level (OUT) model focused on determining the impact of forecasting methods on the bullwhip effect by using statistical approaches, but Hosoda and Disney (2006, a) point out that "the statistical approaches become unmanageable when net inventory variances are considered as the expressions for the covariance between the states of the system are very complex". (Inventory variances represent the net stock variations and are measured by the ratio of net stock variance over the variance of demand. The higher the net stock variance the more safety stock required to meet the desired service. Simulation is applied in this thesis to this analysis so that these intractable expressions between order rate and inventory variances are avoided, and the impact of ES and MMSE forecasting techniques on both order and inventory variations can be investigated. The graphical results gained from simulation studies provide a clearer picture of the situation than the corresponding statistical and mathematical results.

Thirdly, it has been shown that the simple OUT replenishment policy always results in the bullwhip effect (Dejonckheere et al, 2003), (Hosoda and Disney, 2006 b). The simple OUT policy is modified here by adding a proportional controller into the inventory feedback loop. The impact of the proportional controller, in a modified OUT policy, on the demand amplification and inventory variances is analyzed. The modified OUT replenishment rule dampens the variability in the orders to the upstream echelon but this comes at the price of increased inventory variances at the retailer's level. It has been found that by fine tuning of the proportional controller, the order pattern can be smoothed to a considerable extent without affecting the inventory variances.

7.2. Literature Review

The order-up-to level (OUT) policy is a basic periodic review system for issuing orders on the basis of incoming demand and inventory position. OUT policy is optimal when there is no fixed ordering cost and both holding and shortage costs are proportional to the volume of the on-hand inventory or shortage (Dejonckheere et al, 2003). Impacts of forecasting methods on the bullwhip effect with the OUT policy have been studied by several researchers. Chen et al (2000, b) evaluated the moving average (MA) and exponential smoothing (ES) forecasting techniques with respect to bullwhip inducement in a simple order-up-to level (OUT) policy. They found that exponential smoothing forecasts are more likely to amplify demand variations than moving average forecasts. Alwan et al (2003) and Luong (2007) studied the bullwhip effect in an order-up-to-level policy with mean squared error (MMSE) forecasting for the AR (1) demand process. (Autoregressive is a stochastic demand process which can be described by weighted sum of previous demand plus white noise error. AR(1) demand process means only previous immediate demand value has an impact on the current demand process.) They found that using such a forecasting policy, the bullwhip effect can be eliminated or mitigated depending on the demand autocorrelation. Zhang (2004) also investigated the impact of forecasting methods in an OUT policy with autoregressive AR (1) demand process. Zhang found that, in comparison with MA and ES forecasting techniques, the use of MMSE forecasting technique improves the inventory performance for the downstream echelons. Sun et al (2005) made the comparison of the effects of MA, ES, and MMSE forecasting on the bullwhip effect in an OUT model. Sun's findings indicate that for negatively correlated demand process, MMSE forecasting method performs better while for positively correlated demand ES and MA should be preferred.

The impact of lead time on the bullwhip effect has also been investigated by Chen et al (2000,b), Zhang (2004), Chatfield et al (2004), and Kim et al. (2007). Chatfield et al (2004) analyzed the bullwhip effect with stochastic lead time and found that lead time variability exacerbates variance amplification in supply chains. Kim et al (2006) measured the impact of stochastic lead time on bullwhip effects for a k-stage supply chain and found that the bullwhip effect was higher under the lead time variability. Most studies on lead time have shown that longer lead times or larger lead time variations have a negative effect on supply chain performance, implying that lead time or lead time variability should be minimized.

Replenishment strategies have an impact on order and net stock variability. Order variability contributes to the bullwhip effect and the upstream cost while variations in net stock level affect the ability to meet a desired service level. In a make-to-order supply chain, the upstream echelon pursuing the smooth production prefers the minimal variability in the production orders from downstream. Dejonckheere et al (2003) showed that in the OUT replenishment system, bullwhip is unavoidable with exponential smoothing, moving average, and demand signal forecasting and propose a general replenishment rule for order smoothing. Balakrishnan et al (2004) emphasized opportunities to reduce supply chain costs by reducing the variability of orders to upstream echelons. This has led to the creation of new replenishment policies that are able to generate smooth order patterns and which in turn can mitigate the demand amplification. In order to control the dynamics of the supply chain, Hosoda and Disney (2006,b) added a proportional controller in the simple OUT supply chain model with MMSE forecasting. They named the new replenishment policy the generalized OUT policy and found that in a two echelon supply chain it reduced the inventory related cost by 10 %. Boute et al (2007) studied a two level supply chain with I.I.D customer demand. They found that decreasing the order variability at the retailer's level comes at the cost of increased variance of the retailer's inventory level.

Previous research focused on determining the impact of forecasting methods on the bullwhip effect. However, as pointed out by Hosoda and Disney (2006, a), "Statistical approaches become unmanageable when net inventory variances are considered as the expressions for the co-variances between the states of the system are extremely complex". Therefore, it is argued that simulation is better suited to this analysis to avoid these intractable expressions, and the graphical results gained from simulation studies provide a clear picture of the situation.

It has been shown that simple OUT replenishment policy always results in bullwhip effect (Dejonckheere et al, 2003; Hosoda and Disney, 2006, b). In this study the simple OUT policy is modified by adding a proportional controller into the inventory feed back system and the impact of this is analyzed. Taguchi Design of Experiments is applied in analyzing the impact of different factors involved in this study, to understand the effects of the factors and their interactions and to identify the set of parameter values that minimizes the order and inventory variances.

7.3. Model Description

This section studies the basic periodic review inventory and production control system. The basic structure of the model is the same as the one studied by Lee et al (1997). The block diagram of the model studied is presented in Figure 7.1. The details of the model are explained below.

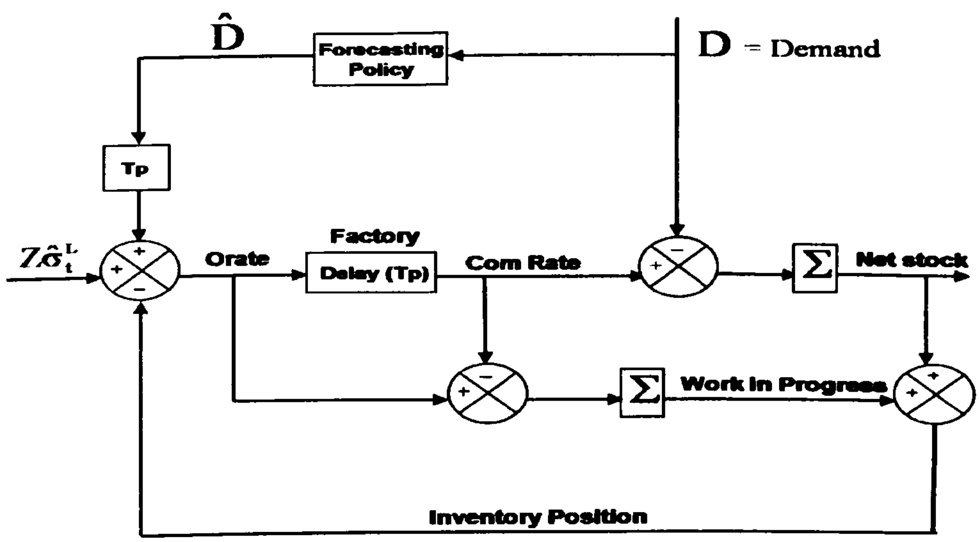


Figure 7.1. Block Diagram of Order-up-to Level (OUT) Model

7.3.1. Demand process

The standard periodic review based stock OUT replenishment policy is used. External demand for a single item occurs at the retailer, where the underlying demand process faced by the retailer is an AR (1) process. The retailer's demand from the customer is a mean centered demand pattern: i.e.

$$D_t = d + \rho(D_{t-1} - d) + \varepsilon_t \tag{7.1}$$

where D_t represents the demand in period t, d is the average demand, ρ is the first order autocorrelation coefficient, $-1 < \rho < 1$, and ε_t is an independent and identically distributed normal process (I.I.D) with mean 0 and variance σ_ε^2. It is assumed that σ_ε is significantly smaller than d, so that the probability of negative demand is negligible, (Lee et al, 2000). The demand variance equals $\sigma_D^2 = \sigma_\varepsilon^2 / (1-\rho^2)$. By varying the value of ρ, a wide range of process behaviors can be observed. When $\rho = 0$, we have an I.I.D process with mean μ and variance σ_ε^2. For $-1 < \rho < 0$, the demand process is negatively correlated and will exhibit period-to-period oscillatory behavior. For $0 < \rho < 1$, the demand process will be positively correlated which is reflected by a wandering or deviating sequence of observations. As ρ approaches one, the process approaches non-stationary behavior; and in particular, a pure random walk model or equivalently, an ARIMA (0, 1, 0) process (Box and Jenkins, 1970).

7.3.2. Inventory Policy

The standard periodic review base stock policy is the (R, S) policy. At the end of every review period R, the inventory position is tracked and a replenishment order is placed to raise the inventory position to an order-up-to or "base stock" level S, which determines the order quantity in period t, as shown in Equ

$$O_t = S_t - IP_t \quad . \qquad (7.2)$$

Where, O_t is the ordering decision made at the end of period *t*, S_t is the order-up-to level used in period t and IP_t is the inventory position. The inventory position is the sum of net stock plus (NS) pipeline inventory (WIP) as shown in Equation 7.3.

$$IP_t = NS_t - WIP_t \qquad (7.3)$$

Where $$NS_t = NS_{t-1} + O_{t-L} - D_t \qquad (7.4)$$

and $$WIP_t = WIP_{t-1} + O_{t-1} - O_{t-L}. \qquad (7.5)$$

The order up to level is determined by Equation 7.6.

$$S_t = \hat{D}_t^L + z\hat{\sigma}_t^L \qquad (7.6)$$

Where $\hat{D}_t^L$ is expected forecasted demand over L periods ($\hat{D}_t^L = L\hat{D}_t$), $\hat{\sigma}_t^L$ is an estimation of the standard deviation of the lead time forecast error, and z is a constant chosen to meet the desired service level and is related to inventory holding and backlog cost. As done by other authors, z is set equal to zero and lead time is increased by 1. For example, a retailer having an order lead time of four weeks may decide to keep stock of five weeks of forecasted demand, with the extra week of inventory representing the safety stock. Such a policy has the potential of $O_t < 0$ but under the assumption $\sigma_\varepsilon < d$, the probability of having $O_t < 0$ is negligible (Lee et al 1997). The standard deviation of the lead time demand forecast error is $\hat{\sigma}_t^L = \sqrt{Var(D_t^L - \hat{D}_t^L)}$, where Var is the variance. Zhang (2004) showed that the standard deviation of the lead time forecast error remains constant over time for the moving average, exponential smoothing, and mean squared error forecasting methods. Hence, $\hat{\sigma}_t^L = \hat{\sigma}_{t-1}^L$, and the replenishment order quantity can be written as Equation 7.7.

$$O_t = \hat{D}_t^L - (NS_t + WIP_t) \qquad (7.7)$$

There is a fixed lead time (denoted by L or Tp) such that an order placed at the end of period t is received at the start of period t + L. All unmet demands are backlogged. In the simulation conducted here, an average demand of 100 per week and standard deviation of 20 are used. Like Lee et al (1997), it is assumed that there is an infinite number of demand data available and the underlying parameters of the demand model are known. Simulation is run for 400 periods for each condition. Replication is carried out for 30 time periods and averages of the results are taken. Performance measures of the simulation analysis are observed on the bullwhip effect. The bullwhip measure is defined by Equation 7.8.

$$\text{Bullwhip} = \frac{\text{Variance of order rate}}{\text{Variance of demand}} = \frac{\text{Var}(O_t)}{\text{Var}(D_t)} \tag{7.8}$$

When Bullwhip = 1, it implies that the variance of orders is equal to the variance of demand or in other words there is no bullwhip effect. Bullwhip < 1 shows the existence of the anti-bullwhip or de-whip effect. Bullwhip > 1 indicates that the variance of orders are greater than the variance of demand and the presence of the bullwhip effect.

7.4. Bullwhip Effect with Exponential Smoothing (ES) Forecasting

The exponential smoothing (ES) forecast is an adaptive algorithm in which the one period ahead demand forecast is adjusted by a fraction of the forecast error. Let α denote the fraction used in this process (also called the smoothing factor), then the ES forecast of next period's demand can be written as:

$$\hat{D}_t = \hat{D}_{t-1} + \alpha(D_t - \hat{D}_{t-1}) \tag{7.9}$$

The smoothing constant (α), is the weight placed on the most recent observation of demand in the exponential smoothing forecast and is subject to the condition $0 < \alpha < 1$. A forecast of one period ahead is made which is then multiplied by the lead time to obtain the value of lead time demand, i.e., $\hat{D}_t^L = L\hat{D}_t$. Now we test Chen's et al (2000, b) findings, later confirmed by other analytical studies, about the effects of the smoothing constant (α), demand correlation coefficient (ρ), and the lead time (L) on the bullwhip effect. Three levels of each factor are simulated. The degrees of freedom (DOF) for three control factors, each with three levels is 3 x (3-1) +1= 6. L_9 arrays which can be used for four factors at three levels are selected. Table 7.2 defines, for each experiment, the level of each factor (parameter) to be used. The factor levels used in the experiments reported here are given in Table 7.1.

Factors	Level 1	Level 2	Level 3
Lead Time (L)	2	4	8
Demand Correlation (ρ)	-0.8	0	0.8
Smoothing Constant (α)	0.2	0.5	0.8

Table 7.1. Parameter and their Levels

Experimental Run	L	ρ	α
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Table 7.2. Inner Arrays (L9)

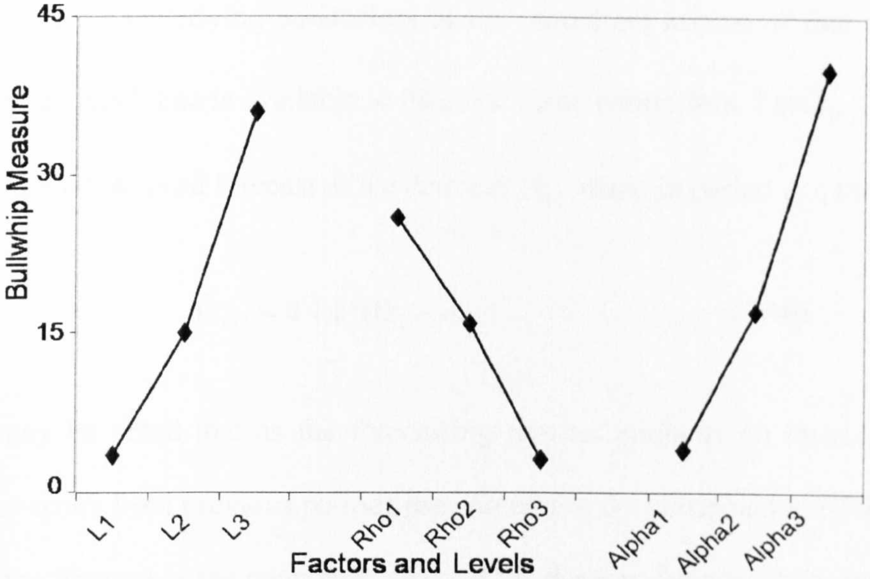


Figure 7.2. Bullwhip Effect with ES

The above results validate Chen's et al (2000, b) findings that the bullwhip effect increases with α and decreases with demand autocorrelation (ρ) and converges to one when $\rho = 1$. When compared to an I.I.D demand process, negatively correlated demand results in an increased bullwhip effect while positively correlated demand results in a decreased bullwhip effect. Figure 7.2 also shows that increasing the lead time also increases the variability of orders.

