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A Model to Mitigate the Bullwhip Effect by Ordering Policies and Forecasting Methods

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A MODEL TO MITIGATE THE BULLWHIP EFFECT BY ORDERING POLICIES AND FORECASTING METHODS

by
Xin Yuan

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Dr. David Wright
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Abstract

Tnis thesis considers an important phenomenon: the bullwhip effect - the amplification of variability of demand as one moves up a supply chain. We apply Agent-Based Modeling (ABM) at the macro level of our system to build relationships among the trading partners; and then we utilize system dynamics to model rules like ordering policy or inventory management at the micro level. We define these rules according to Sterman's generic stock acquisition and ordering heuristic in his Beer Distribution Game Model (Sterman 1989, 321-339). By including additional forecasting methods like moving average, Holts, and double exponential smoothing (DES) method, we extend the model to investigate how different ordering policies and forecasting methods affect the bullwhip effect. Through simulations in the ordering policy space, we demonstrate that fed with a local trend customer order pattern, the bullwhip effect can be mitigated significantly if the suitable forecasting method like Holts or DES is applied under the right ordering policy that has a slow adjustment to the discrepancy of the stock. Comparing with previous research, we extend Sterman's model to investigate what other managerial behaviours, like the aggregation effect, the varied ordering policy and additional forecasting methods would bring to the bullwhip effect. In the "smoothing" method, we extend the moving average and exponential average, which appeared in Forrester's study (Forrester 1961), to Holts and DES method. In modeling, we differ from CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443) and CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286) and Yao (2001) by replacing order-up-to policy with the heuristic ordering policy. Our research has another important managerial insight: through the right ordering policy and forecasting method, trading partners can alleviate the bullwhip effect without adopting information sharing, which may lead to other problems, like mutual trust or additional cost.

Key words: Supply chain management; Bullwhip Effect; System dynamics; Agent-Based Modeling; Forecasting.

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1 Introduction

Today all enterprises face a competitive world. The success of a business is contingent on the performance of its supply chain. Traditionally, trading partners in a supply chain operate independently. To be successful in a more challenging marketplace, business firms need to coordinate with others effectively. Our research focuses on the supply chain management area.

An important phenomenon in supply chain management, called the "Bullwhip Effect", implies that the order variability increases as one moves up the supply chain (figure 1-1). Walker (2005) mentioned that technological core competency, process core competency, and relationship core competency are important factors which allow an organization to compete in the market. We are really interested in the bullwhip effect since it comes from the core competency of process and relationship; however, the bullwhip effect costs money, wastes resources, and leads to the loss of market share. Therefore, our research on the bullwhip effect is significant for it affects core competency of an organization and shows value to the industry.

Many previous papers investigated industrial organizations and showed us that the bullwhip effect is meaningful not only to academics but also to industry. For example, Fisher et al. (1997, 211-225) mentioned a famous real-world example where a price discount induced the bullwhip effect in Campbell's Soups' supply chain. Hau L. Lee, V. Padmanabhan, and Seungjin Whang (1997, 93-102) indicated that the bullwhip effect occurred in the respective supply chains of Procter & Gamble (P&G) and HP. Disney, S.M., and Towill, D.R. (2003, 199-215) all cited the case in analyzing a clothing supply chain that fully demonstrated the bullwhip effect.

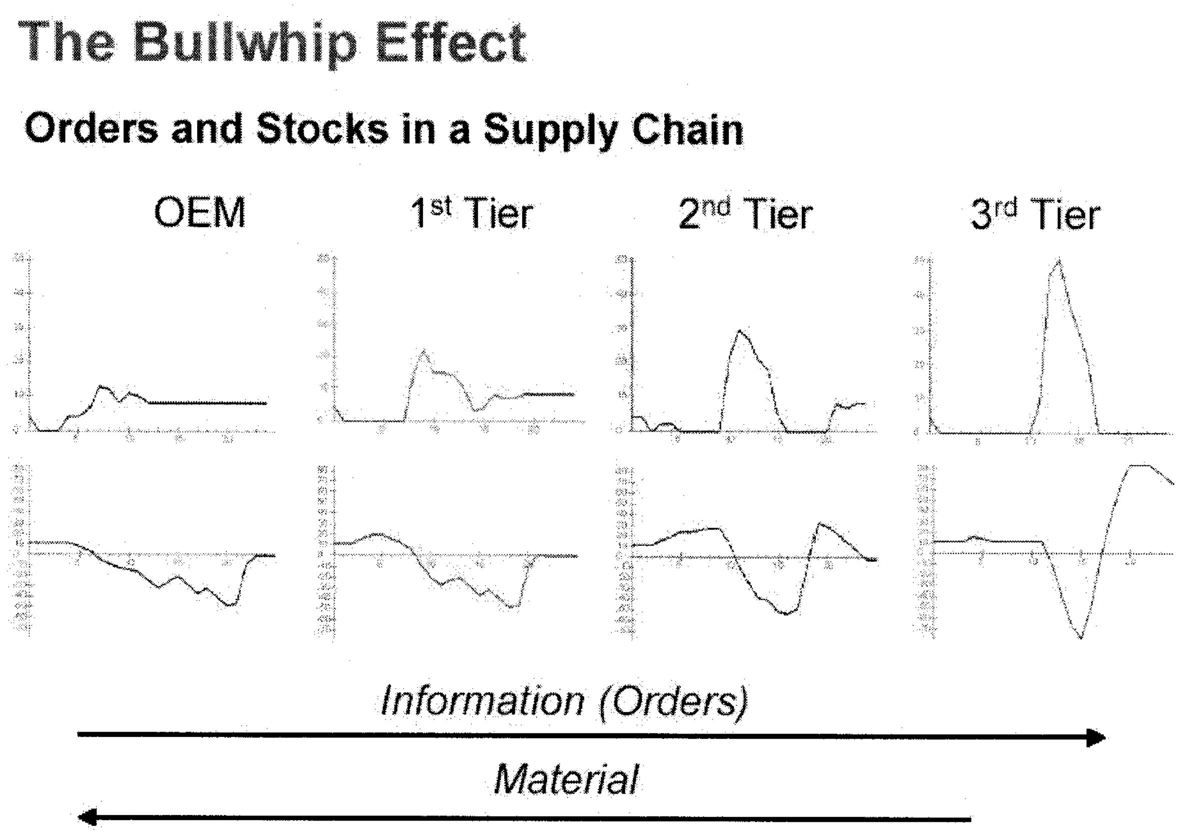


Figure 1-1: Bullwhip Effect, SCM Group (Schonsleben and Baertschi 2002)

Several papers have tried modeling and analyzing the bullwhip effect in order to identify the possible causes or to develop strategies which would reduce the bullwhip effect. Using the theory of system dynamics, Forrester (1961) confirmed the empirical evidence of the bullwhip effect and put forward the assertion that the principal cause of the effect is the difficulties involved in the information feedback loop between companies. Sterman (1989, 321-339) introduced the bullwhip effect by the "*Beer Distribution Game*", and attributed the effect to "*misperception of feedback*". Lee, Padmanabhan, and Whang (1997, 93-102) identified four major causes of the bullwhip effect - namely demand forecasting updating, order batching, price fluctuations, and rationing and shortage gaming. They developed simple mathematical models for each of these causes (Lee et al., 2004, 1875-1886). CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443) and CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286) quantified the impact of demand forecasting on the bullwhip effect using not only the moving average method but also the exponential smoothing forecasting method. Furthermore, they used both the correlated demands and the demands with a linear trend. Their conclusion was that the variability of order depended on both "*the nature of the customer demand and on the forecasting technique*". Yao (2001) applied the order-up-to policy that is the same as CDRS and CRS, but an optimal forecast scheme was used to prove how the bullwhip effect can be reduced.

Based on the previous research, we articulate the overall objective of our thesis and the corresponding project. The purpose of the research is to deeply understand the bullwhip effect across the supply chain. The overall objective is to build a more comprehensive model in order to find out how different forecasting methods and ordering policies affect the bullwhip effect; as a result, we can motivate several managerial insights.

The basic modeling methods we apply are Agent-Based Modeling (ABM) and system dynamics. We integrate them together to reduce the complexity of the model (Schieritz and Größler 2002). The advantage of system dynamics is that the behaviour of a system roots from its structure. Hence we define the rules or policies in the organization using system dynamics, which can keep the internal system stable due to the fixed structure. As ABM has the beneficial feature of defining a complex interaction, we set up all the trading partners in our model as different agent. This can improve the flexibility and extensibility of our model for future research. The implementation for ABM is based on "REcursive Porous Agent Simulation Toolkit" (REPAST) framework, an open-source software framework for creating agent-based simulations using the Java programming language. Its good features, such as "scheduler", can release us from system bottom design and let us focus more on our research topic. In summary, at the macro level of our system, we apply ABM; at the micro level, we utilize system dynamics to define rules like the ordering policy or the stock management strategy.

Our model is based on a simple production-distribution system. Orders for goods propagate from a downstream customer to an upstream provider, and goods are shipped in an opposite direction. The first model is the Basis Model (BM) which gets its insight from Sterman's Beer Distribution Game model. In BM, besides the customer, we have four trading partners: retailer, wholesaler, distributor, and factory. Each trading partner has its stock management system and ordering decision system. The model definition comes from these two systems and is constrained by each trading partner's operation process. We extend BM by adding three forecasting methods: moving average, Holts, and double exponential smoothing (DES) method.

The purpose of our research is to discover how different ordering policies and forecasting methods affect the bullwhip effect; therefore, we use simulation as a tool in our research. We group our simulation experiments by their ordering policies at first level; and then in each ordering policy, we try four different forecasting techniques in a row. We are interested in how the Holts and Double Exponential Smoothing (DES) methods affect local trend demands, so the input customer demand has the local trends feature. The period of our simulation is 100 time steps. The steps in our research involve simulations in ordering policy space, experiments for optimal ordering policy identification, and boundary experiments.

Based on the results from the simulations, we present the comprehensive discussion on the bullwhip effect. After recapitulating the difference among 8 models, detail analysis on how forecasting techniques and ordering policies affect the bullwhip effect is given.

Through our research, we obtain several managerial insights. First, we show that the bullwhip effect happened in 36 ordering policies and each includes 4 forecasting methods for a total of 144 scenarios. The bullwhip effect cannot be eliminated entirely in these 144 scenarios. However, we can control or reduce the bullwhip effect by choosing a suitable forecasting method; the Holts and double exponential smoothing (DES) forecasting methods can help mitigate the bullwhip effect very well when compared to other forecasting methods, since these two forecasting techniques do well in local trend data. Furthermore, the ordering policy has a notable effect on the bullwhip effect. We observe how different ordering policies perform on reducing the bullwhip effect for each of the 4 forecasting methods individually. We noticed that by applying a slow adjustment on the discrepancy of the stock and a relatively large adjustment on the difference of the supply line, we are able to alleviate the bullwhip effect in ordering policies. Information sharing is an important tool which can be used to reduce the bullwhip effect; however, it may lead to other problems, like mutual trust or additional cost. Our research contains another important managerial insight: through the right ordering policy and forecasting method, trading partners can reduce the bullwhip effect without sharing their private information.

In chapter 2, we review the previous literature by grouping them into 6 sub-topics. We put forward our research motivation and problem definition in chapter 3. Then, in chapter 4, we present the main methods and the model definition. In chapter 5, we give the simulation procedure and report on the simulation results. Further comparison and discussion are presented in chapter 6. Chapter 7 contains our conclusions, contributions, and our ideas for future study.

2 Literature Review

2.1 Introduction to Bullwhip in the supply chain

Supply Chain is dynamic and encompasses all activities associated with the constant flow and transformation of goods from the raw materials stage (extraction), through to the end user, as well as the associated information, funds flows (see figure 2-1).

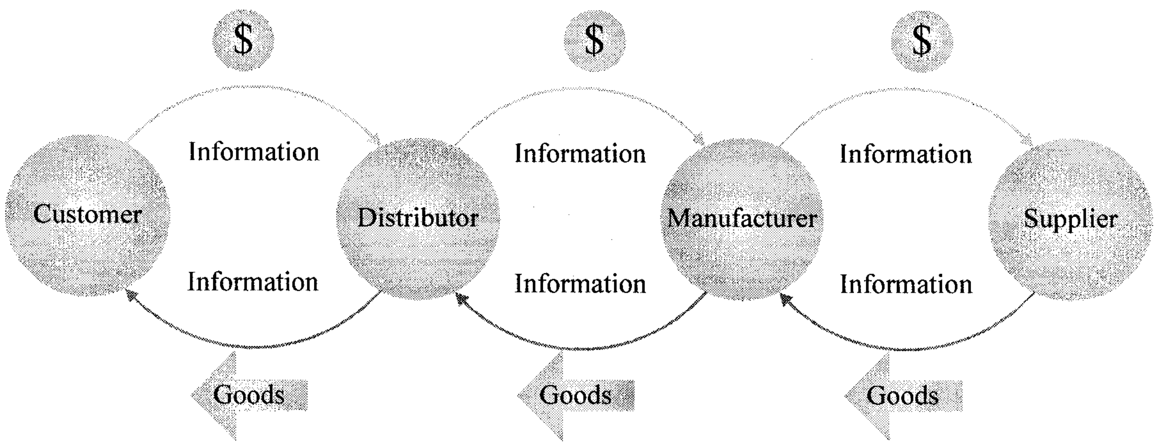


Figure 2-1: Conception diagram of Supply Chain

Supply Chain Management (SCM) can be defined as a set of approaches utilized to efficiently integrate all trading partners (raw material suppliers, manufactures, distributors etc.). Hence merchandise is produced and delivered at the quantities, to the right location, at the right time. SCM can help enterprises minimize the cost while satisfying a required service level. (Simchi-Levi, Kaminsky, and Simchi-Levi 2000)

An important phenomenon in supply chain management, called the "Bullwhip Effect", implies that the order variability increases as one moves up the supply chain. From Lee, Padmanabhan, and Whang (1997, 93-102), the bullwhip effect was defined as "*Distortion of demand information tends to increase as it (demand information) is transferred from downstream to upstream alongside the supply chain.*" The bullwhip effect costs money, wastes resources, which leads to the loss of market share in the fiercely competitive environment. It is a coordination and collaboration problem among "selfish" trading partners (companies may have conflicting goals).

2.2 Bullwhip Effect in Industry

Many previous papers investigated industrial organizations and showed us that the bullwhip effect was not just a phenomenon of interest to academics, but prevalent in many real-world supply chains.

1. McCullen and Towill (2000, 24-30) introduced a case study in the precision mechanical engineering sector that showed the bullwhip effect. In this article, a real world Global Supply Chain (Glosuch) had three echelons: overseas warehouses, a central UK finished goods warehouse, and a UK factory. The order flow was from the overseas warehouses to the central warehouse, then to the UK factory. Figure2-2 shows the Glosuch supply chain and organization.

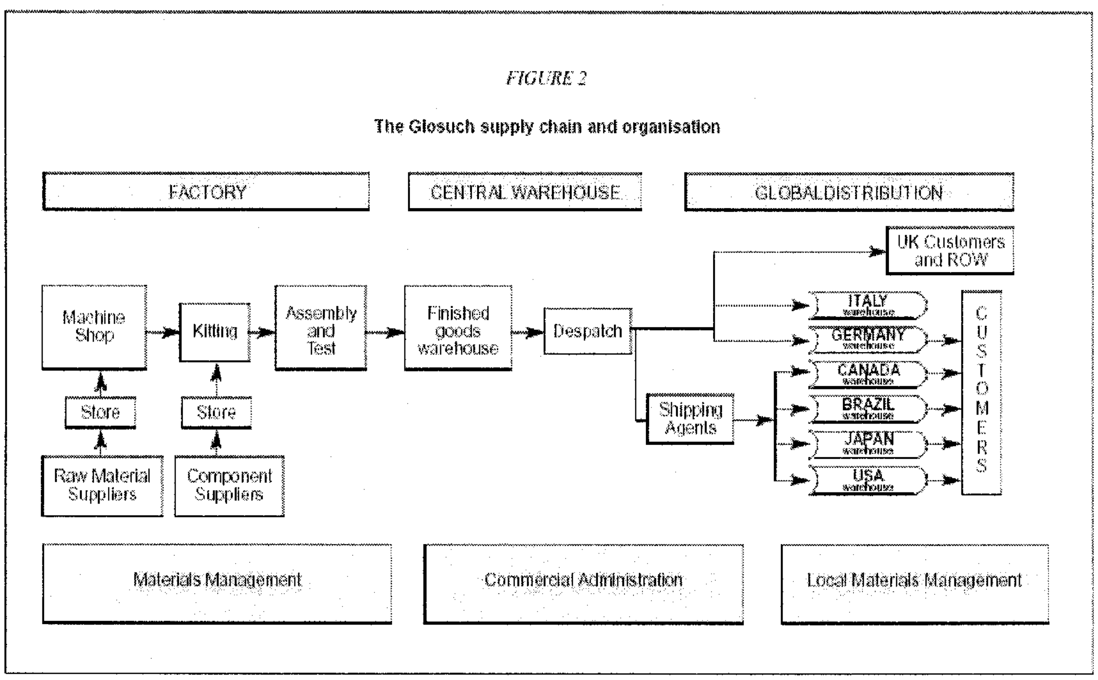


Figure 2-2 Glosuch Supply Chain and Organization (McCullen and Towill 2000, 24-30)

By inspecting six yeas of monthly time-series data on sales, replenishment demands, production, and inventory levels, the existence of the bullwhip effect was presented. Figure 2-3 showed the amplification from the sales to the production. The horizontal axis was the number of the week and the vertical axis was the number of orders (the diamond point line stood for the USA sales while the square point line stood for the UK production of product code 01).

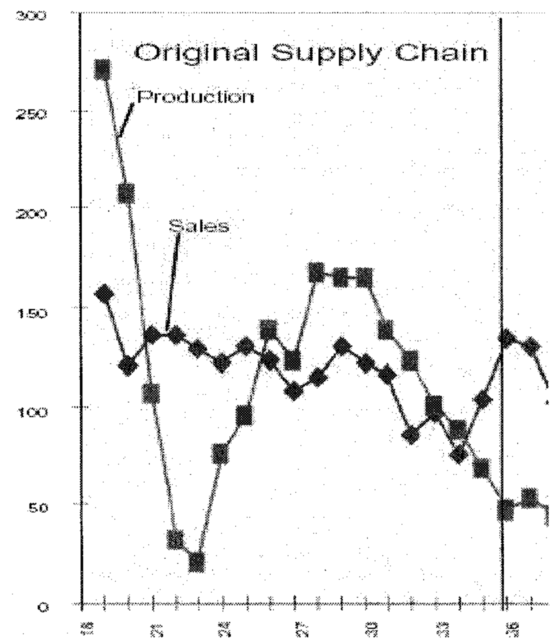


Figure 2-3 USA sales and actual UK production of product code 01 (McCullen and Towill 2000, 24-30)

2. Disney and Towill (2003, 199-215) mentioned that traditional supply chains were extremely prone to the bullwhip effect. A summary given by Towill and McCullen (1999) was referred in this paper. Figure2-4 shows the bullwhip effect from a clothing supply chain. The order rate on the "yarn maker" side was 2*2*2=8 times as much as the order rate from customers. The amplification showed more variability on the upstream manufacture side than on the downstream marketplace side.

S.M. Disney, D.R. Towill / Int. J. Production Economics 85 (2003) 199–215

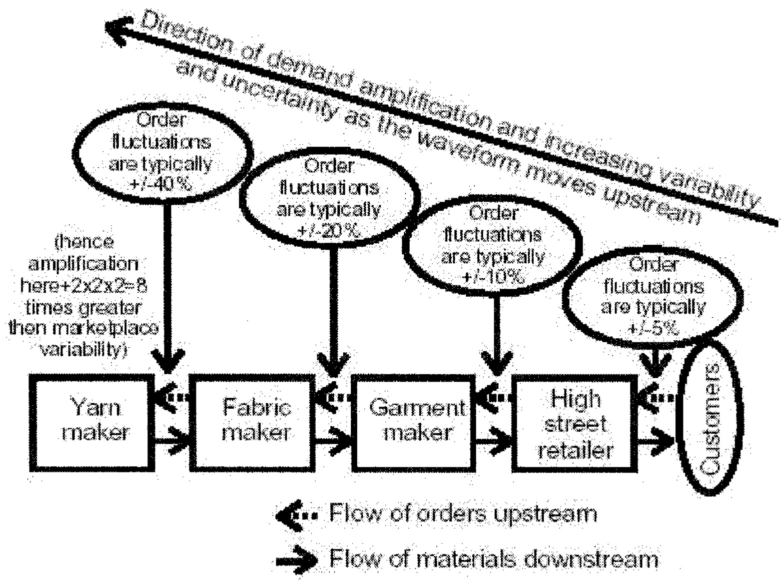


Fig. 3. The Bullwhip Effect in a traditional retail supply chain (taken from Towill and McCullen, 1999).

Figure 2-4 Bullwhip Effect from clothing industry (Disney and Towill 2003, 199-215)

3. Lee, Padmanabhan, and Whang (1997, 93-102) indicated that Procter & Gamble (P&G) had met the bullwhip effect in their respective supply chains of diapers- their famous product. The sales at the retailer got a small variability while the fluctuation of the order at the distributor was excessive. Then the greater swing happened to its material vendor like 3M. From the case, the demand variability was amplified as order went to upstream providers. Another case from HP showed the bullwhip effect on the sales of one of its printers. The integrated circuit business unit of HP faced greater fluctuations than the printer business unit; the order swing of its printer business unit was larger than the resellers. Figure 2-5 showed the bullwhip effect. From the customer to the retailer, the variability of order quantity increased; from the retailer to the wholesaler, the variability increased more; from the wholesaler to the manufacture, this value increased even more.