7.5. Bullwhip Effect with Minimum Mean Squared Error (MMSE) Forecasting

Using MMSE forecasting means that the demand forecast is derived in such a way that the forecast error is minimized (Box and Jenkins,1970). It is the conditional expectation of future demand, given current and previous demand observations. The MMSE forecast for the demand in period D_{t+j}, given current and previous demand observations $D_t, D_{t-1}, D_{t-2}, \ldots$ (Box and Jenkins,1970). This forecasting technique assumes that the underlying parameters of the model are known or that an infinite number of demand data is available to estimate these parameters. Let $\hat{D}_{t+j}, j = 1,2,...,$ be the j-period- a- head forecast of the demand D_{t+j} made in period $_{t+j}$, then

$$\hat{D}_{t+j} = d + \rho^{j}(D_t - d) \qquad (7.10)$$

It may be noted that as the forecasting process contains no moving average terms, the errors from previous periods play no part in the computation of the results. Further, the forecast is the geometric decay from the last demand observation to the mean of the process. In contrast to the exponential smoothing forecast method, the one period ahead demand forecast is not multiplied by lead time, but instead the forecast of the demand over the lead time horizon is calculated by plugging a single period MMSE forecast into the lead time. The mean squared error forecast for the lead time demand is given by, (Zhang (2004).

$$\hat{D}_t^L = Ld + \frac{\rho - \rho^{L+1}}{1-\rho}(D_t - d) \qquad (7.11)$$

Like Lee et al (2000), it is assumed that infinite number of demand data is available and underlying parameters of demand process are known. Figure 7.3 shows the effects of demand correlation and lead time, in an order-up-to level policy, on the bullwhip effect when demand forecasts are estimated using MMSE. A comparison is made between negatively correlated, I.I.D, and positively correlated demand processes. When demand is negatively correlated (-1< ρ < 0), the bullwhip effect does not exist or, the variance of the order quantity is smaller than the variance of demand resulting in an anti-bullwhip or de-whip effect. From the managerial point of view, a de-whip effect means that the production planning phase at the manufacturer level becomes easier and more stable. The manufacturer prefers to smooth production, thus he prefers a smooth ordering pattern from the retailer. Bullwhip effect increases the variances in orders and destabilizes the production planning phase at the manufacturer level. When the variance of the order quantity is smaller than the variance of the demand (de-whip effect) then the production manager can stabilize the production schedule and minimize the production cost.

When the customer demand is given by an I.I.D process, i.e., when $\rho = 0$, there is no correlation in demand and the order-up-to level policy with MMSE forecast generates orders equal to the observed customer demand and results in a "chase sales policy"(Slack et al, 2004) that reduces to mean demand forecasting. In production and inventory control systems, a chase sales policy implies that production can be smoothed at a fixed rate without having to increase at inventory levels to provide the same customer service level. A chase sales policy is usually adopted by operations which cannot store their output, such as customer-processing operations or manufacturer of perishable goods (Slack et al, 2004). A chase sales policy avoids wasteful provision of excess staff and capacity yet satisfies customer demand. When demand is positively correlated ($0 < \rho < 1$), with the increase of demand correlation the bullwhip effect increases first, reaches the maximum value, and then starts decreasing. The bullwhip effect is an increasing function of lead time over a certain range of demand correlation. When there is a loose positive correlation; i.e. when $\rho \leq 0.3$, smaller amplifications in the order rates are observed and an increase in lead time does not cause much difference to demand amplification. When $\rho \geq 0.5$, the bullwhip effect is more significant and an increase in the lead time leads to an increased bullwhip effect. Lead time has much impact on bullwhip effect when

0.9> ρ >0.3. In Figure 7.3 it can be seen that the maximum value of the bullwhip effect is observed when ρ = 0.8.

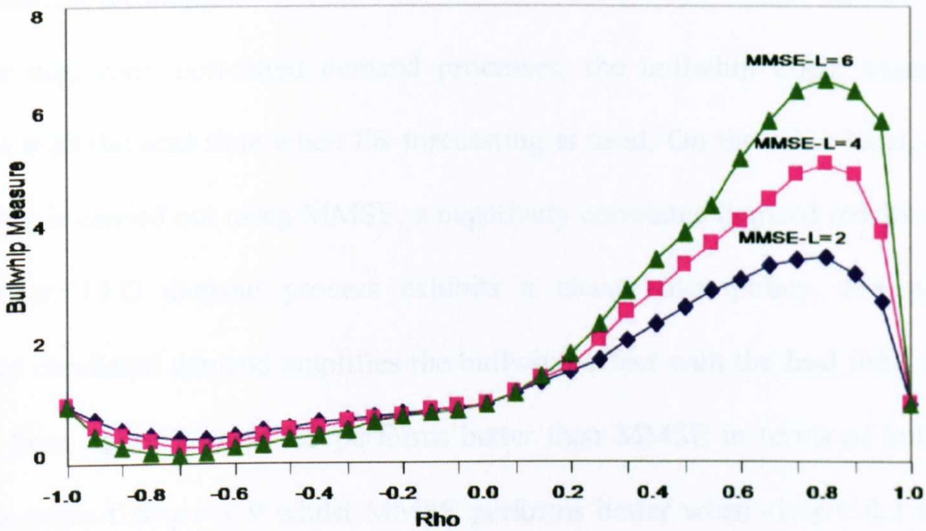


Figure 7.3. Impact of Rho on the Bullwhip Effect under MMSE Forecasting

7.6. Comparison of ES and MMSE

Figure 7.4 shows the impact of MMSE and ES (α = 0.2) as a function of lead time on the bullwhip effect. The bullwhip effect observed using the ES technique is a decreasing function of ρ and converges to one as ρ approaches one. An obvious difference between the results for MMSE forecasting and the results for ES is that the bullwhip effect is no longer decreasing with autocorrelation. When demand is negatively correlated (-1< ρ < 0), the bullwhip effect exists for the ES forecasting technique whilst it diminishes under MMSE. Lead time reduction can significantly reduce the bullwhip effect when 1> ρ >0.3 with MMSE. In contrast, with the order up to policy with ES technique, when -1< ρ < 0, shortening the lead time has a significant impact on bullwhip reduction. From the managerial point of view, these findings suggest that bullwhip effect does not automatically increase with the lead time rather it depends on the forecasting technique and the parameters of the demand. The effort to reduce the bullwhip effect through shortening lead time will be misleading, especially when managers have little knowledge of underlying demand and forecasting techniques.

For negatively correlated demand processes, the bullwhip effect exists and increases with the lead time when ES forecasting is used. On the other hand, when forecasting is carried out using MMSE, a negatively correlated demand results in de-whip effect, I.I.D demand process exhibits a chase sales policy, and perfect positively correlated demand amplifies the bullwhip effect with the lead time. It can be seen from figure 7.4 that ES performs better than MMSE in terms of bullwhip reduction when $0.6<\rho<0.9$ whilst MMSE performs better when $-1<\rho<0.3$ with a transition occurring when $0.3<\rho<0.6$. When a low weighting factor ($\alpha = 0.1$ or 0.2) is used as the smoothing constant then the magnitude of the amplification is lower for ES when compared with MMSE. Increasing the weighting factor of α to 0.4 increases the bullwhip effect as compared to MMSE. This reveals that the bullwhip effect is more sensitive to α than to the demand correlation. Table 7.3 shows the selection of appropriate forecasting technique with respect to demand correlation.

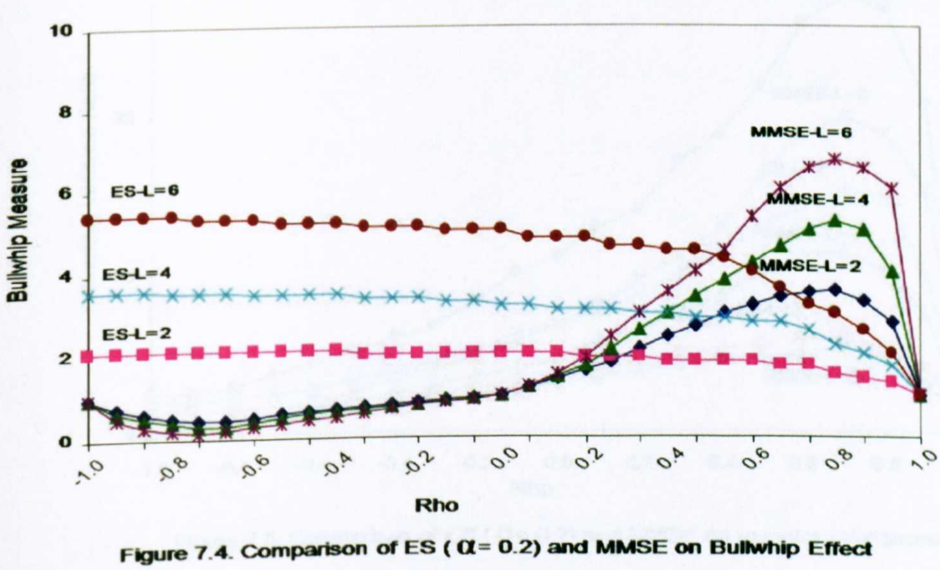


Figure 7.4. Comparison of ES (α= 0.2) and MMSE on Bullwhip Effect

RHO	ES	MMSE
-1.0	No	Yes
-0.8	No	Yes
-0.6	No	Yes
-0.4	No	Yes
-0.2	No	Yes
0	No	Yes
0.2	Yes	Yes
0.4	Yes	No
0.6	Yes	No
0.8	Yes	No
1.0	Yes	Yes

Table 7.3. Selection of Forecasting Technique

7.7. Impact of ES and MMSE on Inventory Variance

Most of the previous research on demand amplification and forecasting in a periodic review order-up-to level model has used statistical approaches. These are useful for gaining an insight into the structure of the ordering process as it moves into the upper levels of the supply chain. However, as pointed out by Hosoda and Disney (2006,a), "the statistical approaches become unmanageable when net inventory variances are considered as the expressions for the covariance between the states of the system are very complex". Therefore, it is argued that simulation is better suited to this analysis to avoid these intractable expressions, and the graphical results gained from simulation studies provide a clear picture of the situation.

The variance of the net stock has a greater impact on the customer service level; the higher the net stock variance the more safety stock required to meet the desired service level. The variance of inventory measure is defined by Equation 7.12.

$$\text{Varaince of inventory} = \frac{\text{Varaince of net stock}}{\text{Varaince of demand}} = \frac{\text{Var}(NS_t)}{\text{Var}(D_t)} \qquad (7.12$$

Figure 7.5 shows the quantification of the net inventory variance at the retailer's level by using ES and MMSE forecasting for different levels of lead time. The net inventory variance is also affected by demand correlation. The net inventory variance under MMSE and ES forecasting techniques, increases at first, then reaches its maximum value, starts to decrease before it converges to one. The net inventory variances for the ES are greater than the MMSE forecasting method and that gap increases as lead time increases. Increasing the lead time for a particular level of the supply chain increases the net inventory variances to a greater extent then the bullwhip measure under both ES and MMSE forecasting methods. This shows that inventory variances are more sensitive to lead time than the order variances. This result is intuitive as the inventory fluctuates on the basis of demand and supply. Higher variances in net inventory levels are observed for positively correlated demand under both forecasting schemes. It can be concluded that net inventory variances are greater for the higher lead times and for positively correlated demand. It can be seen in Figure 7.5 that, for both forecasting methods, the maximum inventory variations are observed when ρ is in the region of 0.75.

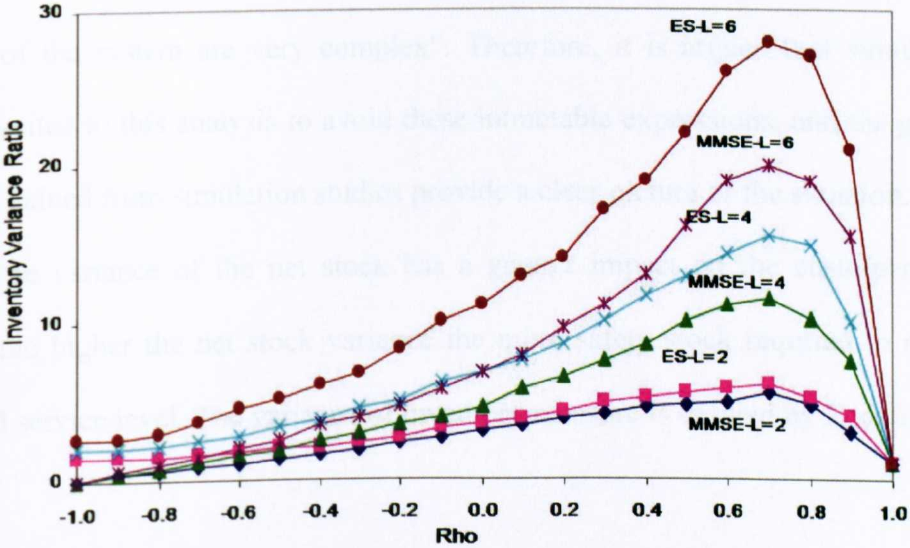


Figure 7.5. Comparison of ES (α= 0.2) and MMSE on Inventory Variances

7.8. Modified OUT Policy

It has been shown that the OUT replenishment policy always results in bullwhip effect (Dejonckheere et al., 2003), (Hosoda and Disney, 2006, b). So the simple OUT replenishment policy needs to be modified to issue a smoothed ordering pattern as this is a way to reduce variability. Dejonckheere et al. (2003), Balakrishnan et al. (2004) and Hosoda and Disney (2006) proposed a number of smoothing replenishment rules. In this study, a proportional controller is added in the inventory feedback loop of the simple OUT replenishment policy. This new replenishment policy is named the 'modified' OUT policy. First, taking Equation 7.7 and substituting $\hat{D}_t^L = T_{p+1}\hat{D}_t$, equation 7.13 is obtained, which is then rearranged to give Equation 7.14.

$$O_t = \hat{D}_t^L - (NS_t + WIP_t) \qquad \text{(7.7) (repeated here)}$$

$$= T_{P+1}\hat{D}_t - (NS_t + WIP_t) \qquad (7.13)$$

$$= (\hat{D}_t + T_P\hat{D}_t) - (NS_t + WIP_t) \qquad (7.14)$$

$T_P\hat{D}_t$ can be treated as a desired inventory position (DIP). The difference between the desired inventory position and actual inventory position is called the error of inventory position (EIP), where, $EIP_t = DIP_t - (NS_t + WIP_t)$. Incorporating a proportional controller, β, into Equation (7.14) yields the 'modified order-up-to level policy'.

$$O_t = \hat{D}_t + \beta(DIP_t - NS_t + WIP_t) \qquad (7.15)$$

with $0 < \beta < 2$. Forrester (1961) and control theorists refer to $1/\beta$ as the inventory adjustment time (Ti) and propose not to recover the error of inventory position in one time period. Instead, recovery should be spread over time by ordering only fraction β of the inventory deficit. In the simple order up to level policy, the error of the inventory position is completely taken into account while in modified order up to level policy, a fraction of the inventory discrepancy is ordered. Forrester (1961) acknowledges that when $\beta < 1$, the recovery time for the error of the inventory should be spread over time and when $\beta > 1$ recovery will be much quicker as overreaction to the error of the inventory will be observed. It is important to note that when $\beta = 1$, both order up to level policies are identical. A block diagram of the modified OUT policy is presented below.