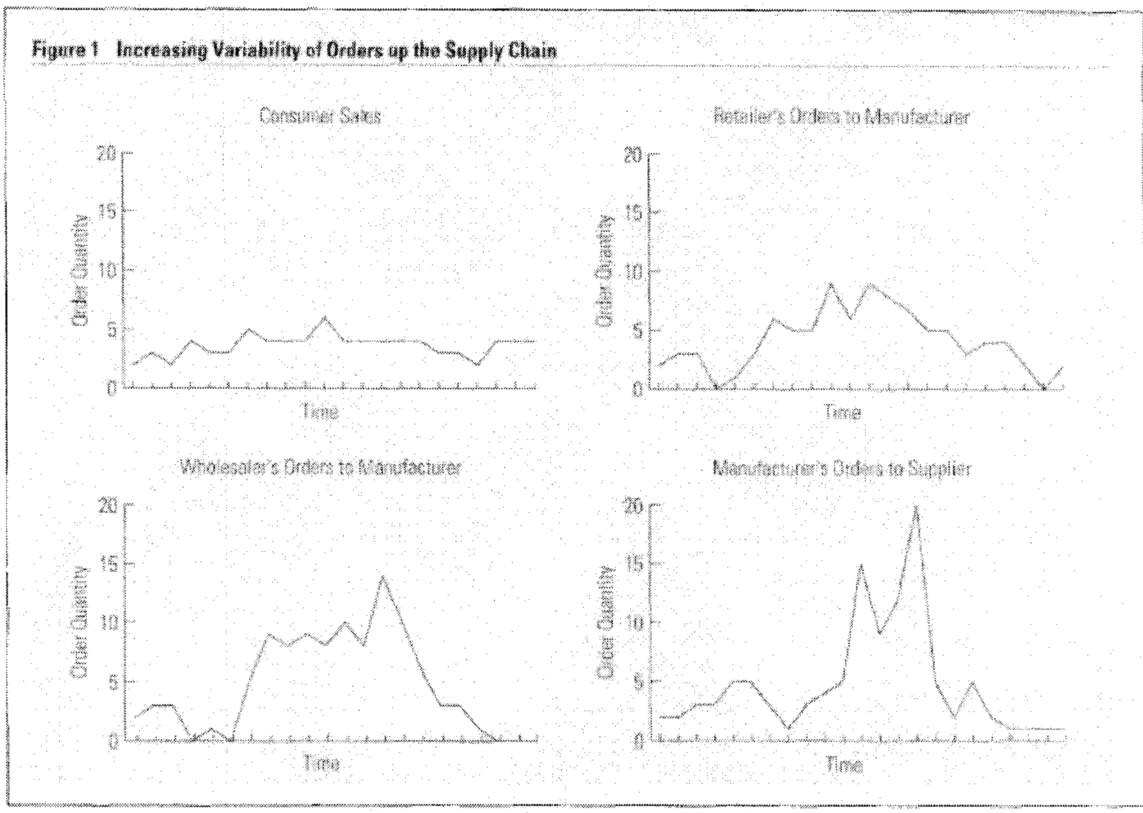
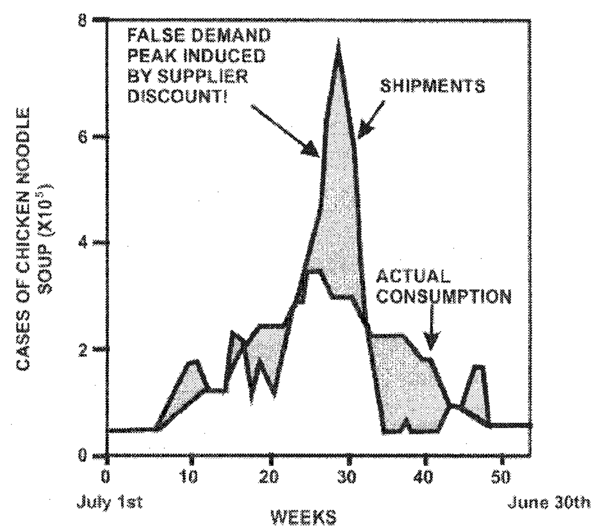


Figure 2-5 Increasing Variability of Orders up the Supply Chain (Lee et al. (1997, 93-102)



Source: Fisher *et al.* (1997)

Figure 2-6: False Demand in Campbell's Soups supply chain (Fisher et al. 1997)

4. Fisher et al. (1997, 211-225) mentioned a famous real-world example that a price discount induced bullwhip in Campbell's Soups supply chain. The amplification and

demand variability were showed through a time series result (Figure2-6).

2.3 Cause and Remedy Analysis Review

1. Forrester (1961) proved that the time delay in the product distribution system would amplify the demand variation of an upstream supplier. He emphasized that the demand was magnified at the upstream supplier in the supply chain because of the over-reacting tendency, which could be explained by the information feedback loop among trading partners. By understanding the system as a whole, and modelling that system with "system dynamics" simulation models, he showed the remedies to the bullwhip effect. Forrester's solutions to control fluctuation included "*reduction in clerical delays*" and "*removal of the distributor sector*", which means e.g. decreasing a three-level distribution system to a two-level system. As a result, management teams can determine an appropriate action.

2. Blackburn (1991) mentioned that besides many other business problems, the time delay between organizations in a supply chain was the cause of the bullwhip effect. The range of these time delays was even up to 66 weeks between orders requested and goods acquired in apparel industry. By "*compressing the time delays*" between the supply chain links, the forecast errors can be tremendously reduced.

3. As an economist, Naish (1994, 864-875) noted that variance of output/production was greater than the variance of sales. The reason was attributed to the rational responses towards demand shocks for enterprise profit optimization. (Remedy) Naish argued that the effect disappeared if demand shock was known before the decision making on price and products.

4. Lee, Padmanabhan, and Whang (1997, 93-102) identified four major causes of the bullwhip effect:

(1) Demand forecast updating. A trading partner makes a higher forecasting when an end customer increases orders; then the trading partner places more from its upstream trading partner (supplier) based on the forecasting. Similarly the upstream supplier makes an increase in demand forecast, so generates bigger distortion on the order rates. When the end customer demand decreases, it works in the reverse way.

A possible solution is to make demand data directly available to companies further upstream in the supply chain. One popular way is called Vendor Managed Inventory (VMI). Furthermore, a single source of forecasting can be determined for the entire supply chain. Another remedy is to sell its product bypassing the distribution channel. Finally, just-in-time (JIT) replenishment can mitigate the bullwhip effect since it improves the operation efficiency which reduces the lead time.

(2) Order batching (Burbidge Effect). A company may not place an order with its supplier right away while inventories deplete. It often accumulates demands before issuing an order because of, for instance, fixed order costs or distribution efficiency. A practical example could be a company which receives daily orders but places orders with its suppliers once a month. The variability of orders placed with the suppliers is higher than the demands the company itself faces.

(Remedy) Besides making consumer demand data available through the whole chain, EDI (Electronic Data Interchange) is a method to reduce administrative ordering costs by reducing batch sizes and increasing order frequencies. Another way is to use third-party logistics service providers to make less-than-full truckloads economically viable.

(3) Price fluctuations. The price of a product fluctuates based on promotions and trade deals, which increases variability of demand. A customer buys in much more than what they really need while products are cheaper. The customer buys less than needed to deplete their inventory when price comes to normal. Hence, the demand

from customers cannot reflect the real needs, which causes more variability of demands.

(Remedy) Stabilizing prices and decreasing the number of promotions are the two ways to reduce such effect (it could not be a practical way). The simplest way is to reduce both frequency and the level of wholesale discount. To form a uniform wholesale pricing policy could decrease the incentives from the forward buying.

(4) Rationing and shortage gaming. When product demands exceed supply, a supplier has to ration its product to customers. As a result, customers may order more than what they really need. Later, when there are no shortages, orders disappear.

(Remedy) Introducing rationing methods based on historical sales rather than on orders placed by customers can control the bullwhip effect here.

5. Metters (1997, 89-100) mentioned that the fundamental problems of the bullwhip effect are "*lack of the communication among trading partners and the time lags between the transmitting and receiving*" of information among members within a supply chain and these lags could cause the extraordinary forecast.

   (Remedy) To reduce the lead time and increase the coordination among companies are the solutions here.

6. McCullen and Towill (2000, 24-30) have identified major dimensions of the bullwhip effect. They mentioned that there were three prime dimensions of the bullwhip effect: replenishment which affected material and information flow, geographical (different locations), and temporal (different times).

   They listed four "*material flow principles*" to reduce the bullwhip effect(remedy):

(1) "*Control systems Principle*": using right decision support systems to control the dynamic stability of the whole.

(2) "*Cycle Time Compression Principle*": through business processes re-engineering, the material flow and information processing lead times could be decreased.

(3) "*Information Transparency Principle*": sharing integrity information among all the attendees in a supply chain to ease the bullwhip effect.

(4) "*Echelon Elimination Principle*": this includes the elimination of echelons and functional interfaces.

7. Disney and Towill (2003, 625-651) have identified major causes of the bullwhip effect: "*Demand signal processing and non-zero lead-time or the Forrester Effect*", "*Order batching or the Burbidge Effect*", "*Rationing and gaming or the Houlihan Effect*", and "*Price fluctuations or the Promotions*".

(1) Demand signal processing was called the "demand amplification" or the "Forrester effect" after Forrester (1961) who encountered the problem and demonstrated it via DYNAMO simulation. Feedback theory explains how decisions, delays and predictions can produce either good control or dramatically unstable operation.

(2) Order batching is also known as the "Burbidge Effect" (Burbidge, 1991). It refers to the practice of placing orders from upstream suppliers in batches. In order to achieve economies of scale in set-up activities (such as setting up a machine or placing and receiving an order), it happens frequently.

To deal with these problems, Towill (1997) brought the contributions of Forrester and Burbidge together to innovate an integrated approach termed "*Forridge*". (Remedy) As is known the longer the lead time, the greater the problems arise from system instabilities, and the more uncertainty output in the marketing; therefore, time compression is good to improve the performance of the supply chain.

Synchronization of lead time and capacities among the echelons could streamline the cooperation.

The input-output diagram in Figure2-7 highlighted the root causes of either the Forrester effect or the "Burbidge effect" and in some cases both.

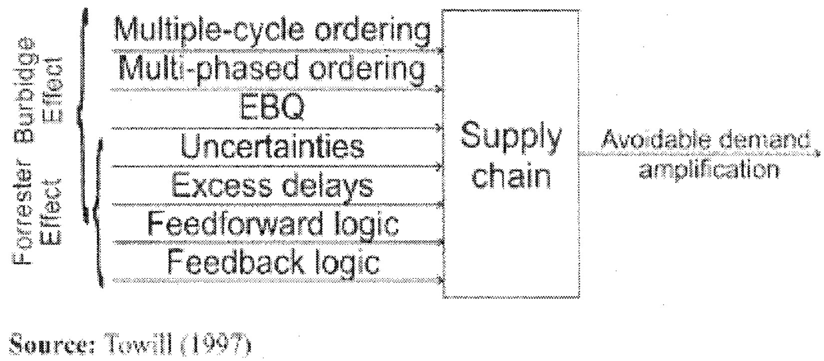


Figure 2-7 Root causes of Forrester effect or the "Burbidge effect" (Towill 1997)

(3) "*Rationing and gaming*", or the Houlihan Effect, or the flywheel effect was another cause highlighted by Houlihan (1987, 51-66). Customers overload their orders to avoid shortages or missed deliveries in supply chains. This results in more demands on the production system that is the reason of more unreliable deliveries. A vicious circle happens since customers then increase their safety stock target that further distorts the demand signal.

(4) Price variations or the promotion effect: the practice at reduced prices to stimulate demands. As a result, customers forward buy by taking this opportunity, but not depend on their really needs. "*However this has serious impacts on the dynamics of the supply chain, for instance, as when the price stop discounted plan, demand slump, creating a perceived need for further discounting in order to stimulate demand.*" A famous real-world example is due to Fisher et al. (1997) (Figure2-6).

VMI Solution to the bullwhip effect (remedy):
Figure2-8 shows us the conception model of VMI (Vendor Managed Inventory) which is a practical way to get the benefits of the echelon elimination. By sharing

demands and inventory information with their supplier or customers, the bullwhip effect could be decreased. Related forms to VMI are: quick response (QR), synchronized consumer response (SCR), continuous replenishment (CR), efficient consumer response (ECR), rapid replenishment (RR), collaborative planning, forecasting, replenishment (CPFR), and centralized inventory management.

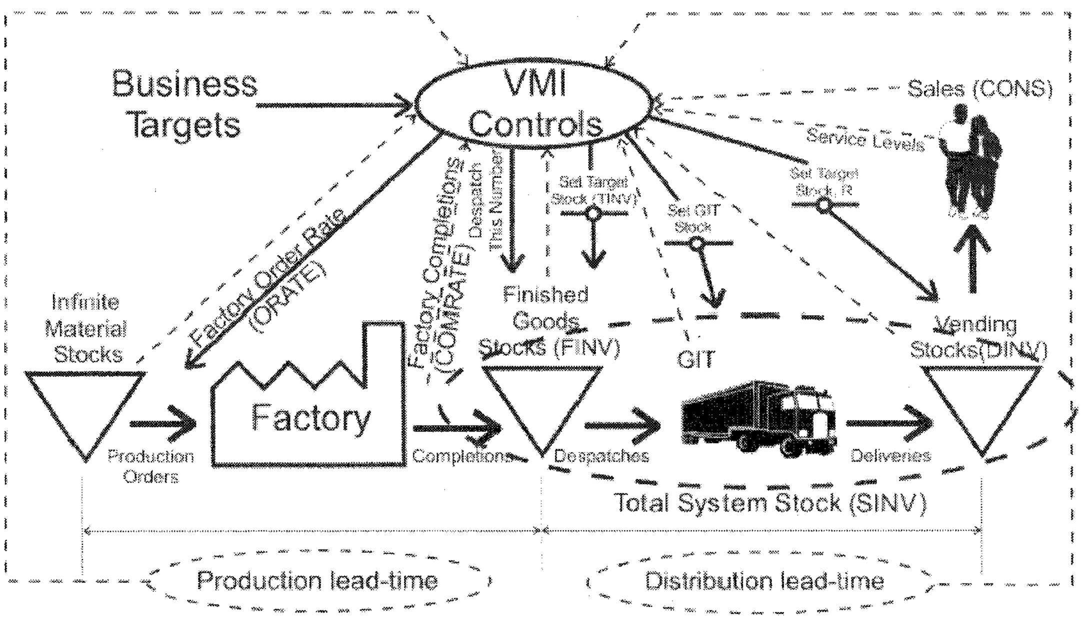


Figure 2-8 the conception model of VMI (Disney and Towill 2003, 625-651)

8. Nienhaus, Ziegenbein, and Duijts (2003) mentioned that lead time of information and material were the primary reasons for the bullwhip effect. The longer a supply chain is, the heavier it needs to react to a changed demand. Hence, the bullwhip effect reaches up more while lead times become longer. The second reason is planning and behavioural aspect. It comes from the demand forecast which is based on orders of back-fence echelon rather than the demand of the end customer. Batching order, price fluctuation and exaggerated order quantity in the case of delivery bottlenecks are the same causes as what Lee mentioned (1997, 93-102).

   (Remedy) They suggested that further research would show the visualization of stock levels and orders throughout the supply chain to reduce the bullwhip effect since that equals a reduction of information lead time.

2.4 Forecasting Methods in Bullwhip Effect that have been investigated

1. Forrester (1961) put forward "*smoothing of information*" that would be an earlier mention on how forecasting method affected production-distribution system. In his book, the effort to filter out the fluctuations would be smoothing method. "*Smoothing processes are fundamental to a proper treatment of system dynamics.*" He also mentioned that though smoothing method could filter out short-period noise, it brought information delay. The leverage between more smoothing to reduce noise and less smoothing for less delay was a compromised task. He only dealt with moving average and exponential average in his book. These smoothing methods were used in customer order information.

2. Graves (1999, 50-61) considered an adaptive base-stock policy for a single item inventory system. A first order exponential-weighted moving average was applied. Through the forecast which was updated every period using minimum mean squared error forecast (MMSE), he showed that the demand process from the upstream held more variability than that from the downstream.

3. CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443) and CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286) quantified the impact of the demand forecasting on the bullwhip effect using not only the moving average method but also the exponential smoothing forecasting method. Furthermore, they used both the correlated demands and the demands with a linear trend. Their conclusion was that the variability of order depended on both "*the nature of the customer demand*" *and* "*the forecasting technique*". The bullwhip effect was due to the effect of demand forecasting partially. They pointed out that under certain demand process the exponential smoothing forecasting method generated a larger variability than the moving average. However, they assumed that the excess inventory was returned without cost, which may be

unrealistic in some cases. Finally they mentioned that although these two forecasting techniques may not be "*optimal*", it was the most appropriate technique since it applied most commonly used forecasting methods.

4. Yao (2001) in the PhD dissertation restated that demand forecasting and ordering policies were two key causes of the bullwhip effect. In one of the lemmas, he mentioned that forecasting had smaller variance than the real demand if time was long enough, which showed their conclusion that forecasting and ordering policy (order batching) together led to bullwhip effect. Yao applied the order-up-to policy that was the same as CDRS and CRS, but an optimal forecast scheme was applied. To be clear, a mean square error optimal (MSE-optimal) forecast model was used. As a result, for a positively correlated stationary AR(1) process, the bullwhip effect under MSE-optimal forecast model, approached a limiting value, which was different to normal forecasting model, such as the moving average and the EWMA. More interesting result was that the bullwhip effect disappeared for a negatively correlated process under MSE-optimal forecast model.

5. Miyaoka and Hausman (2004, 149-162) considered a two-stage supply chain (manufacture at downstream level and supplier at upstream level) using an adaptive based inventory policy and the forecast updating. They proposed the "*stale*" forecasts to decide the base stock levels. By using both a decentralized setting (supplier affords a high service level to manufacture) and a cooperative setting (both two trading partners set safety stock level together), they studied the policy. Their conclusion was that old forecast policy could reduce the fluctuations in production levels.

6. Paik in the PhD dissertation (2003) contributed more on the investigation of the causes of the bullwhip effect. After reviewing nine causes from previous literature, through experiments, the author identified one of the statistically significant main-effect variables was the demand forecast updating. The other two statistically significant main-effect variables were identified as the level of echelons and the price variations.

2.5 Simulation Modeling on Bullwhip Effect

1. Forrester (1961) illustrated the process of using a "*statement of the objectives*" and a verbal description to build a mathematical model of the production-distribution system. The relationship among retailer, distributor, and factory was represented by seventy-three equations. Although the model was simple, it described the "*fundamental economic*" phenomenon. By this model definition, Forrester introduced his "industrial dynamics" theory. Based on the "*DYNAMO*" complier, system experiments was used to test how his production-distribution system responded to specified input: step input, one year periodic input, and random fluctuation in retail sales.

2. The Beer Distribution Game is a classic supply chain simulation. Sterman (1989, 321-339) modeled the Beer Distribution Game to conduct an experiment on managing a simulated industrial production and distribution system. The main purpose of his paper was to show how misperceptions of the feedback accounted for the poor performance in dynamic systems. By using generic stock acquisition and an ordering heuristic, he proposed three ordering motives: expected demand, adjustment of inventory, and adjustment of supply line. From Beer Game, the bullwhip effect was showed. Later he mentioned that "lack of system thinking" was one of causes of the bullwhip effect.

3. Chatfield, Kim, Harrison, and Hayya (2004, 340-353) used a simulation model called "*SISCO*" to build a k-stage serial supply chain simulation model. By a series of experiments, they investigated how lead-time, information quality, and information sharing affected the bullwhip effect. They showed that nearly 50 percent attenuation on variance amplification at factory was due to the information sharing in a customer-retailer-wholesaler-distributor-factory supply chain.

2.6 Bullwhip Causes and Counter-Measures Summary

Based on the literature review in chapter 2, we summarize all the causes and remedies of the bullwhip effect. Table 2-1 and Figure 2-9 can give us an overview. According to Nienhaus, Ziegenbein, and Duijts (2003), we divide the reasons into two groups: time lag and planning & behavioural aspect. (Lee, Padmanabhan, and Whang 2004, 1875-1886)

Group	Main Causes	Sub Factors	Remedy measures	Authors	Practical operations
Time lags	Time lags or long lead time		reduction in clerical delays	Forrester(1961)	
			Compressed time delays	Blackburn (1991)	
			Lead time reduction	Lee (1997)	Quick Response mfg strategy
			Reduced Lead time	Metters (1997)	
			Echelon Elimination Principle & Cycle Time Compression Principle	McCullen, Towill (2000)	
Planning and behavioural aspects	Demand Signal Processing	Invisibility of demand from end customers/ lack of	Demand shock was known before the decision making on price and products	Naish (1994)	

		communication among partners	Information Transparency Principle/ Synchronization of capacities and lead time/JIT (just-in-time) replenishment	Lee (1997) Towill (1997)	Sell-thru data (HP, Apple and IBM)
			Increase coordination among companies	Metters (1997)	
			Information Transparency Principle	McCullen, Towill (2000)	
			VMI	Towill (1997)	Glosuch
		Multiple forecast	Single control of replenishment	Lee (2004)	
			VMI	Towill (1997)	Glosuch
	Order Batching	High order cost	EDI	Lee (1997)	McKesson
		Full Truck Load factor	3rd party logistics	Lee (1997)	3rd party logistics in Europe
	Fluctuating prices	Price changing	EDLP	Lee (1997)	P&G

			reduce both frequency and the level of wholesale price discounting /form a uniform wholesale pricing policy	Lee (1997)	
	Rationing and shortage gaming (flywheel effect)	Proportional rationing method	Allocating products based on the history of sales	Lee (2004)	HP, Saturn
		Unrestricted orders& free return policy	Capacity reservation	Lee (2004)	Seagate, Sun, HP

Table 2-1 Bullwhip effect causes and remedy summary

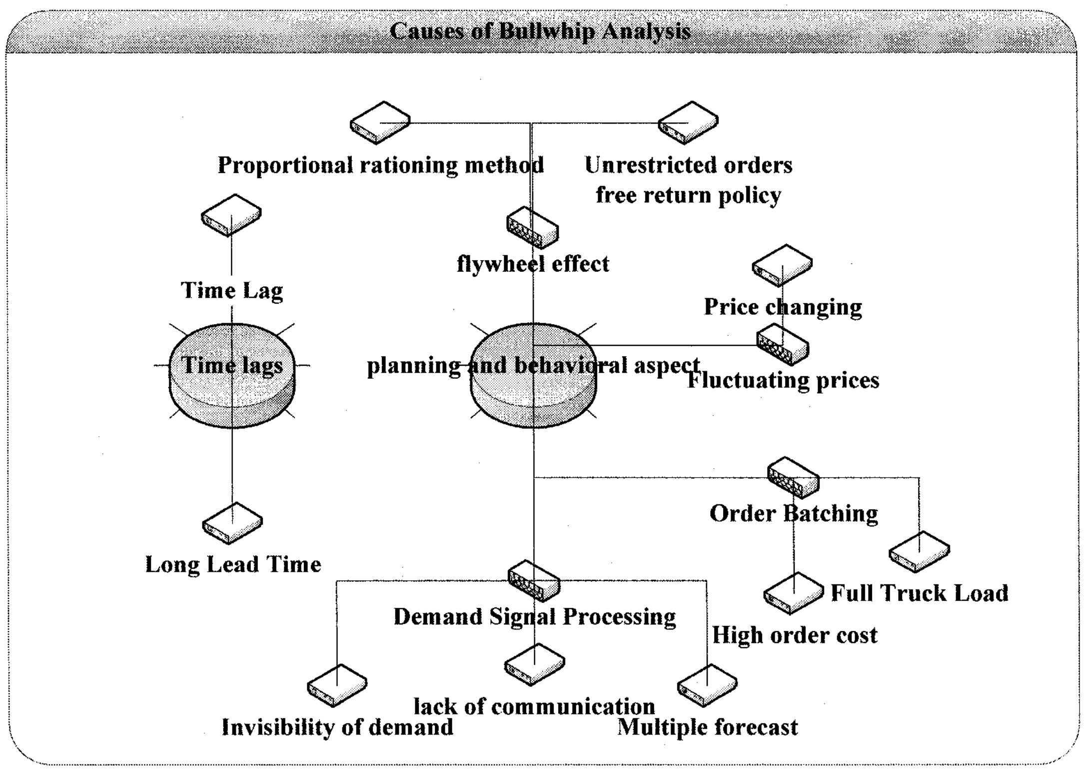


Figure 2-9 Causes of Bullwhip Analysis

In Figure 2-9 the Blue circles stand for the group of the cause of bullwhip effect, the square box like a hub means the main cause of bullwhip effect and the terminal match boxes are the sub factors of bullwhip effect in the Table 2-1.

3 Problem Statement

3.1 Research Motivation

We are really interested in the bullwhip effect since the success of a business is contingent on the performance of its supply chain. The bullwhip effect in a supply chain costs money, wastes resources, and leads to the loss of market share. Therefore, our research on the bullwhip effect is significant for it affects core competency of an organization and shows value to the industry.