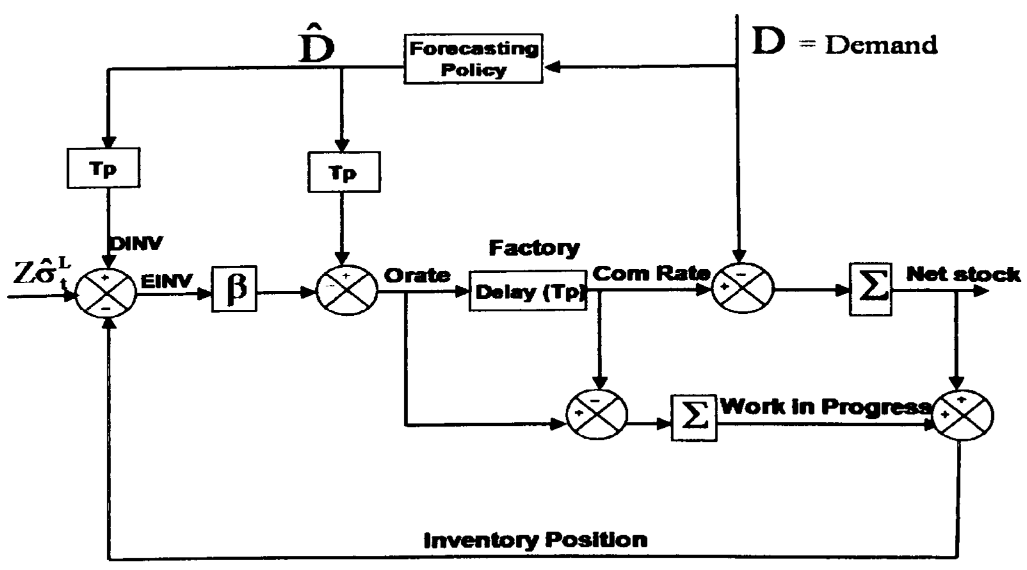


Figure 7.6. Block Diagram of Modified Order-up-to Level (OUT) Model

7.8.1. Orthogonal Arrays

In this study, the degree of freedom (DOF) for three control factors with three levels is 3(3-1) +1=7. This leads to choosing the $L_9(3^4)$ arrays, which are the best option for studying up to four factors at three levels. The selected orthogonal arrays are presented in Table 7.5 that defines, for each experiment, the level of each factor to be used. The factor levels used in the experiments reported here are given in Table 7.4. The purpose of this research is to minimize the order and net stock variance ratio by exploring the best parameter levels, therefore the smaller-the-better quality characteristic is applied in this study. For the analysis of experimental results obtained from the simulations, Taguchi standard analysis is carried out as before in Chapter 5.

Factors	Level1	Level2	Level3
Lead Time (L)	2	4	6
Beta (β)	0.5	1	1.5
Rho (ρ)	0.2	0.5	0.8

Table 7.4. Factors and Levels

Experimental Run	L	β	ρ
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Table 7.5. Inner Arrays (L9)

7.8.2. Analysis of Results

Figure 7.7.a shows the impact of β, lead time, and demand correlation on the bullwhip effect when forecasting is carried out using the MMSE method. It should be remembered that when $\beta = 1$, the modified order up to policy is the same as the simple order up to level policy. When $\beta < 1$, a smoothed replenishment pattern is created. Smoothing is a well known method to reduce variability and hence demand

amplification. When $\beta > 1$ the variability of the order quantity is increased and the bullwhip effect is increased and when $0 < \beta < 1$, the bullwhip effect is dampened. Figure 7.7.a also shows that the bullwhip effect is very sensitive to β. Demand correlation is the second most significant factor, whilst the lead time has the least effect on demand amplification.

Figure 7.7.b shows the impact of β, lead time, and ρ on the net stock variance. In terms of β, it can be seen that the modified order up to level policy increases the net stock variance ratio of the retailer. This means that the upstream echelon benefits from the smoothing of the replenishment order. For the retailer, this smoothing comes at the price of larger inventory variations; and variations in the inventory level increase the inventory related cost. Larger inventory variations are observed when $\beta > 1$. Figure 7.7.b also shows that variances in stock level are highly sensitive to lead time. It is important to note that the effect of demand correlation (ρ) and lead time on inventory variance is linear while the impact of β is non-linear. As $\beta = 1$ gives the lowest inventory variance ratio, the simple OUT policy is an optimal policy for the retailer's inventory variances. This result shows that inventory control policies at the retailer level often propagate customer demand variability in an amplified form to upper levels of the supply chain as found by Boute et al. (2007). Damping variability in orders may have negative impact on customer service by increasing inventory variances. The bullwhip effect contributes to upstream costs, while the variance of the net stock increases the cost of the retailer.

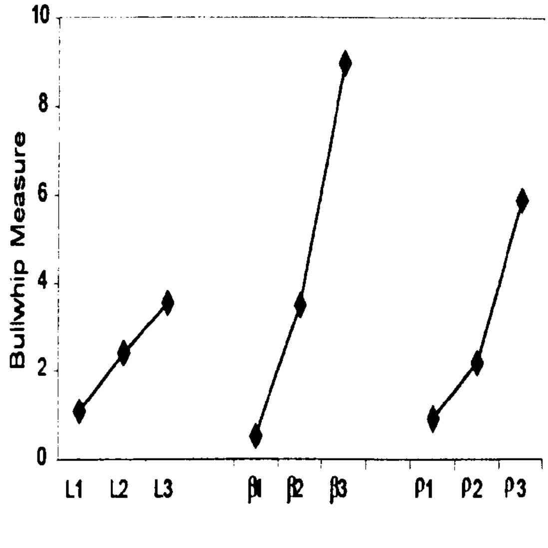


Figure 7.7.a. Impact of Factors on Bullwhip Effect

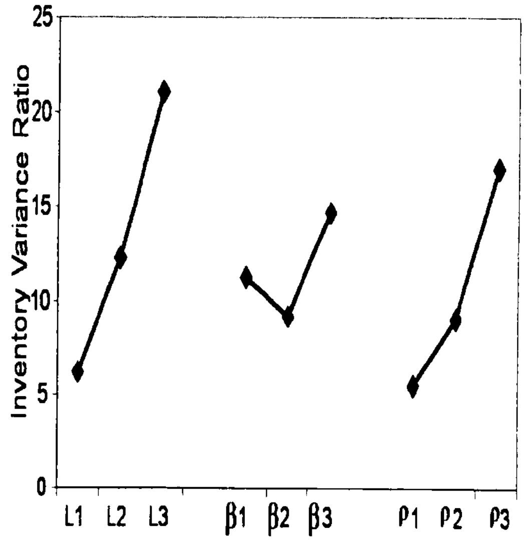


Figure7.7.b.Impact of Factors on Inventory Variance Ratio

The next step is to explore the interactions among the parameters. Two important interactions are observed; interaction between β and demand correlation and between β and lead time. These interactions have been discussed already in Chapter 5. In general, β compensates for demand correlation and vice-versa. The last step in the Taguchi approach is to find the optimum values for the factors investigated. Disney and Towill (2003) ask, "To what extent can production rates be smoothed in order to minimize the production adaption cost without adversely increasing inventory costs". In order to calculate the optimal value of β, a trade off needs to be developed between the order and inventory variances. From Figure 7.7.a and 7.7.b, it can be seen that when $\beta > 1$; both the bullwhip effect and inventory variances are amplified. On the other hand, when $\beta < 1$ inventory variation increases but the bullwhip effect is damped. Hence, in order to evolve the trade off between bullwhip effect and inventory variances, the optimum value of β is between 0 and 1.

Again, Taguchi's orthogonal arrays are used to explore the best values of the factors for both order and inventory variances. Four levels of each parameter are selected as shown in Table 7.6. The L_{16} orthogonal arrays, which can be used to study the fifteen factors at two levels, are modified. The modified L_{16} arrays provide the best opportunity to study two to five factors at four levels (Roy, 2001). The selected orthogonal arrays are presented in Table 7.7 that defines, for each experiment, the level of each factor to be used.

Figure 7.8 shows the main effect of the factors on the sum of net stock variance and bullwhip effect. By adding net stock amplification and bullwhip, it is assumed that the inventory variance is equally as important as the order variance. The optimum value of β should set at 0.6, lead time and demand correlation should be minimum.

Factors	Level1	Level2	Level3	Level4
Lead Time (L)	2	3	4	5
Beta (β)	0.2	0.4	0.6	0.8
Rho (ρ)	0.2	0.4	0.6	0.8

Table 7.6. Factors and Levels

Experimental Run	L	β	ρ
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

Table 7.7. Inner Arrays (M16)

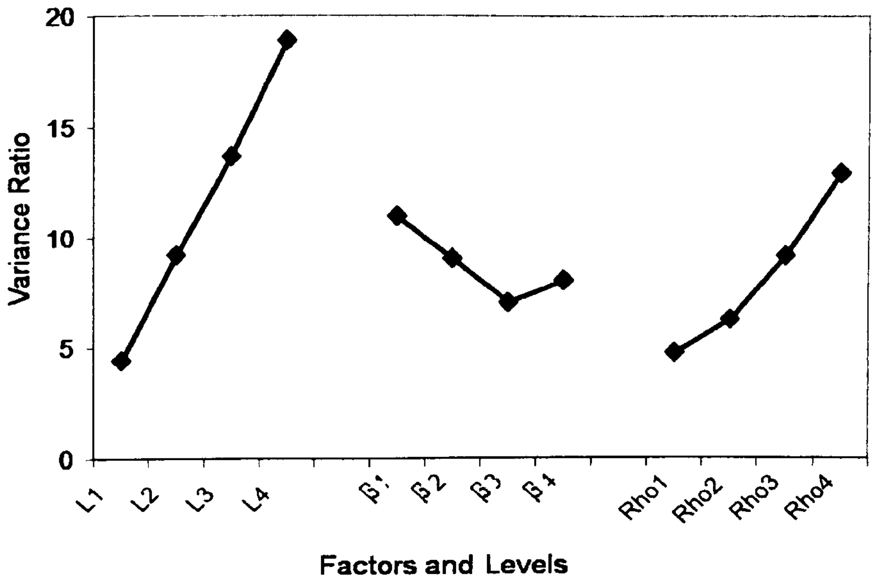


Figure 7.8. Impact of Factors on Variance Ratio

7.9. Conclusion

In this chapter, the bullwhip effect and inventory variances induced by different forecasting techniques in an order-up-to level supply chain where end customer demand is an AR (1) process have been analyzed. Through simulation experiments designed using orthogonal arrays and subsequent analysis of the results, it has been found that:

i. For the ES forecasting method, negatively correlated demand can lead to larger increases in order variability than positively correlated demand. For the *MMSE* forecasting technique, there is no bullwhip effect for I.I.D and negatively correlated demand.

ii. For a negatively or loose positively correlated demand process, the MMSE forecasting technique should be used so that the bullwhip effect is eliminated. MMSE forecasting technique eliminates the bullwhip effect for a negatively correlated demand process and greatly reduces demand amplification for a loose positively correlated demand process. For a strong positively correlated demand process, the ES forecasting technique is preferred because it minimizes the bullwhip effect.

iii. The MMSE forecasting technique can significantly reduce the net stock amplification for all types of demand process when compared with ES. For both forecasting techniques, net inventory variances are more for the higher lead times and for positively correlated demand. Net stock amplification is more sensitive to lead time than order variance.

iv. It has been shown that order up to level policies always result in demand amplification. A smoother order pattern can be generated by incorporating a proportional feedback controller into the simple order up to level policy, but this smoothing comes at the price of increased inventory variance at the retailer's level. Through fine tuning of the proportional controller, the order pattern of the retailer can be smoothed without adversely affecting the net stock level.

v. The sum of variances of net stock plus order level is more sensitive to lead time and less sensitive to the demand correlation.

This research can be extended in many directions. A more complicated demand process such as an ARMA(p,q) process could be analyzed. The model considered simple forecasting techniques. The use of more sophisticated forecasting techniques should be considered. The impact of a proportional controller should be analyzed on multi-echelon supply chain models.

Chapter 8: Conclusion and Future Work

8.1. Conclusion

This chapter brings to a conclusion the results of the work undertaken, providing a summary of the findings, highlighting the contribution to knowledge, and proposes future research. This thesis consists of eight chapters. Chapter 1 of this thesis outlines the research background, research needs, and the motivation for this research. Current understanding of the causes of the bullwhip effect has been reviewed through the literature review presented in Chapter 2. As a prelude to further studying these causes and remedies through a supply chain simulation modeling approach, a review of supply chain models and modeling techniques have also been presented in Chapter 2. The research methods and tools employed in this thesis, i.e. iThink, Taguchi Design of Experiments, and analysis of variance (ANOVA), were introduced in Chapter 3.

Chapter 4 presents the iThink model of a multi-echelon supply chain. The impact of this model's design parameters on the response of the actual inventory and order rate at each echelon is simulated. Using Taguchi's orthogonal arrays technique, the effects of the design parameters are analyzed and the best settings of the design parameter values for the stable response are identified. The main outputs and findings of Chapter 4 are given below.

i. A simulation model of the APVIOBPCS production and inventory control system has been developed, using iThink, **to understand the effects of its parameters on its dynamic responses**; this model combines the *make to stock* and *make to order* control strategies. Four *APVIOBPCS* models have been linked to create a four-tier supply chain model of the beer game.

ii. Implementing the model in iThink has demonstrated how a control theoretic type model can be implemented in a way that **makes it more amenable** to supply chain operations manager and similar 'business professionals' rather than those who are highly mathematically trained.

iii. It has been demonstrated that parameter values that give very poor dynamics across the whole supply chain do not necessarily yield poor dynamics within a single echelon, so it is essential to consider the whole supply chain when setting parameter values. Mason-Jones et al. (1997) found that Ti = Tw = Tp and Ta = 2Tp is a condition for a 'good' or 'near best' response across the supply chain and **this has been borne out by the results presented here**, although for the 'best' result the parameter values may be close to this condition rather than absolutely satisfying it.

iv. Riddalls and Bennett (2001) reported that the condition Ti = Tw avoids oscillatory behavior in the dynamic responses of the order rate and inventory and this has been borne out here, except when Ti = Tw is very small, in such case the over-lively inventory feedback, due to the small Ti, causes very large oscillations and, indeed, the worst response; **this means that it has been found here that the Ti = Tw condition is subject to Ti not being very small.**

v. As in human endeavour in general, in selecting parameter values for the APVIOBPCS supply chain there is a choice between safe and stable without over-reacting but with the danger of becoming too slow to react to real change, i.e. too cautious, versus fast to react to real change (as opposed to noise) in a stable manner but with the danger of over-reacting and moving towards instability. This is seen in the dynamic responses here. Generally, a small Ti leads to over-reaction tending towards instability. However, within the range of experiments with a small Ti, two produce the very best results; fast but without load overshoots. Similarly, within the range of experiments with a larger Ti that yield more stable responses, there are two experiments that produce very slow responses that would typically be unacceptable in practice. **So two groups of 'good' or 'stable' response have been seen. One of these groups is within the area of fast responses and one is within the area of slow and very stable responses.** In this respect, with careful management parameter values associated with the first group may be adopted to give good results, but if one cannot safeguard against or afford to risk falling towards instability, then one might take the safer option of using the other group of parameter values, but then one must safeguard against the danger of slipping into too slow a response.

vi. Endorsed by the stochastic response results, in Chapter 4 it has been seen that there are two group responses that define the regions of acceptable and unacceptable parameter values, particularly in respect of their closeness to instability. The value of the ITAE of the step response gives a rough-cut between the two groups, although a few experiments had a very good ITAE but poor stochastic demand response. So **the use of ITAE needs to be tempered by consideration of the stochastic response**. Furthermore, the interpretation of the ITAE must also be tempered by the detailed features of the dynamic responses; with specific applications/situations determining which are the most important features and their desired characteristics, e.g. will the situation tolerate large overshoots to achieve rapid rise times?