Our research motivation originates from previous research on the bullwhip effect since many papers investigated industrial organizations and showed us that the bullwhip effect was not just a phenomenon of interest to academics but prevalent in many real-world supply chains. For instance, Fisher et al. (1997, 211-225) mentioned a famous real-world example of a price discount induced bullwhip in Campbell's Soups' supply chain. Lee, Padmanabhan, and Whang (1997, 93-102) indicated that bullwhip effect affected the supply chains of Procter & Gamble (P&G) and HP. Disney and Towill (2003, 199-215) cited the case in a clothing supply chain that fully demonstrated the bullwhip effect.

Walker (2005) noted that supply chains are separate interwoven networks of material, information and cash. He stated that "*technological core competency, process core competency, and relationship core competency*" are essential for an organization's ability to compete in the market. Not technology, but rather the process and relationship competency, set the threshold of supply chain competitiveness. The bullwhip effect comes from the core competency of process and relationship (e.g. information distortion of demands). From the point of view of interwoven networks, it is valuable for us to deeply understand bullwhip effect. As most companies put velocity and variability as the Key Performance Indicator (KPI) of their supply chain, and based on the analysis of table2-1, these two factors have a close relationship with the bullwhip effect, we should definitely investigate the effect.

Previous research on the bullwhip effect focused on cause and remedy analysis. In table 2-1, we can see all known causes and their corresponding remedies. For example, Lee, Padmanabhan, and Whang (1997, 93-102; 2004, 1875-1886) identified four major causes of the bullwhip effect as demand forecasting updating, order batching, price fluctuations, and rationing and shortage gaming.

As Yao (2001) indicated that demand forecasting and ordering policies are two key causes for the bullwhip effect, we decided to focus on these two factors. The research paper on the relationship between forecasting technique and bullwhip effect came from 1961 in Forrester's study. Only two smoothing methods were used in customer order information: moving average and exponential average methods. By an adaptive base-stock policy, Graves (1999, 50-61) considered a first order exponential-weighted moving average for a single item inventory system. CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443) and CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286) quantified the impact of demand forecasting on the bullwhip effect using the moving average method and the exponential smoothing forecasting method. The forecast methods used in the bullwhip effect study was limited, so we identify the first research motivation: introducing additional forecasting techniques into bullwhip effect model.

For the ordering policy, most authors used the order up-to policy, such as CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443), CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286), and Lee, Padmanabhan, and Whang (2004, 1875-1886). Sterman (1989, 321-339) applied generic stock acquisition and ordering heuristic in his Beer Game Model. He showed the bullwhip effect by generating a complex oscillation from a single chain structure with a serial communication. Our research is illustrated by using his model for supply chain networks are complex systems that often respond in a non-linear manner. Unlike his research on misperceptions of feedback, we identify our second research motivation: focusing our study on how different forecasting techniques are incorporated into this model to control the bullwhip effect.

Forrester (1961) defined his dynamic ordering policy equation in the production-distribution system. In the equation, order rate was decided by requisitions received from the upstream trading partner, the gap between desired and actual inventory, and the delay in inventory. By changing the definition of desired and actual inventory, Kohli (2005) gave a new equation of ordering policy including lead time, safety stock, and order frequency. The third study motivation is to modify ordering policy to see aggregation results if we combine different ordering policies with different forecasting methods.

Each of the above three motivations is based on gap analysis in the theory model. Accompanying these theory models, many authors also conducted their simulation experiments based on different frameworks, such as "*DYNAMO*" from Forrester or "*SISCO*" from Chatfield, Kim, Harrison, and Hayya (2004, 340-353). As a result, our fourth motivation is to present a more vivid demonstration by using a dynamic simulation. Our research uses agent-based modelling (ABM), which brings us more realistic results than equation-based modelling (EBM). Based on a framework named "REPAST", we implement our ABM using the object oriented (OO) method.

In summary, this thesis has four motivations:

- to introduce additional forecasting techniques into the bullwhip model,
- to focus our study on how different forecasting techniques are incorporated in Beer Distribution model to control the bullwhip effect,
- to modify the ordering policy in order to see aggregation results when we combine different ordering policies with different forecasting methods, and
- to present a more vivid demonstration by using a dynamic simulation which uses agent-based modelling

3.2 Problem Definition

Based on the motivation of our research, we articulate the overall objective of our thesis and the corresponding project. We detail the specific steps by which our work is intended to accomplish the overall objective.

The purpose of this research is to deeply understand the bullwhip effect across the supply chain. The overall objective is to build a more comprehensive model in order to discover how different forecasting methods and ordering policies affect the bullwhip effect. As a result, we can propose several managerial insights.

Our research differs from previous papers in four ways. First, differing from Sterman who investigated supply chain dynamics from the perspective of managerial behaviour, we focus on how specific techniques such as forecasting methods and ordering policies affect the bullwhip effect. Based on Sterman's "Beer Distribution Game" model, we add three other forecasting methods: moving average, Holt's method, and double exponential smoothing (Browns method). We also analyze different ordering policies. Moreover, differing from CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443) and CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286) who showed forecasting techniques as a cause of the bullwhip effect, we try to identify benefits arising if more forecasting techniques are applied. Since Holt's method and double exponential smoothing (Browns method) are good at forecasting local trends, we add these two forecasting methods into our model. Furthermore, illustrated by Yao (2001), we update the forecasting process by introducing "*MSE-optimal forecast*" into our model. However, differing from his study, we extend the "*MSE-optimal forecast*" to a generic stock acquisition and ordering heuristic supply chain system. Finally, we model and simulate the bullwhip effect based on multi-agent methodology and system dynamics theory.

In order to reach our overall objective, we will complete the following phases:

Firstly, we carry out further study on previous literature related to the bullwhip effect. This literature should include real world case study, cause and remedy analysis, forecasting methods application, and modeling simulation in the bullwhip effect.

Secondly, based on the "Beer Distribution Game", we build our basic mathematical model including the generic stock acquisition and the ordering heuristic. We then extend this basic model by adding three other forecasting methods: moving average, Holt's method, and double exponential smoothing (Browns) method. We also add an ordering policy: one without supply line support.

Thirdly, we implement our theory model based on a framework named "REPAST" using multi-agent techniques. Tasks in this phase include "REPAST" framework study, basic model design and implementation, and extending the basic model by adding three forecasting methods and one ordering policy formulated during second phase.

Fourthly, we design simulation experiments according to our overall objective and applications. The experiments cover all combinations between forecasting methods and ordering policies.

Finally, based on our simulation results, we do synthesis analysis and propose some managerial insights. Our conclusions illuminate our contributions.

4 Methods and Models

4.1 Research Methods

This study is based on the approach of system dynamics and multi-agent technology.

4.1.1 Systems Dynamics

System dynamics is to investigate how systems change over time. It examines the interaction among individual components and the effect which various changes bring to the system. By qualitative diagrams and quantitative simulation modes, the system dynamics technique can help us understand complex systems. One of the most important features of systems dynamics is that the underlying structure of the system determines systems behaviour.

System dynamics modeling is to describe the structure of the system, which begins with identifying time dependent variables that show the dynamics feature. Stocks (levels) and flows are the key components of system dynamics models. The stocks stand for the quantities that accumulate over time such as inventory or bank account. The flows stand for the sources or the sinks that increase or decrease the stocks. By using flows, behaviour is generated. System dynamics focuses on feedback flows among their components. Finally, equations are defined based on the understanding to the system. These equations control all the relationships in the model.

In the system dynamics area, supply chain modeling was an old story. In 1961, Forrester at MIT modeled a simple production-distribution system by introducing feedback loops and time delay (Forrester 1961). At that time, he showed demand amplification and inventory swings in a supply chain. Later on, Sterman (1989, 321-339) at MIT modeled the Beer Distribution Game, a classic supply chain simulation, to conduct an experiment on managing a simulated industrial production and distribution system. By generic stock acquisition and an ordering heuristic, he proposed three ordering motives: expected demand, adjustment of inventory, and adjustment of supply line. By the Beer Game, the bullwhip effect was showed, and then Sterman mentioned that "*lack of system thinking*" was one of causes of the bullwhip effect. His conclusion was that misperceptions of the feedback accounted for the poor performance of supply chain in dynamic systems.

4.1.2 Multi-agent technology

Our simulation is based on multi-agent technology, so firstly we introduce multi-agent conception. Moreover, we give a general description on REPAST, a multi-agent framework on which we build our simulation model.

4.1.2.1 Multi-agent Modeling

As any entities in systems can be grouped into two categories: individuals (e.g. people, computer), and observables (e.g. orders per month, lead time), approaches for system modeling can be divided into agent-based modeling (ABM) and equation-based modeling (EBM). ABM deals with behaviour through individual while EBM describes relationships in the system. (Baumgaertel et al. 2003, 315-343)

We decide to use ABM over EBM since its advantages is as following: (Parunak*, Savit**, and Riolo** 1998, 10-25)

- ABM is easy to model, which can help us avoid the difficulties on translating certain behaviour into equations.
- ABM supports more straight-forward experiments, which help us focus more on business process but not on how to explain these processes into hard-to-be-read equations.
- ABM can be translated back into practice easier.

In complex supply chain industries, using ABM can accommodate us to deal with complex aggregate behaviours. Actually in a supply chain, there are a number of individual trading partners who can interact with each other based on their own decision policies.

4.1.2.2 REPAST Framework Introduction

Our simulation model is built on REPAST framework. REPAST stands for "REcursive Porous Agent Simulation Toolkit". REPAST is an open-source software framework for creating agent-based simulations using Java programming language. The framework was developed by the Social Science Research Computing at the University of Chicago. Repast is now managed by the non-profit volunteer Repast Organization for Architecture and Development (ROAD).

The reasons we applied REPAST as our framework since its features listed below: (Anonymous 2005)

- Repast includes a variety of agent templates and examples, easy to learn and apply.
- Repast gives users complete flexibility as to how they specify the properties and behaviours of agents; hence, we can customize our supply chain and forecasting specific features.
- Repast is fully object-oriented and is implemented in a variety of languages including Java and C#, so we choose Java as implementation program language.
- Repast includes a fully concurrent discrete event scheduler. This scheduler supports both sequential and parallel discrete event operations, which save our time on scheduler design.
- Repast offers built-in simulation results logging and graphing tools, easy to view experimental results.
- Repast allows users to access and modify agent properties dynamically, agent behavioural equations, and model properties at run time, which saves our time on experiments.

REPAST has been used in a list of publications and projects. (Anonymous2005)

- A simulation of competitive management/business strategy using Repast has been published in Robertson, D. A. (2003) "Agent-Based Models of a Banking Network as an Example of a Turbulent Environment: The Deliberate vs. Emergent Strategy Debate Revisited", Emergence, 5(2), 56-71.
- Professor Robert Axelrod of the University of Michigan used Repast to implement an agent-based model of consumer choice.
- Lars-Erik Cederman of Harvard University is using REPAST to study world politics. Specifically, he has modeled state formation, nationalism and the democratic peace with various agent-based models.
- Ravi Bhavnani (Political Science, University of Illinois at Urbana Champaign), together with David Backer (Political Science, University of Michigan) and Rick Riolo (Complex Systems, University of Michigan) are using REPAST to study the dynamics of decision-making in closed political regimes such as Iraq, North Korea and Syria in a project sponsored by the Department of Defense, USA.
- Stephan Deschamps from Victoria University Wellington in New Zealand is using REPAST to simulate a knowledge network involving heterogeneous agents such as Small and Medium Enterprises, Universities and Public Research Institutes.

4.1.3 Integrating System Dynamics and Agent-Based Modeling

We integrate system dynamics and Agent-Based modeling in order to reduce the complexity of the model (Schieritz and Größler 2002). The advantage of the system dynamics is that the behaviour of a system roots from its structure, so the system is stable if we keep its structure fixed. Hence, we define the rules or policies in a trading partner using system dynamics. However, if we still apply system dynamics to describe the interrelationship among different trading partners, it is not realistic. As ABM has the beneficial feature of defining a complex interaction, we set up all the trading partners in our model as different agents. This can improve the flexibility and extensibility of our model for future research. When we use REPAST as our framework, good features like "scheduler" can release us from system bottom design and let us focus more on our research topic. In summary, in macro level of our system, we apply ABM; in micro level, we utilize system dynamics to define rules like the ordering policy or the inventory management. Figure 4-1 illustrates the relationship between ABM and system dynamics modeling.

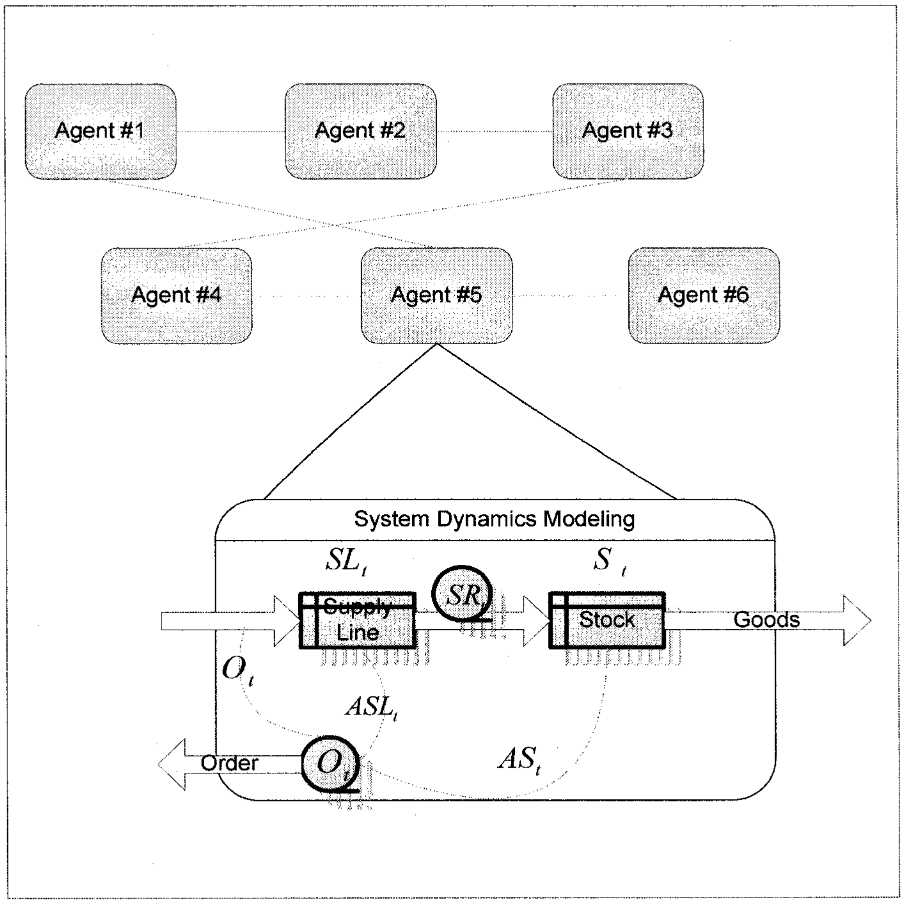


Figure 4-1: ABM & System Dynamics Modeling

4.2 Bullwhip Models' Definition

Our model is based on a simple production-distribution system. Orders for goods propagate from left to right (from downstream to upstream), and goods are shipped in an opposite direction (see figure 4-2). The circle stands for trading partners and the arrow means the goods or information flow. At each time step, the trading partner receives goods from its upstream supplier and sends goods to its downstream customer; meanwhile, the trading partner places an order from its upstream supplier and receives order from its client. We will introduce the operation flow of the trading partner by detail in section 4.2.1.

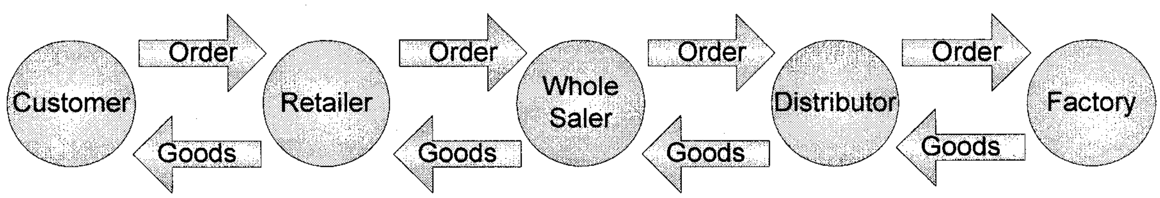


Figure 4-2: Production-Distribution System

In this chapter, we define the 8 models: Basic Model based on Beer Game (BM), Basic Model using Moving Average Forecasting (BM+MA), Basic Model using Holts Forecasting (BM+Holts), Basic Model using Double Exponential Smoothing or Browns Forecasting (BM+Browns), Basic Model without Supply line (BM-SL), Basic Model using Moving Average Forecasting without Supply line (BM-SL+MA), Basic Model using Holts Forecasting without Supply line (BM-SL+Holts), and Basic Model using Double Exponential Smoothing or Browns Forecasting without Supply line (BM-SL+Browns). These models can be grouped by two different ordering policies: the one with the adjustment on the supply line and the one without the adjustment on the supply line. As Sterman's adaptive forecasting is used in the BM, we keep it; besides, we add other three forecasting methods, which are most commonly used in practice, under each ordering policy: Moving Average Forecasting, Holts forecasting method and Browns Forecasting.

4.2.1 Basic Model (BM): Stock management model based on Beer Game

The Basis Model gets insight from Sterman's Beer Distribution Game model. In the Basic Model, besides the customer, we have four trading partners: retailer, wholesaler, distributor, and factory. (See figure 4-2.) Each trading partner has its stock management system and ordering decision system. The model definition comes from these two systems and is constrained by trading partner's operation process. Figure 4-3 shows how one of the trading partners, but not the Factory, operates at each time step (the corresponding legend definition is in table 4-2). By its actual demand history, the trading partner forecasts. Ordering policy, status of stock, and status of supply line (the amount of products that has been ordered but not receive from its supplier) determine how to calculate the indicated order, which is the model's ordering decision system. The stock can be negative since the unimplemented order becomes a backlog order and orders can be split if the inventory cannot afford the whole order, which is the model's stock management.

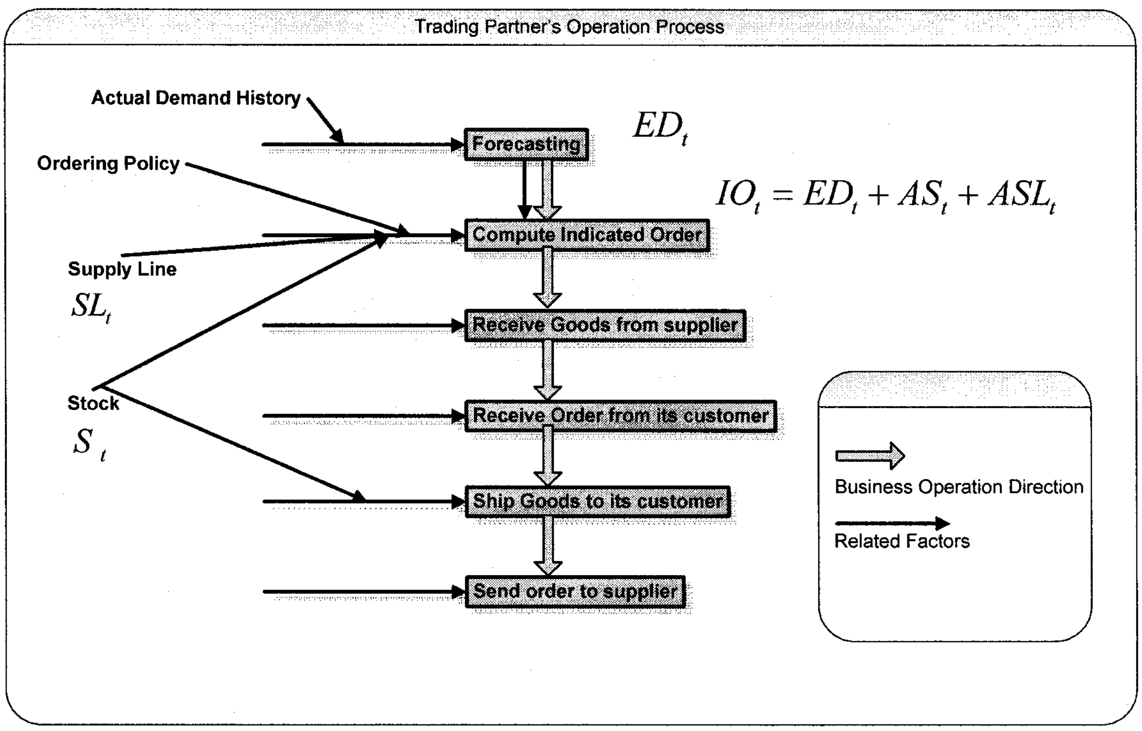


Figure 4-3: Trading Partner's Operation Process

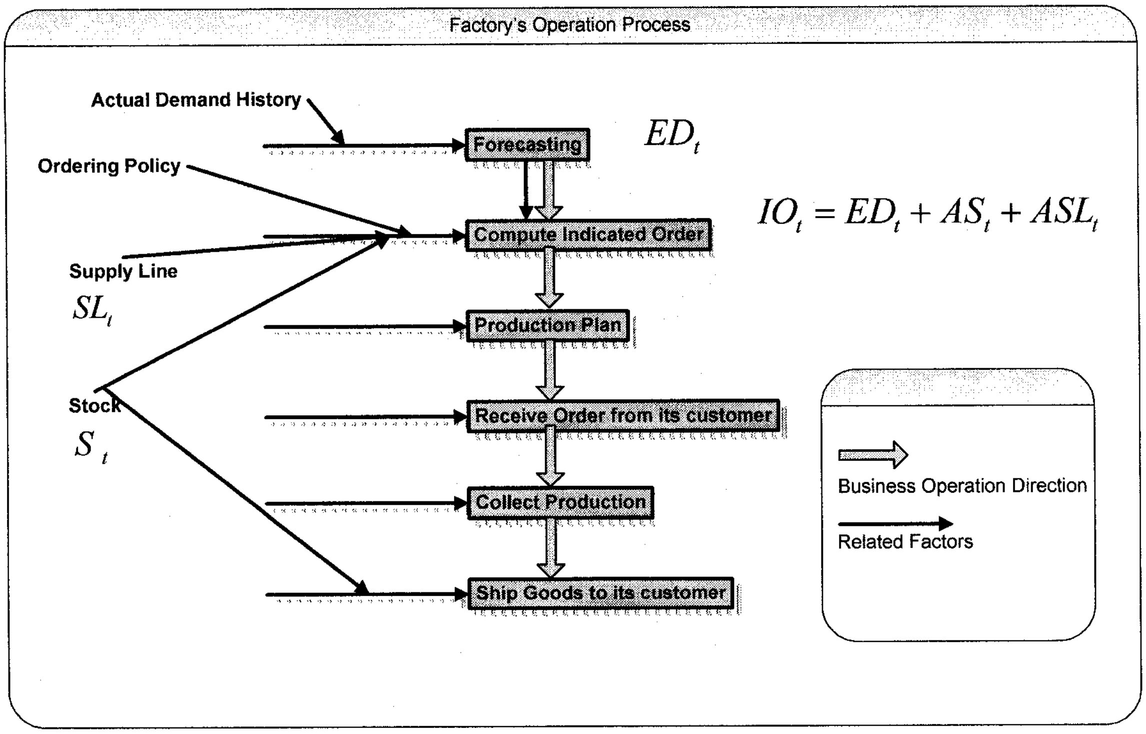


Figure 4-4: Factory's Operation Process

Figure 4-4 shows how the Factory operates at each time step. Like other trading partners, the factory forecasts and calculates the indicated order. The difference between the factory and other trading partners is that the factory does not need to request an order from its upstream supplier, but to make its own production plan. After a production time, the factory collects its products. We assume that there is no capacity limit in the production line.