Chapter 5 has explored the impact of order batching on the bullwhip effect in the 4-tier APVIOBPCS supply chain, with and without information sharing. It is generally advocated that batch size should be reduced as much as possible (Burbidge, 1981), but there has been limited detailed investigation into the impact of batch size on demand amplification, which raises the question, does this hold totally true in respect of minimizing demand amplification? Chapter 5 has addressed this gap in the research by introducing batching into the 4-tier supply chain model and then conducting simulation experiments to understand: the impact of batch sizes on the bullwhip effect under deterministic and stochastic demand processes; the impact of information sharing across wide ranges of batch sizes; the impact of design parameters on the bullwhip effect (which is measured quantitatively) and the severity of the interaction among these parameters when there is batching; finally, the best values of design parameters for mitigating the bullwhip effect when there is batching. The main findings of Chapter 5 are:

i. It has been seen that the **relationship between batch size and demand amplification is non-monotonic**. Although Burbridge (1981) emphasised reducing the batch size, the results presented here show that when the quotient of the average demand and batch size is integer, demand amplification does not grow with increases in batch size. Large batch sizes, that when combined in integer multiples can produce order rates that are close to the actual demand, produce little demand amplification, i.e. it is the size of the remainder of the quotient that is the determinant. Unless the batch size is made very small, demand amplification is not suppressed simply by reducing the batch size, rather it can be controlled by a judicious mix of decreases in batch size and adjusting the batch size so that the remainder of demand divided by batch size is zero or close to zero. However, it has been noted that use of a large batch size placed at one of the local minima amplification points has the danger that changes in average demand can lead to large increases in amplification, i.e. there is high sensitivity.

ii. If the batch size is increased beyond the average demand then the output variance, i.e. the bullwhip effect, increases rapidly and **linearly**. A corollary to this is that if the demand per order period starts to decrease below the batch size then the bullwhip effect will grow rapidly. Again, operations managers could monitor for this condition.

iii. In percentage terms, the increase in demand amplification between tiers 1 and 4 is greatest with the smaller batch sizes, i.e. a large batch size may cause a large output variance at Tier 1, but this output variance does not increase much in percentage terms, as it passes up the supply chain. So the ubiquitous drive to reduce batch sizes in manufacturing can lead to greater demand amplification in **percentage terms**. It is further noted that the value of information sharing is greatest for smaller batch sizes, for which there is a much greater improvement in the amplification ratio when IEP (information enrichment percentage) changes from 0% to 100%.

iv. Whilst the amplification ratio beyond Tier 1 is much less for large batch sizes, making it a less significant problem, information sharing can almost eliminate any significant demand amplification. There is a dilemma here because information sharing will have a cost associated with its implementation, and whilst it may deal with the problem of demand amplification very well, the problem is primarily caused at Tier 1 with very large batch sizes. In contrast, information sharing is clearly of great value when the batch size is smaller. So, with the increasing drive to reduce batch sizes, there is an increasing justification for adopting and investing in information sharing.

v. The interactions between the design parameters of the APVIOBPCS in respect of their effect on demand amplification has been analysed. The strongest interaction is seen in the beneficial impact of information sharing on demand amplification being dependent upon the batch size, with information sharing being most beneficial with small batch sizes. The next strongest interaction is seen in increased values of Ta reducing the sensitivity of demand amplification to batch size. The third strongest interaction is observed between IEP and Ta, i.e. the value of information sharing is affected significantly by the forecasting error. Without information sharing, demand amplification increases considerably as Ta is reduced, and then the smaller Ta (with the much higher amplification to start with) benefits most from information sharing, indeed it benefits considerably. There is a strong interaction between IEP and Ti; decreasing Ti causes over-reaction and oscillatory behavior, as seen in Chapter 4, so the benefit of 100% information sharing increases.

Chapter 6 identified that most of the previous studies involving the APIOBPCS model are based on unconstrained capacity. So the model has been extended by adding capacity constraints at each of the 4-tiers of APIOBPCS. Capacity constraints determine the stability boundaries of the system. The stability of each echelon can be ensured through the related echelon's 'shortfalls', also known as backlogs, which are measured by the shortfall in the actual inventory. The model has been simulated for different capacity constraint levels and the stability boundaries of the model have been explored.

Determining the safety stock placement at different echelons to achieve the desired level is extremely complex when production and distribution have capacity constraints (Sitompul and Aghezzaf, 2006). An important question in supply chain management is how to co-ordinate inventories and capacities in multi-echelon supply chains under stochastic demand processes, while providing a high level of customer service. To answer this question, Taguchi Design of Experiments has been applied to analyze the effects of capacity, safety stock, and design parameters for two tiers of APIOBPCS on the total backlog bullwhip effect. The main findings of Chapter 6 are:

i. The stability boundaries of a multi-echelon supply chain with capacity constraints have been explored. Inventory shortfall determines the stability boundaries of the capacity constraint supply chain. The system may experience immense backorders if capacity constraints are not dealt with effectively. It has been seen that tight capacity constraints (e.g. capacity / mean demand = 1.05) result in high inventory shortfalls at the upstream tiers. When capacity tightness is not so tight (capacity / mean demand = 1.3) then the system behaviour approaches that of the APIOBPCS without capacity constraints.

ii. It has been seen that safety stock and capacity constraints determine the service level of the supply chain. When capacity constraints are very tight then larger safety stocks are required to achieve the desired service level and vice versa.

iii. It has been shown that when the order rate of the farthest upstream tier saturates due to capacity constraints then over-ordering by the previous tiers magnifies the total backlog of the supply chain. This phenomenon has been termed the "reverse bullwhip effect". Hence, a more cautious approach toward the ordering pattern is required by downstream tiers when production and distribution have capacity constraints.

iv. The sensitivity of the backlog bullwhip effect to the capacity, the safety stock, and the design parameters of APIOBPCS has been explored. The degree of sensitivity to capacity constraints has been found to be very significant, especially the capacity constraints at the farthest tier, which contribute 40% to the total backlog variance This shows the importance of the capacity constraints of the farthest tier.

v. It has been found that smooth ordering by Tier 1 can be achieved when Tier 1 has medium capacity constraints and low safety stocks. This smooth ordering reduces the total backlog variations of the supply chain. Increasing the value of Ti and Ta stabilizes the system and less capacity is required to meet the desired service level.

In Chapter 7 the analysis of the bullwhip effect and inventory variances induced by different forecasting techniques and replenishment rules has been presented. Previous research focused on determining the impact of forecasting methods on the bullwhip effect. However, as pointed out by Hosoda and Disney (2006, a), "Statistical approaches become unmanageable when net inventory variances are considered as the expressions for the co-variances between the states of the system are extremely complex". The application of simulation to this analysis has avoided these intractable expressions between order rate and inventory variances, and it has been possible to investigate the impact of ES and MMSE forecasting techniques on both order and inventory variations. It has been shown that the simple OUT replenishment policy always results in bullwhip effect (Dejonckheere et al, 2003; Hosoda and Disney, 2006, b). So, in this study the simple OUT policy has been modified by adding a proportional controller into the inventory feedback system and the impact of this has been analyzed.

In Chapter 7 through simulation experiments designed using orthogonal arrays and subsequent analysis of the results, it has been found that:

i. For the ES forecasting method, negatively correlated demand can lead to larger increases in order variability than positively correlated demand. For the MMSE forecasting technique, there is no bullwhip effect for I.I.D (independently and identically distributed) and negatively correlated demand.

ii. For a negatively or loose positively correlated demand process, the MMSE forecasting technique should be used so that the bullwhip effect is eliminated. The MMSE forecasting technique eliminates the bullwhip effect for a negatively correlated demand process and greatly reduces demand amplification for a loose positively correlated demand process. For a strong positively correlated demand process, the ES forecasting technique is preferred because it minimizes the bullwhip effect

iii. The MMSE forecasting technique can significantly reduce the net stock amplification for all types of demand process when compared with ES. For both forecasting techniques, net inventory variances are more for the higher lead times and for positively correlated demand. Net stock amplification is more sensitive to lead time than order variance.

iv. It has been shown that order-up-to level inventory control policies result in demand amplification. A smoother order pattern can be generated by incorporating a proportional feedback controller into the simple order-up-to level policy, but this smoothing comes at the price of increased inventory variance at the retailer's level (Tier 1). Through fine tuning of the proportional controller, the order pattern of the retailer can be smoothed without adversely affecting the net stock level.

8.2. Future Work

This work reveals many promising areas where further investigation could take place. As explained earlier this dissertation consists of four main analytical chapters (Chapters 4-7) and each chapter makes its own contribution. Hence, the future work relating to each chapter can be extended in different directions as explained below.

Chapter 4 has presented the condition of design parameters for a 'good' or 'near best' response across the multi-echelon supply chain. The specific results obtained in Chapter 4 are those for the specific values of lead time (Tp) and inventory cover (n) used here. In APIOBPCS, lead time is normally assumed to be constant. However, in reality lead times are never constant so future research should evolve the set of design parameters for a 'stable' response under stochastic lead time and different values of inventory cover.

Chapter 5 has explored the impact of batch sizes on the bullwhip effect and the severity of interactions of interaction among design parameters. Future work for Chapter 5 should investigate the cost implications of order batching in a multi-echelon supply chains. The interaction graphs presented in Chapter 5 give a general idea about the severity of interaction among design parameters. However, a few authors, e.g. (Montgomery, 2001), have pointed out that Taguchi's Orthogonal Arrays are not efficient for analyzing the interaction among parameters. Hence, Response Surface Methodology should be applied to better explore these interactions. Further, this research has focused on the periodic review inventory control system, the continuous review inventory control system should be considered in future work.

The analysis of Chapter 6 has presented the stability boundaries and the policies to minimize total backlog bullwhip effect in a multi-echelon capacity constrained supply chain. The stability boundaries have been explored for the deterministic demand process for fixed inventory levels. Future work should need to investigate the stability boundaries for different stochastic demand processes in flexible capacity constrained models. Another important dimension for further work is the cost implications of capacity constraints and safety stocks in multi-echelon supply chains.

Chapter 7 dealt with the impact of forecasting methods on the bullwhip effect with the first-order auto-regressive (AR1) demand process. This research can be extended in many directions. A more complex demand process such as an ARMA (p,q) process could be analyzed. The model considered simple forecasting techniques. The use of more sophisticated forecasting techniques should be considered. The impact of an inventory feedback proportional controller with a modified order-up-to level replenishment policy should be analyzed in multi-echelon supply chain models.

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Appendix 1;

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Quantifying the Impact of a Supply Chain's Design Parameters on the Bullwhip Effect

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ABSTRACT

This paper is concerned with understanding the effects of design parameters on demand amplification in a model of a multi-echelon supply chain with information sharing. The model uses the control theoretic concepts of variables, flows and feedback processes. Previous, similar studies have used traditional operational research techniques such as mathematical programming and stochastic process modeling and, as pointed out by Riddalls et al. (2000), differential equations produce smooth outputs that are not suitable when modeling supply chains. A combination of simulation and Taguchi Design of Experiments is applied here to quantify the impact of the supply chain's design parameters on its dynamic performance and the interactions that occur between the parameters. This study presents an approach to determining the relative contribution of the design parameters in controlling demand amplification (the Bullwhip Effect). The overall aim is to give supply chain operations managers and designers a way to understand supply chain dynamics and the effects of design parameters and their interactions.

Keywords: Bullwhip, Simulation, Taguchi Design of Experiments, Information Sharing.

INTRODUCTION

Supply chain dynamics has been studied for more than four decades. Since Forrester (1961) discovered the fluctuation and amplification of demand moving upstream in the supply chain, there has been a lot of research analyzing this phenomenon. Forrester (1961) pointed out that demand amplification is due to the "system dynamics phenomenon" and can be tackled by reducing delays, while

Sterman (1989) through his "beer game" interprets the phenomenon as a consequence of players' irrational behaviours or misperceptions of feedback. Towill (1996) confirmed the findings of Forrester that reducing delays and collapsing all cycle times improves the performance of the system. Lee et al. (1997) found that demand amplification or the "Bullwhip Effect" was due to demand signal processing, order batching, price variations and rationing and gaming and can be reduced through information sharing. Slack and Lewis (2002) give a textbook introduction to its causes and remedies. Its effects include inaccurate forecasting leading to periods of low capacity utilization alternating with periods of having not enough capacity, i.e. periods of excessive inventory caused by over production alternating with periods of stock-out caused by under production, leading to inadequate customer service and high inventory costs.

Several supply chain models have been analyzed to quantify the Bullwhip Effect. For example, Lee et al. (2000), while studying a two-tier supply chain, showed that manufacturer inventory levels can be reduced dramatically by sharing point-of-sales data. Yu et al. (2001) used information sharing to reduce the variability of demand placed on the supplier in a two-tier supply chain model. Riddalls and Bennet (2002) investigated the use of pure delays in a single echelon of Sterman's beer game model and showed that transient inability to supply all that is demanded is an important cause of amplification.

The multi-echelon supply chain model was developed originally by Forrester (1961). Towill (1982) introduced a greater level of detail using the *Inventory and Order Based Production Control System* (IOBPCS) to model each echelon in more detail, applying a basic periodic review algorithm for issuing orders into the supply pipeline, based on current inventory deficit and incoming demand from customers. Later, a work-in-progress feedback loop was added to the IOBPCS, "Let the production targets be equal to the sum of an exponentially smoothed demand (over Ta time units) plus a fraction (1/Tai) of the inventory error, plus a fraction (1/Tw) of the WIP error.". This was then termed the "Automatic Pipeline Inventory and Order Based Production Control System" (APIOBPCS) (John et al., 1994). This model and the model used latterly by Riddalls and Bennett (2002) form the basis of the echelon model (or building block) used here.

Finding the best operating conditions for a supply chain is complex due to the interactions among the design parameters. Previous studies used traditional operational research techniques such as mathematical programming, stochastic process modeling, heuristic methods and as pointed out by Riddalls et al. (2000) differential equations produce a smooth output that is not suitable for the modeling of all supply chains. Mathematical and control theoretic approaches can require an academically advanced understanding of mathematics that many (if not most) supply chain operations managers do not have. In contrast, the use of simulation methods involving simple equations can help practitioners to understand the basic phenomena and to examine the effects of parameters, interactions that occur and to search for the best combination of parameter values in conjunction with Taguchi Design of Experiments.

This study differs from previous research in many ways. Previous studies have identified several possible causes of the Bullwhip Effect but little attention has been given to measuring quantitatively the impact of these causes on the Bullwhip Effect (Paik et al., 2007). Some studies changed the value of one variable at a time and measured its effect on demand amplification. This 'one-at-a time' methodology reveals the effect of one factor with one particular set of values for the other factors but does not provide the information for calculating the effects of the factor with any values for the other factors. A more appropriate methodology is Taguchi's Orthogonal Arrays Technique in which levels of each factor are systematically varied and all possible combinations of factor levels (parameter values) are considered. Furthermore, it measures quantitatively the effects of the design parameters on demand amplification, the interactions among the parameters are explored and the best combination of parameter values for mitigating the impact of demand amplification is considered.

The remainder of this paper is organized as follows. First the methodology is introduced and then the supply chain simulation model is presented. After that, the impact of the design parameters on the dynamics of the inventory levels and order rates is studied and the orthogonal arrays technique is applied to explore the impact of various levels of the design parameters on a measure of demand amplification or the Bullwhip Effect.

Methodology.

The *System Dynamics* approach is used to analyze complex, dynamic and non-linear interactions and to develop new structures and policies to obtain the improved behaviour of a system. It allows one to visualize and solve a problem holistically. A *System Dynamics* computer simulation model is developed here to study the time varying or *dynamic* behaviour of a supply chain and thereby the Bullwhip Effect. The model uses levels, flows (or rates) and feedback processes and is implemented using the *iThink* software package (*http://www.iseesystems.com/*).

A four-echelon supply chain is modeled and simulated, so it is the fourth echelon that experiences the greatest demand amplification as it is farthest from the end-customer. The dynamics of the inventory and order rate at the fourth echelon present the 'worst-case' scenario so the Bullwhip Effect experienced at this echelon is studied in the work presented here. Taguchi and analysis of variance (ANOVA) techniques are used to analyse the dynamic performance of the fourth echelon with respect to its design parameters. As the design parameter values are varied, the values are applied at all echelons.

The Model

iThink uses the four basic building blocks in Figure 1: *Stock*, represents something that accumulates; *Flow*, an activity that changes the magnitude of the stock; *Converter*, modifies an activity; *Connector*, transmits inputs and information. Figure 2 presents the discrete continuous simulation model of a 4-echelon supply chain produced in *iThink* using these building blocks.