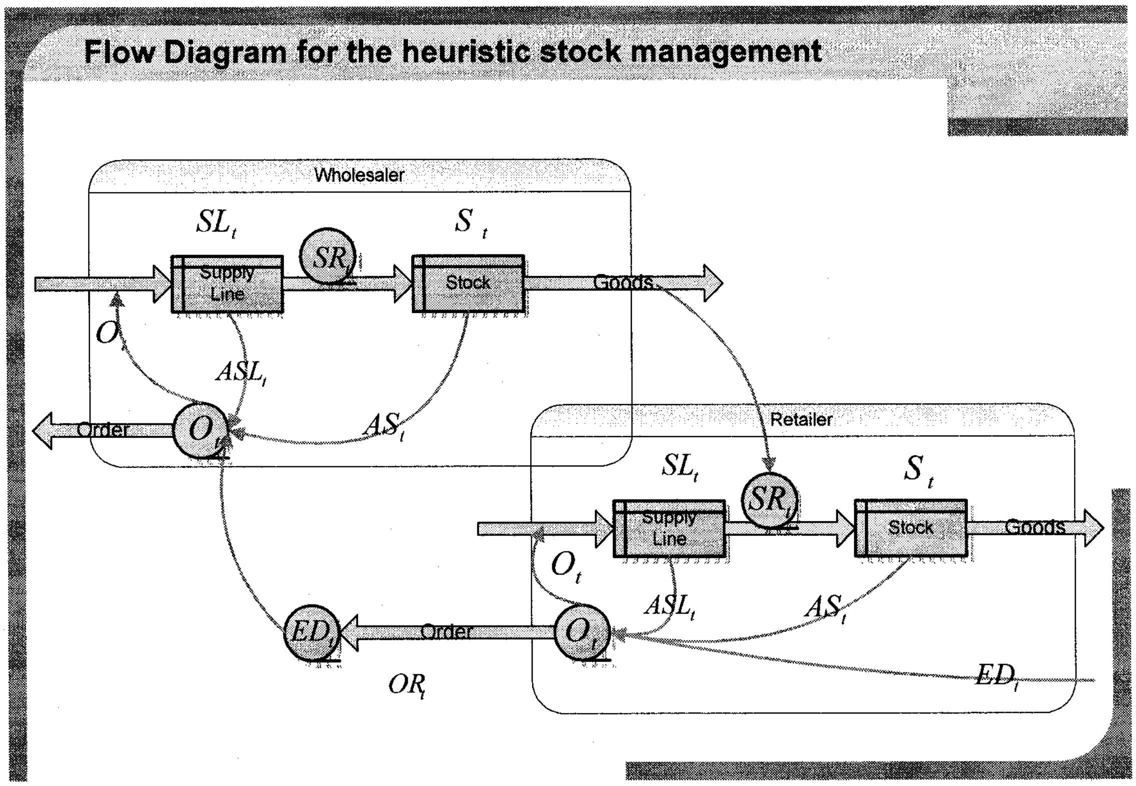


Figure 4-5: Flow diagram for the heuristic stock management

Figure 4-5 shows a perspective on flow relationships between two trading partners. The variables definition is in section 4.2.1.1 and section 4.2.1.2. The heuristic order decision system comes from expected demand (ED_t), adjustment of stock (AS_t), and adjustment of supply line (ASL_t). Orders (O_t) as an input flow increase the supply line while shipment received (SR_t) decreases the supply line. Goods flows out of a stock to decrease the inventory while shipment received (SR_t) flows in the stock to increase the inventory.

4.2.1.1 Model Definition for Retailer, Wholesaler, and Distributor

Since the business process model for the Factory is different from other trading partners, we introduce model definition on Retailer, Wholesaler, and Distributor here. In section 4.2.1.1.1, a basic conceptual model is defined and in section 4.2.1.1.2 we identify constant variables to simplify the model. Each variable has its meaning, initial conditions (value at time = 0), and constraints. In figure 4-2, figure 4-3, and figure 4-4 are variables illustrated.

4.2.1.1.1 Basic Conceptual Model Definition

The following equations formalize the heuristics concept based on "Beer Game" Model (Table 4-1). The formula below describes retail, wholesaler, or distributor's operation process in figure 4-2.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + AS_t + ASL_t$	(2)
$AS_t = \alpha_S(S^* - S_{t-1}),$	(3)
$ASL_t = \alpha_{SL}(SL^* - SL_{t-1}),$	(4)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = \theta \cdot OR_{t-1} + (1-\theta) \cdot ED_{t-1},\ 0 \le \theta \le 1,$	(7)

Table 4-1: Original Conceptual Model

Variables	Specification	Initial Condition
O_t	Order quantity that trading partners place, should be non-negative, which means trading partners cannot cancel or reverse order.	$O_0 = 0$
IO_t	The indicated order rate is the order the trading partners will place, which is based on the anchoring and adjustment heuristic (Tversky and Kahneman 1974, 1124-1131). Anchoring and adjustment is a common strategy used to estimate a reference point (the anchor) and then to make an adjustment according to "the effects of other factors which may be less salient or whose effects are obscure" (Mosekilde, Larsen, and Sterman 1991, 199-229). In the model, the anchor is a forecasted demand at each	

	time step, and we adjust it based on the status of the stock and supply line.	
OR_t	Order received at time t. The quantity the downstream trading partner requests.	
ED_t	ED_t stands for an expected demand rate at time t. We forecast the expected demand rate based on the history demands that the direct downstream trading partner asked for. In (7), the expected loss is formed as "adaptive expectations, widely used in simulation modeling of economic systems" (Mosekilde, Larsen, and Sterman 1991, 199-229). It actually is the Exponential Smoothing Forecasting method.	$ED_0 = 0$
AS_t	Adjustment to correct the discrepancies between the desired and actual stock, the adjustment for the stock creates a negative feedback loop which regulates the stock. For simplicity, the adjustment is linear.	
S^*	Desired stock or inventory.	
S_t	Actual stock or inventory at time t. Inventory at time t is the inventory at time t-1 plus goods received at time t-1 from its upstream trading partner minus goods sent to its downstream trading partner at time t-1.	$S_0 = 12$
L_t	Loss of the inventory that is equal to the amount of goods shipped to the downstream trading partner. If we define the lead time between two trading partners is μ, the L_t of current trading partner is equal to the $SR_{t+\mu}$ of its downstream trading partner.	
α_S	The fraction of the discrepancy ordered in each period. In remainder chapters, for simple, we only use α to present α_S.	$0 \le \alpha_S \le 1$
ASL_t	Adjustment to correct the discrepancies between the desired and actual supply line. Similar with AS_t, the adjustment for the supply line creates a negative feedback too. For simplicity, the adjustment is linear.	

SL^*	The desired supply line.	
SL_t	The actual supply line records the amount of products that has been ordered but not receives from its supplier. Each trading partner has its own supply line. The amount of the supply line includes orders in transit or orders held by the supplier without processing. The supply line at time t is the supply line at time t-1 plus the new order placed by trading partner itself minus the fulfilled order by supplier at time t-1. As we define the lead time is 1 and define the distribution of customer demand is normal distribution with mean 0 and variance 4 (StdDevCustomerDemand), we define the initial supply line as StdDevCustomerDemand*(leadTime+1) = 4*2=8.	$SL_0 = 8$
α_{SL}	The fractional adjustment rate for the supply line	$0 \le \alpha_{SL} \le 1$
SR_t	Shipment received from the upstream trading partners to increase stock or inventory at time t. For example, as a retailer, SR_t means the goods received from its wholesaler at time t. If we assume the lead time is τ, which means the time when goods is sent out by wholesaler until received by retailer is τ, SR_t at retailer is equal to $L_{t-\tau}$ at wholesaler.	

Table 4-2: Variables Definition

4.2.1.1.2 Model Definition after identifying constant variables

The desired stock S^* and supply line SL^* are assumed to be constant. While S^* and SL^* are constants, defining $\beta = \alpha_{SL} / \alpha_S$ and $S' = S^* + \beta * SL^*$, yields (8)

$$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t) \quad (8)$$

We have $S^* \geq 0$, $SL^* \geq 0$, $\alpha_{SL} \geq 0$ and $\alpha_S \geq 0$, $S' \geq 0$. Moreover, the trading partners normally pay more attention to the inventory rather than the supply line, so $\alpha_{SL} \leq \alpha_S$, which means $0 \leq \beta \leq 1$. In another words, β can be interpreted as the fraction of the supply line.

The simulation is initialized in equilibrium. Each inventory contains 12 units $S_0 = 12$. The value of S' is 17.

4.2.1.1.3 Summarized Model definition

Based on the analysis above, we tidy up the whole model for the non-factory trading partners: Retailer, Wholesaler, and Distributor as following. The number of each equation is in accordant with previous sections (See Table 4-3).

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = \theta * OR_{t-1} + (1-\theta) * ED_{t-1},\ 0 \leq \theta \leq 1,$	(7)

Table 4-3: BM for Retailer, Wholesaler, and Distributor

4.2.1.2 Model Definition for Factory

As the last node of the supply chain, trading partner Factory does not place order from outside. We assume that there is a production line in the factory. As a result, at each time step, the factory retrieves goods from its production line rather than requests orders from other trading partners. We also assume that the production line and warehouse are adjacent, so there is no any transportation delay in between. By the similar strategy with other trading partners, the factory decides indicated orders based on its stock or inventory, forecasting method, and supply line. The supply line is defined to record the amount of products that has been made in production plan but not been produced (See Table 4-4 and Table 4-5).

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = \theta * OR_{t-1} + (1-\theta) * ED_{t-1},\ 0 \le \theta \le 1,$	(7)

Table 4-4: BM for Factory

Variables	Specification	Initial Condition
PL_t	Goods produced by production line to increase stock or inventory at time t. If we assume the production time is τ, which means the time when the production plan is made until retrieved from production line is τ, PL_t is equal to $IO_{t-\tau}$. In our simulation experiment, we assume $\tau = 3$, so we put 3 production delays into production line with 4 units each as our initial condition.	

Table 4-5: Additional Variable definition for Factory

4.2.2 Basic Model combined with Moving Average Forecasting (BM+MA)

4.2.2.1 Moving Average Forecasting Method Definition

Based on the Basic Model (for parameter definition, please refer to section 4.2.1), we replace the Sterman's adaptive expectation with Moving Average Forecasting Method as BM+MA.

The Moving Average Method is as following in the formula (MA1) (Hanke and Reitsch 1991, 128)

$$M_{t+1}(SeriesName) = \hat{y}_{t+1}(SeriesName)$$
$$= \frac{(y_t(SeriesName) + y_{t-1}(SeriesName) + y_{t-2}(SeriesName) + \cdots + y_{t-n+1}(SeriesName))}{n}$$
(MA1)

$M_t(SeriesName)$:	Moving average at time t
$\hat{y}_{t+1}(SeriesName)$:	Forecasted value for next period
$y_t(SeriesName)$:	Actual value at period t
n:	Number of terms in the moving average. We define n=6 in our simulation experiments.