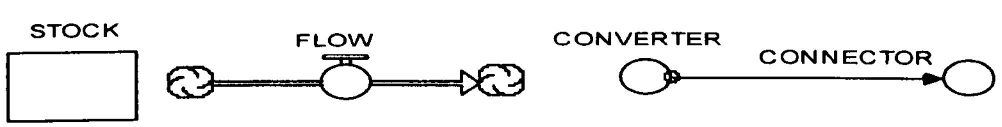


Figure 1: Building blocks of *iThink* software.

At the material flow level, each echelon or tier constitutes one inventory and one time delay (factory). Each echelon operates individually based on demand information gained from downstream (towards the end-customer). This situation is the same as that modeled in the beer game, where a brewery and a distribution centre try to cope with changes in demand. The input to the factory is the *order rate* (ORATE). Production is controlled by feeding forward the exponentially *smoothed sales* (SSALES) and feeding back the error in the inventory and the work-in-progress to determine the ORATE with the aim of keeping the inventory at a desired level. The *error in the inventory* (EINV) is the difference between the *desired inventory* (DINV) and the *actual inventory* (AINV). DINV is adaptive. In this case it is simply equal to the current (one week's) sales. The *work in progress* (WIP) is the accumulation of orders that have been placed on the factory but not yet completed and the *desired WIP* is DWIP. The *error in the WIP* (EWIP) is the difference between the *desired WIP* (DWIP) and the *actual WIP* (WIP). Ti is a divisor applied to the inventory deficit to control the rate of recovery and Tw is a divisor that controls the WIP replenishment rate. In summary:

$$\text{DINV} = \text{SSALES} \qquad (1)$$

$$\text{EINV} = \text{DINV-AINV} \qquad (2)$$

$$\text{DWIP} = \text{Tp x SSALES} \qquad (3)$$

$$\text{EWIP} = \text{DWIP-WIP} \qquad (4)$$

$$\text{ORATE} = \text{SSALES} + \text{EINV/Ti} + \text{EWIP/Tw} \qquad (5)$$

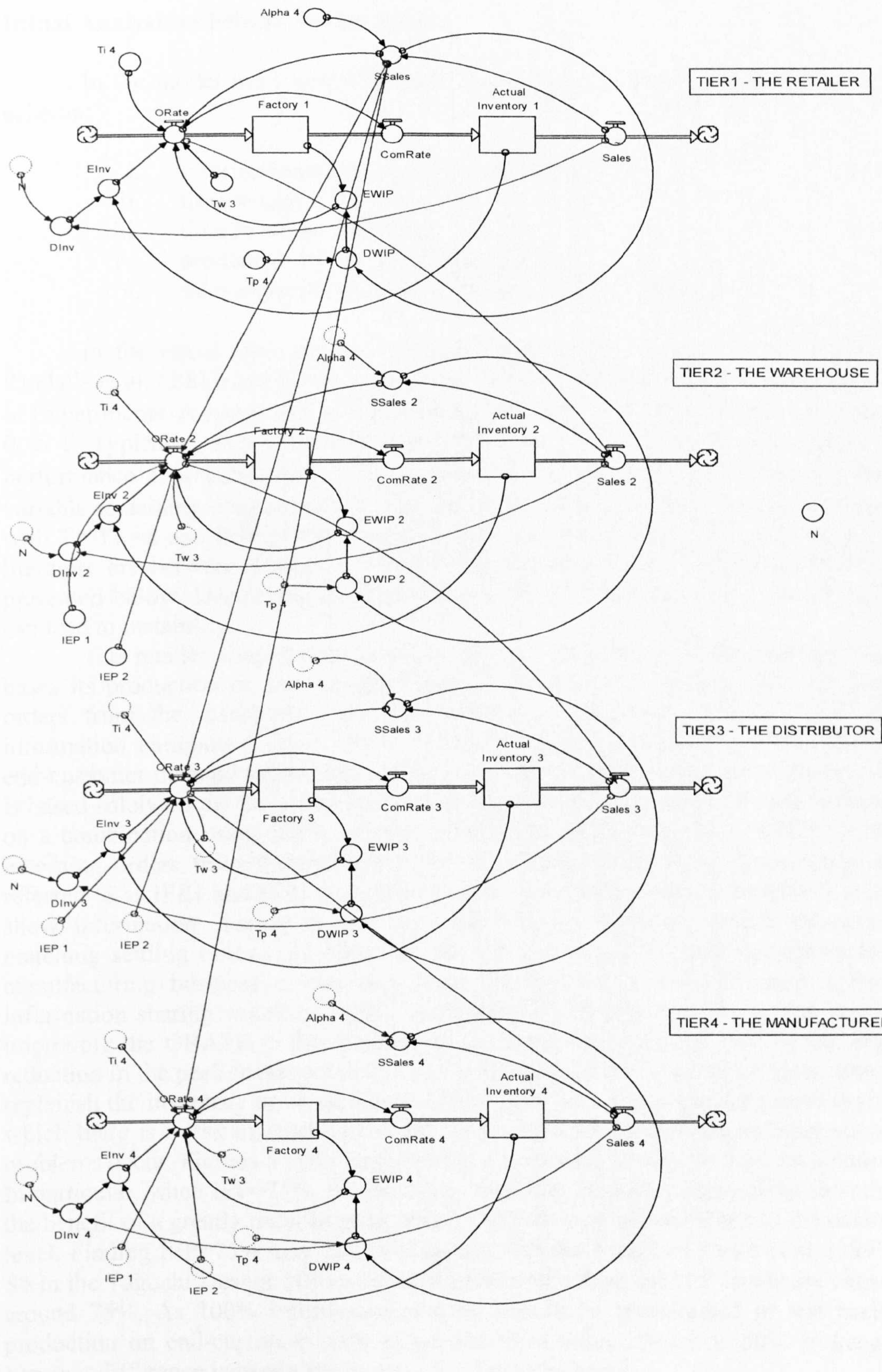


Figure 2: *iThink* Model of Multi-Echelon Supply Chain.

Initial Analysis of Effects of Parameters

In the model used here there are five control or design parameters at each echelon:

i. information enrichment percentage (IEP);
ii. time to adjust inventory (Ti);
iii. time to adjust WIP (Tw);
iv. production (or pipeline) delay (Tp);
v. sales exponential smoothing (forecasting) constant α.

In the initial simulations, Tp is set equal to six weeks as in the work of Riddalls et al. (2002) and levels around this value are chosen for the Taguchi Design of Experiments. A constraint in exponential smoothing is that α must lie in the range 0 to 1. Typically, values between 0.2 and 0.8 are used as beyond this range the performance approaches that of no exponential smoothing (α=1) or the smoothed variable remaining constant (α=0). Figures 3 and 4 illustrate the effect of varying α with Ti=Tw=8 and IEP=100%. Typical values used for Ti and Tw elsewhere in the literature are between 4 and 12, so this range is used in the Taguchi experiments presented below. Depending on the values of other parameters, small values of Ti can lead to instability.

The retailer shares end-customer demand with the manufacturer that then bases its production on the weighted sum of end-customer demand and incoming orders from the distributor (the next echelon in the supply chain). With full information enrichment (IEP=100%) the manufacturer bases production solely on end-customer demand whilst with no information enrichment (IEP=0%) production is based solely on the incoming orders from the distributor. Production can be based on a combination using IEP% of end customer demand plus (100 – IEP)% of the incoming orders from the distributor; in the *iThink* model these percentages are referred to as IEP1 and IEP2 respectively. The simulation results in Figures 5 and 6 show information sharing damps the peaks in the responses whilst effectively matching settling times. The effect on the ORATE would be most beneficial to a manufacturing business as the very large fluctuations in ORATE seen without information sharing would be highly destructive and costly to achieve. The cost of improving the ORATE is the damping of the inventory response. Whilst the large reduction in the peak inventory deficit is a good thing, there is a much longer time to replenish the inventory up to the desired level, causing a much greater period during which there is a risk of stock-out if any other increases in demand or other supply problems occur. Figures 5 and 6 suggest that a compromise may be the best solution. In particular, when IEP=75%, the inventory response is much faster, whilst retaining the benefit of a greatly reduced peak deficit and only a small overshoot of the desired level. Finding IEP=75% may be better agrees with the results of Jones et al. (1997). So in the Taguchi Design of Experiments presented below, the IEP levels are chosen around 75%. As 100% information sharing should be investigated to test basing production on end-customer sales alone, the third value chosen is 50% to keep a constant difference between the levels, i.e. a linear increase.

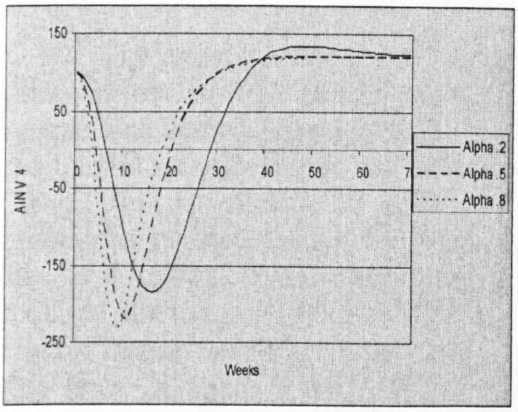


Figure 3: Effect of α on AINV 4

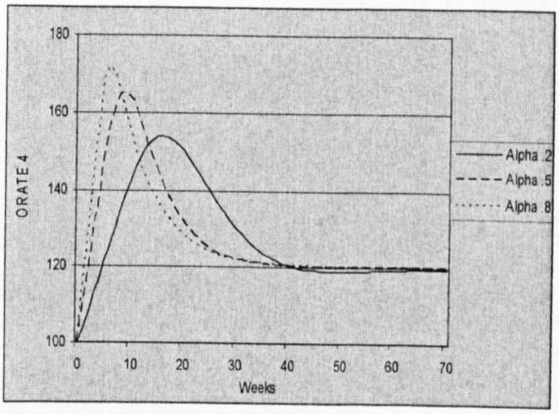


Figure 4: Effect of α on ORATE.

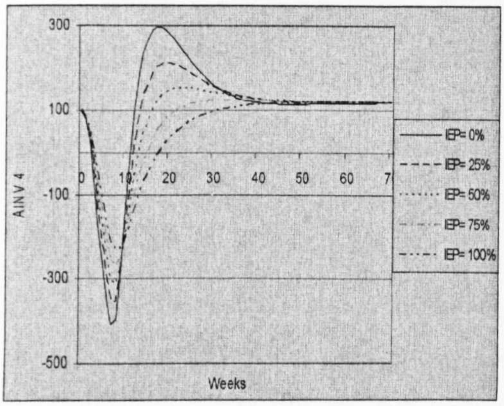


Figure 5: Impact of IEP on AINV 4.

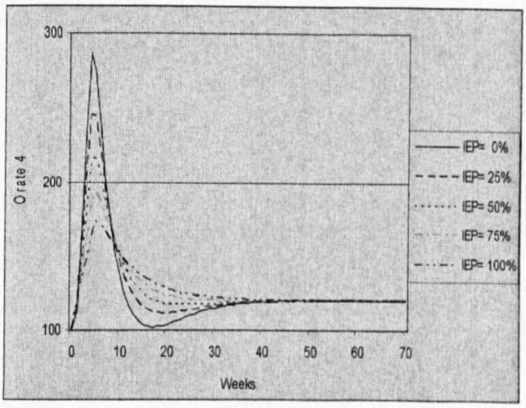


Figure 6: Impact of IEP on ORATE 4.

Measuring the Bullwhip Effect

Different approaches can be applied to measure the Bullwhip Effect. A common approach is to divide the *coefficient of variation of orders placed* by the *coefficient of variation of orders received* (Fransoo and Wouters, 2000):

$$\text{Bullwhip} = C_{out} / C_{in}$$

where $C_{out} = \sigma\,(D_{out}(t, t+T))/\mu(D_{out}(t, t+T))$

and $C_{in} = \sigma\,(D_{in}(t, t+T))/\mu(D_{in}(t, t+T))$.

$D_{out}(t, t+T)$ and $D_{in}(t, t+T)$ are the factory orders and completions during the time interval (t, t+T). Since demand is deterministic, C_{in} is constant and only C_{out} needs to be considered in the analysis.

Taguchi Design of Experiments.

The arguably ubiquitous Taguchi approach is used to identify the effects of different levels of the design parameters on the measure of the Bullwhip Effect, the interactions that occur and ultimately the best values. The technique is used to obtain the maximum information with the minimum number of experiments (Shang et al, 2004). This is valuable in studying supply chain dynamics as there are a large number of possible parameter value combinations. The choice of orthogonal array size used in the design of experiment depends on the *total degrees of freedom* (DOF) required for the parameters and their interactions. In this study, the DOF for five control factors with three levels is 5 x (3-1) +1= 11. This leads to choosing the $L18$ (3^5) array in Table 1 that defines, for each experiment, the level of each factor (parameter) to be used. The factor levels used in the experiments reported here are given in Table 2.

Experimental Run	Tp	IEP	A	Ti	Tw
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	2	1	1	2	2
5	2	2	2	3	3
6	2	3	3	1	1
7	3	1	2	1	3
8	3	2	3	2	1
9	3	3	1	3	2
10	1	1	3	3	2
11	1	2	1	1	3
12	1	3	2	2	1
13	2	1	2	3	1
14	2	2	3	1	2
15	2	3	1	2	3
16	3	1	3	2	3
17	3	2	1	3	1
18	3	3	2	1	2

Table 1: Inner Arrays ($L18$)

Factor	Level 1	Level 2	Level 3
Production (Pipeline) Delay (Tp)	4	6	8
Information Enrichment Percentage (IEP)	50%	75 %	100%
Alpha (α)	0.2	0.5	0.8
Time to adjust Inventory (Ti)	4	8	12
Time to adjust WIP (Tw)	4	8	12

Table 2: Factors and Levels

Statistical Analysis of Results

The effect of a design parameter on the measured response when the parameter's value is changed from one level to another is known as a 'main effect' and is calculated for a particular level of a factor by examining the orthogonal array, the factor assignment, and the experimental results (Roy, 2001). For example, to calculate the average effect of information sharing (IEP) at Level 1, all results of IEP at Level 1 are averaged. Figure 7 shows that the Bullwhip Effect measurement is most sensitive to Tp and Ti is the next most significant factor. The least sensitivity is seen with IEP, although it must remembered that the experimental range is 50-100% and not 0-100%. It is observed that reducing Tp minimizes the Bullwhip Effect and this result verifies the time compression paradigm and the importance of compressing Tp to reduce demand amplification. Increasing the value of Ti reduces the Bullwhip Effect. Decreasing α increases the damping effect of the exponential smoother, so it is not surprising that it also reduces the Bullwhip Effect, as does reducing Tw. An interesting finding is that increasing the information enrichment percentage to 100% reduces the Bullwhip measure used here; there is no optimum around 75% as intimated earlier and in the work of Jones et al. (1997).

The next step is to explore the interactions among the parameters. Interaction here refers to factors behaving differently in the presence of other factors such that the trend of influence changes when the levels of the other factors change. Simple but powerful "interaction graphs" (Figures 8-11) are used to determine the severity of the interactions between control parameters. If the lines in the graph are parallel there is no interaction between the parameters, whilst non-parallel lines indicate interaction with intersecting lines indicating strong interaction (Antony, 2001). Four important interactions are observed in this analysis. Figure 8 shows the strong interaction between IEP and α. The value of information sharing is affected significantly by the forecasting error generated due to inaccurate forecasts. It is important to note that information sharing decreases the sensitivity to α. The next significant interaction occurs between Ti and α as shown in Figure 9. A third important interaction is observed between Ti and Tw as shown in Figure 10. Smaller values of Ti yield quicker responses but poor filtering properties and smaller values of Tw result in larger settling times. Figure 11 shows the small interaction between α and Tw.

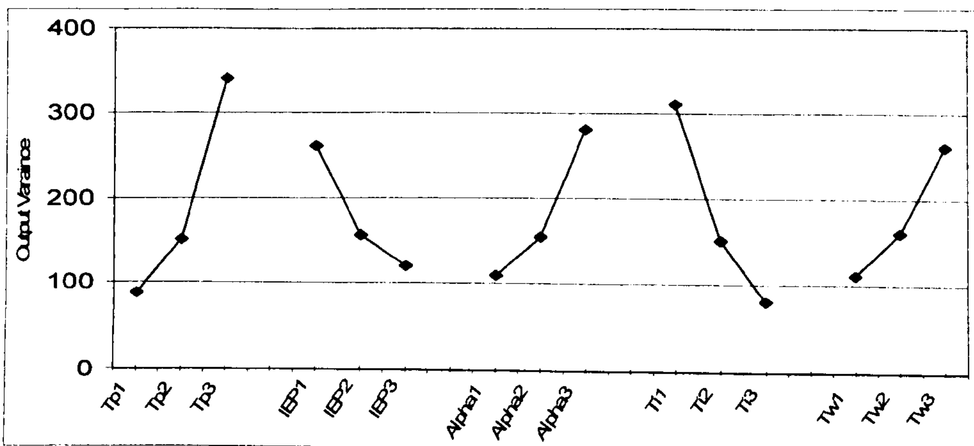
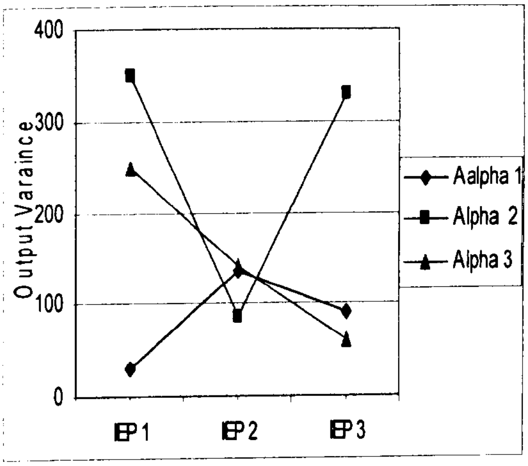


Figure 7: The plot of main effect response



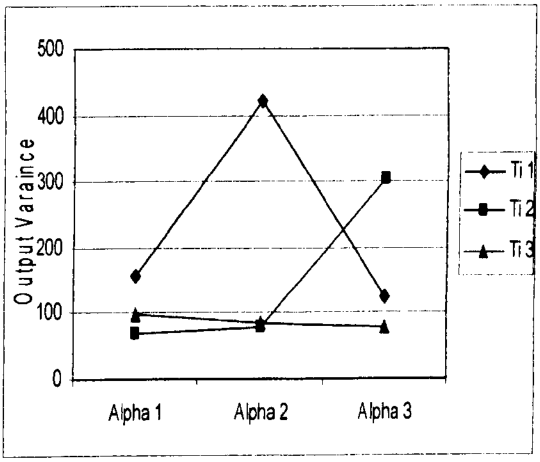
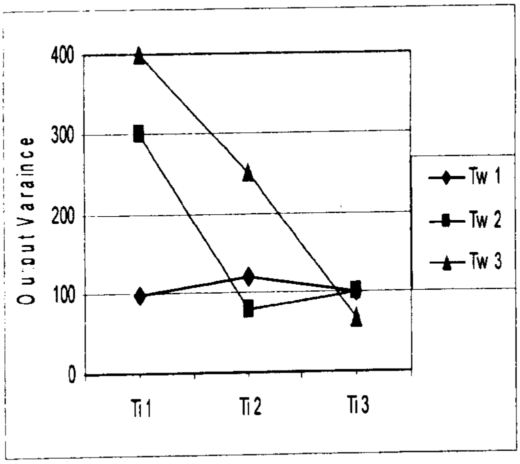


Figure 8: Interaction between IEP & α Figure 9: Interaction between α & Ti



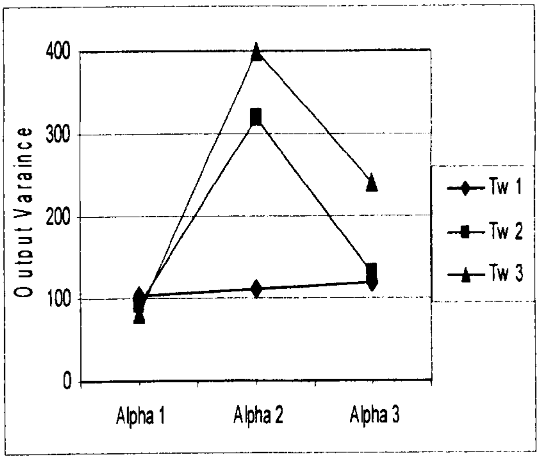


Figure 10: Interaction between Ti &Tw Figure 11: Interaction between α & Tw

In order to discover which of the effects are statistically significant, *analysis of variance* (ANOVA) is performed to quantify the contribution of each parameter to the total variation in the experimental data. The ANOVA results (Table 3) show that Tp makes the largest contribution to the variation in the measurement of the Bullwhip Effect, with a contribution of 37 % and next is Ti, with the two parameters accounting for 64% of the variation. The percentage contribution of the remaining three parameters is much smaller. The F-ratios can also be used to see the relative significance of the parameters.

Little research has been carried out to identify 'optimal' or 'good practice' values and relationships among the different design parameters of supply chains. The best parameter levels within the range of values considered here are given in Table 4; this is in the context of minimizing the chosen measure of the Bullwhip Effect. It is found that Tp should be made as small as possible, which verifies the value of the time compression paradigm for reducing bullwhip. According to the measure chosen here 100% information enrichment is preferred. This is contrary to the initial analysis and the results of Jones et al. (1997). This suggests that further study of how the Bullwhip Effect should be measured is required. The result indicates the use of a small α and Tw, which will give faster responses to change, whilst the largest Ti is used to control excessively large fluctuations in the ORATE by damping the reaction to errors in the inventory.

Factor	DOF	Sum of Squares	Variance	F-Ratios	Pure Sum	P
Production Delay (Tp)	2	256454	28227	160	254850	37%
Information Enrichment Percentage (IEP)	2	69063	34532	43	67460	9%
Exponential smoothing constant (α)	2	103297	51649	64	101694	14%
Time to adjust Inventory (Ti)	2	187016	93508	117	185412	27%
Time to adjust WIP (Tw)	2	83875	41937	52	82271	12%
Error	7	5612	802			1%
Total	17	705317				100%

Table 3: Results of ANOVA

Factor	Level	Level description
Production (pipeline) Delay (Tp)	1	4
Information Enrichment Percentage (IEP)	100%	3
Exponential smoothing constant (α)	0.2	1
Time to adjust inventory (Ti)	12	3
Time to adjust WIP (Tw)	4	1

Table 4:Factors at optimal condition

Conclusion

This paper has demonstrated the use of simulation and the Taguchi Design of Experiments technique to quantify the effects of design parameters in controlling the Bullwhip Effect in supply chains. An approach to gaining an understanding of the relative contributions of design parameters and the interactions between them has been presented as an aid to those concerned with designing and managing supply chain operations. This initial study paves the way for a more detailed study into controlling the Bullwhip Effect and to extending the supply chain model to incorporate capacity constraints and order batching, as these are know to be further sources of demand amplification.

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Appendix 2;

(International Conference of the Global Business Development Institute (GBDI), Los Vegas, March 23-26, 2008)

QUANTIFYING THE IMPACT OF FORECASTING AND LEAD TIME ON VARAINCE AMPLIFICATION IN A TWO LEVEL SUPPLY CHAIN

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ABSTRACT

This paper considers a two level supply chain model in which an AR (1) process describes the customer demand and order up to level characterises the inventory replenishment policy. The impact of exponential smoothing and minimum mean squared error forecasting is quantitatively measured for both the bullwhip effect and variance of the net stock level. A proportional controller is then added into simple order up to level policy and through fine tuning it is found that the bullwhip effect can be minimized without adversely affecting the retailer's inventory level. Simulation and Taguchi Design of Experiment is sued as a methodology.

Key Words: Bullwhip, Forecasting, Taguchi Design of Experiments, Supply Chain.

INTRODUCTION

Supply chain dynamics has been studied for more than four decades. Since Forrester (1) discovered the fluctuation and amplification of demand moving upstream in the supply chain, there has been a lot of research analyzing this phenomenon. Forrester (1) pointed out that demand amplification is due to the "system dynamics phenomenon" and can be tackled by reducing delays, while Sterman (2) through his "beer game" interprets the phenomenon as a consequence of players' irrational behaviors or misperceptions of feedback. Towill (3) confirmed the findings of Forrester that reducing delays and collapsing all cycle times improves the performance of the system. Lee et al. (4) found that demand amplification or the "*Bullwhip Effect*" is due to demand signal processing, order batching, price variations and rationing and gaming and can be reduced through information sharing. Its effects include inaccurate forecasting leading to periods of low capacity utilization alternating with periods of having not enough capacity, i.e. periods of excessive inventory caused by over production alternating with periods of stock-out caused by under production, leading to inadequate customer service and high inventory costs.

It has been recognized that demand forecasting, ordering policies, and lead times are among the key causes of the bullwhip effect. Impacts of forecasting methods on the bullwhip effect have been studied by several researchers.. Chen et al (5) evaluate moving average and exponential smoothing forecasting techniques with respect to bullwhip inducement. They found that exponential smoothing forecasts are more apt to amplify variation than moving average forecast. Dejonckheere et al (6) quantified the bullwhip effect for order-up-to policies using exponential smoothing, moving average, and demand signaling process. Alwan et al (7) studied the bullwhip effect in an order-up-to-level policy with mean squared forecasting. They found that using such a forecasting policy, the bullwhip effect can be eliminated or mitigated depending on the correlative structure of the demand process. Zhang (8) investigated *the impact of forecasting methods* on the bullwhip effect in a simple order up to level policy with AR (1) demand process. Findings *indicate that MA, ES, and MSE forecasting* techniques lead to bullwhip effect measures with distinct properties with respect to *demand* autocorrelation and lead time. Luong (9) developed a bullwhip measure for the AR(1) demand process in a simple order up to level supply chain under the MMSE forecasting technique. He found that the bullwhip effect depends on the value of demand autocorrelation and a upper bound for the demand amplification exists when lead time increases.

Replenishment strategies have an impact on order and net stock variability. Order variability contributes to the bullwhip effect and the upstream cost while variations in net stock level affect the ability to meet a desired service level. In a make-to-order supply chain, the upstream level pursuing the smooth production prefers the minimal variability in the production orders from downstream player. Balakrishnan et al (10) emphasised opportunities that reduce supply chain costs by dampening upstream demand variability. This has led to the creation of new replenishment policies that are able to generate smooth order patterns and which in turn can mitigate the demand amplification. In order to control the dynamics of the supply chain, Hosoda and Disney (11) added a proportional controller in simple order up to level supply chain model with MMSE forecasting. They named the new replenishment policy as generalised OUT policy and found that two echelon supply chain with this generalised OUT policy can reduce the inventory related cost by ten percent. Boute et al (12) studied a two level supply chain with i.i.d customer demand. They found that decreasing the order variability at the retailer's level comes at the cost of increased variance of the retailer's inventory level. Smoothing the ordering pattern mitigates the bullwhip effect and results in shorter and less variable replenishment lead time which in turn can benefit the retailer.

The impact of lead time on the bullwhip effect has also been investigated by Chen et al. (6), Zhang (10), Chatfield et al (13), and Kim et al. (14). Chatfield et al (13) analysed the bullwhip effect with stochastic lead time and found that lead time variability exacerbates variance amplification in supply chain. Kim et al. (14) measured the impact of stochastic lead time on bullwhip effects for a k-stage supply chain and found that the bullwhip effect was higher under the lead time variability. Most studies on lead time have shown that longer lead times or larger lead time variations have a negative effect on supply chain performance, implying that lead time or lead time variability should be minimised

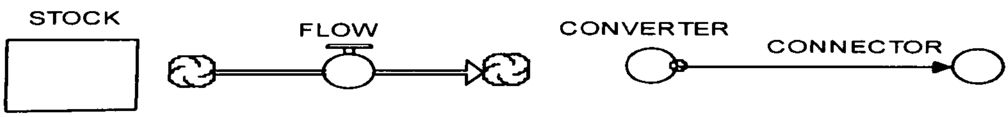
This research differs from previous studies in many ways. First, previous research focused on determining the impact of forecasting methods on the bullwhip effect. However, as pointed out by Hosoda and Disney (15), these statistical approaches become unmanageable when net inventory variances are considered as the expressions for the co variances between the states of the system are extremly complex. While simulation involving the simple equations is better suited with which these intractable expressions are completely avoided. Hence, in this study the impact of ES and MMSE is investigated on both order and inventory variations. Second, simple order up to level policy is modified by adding a proportional controller into the inventory feed back system. The impact of a proportional controller in a modified order up to level policy on the demand amplification and inventory variance is analysed. Boute et al (12) suggest that bullwhip reduction comes at the cost of an increased variance in the inventory levels. Calibration of the proportional controller is explored in order to evolve a trade off between bullwhip and inventory variance is explored. Third, our graphical results give a much better picture about the effect of demand correlation, lead time, forecasting techniques, and proportional controller on both the bullwhip effect and net inventory variance than the corresponding statistical and mathematical results. Finally, as pointed out by Luong (9) the problem of quantifying the bullwhip effect still remains unresolved due to the complex nature of supply chains. We apply the *Taguchi Design of Experiment* technique to quantitatively measure the impact of different factors involved in this study on the both bullwhip and inventory variance, to explore the interaction among these parameters, and to drive the best possible values of these factors in order to minimise both order and inventory variance.

The structure of this research is as follows. Section 2 describes the methodology. Section 3 discusses the order-to-level model, and AR(1) demand process. Section 4 compares the bullwhip effect under ES and MMSE forecasting techniques. Section 5 introduces a modified order-up-to policy to further dampen down the demand amplification. Section 6 presents the Taguchi Orthogonal Arrays technique to quantitatively measure the impact of factors on both bullwhip and inventory variance. Section 7 offers some concluding remarks.

Methodology

In this work a *System Dynamics* computer simulation model is developed to study the time varying or *dynamic* behaviour of a supply chain. The model uses levels, flows (or rates) and feedback processes and is implemented using the *iThink* software package (*http://www.iseesystems.com/*). *iThink* software package is one of the several computer applications created to implement concepts of *System Dynamics*. *iThink* uses the four basic building blocks shown in Figure 1: *Stock*, represents something that accumulates; *Flow*, an activity that changes the magnitude of the stock; *Converter*, modifies an activity; *Connector*, transmits inputs and information.

FIGURE 1: BUILDING BLOCKS OF *iTHINK* SOFTWARE



Results from the simulation output are analysed by using the *Taguchi Design of Experiment* Technique. The Taguchi method is based on the statistical design of an experiment and is applied to establish the main effect, interaction effect, and optimum design parameters. Details of Taguchi methods are discussed in section 6.

The Model.

Demand process

The standard periodic review base stock order up to level replenishment policy is observed. External demand for a single item occurs at the retailer, where the underlying demand process faced by the retailer is an auto correlated AR(1) process. The retailer's demand from the customer is a mean centred demand pattern: i.e.

$$D_t = d + \rho\,(D_{t-1} - d) + \varepsilon_t \,. \qquad (1)$$

Where D_t represents the demand in period t, d is the average demand, ρ is the first order autocorrelation coefficient, $-1 < \rho < 1$, and ε_t is an independent and identically distributed normal process *(i.i.d)* with mean 0 and variance σ_ε^2. It is assumed that σ is significantly smaller than d, so that the probability of negative demand is negligible, Lee et al (4). The demand variance equals. $\sigma_D^2 = \sigma_\varepsilon^2 / 1 - \rho^2$. By varying the value of ρ, a wide range of process behaviours can be observed. When $\rho = 0$, we have an *i.i.d* process with mean μ and variance σ_ε^2. For $-1 < \rho < 0$, the demand process is negatively correlated and will exhibit period to period oscillatory behaviour. For $0 < \rho < 1$, the demand process will be positively correlated which is reflected by wandering sequence of observations. As ρ approaches one, the process approaches non stationary behaviour; and in particular, a pure random walk model or equivalently, an ARIMA (0, 1, 0) process. In the simulation conducted here, an average demand of 100 and standard deviation of 20 are used. We assume that there is an infinite number of demand data available and the underlying parameters of the demand model are known.

Inventory Policy.

The standard periodic review base stock policy is the (R, S) policy. At the end of every review period R, the inventory position is tracked and a replenishment order is placed to raise the inventory position to an "order-up-to" or "base stock" level S, which determines the order quantity in period t;

$$O_t = S_t - IP_t \quad . \qquad (2)$$

Where O_t is the ordering decision made at the end of period t, S_t is the order-up-to level used in period t, and IP_t is the inventory position. The inventory position is the sum of net stock plus pipeline inventory.

$$IP_t = NS_t + WIP_t \cdot \qquad (3)$$

$$NS_t = NS_{t-1} + O_{t-L} - D_t \cdot \qquad (4)$$

$$WIP_t = WIP_{t-1} + O_{t-1} - O_{t-L} \cdot \qquad (5)$$

Order up to level is determined by:

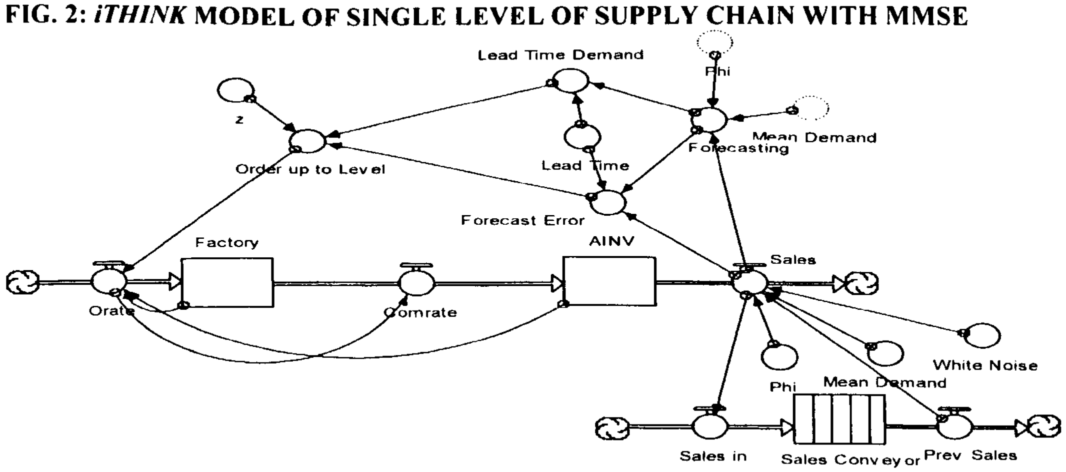
$$S_t = \hat{D}_t^L + z\,\hat{\sigma}_t^L \, . \qquad (6)$$

Where $\hat{D}_t^L$ is expected forecasted demand over L periods $(\hat{D}_t^L = L\,\hat{D}_t,)$, $\hat{\sigma}_t^L$ is an estimation of the standard deviation of the lead time forecast error, and z is chosen constant to meet the desired service level and is related to inventory holding and backlog cost. Such a policy has the potential of $O_t < 0$ but the under the assumption of $\sigma < \mu_d$, the probability of having $O_t < 0$ is negligible, Lee et al (4). The standard deviation of the lead time demand forecast error is $\hat{\sigma}_t^L = \sqrt{V(D_t^L - \hat{D}_t^L)}$. Zhang (10) showed that the standard deviation of the lead time forecast error remains constant over time for the moving average, exponential smoothing, and mean squared error forecasting methods. Hence, $\hat{\sigma}_t^L = \hat{\sigma}_{t-1}^L$, and the replenishment order quantity can be written as.

$$O_t = \hat{D}_t^L - (NS_t + WIP_t) \qquad (7)$$

In our simulation, first we receive the inventory and demand is either fulfilled or backlogged at the beginning of the period. Next, the inventory position is observed and order is placed at the end of every review period. Thus, even if the physical production lead time is zero, it does not appear in the order decision

FIG. 2: *iTHINK* MODEL OF SINGLE LEVEL OF SUPPLY CHAIN WITH MMSE



until the end of next planning period. So, the lead (L) includes a nominal sequence of events delay. In short, the lead time not only includes the production delay (Tp) but also a single period of events delays or review period. Hence, Lead time (L) = Tp+1 and we estimate the demand during Tp+1 period when we calculate the order up to level in our simulation. Simulation is run for 1000 periods for each condition and observations are made from 200-800 time periods. Replication is carried out for 100 time periods and averages of the results are taken. Results are verified from spreadsheet and previous research. Performance measures of the simulation analysis are observed on the bullwhip effect. We define bullwhip measure as:

$$Bullwhip = \frac{Var(O_t)}{Var(D_t)}$$

When Bullwhip = 1, it implies that the variance of orders is equal to the variance of demand or in other words there is no bullwhip effect. In case where Bullwhip < 1, it shows the existence of the Anti-Bullwhip or De-Whip Effect. In scenario when Bullwhip > 1, it indicates that the variance of orders are greater than the variance of demand and the presence of the bullwhip effect.

Bullwhip Effect with Exponential Smoothing (ES) Forecasting.

The exponential smoothing (ES) forecast is an adaptive algorithm in which the one period ahead demand forecast is adjusted by a fraction of the forecast error. Let α denote the fraction used in this process (also called the smoothing factor), we can write the ES forecast for next period's demand

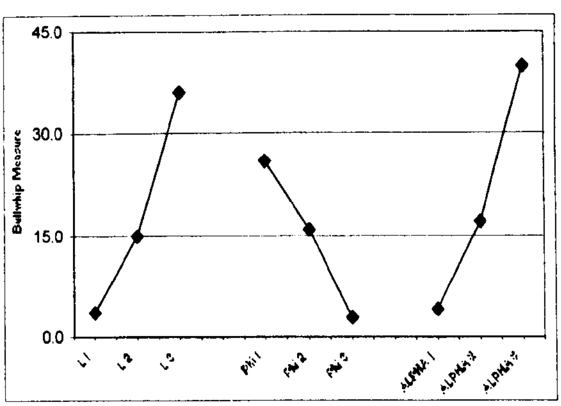
$$\hat{D}_t = \hat{D}_{t-1} + \alpha(D_t - \hat{D}_{t-1}) \tag{8}$$

The smoothing constant α is the weight placed on the most recent observation of demand in the exponential smoothing forecast and is subject to the condition $0 < \alpha > 1$. We assume that both retailer and manufacturer use the exponential smoothing technique to forecast one period ahead demand. This is then multiplied by the lead time to obtain the value of lead time demand. Now we test Chen's findings, later confirmed by other analytical studies, about the effects of the smoothing constant, α, demand correlation coefficient ρ, and the lead time L on the bullwhip effect. The L_9 Taguchi Array is applied to study the impact of three different levels for each of smoothing constant (0.2, 0.5, 0.8), lead time (2, 4, 8), and demand correlation coefficient (-0.8, 0, 0.8), giving nine experiments in total. Details of Taguchi methods are discussed in the last section.

TABLE: INNER ARRAYS(L9)

Experiment al Run	L	Phi	Alph a
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

FIG.3: BULLWHIP EFFECT WITH ES



The Above results validate Chen's findings that the bullwhip is increasing in alpha and decreasing in demand autocorrelation and converges to one when ρ = 1. When compared to an *i.i.d* demand process, negatively correlated demand increases the bullwhip effect while positively correlated demand decreases the bullwhip effect. For all autocorrelation demand process, the bullwhip effect is increasing in lead time. Lead times magnify the increase in variability due to demand forecasting. The longer lead time triggers larger changes in the target inventory level resulting in higher volatility of the orders placed. Retailers having longer lead times should prefer to use smaller values of the smoothing constant in order to reduce the demand amplification. The high weighting factor used for alpha is highly responsive to recent changes in underlying demand pattern and results in demand amplification. While the low alpha value provides less sensitive response to current demand variation and hence reduces the demand amplification. Above result also shows that least effect is that of demand correlation.

Bullwhip Effect with Minimum Mean Squared Error (MMSE) Forecasting.

Using MMSE forecast means that the demand forecast is derived in such a way that the forecast error is minimized. It is the conditional expectation of future demand, given current and previous demand observations. The MSE forecast for the demand in period $D_{t+\tau}$, given current and previous demand observations $D_t, D_{t-1}, D_{t-2}, \ldots$. This forecasting technique assumes that the underlying parameters of the model are known or that an infinite number of demand data is available to estimate these parameters. Let $\hat{D}_{t+\tau}$, $\tau = 1,2,\ldots,$ be the τ period a head forecast of the demand $D_{t+\tau}$ made in period t, then

$$\hat{D}_{t+\tau} = d + \rho^{\tau}(D_t - d) \qquad (9)$$

It may be noted that as the forecasting process contains no moving average terms, the errors from previous periods play no part in the computation of the results. Further, forecast is the geometric decay from the last demand observation to the mean of the process. In contrast to the exponential smoothing forecast method, the one period ahead demand forecast is not multiplied by lead time, but instead the forecast of the demand over lead time horizon is calculated by plugging single period MMSE forecast into the definition of lead time. The mean squared error forecast for the lead time demand is given by;

$$\hat{D}_t^L = Ld + \frac{\rho - \rho^{L+1}}{1 - \rho}(D_t - d). \qquad (10)$$

Figure 3 shows the effects of demand correlation and lead time in an order-up-to level policy on the bullwhip effect when demand forecasts are estimated using MMSE. A comparison is made between negatively correlated, *i.i.d*, and the positively correlated demand process. When demand is negatively correlated ($-1 < \rho < 0$), the bullwhip effect does not exist or, the variance of the order quantity is smaller than the variance of demand resulting in Anti-Bullwhip or De-whip effect. From the managerial point of view, the De-whip effect means that the production planning phase at manufacturer level becomes easier and more stable. When the customer demand is given by an *i.i.d* process, i.e., when $\rho = 0$, there is no correlation in demand and the order-up-to level policy with MMSE forecast generates orders equal to the observed customer demand and results in chase sales policy. A chase sales strategy reduces to mean demand forecasting. When demand is positively correlated ($0 < \rho < 1$), with the increase of demand correlation the bullwhip effect increases first, reaches the maximum value, and then starts decreasing. The bullwhip effect is an increasing function of lead time over a certain ranges of demand correlation. When there is a loose positive correlation; i.e. when $\rho \leq 0.3$, the bullwhip effect is nominal and the increase in lead time does not cause a much difference to demand amplification. This scenario is in contrast to the results of Chen et al (5), that increasing the lead time magnifies the bullwhip effect .When $\rho \geq 0.5$, the bullwhip effect is more significant and an increase in the lead time leads to bullwhip effect. Lead time has much impact on bullwhip effect when $0.9 < \rho > 0.3$. The maximum value of bullwhip effect is observed when $\rho =$ 0.8.

Comparison of ES and MMSE.

Figure 5 shows the impact of MMSE and ES ($\alpha = 0.2$) as a function of lead time on the bullwhip effect. The bullwhip effect observed using the ES technique is a decreasing function of ρ and converges to one as ρ approaches one. An obvious difference of MMSE forecasting with the results for ES, however, is that the bullwhip effect is no longer decreasing in autocorrelation. When demand is negatively correlated ($-1 < \rho < 0$), the bullwhip effect exists and amplifies with the lead time for the ES forecasting technique whilst it diminishes under MMSE. Lead time reduction can significantly reduce the bullwhip effect when $1 < \rho > 0.3$ with MMSE. In contrast, in order up to policy with ES technique, when $-1 < \rho < 0$, shortening the lead time has a significant impact on bullwhip reduction. For all demand processes, the bullwhip effect exists and amplifies with the lead time when ES forecasting technique is used. On the other hand, when forecasting is carried out using the MMSE technique, a negatively correlated demand results in De-Whip effect, i.i.d demand process exhibits a chase sale policy, and perfect positively correlated demand amplifies the bullwhip effect with the lead time. Further, the MMSE forecasting technique minimizes the variance of the forecast error and therefore leads to lower inventory variations and hence cost. ES performs better then MMSE in terms of bullwhip reduction when ρ is between 0.6 to 0.9 whilst MMSE performs better when $-1 < \rho < 0.3$.

When a low weighting factor (α = 0.1 or 0.2) is used as the smoothing constant then the magnitude of the amplification is lower for ES when compared with MMSE. Increasing the weighting factor of alpha to 0.4 and further exhibits greater magnitude of bullwhip effect as compared to MMSE. This reveals that the bullwhip effect is more sensitive to the smoothing constant than to the demand correlation.

FIG.4:BULLWHIP EFFECT WITH MMSE

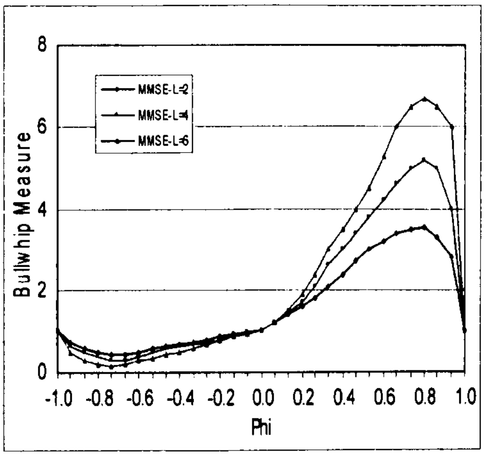
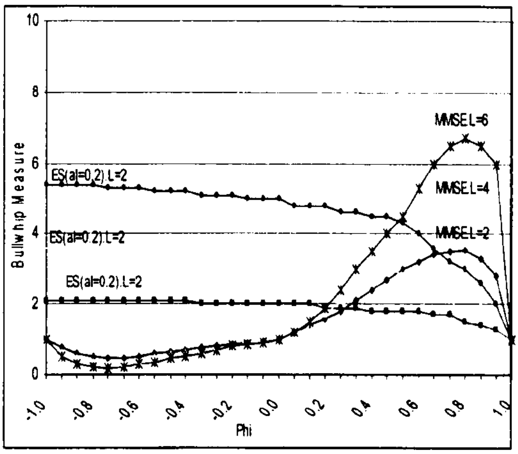


FIG. 5: COMPARION OF ES AND MMSE



Impact of ES and MMSE on Inventory Variance.

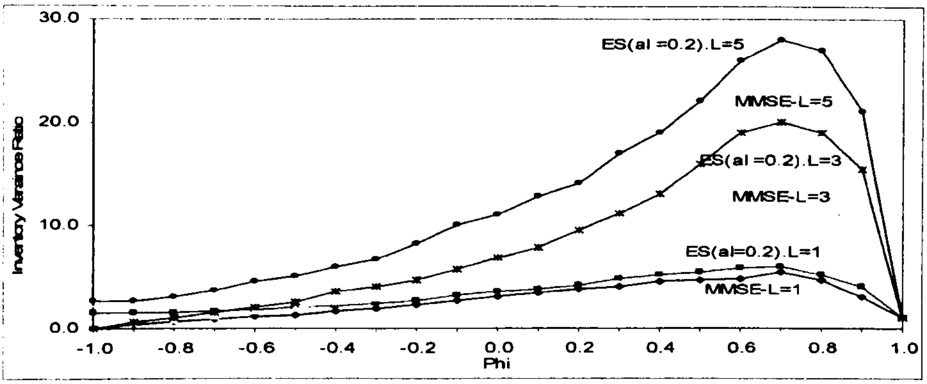
Much of the previous research on demand amplification and forecasting in a periodic review order-up-to level model has used statistical approaches. The statistical approach is useful for gaining an insight into the structure of the ordering process as it moves into the upper levels of the supply chain. However, as pointed out by Hosoda and Disney (2006), the statistical approaches become unmanageable when net inventory variances are considered as the expressions for the covariance between the states of the system are very complex. While simulation is better suited with which these intractable expressions are completely avoided and the graphical results gained from simulation studies provide the clear and the better picture of the situation.

The order-up-to level periodic review replenishment system is optimal when there is no fixed ordering cost and both holding and shortage costs are proportional to the volume of the on hand inventory or shortage. In such systems the inventory for the retailer is determined on the basis of the end customer demand and the inventory expression for the manufacturer is calculated by retailer's order quantity. Variance of the net stock has a greater impact on the customer service level; the higher the net stock variance the more safety stock required to meet the desired service level.

$$VR_{inv} = \frac{Var(NS_t)}{Var(D_t)}$$

Figure 6 shows the quantification of the net inventory variance at the retailer's level by using ES and MMSE forecasting for different levels of lead time. The net inventory variance is also effected by demand correlation. The net inventory variance under MMSE and ES forecasting techniques, increases at first, then reaches its maximum value, starts to decrease before it converges to one. The net inventory variances for the ES are greater than the MMSE forecasting method and that gap increases as lead time increases. Increasing the lead time for a particular level of the supply chain increases the net inventory variances to a greater extent then the bullwhip measure under both ES and MMSE forecasting methods. This shows that inventory variances are more sensitive to lead time than the order variances. This result is intuitive as the inventory fluctuates on the basis of demand and supply. Higher variances in net inventory levels are observed for positively correlated demand under both forecasting schemes. It can be concluded that net inventory variances are more for the higher lead times and for positively correlated demand. For both forecasting methods, the maximum inventory variations are observed when demand autocorrelation lies between 0.3 and 0.8 (.2> ρ <0.9).

FIG. 6: IMPACT OF ES & MMSE ON INVENTORY VARAINCE



Modified OUT Policy.

A proportional controller is added in simple order up to level policy presented in equation 7. This new replenishment policy is named as modified order up to level policy.

$$O_t = \hat{D}_t^L - (NS_t + WIP_t)$$
$$= (T_{p+1})\hat{D}_t - (NS_t + WIP_t)$$
$$= \hat{D}_t + (T_p\hat{D}_t - (NS_t + WIP_t)) \qquad (11)$$

$T_p\hat{D}$ can be treated as a *Desired Inventory Position(DIP)*. Note that *DIP* = 0 if L = 1. The difference the desired inventory position and actual inventory position is called the *Error of Inventory Position* (*EIP*), where, $EIP_t = DIP_t - (NS_t + WIP_t)$.Incorporating a proportional controller, β, into equation (11) yields the *Modified Order-Up-to Level* policy.

$$O_t = \hat{D}_t + \beta(DIP_t - (NS_t + WIP_t)) \qquad (12)$$

With 0 < β < 2. Forrester (1) and control theorists refer to 1 / β as the "*Recovery Time*" and propose not to recover the *Error of Inventory Position* in one time period. Instead, recovery should be spread over time by ordering only fraction β of the inventory deficit .In the simple order up to level policy, the error of the inventory position is completely taken into account while in modified order up to level policy, a fraction of the inventory discrepancy is ordered. Forrester (1) acknowledges that when β <1, the recovery time for the error of the inventory should be spread over time and when β >1 recovery will be much quicker as overreaction to the error of the inventory will be observed. It is important to note that when β = 1, both order up to level policies are identical.

Now we use the Taguchi Orthogonal Arrays technique to quantitatively measure the impact of beta, demand correlation, and lead time on the bullwhip and the inventory variance ratio and to determine the optimum value of beta in order to minimize the variations.

Taguchi Design of Experiments

Orthogonal Arrays

The arguably ubiquitous Taguchi approach is used to identify the effects of different levels of the design parameters on the measure of the bullwhip effect, the interactions that occur and ultimately the best values for them. The technique is used to obtain the maximum information with the minimum number of experiments . This is valuable in studying supply chain dynamics as there are a large number of possible parameter value combinations. *Orthogonal Arrays (OA)* comprises of inner arrays and outer arrays. Inner arrays are those variables which are controllable in real life while outer arrays or noise factors are controlled in experiments but are uncontrollable in real world.

The first step in parameter design technique is the selection of quality characteristics. There are three types of quality characteristics in Taguchi methods, such as smaller-the-better, larger-the-better, and nominal-the-best. The purpose of this research is to minimize the order and net stock variance ratio by exploring the best parameter levels, therefore a smaller-the-better quality characteristics is applied in this study. The next step is the selection of parameters and their suitable levels. Once the parameters and their levels are selected, the third step is to choose the *Orthogonal Arrays* (*OA*). The choice of orthogonal array size used in the design of experiment depends on the *total degrees of freedom* (DOF) required for the parameters. In this study, the DOF for seven control factors with three levels is 3 x (3-1) +1= 6, Roy (16). This leads to choosing the L_9 (3^4) array in Table 1 that defines, for each experiment, the level of each factor to be used. The factor levels used in the experiments reported here are given in Table 2.

For the analysis of experimental results obtained from the simulations, Taguchi standard analysis is carried out and quality characteristics of "*Smaller is Better*" is applied. The effect of a factor on the measured response when the factor's value is changed from one level to another is known as the 'main effect' and is calculated for a particular level of a factor by examining the orthogonal array, the factor assignment, and the experimental results, Roy (16). For example, to calculate the average effect of lead time at Level 1, all results of lead time at Level 1 are averaged.

Statistical Analysis of Results

Figure 7 shows the impact of beta, lead time, and demand correlation on the bullwhip effect when forecasting is carried out using the MMSE method. It should be remembered that when $\beta = 1$, then modified order up to policy is the same as the simple order up to level policy. When $\beta < 1$, a smooth replenishment pattern is created. Smoothing is a well known method to reduce variability and hence demand amplification. When $\beta > 1$ the variability of the order quantity is increased and the bullwhip effect is amplified. The bullwhip effect is an increasing function of the β. When $1 < \beta < 2$, the bullwhip effect is amplified and when $0 < \beta < 1$, the bullwhip effect is dampened. Figure 7 also shows that bullwhip effect measurement is very sensitive to beta. The larger beta results in quicker restoration of the discrepancy between desired and actual inventory levels but poor filtering properties and thus creates demand amplification. Demand correlation is the second most significant factor, whilst the lead time is the least significant factor in demand amplification.

It is well known phenomenon that inventory control policies at the retailer level often propagate customer demand variability in an amplified form to upper levels of the supply chain. Dampening variability in orders may have negative impact on customer service by increasing inventory variances. Bullwhip effect contributes to the upstream cost while the variance of the net stock increases the cost of the concerned level of the supply chain. Figure 8 shows the impact of beta, lead time, and demand correlation on the net stock variance. In terms of beta, it can be seen that

TABLE 2: INNER ARRAYS (L9)

Experimental Run	L	Beta	Phi
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

TABLE 3: FACTORS AND LEVELS

Factors	Level 1	Level 2	Level 3
Beta (β)	0.5	1	1.5
Phi (ρ)	0.2	0.5	0.8
Lead Time (L)	2	3	4

FIG.7: IMPACT ON BULLWHIP EFFECT

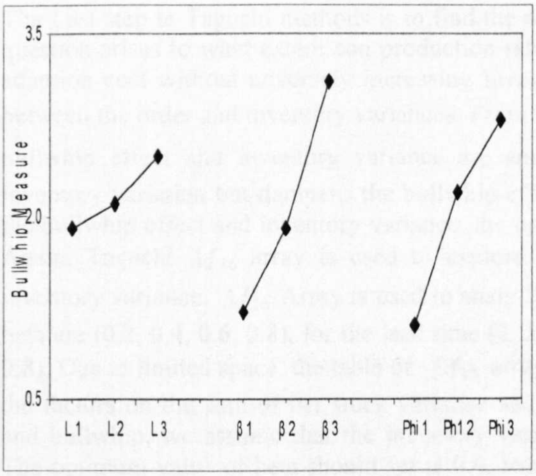
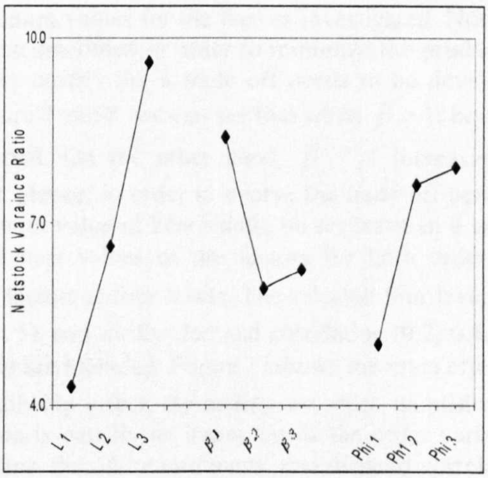


FIG.8: IMPACT ON NETSTOCK VAR.



the modified order up to level policy increases the net stock variance ratio of the retailer. This means that the manufacturer benefits from the smoothing of the replenishment order. For the retailer, this smoothing comes at the price of larger inventory variations; and variations in the inventory level increase the inventory related cost. Larger inventory variations are observed when β<1. Figure 8 also shows that variances in stock level are highly sensitive to lead time. Among the factor studied, the contribution of the lead time in inventory variances is almost 50 percent. The second significant factor is demand correlation and the beta is least significant factor involved in this study. Further, the impact of beta is nonlinear.

The next step is to explore the interactions among the parameters. Interaction here refers to factors behaving differently in the presence of other factors such that the trend of influence changes when the levels of the other factors change. Simple but powerful "*Interaction Graphs*" (Figures 9 & 10) are used to determine the severity of the interactions between control parameters. If the lines in the graph are parallel there is no interaction between the parameters, whilst non-parallel lines indicate interaction and intersecting lines indicating strong interaction, Roy (16). Two important interactions are observed in this analysis. Figure 9 shows a strong interaction between beta and demand correlation. The value of beta is affected significantly by the forecasting error generated from inaccurate forecasts. The next significant interaction occurs between beta and lead time as shown in Figure 10.The interaction between beta and lead time shows that when beta increases, the variability of orders increases which in turn increases the lead time. The longer the lead the smaller the impact of beta on net stock variations. Small interaction occurs between lead time and demand correlation.

FIG.9: INTERACTION BETWEEN β & ρ

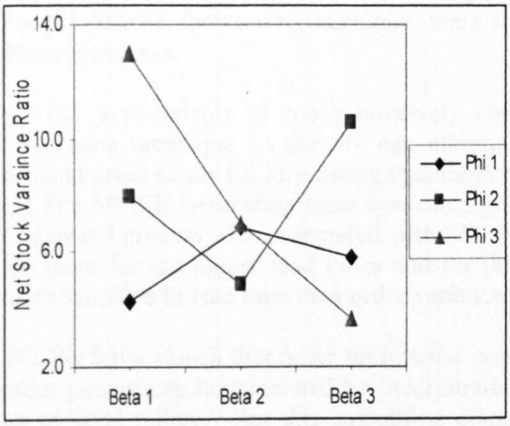
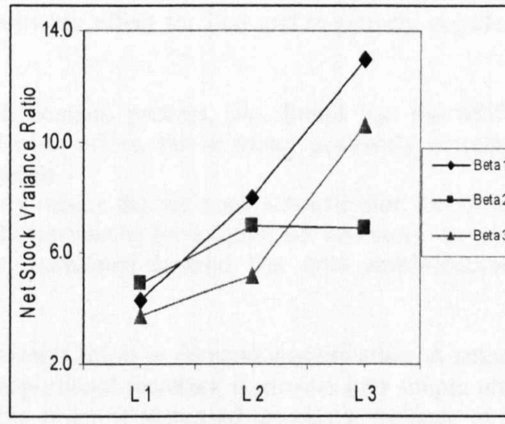
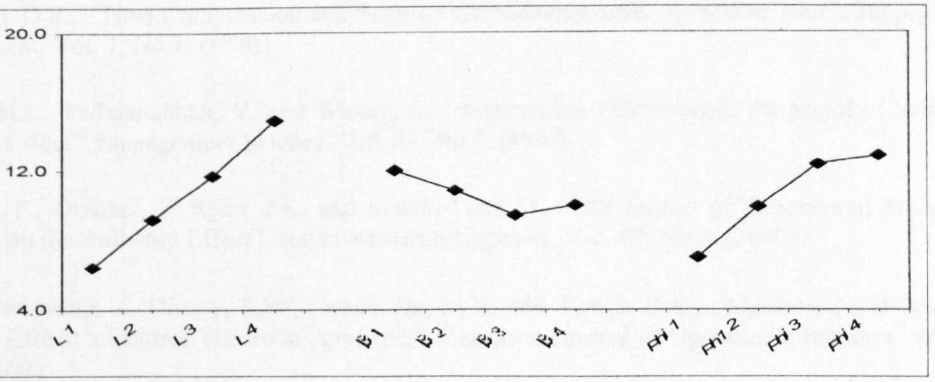


FIG.10: INTERACTION BETWEEN β & L



The Last step in Taguchi methods is to find the optimum values for the factors investigated. Now the question arises to what extent can production rates be smoothed in order to minimize the production adaption cost without adversely increasing inventory costs". So, a trade off needs to be developed between the order and inventory variances. From figure 7 and 8, we can see that when $\beta > 1$; both the bullwhip effect and inventory variance are amplified. On the other hand, $\beta < 1$ increases the inventory variation but dampens the bullwhip effect. Hence, in order to evolve the trade off between the bullwhip effect and inventory variance, the optimum value of beta should be set between 0 and 1. Again, Taguchi M_{16} array is used to explore the best values of the factors for both order and inventory variance. M_{16} Array is used to study 2-5 factors at four levels. The selected four levels for beta are (0.2, 0.4, 0.6, 0.8), for the lead time (2, 3, 4, 5), and for the demand correlation (0.2, 0.4, 0.6, 0.8). Due to limited space, the table of M_{16} arrays is not included. Figure 11shows the main effect of the factors on the sum of net stock variance and bullwhip effect. By adding net stock amplification and bullwhip, we assume that the inventory variance is equally as important as the order variance. The optimum value of beta should set at 0.6, lead time should be minimum, and demand correlation should set at 0.2.

FIG. 11: IMPACT OF β, ρ, & L ON VARAINCE RATIO



Conclusion

In this paper, we have analyzed the bullwhip effect and net inventory variances induced by different forecasting techniques in an order up to level supply chain where end customer demand is an AR (1) process. Through comprehensive simulation experiments and subsequent analysis of simulation outputs by Taguchi orthogonal arrays, we found:

(1) For the ES forecasting method, negatively correlated demand can lead to larger increases in order variability than positively correlated demand. The high weighting factor used for alpha is highly responsive to recent changes in the underlying demand pattern and results in demand amplification. For the MMSE forecasting technique, there is no bullwhip effect for i.i.d and negatively correlated demand process.

(2) For a negatively or loose positively correlated demand process, we should use the MMSE forecasting technique so that we can eliminate bullwhip effect. For a strong positively correlated demand process, the ES forecasting technique is preferred.
(3) The MMSE forecasting technique can significantly reduce the net stock amplification for all type of demand process when compared with ES. For both forecasting techniques, net inventory variances are more for the higher lead times and for positively correlated demand. Net stock amplification is more sensitive to lead time than order variance.

(4) We have shown that order up to level policies always result in demand amplification. A smooth order pattern can be generated by incorporating a proportional feedback controller into simple order up to level policy. But this smoothing comes at the price of increased inventory variance at the retailer's level. Through fine tuning the proportional controller, we can smooth the order pattern of the retailer without adversely affecting her net stock level.

(5) The sum of variances of net stock plus order level is more sensitive to lead time and less sensitive to the proportional controller.

This research can be extended in many directions. A more complicated demand process such as an ARMA(p,q) process could be analyzed. The model considered simple forecasting techniques. The use of more sophisticated forecasting techniques such as Box and Jenkins should be considered. Impact of proportional controller should be analyzed on multi echelon supply chain models

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