4.2.2.2 Model Definition for Retailer, Wholesaler, and Distributor

We define the expected demand using the moving average forecasting in the formula 12. We define n=6 in our simulation model

$$ED_t = M_t(Order) \quad (12)$$

$M_t(Order)$ is a forecasted order at time step t and we replace the parameter "*SeriesName*" in the formula (MA1) with "*Order*", which means the value of the series to be used in the moving average method is the order which the downstream trading partners place. Since the "order" in previous notation is OR_t at time t, we have

$$y_t(Order) = OR_t \quad (13)$$

The summary for the model BM+MA is listed in table 4-6.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = M_t(Order)$	(12)
$y_t(Order) = OR_t$	(13)

Table 4-6: Model of BM+MA for Retailer, Wholesaler, and Distributor

4.2.2.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)

$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = M_t(Order)$	(12)
$y_t(Order) = OR_t$	(13)

Table 4-7: Model of BM+MA for Factory

4.2.3 Basic Model combined with Holts Forecasting (BM+Holts)

4.2.3.1 Holts (Exponential Smoothing Adjusted for Trend) Forecasting Method Definition

Exponential Smoothing Adjusted for Trend: Holt's Method is as following. (Hanke and Reitsch 1991, 128)

1. The exponential smoothed series:

$$A_t = \lambda * y_t(SeriesName) + (1-\lambda) * (A_{t-1} + b_{t-1}) \qquad \text{(Holt1)}$$

2. The trend estimate:

$$b_t = \gamma * (A_t - A_{t-1}) + (1-\gamma) * b_{t-1} \qquad \text{(Holt2)}$$

3. Forecast p periods into the future:

$$H_{t+p}(SeriesName) = \hat{y}_{t+p}(SeriesName) = A_t + p * b_t \qquad \text{(Holt3)}$$

A_t: New smoothed value

λ: Smoothing constant for the data $(0 \le \lambda \le 1)$.

$y_t(SeriesName)$: New observation or actual value of series with specific Series Name in period t.

γ: Smoothing constant for trend estimate $(0 \le \gamma \le 1)$.

b_t: Trend estimate.

p: Periods to be forecast into future. We use p=1 in our simulation experiment.

$\hat{y}_{t+p}(SeriesName)$: Forecast for p periods into the future with specific Series Name.

4.2.3.2 Model Definition for Retailer, Wholesaler, and Distributor

Based on the Basic Model (for parameter definition, please refer to chapter1.1), we replace the Sterman's adaptive expectation with the Holt's method.

$$ED_t = H_t(Order) \tag{14}$$

$H_t(Order)$ is a forecasted order at time step t and we replace the parameter "*SeriesName*" in the formula (Holt3) with "*Order*", which means the value of the series to be used in Holt's method is the order which the downstream trading partners place. $y_t(Order)$ is an actual value of an order at time step t. Since the "order" in previous notation is OR_t at time t, we have

$$y_t(Order) = OR_t \tag{13}$$

The summary for the model BM+Holts is listed in table 4-8.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = H_t(Order)$	(14)
$y_t(Order) = OR_t$	(13)

Table 4-8: Model of BM+Holts for Retailer, Wholesaler, and Distributor

4.2.3.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = H_t(Order)$	(14)
$y_t(Order) = OR_t$	(13)

Table 4-9: Model of BM+Holts for Factory

While forecasting the future demand using the Holts method, we use MSE (Mean Square Error) to decide parameter λ and γ. Based on the history demand data, we choose λ and γ to satisfy the smallest MSE, and then we forecast the expected data.

4.2.4 Basic Model combined with Double Exponential Smoothing (Browns) Forecasting (BM+Browns)

4.2.4.1 Browns (Double Exponential Smoothing) Forecasting Method Definition

Double Exponential Smoothing: Brown's Method is as following. (Hanke and Reitsch 1991, 128)

1. The simple exponential value:

$$A_t = \alpha_b * y_t(SeriesName) + (1-\alpha_b) * (A_{t-1}) \qquad \text{(Brown1)}$$

2. The double exponentially smoothed value:

$$A'_t = \alpha_b * A_t + (1-\alpha_b) * A'_{t-1} \qquad \text{(Brown2)}$$

3. Compute the difference between the exponentially smoothed values.

$$a_t = 2 * A_t - A'_t \qquad \text{(Brown3)}$$

4. Additional adjustment for a slope measurement

$$b_t = \frac{\alpha_b}{1-\alpha_b}(A_t - A'_t) \qquad \text{(Brown4)}$$

5. Make the forecast p periods into future.

$$B_{t+p}(SeriesName) = \hat{y}_{t+p}(SeriesName) = a_t + b_t * p \qquad \text{(Brown5)}$$

A_t:	Exponentially smoothed value of y_t at time t
A'_t:	Double exponentially smoothed value of y_t at time t
$y_t(SeriesName)$:	New observation or actual value of series with specific Series Name in period t.
α_b:	Smoothing constant.
a_t	Difference between the exponentially smoothed values.
b_t:	Additional adjustment factor similar to a slope measurement.
p:	Periods to be forecast into future. We use p=1 in our simulation experiment.
$\hat{y}_{t+p}(SeriesName)$:	Forecast for p periods into the future with specific Series Name.

4.2.4.2 Model Definition for Retailer, Wholesaler, and Distributor

Based on the Basic Model (for parameter definition, please refer to chapter1.1), we replace the Sterman's adaptive expectation with the Brown's method.

$$ED_t = B_t(Order) \tag{15}$$

$B_t(Order)$ is a forecasted order at time step t and we replace the parameter "*SeriesName*" in the formula (Brown5) with "*Order*", which means the value of the series to be used in Brown's method is the order which the downstream trading partners place. $y_t(Order)$ is an actual value of an order at time step t. Since the "order" in previous notation is OR_t at time t, we have

$$y_t(Order) = OR_t \tag{13}$$

The summary for the model BM+Browns is listed in table 4-10.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = B_t(Order)$	(15)
$y_t(Order) = OR_t$	(13)

Table 4-10: Model of BM+Browns for Retailer, Wholesaler, and Distributor

4.2.4.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$	(8)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^* + \beta * SL^*$	(10)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = B_t(Order)$	(15)
$y_t(Order) = OR_t$	(13)

Table 4-11: Model of BM+Brwons for Factory

4.2.5 Basic Model without Supply line (BM-SL)

4.2.5.1 Model Definition

In this model, we just remove the $(\beta * SL_t)$ in the formula (8) in section 4.2.1 and other formulas are the same to section 4.2.1. The idea is to see whether the supply line affects the bullwhip effect based on the Basic Model (See Table 4-12 and Table 4-13).

$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)

4.2.5.2 Model Definition for Retailer, Wholesaler, and Distributor

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(17)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = \theta * OR_{t-1} + (1-\theta) * ED_{t-1},\ 0 \le \theta \le 1,$	(7)

Table 4-12: Model of BM-SL for Retailer, Wholesaler, and Distributor

4.2.5.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)

$S' = S^*$	(17)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = \theta * OR_{t-1} + (1-\theta) * ED_{t-1},\ 0 \le \theta \le 1,$	(7)

Table 4-13: Model of BM-SL for Factory

4.2.6 Basic Model combined with Moving Average Forecasting without Supply line (BM-SL+MA)

4.2.6.1 Model Definition

In this model, we just remove the $(\beta * SL_t)$ in the formula (2) in section 4.2.2 and other formulas are the same to the section 4.2.2. The idea is to see whether the supply line affects the bullwhip effect based on the moving average forecasting and without supply line (See Table 4-14 and Table 4-15).

4.2.6.2 Model Definition for Retailer, Wholesaler, and Distributor

The summary for the model BM-SL+MA is listed in table.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(17)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)

$ED_t = M_t(Order)$	(12)
$y_t(Order) = OR_t$	(13)

Table 4-14: Model of BM-SL+MA for Retailer, Wholesaler, and Distributor

4.2.6.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(17)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = M_t(Order)$	(12)
$y_t(Order) = OR_t$	(13)

Table 4-15: Model of BM-SL+MA for Factory

4.2.7 Basic Model combined with Holts Forecasting without Supply line (BM-SL+Holts)

4.2.7.1 Model Definition

In this model, we just remove the $(\beta * SL_t)$ in the formula (2) in section 4.2.3 and other formulas are the same to section 4.2.3. The idea is to see whether the supply line affects the bullwhip effect based on the Holts forecasting and without supply line (See Table 4-16 and Table 4-17).

4.2.7.2 Model Definition for Retailer, Wholesaler, and Distributor

The summary for the model BM-SL+Holts is listed in table.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(17)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = H_t(Order)$	(14)
$y_t(Order) = OR_t$	(13)

Table 4-16: Model of BM-SL+Holts for Retailer, Wholesaler, and Distributor

4.2.7.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(17)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = H_t(Order)$	(14)
$y_t(Order) = OR_t$	(13)

Table 4-17: Model of BM-SL+Holts for Factory

4.2.8 Basic Model combined with Browns Forecasting without Supply

line (BM-SL+Browns)

4.2.8.1 Model Definition

In this model, we just remove the $(\beta * SL_t)$ in the formula (2) in section 4.2.4 and other formulas are the same to the section 4.2.4. The idea is to see whether the supply line affects the bullwhip effect based on the Holts forecasting and without supply line (See Table 4-18 and Table 4-19).

4.2.8.2 Model Definition for Retailer, Wholesaler, and Distributor

The summary for the model BM_SL+Browns is listed in table.

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)
$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(17)
$S_t = S_{t-1} + SR_{t-1} - L_{t-1}$	(5)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = B_t(Order)$	(15)
$y_t(Order) = OR_t$	(13)

Table 4-18: Model of BM-SL+Browns for Retailer, Wholesaler, and Distributor

4.2.8.3 Model Definition for Factory

$O_t = MAX(0, IO_t)$	(1)
$IO_t = ED_t + \alpha_S * (S' - S_t)$	(16)

$\beta = \alpha_{SL} / \alpha_S$	(9)
$S' = S^*$	(10)
$S_t = S_{t-1} + PL_{t-1} - L_{t-1}$	(11)
$SL_t = SL_{t-1} + IO_t - SR_t$	(6)
$ED_t = B_t(Order)$	(15)
$y_t(Order) = OR_t$	(13)

Table 4-19: Model of BM-SL+Browns for Factory

4.3 Implementation Design

Since our implementation is based on Java programming language, we use UML diagrams to describe our design based on REPAST framework. As mentioned in section 4.1, we use "agents" to model trading partners; in each agent, we implement its ordering policy and inventory management model in section 4.2. The contents in this section begin with a package definition; then follow with agent definitions; and end with a model structure and schedule mechanism.

4.3.1 Packages definition

We have 5 main packages in our design: 2 for the forecasting method, 1 for the bullwhip effect modeling, 1 for system input, and 1 for system output control (See figure 4-6). In the Forecast Basic package, we define the basic data structure such as DataPoint and DataSet to store data in each time step. In the Forecast Models package, we define our forecasting models including the moving average model, the Holts models, and the double exponential smoothing model. In the system input and output package, we define our basic input/output interface and utilities. In the bullwhip effect package, we include all the agents and their model structure.

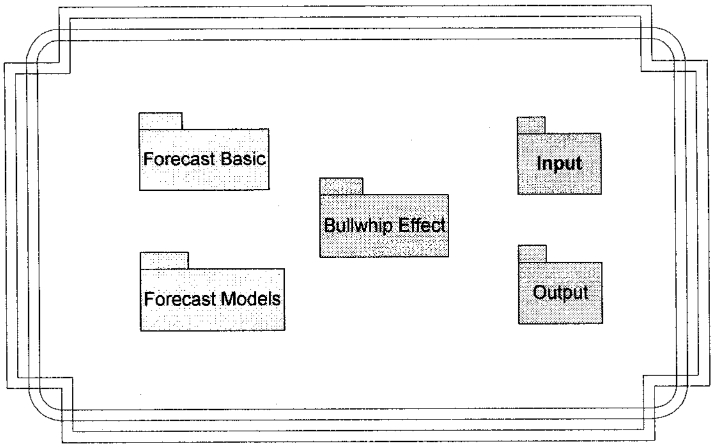


Figure 4-6: Package Definition

4.3.2 Agents definition

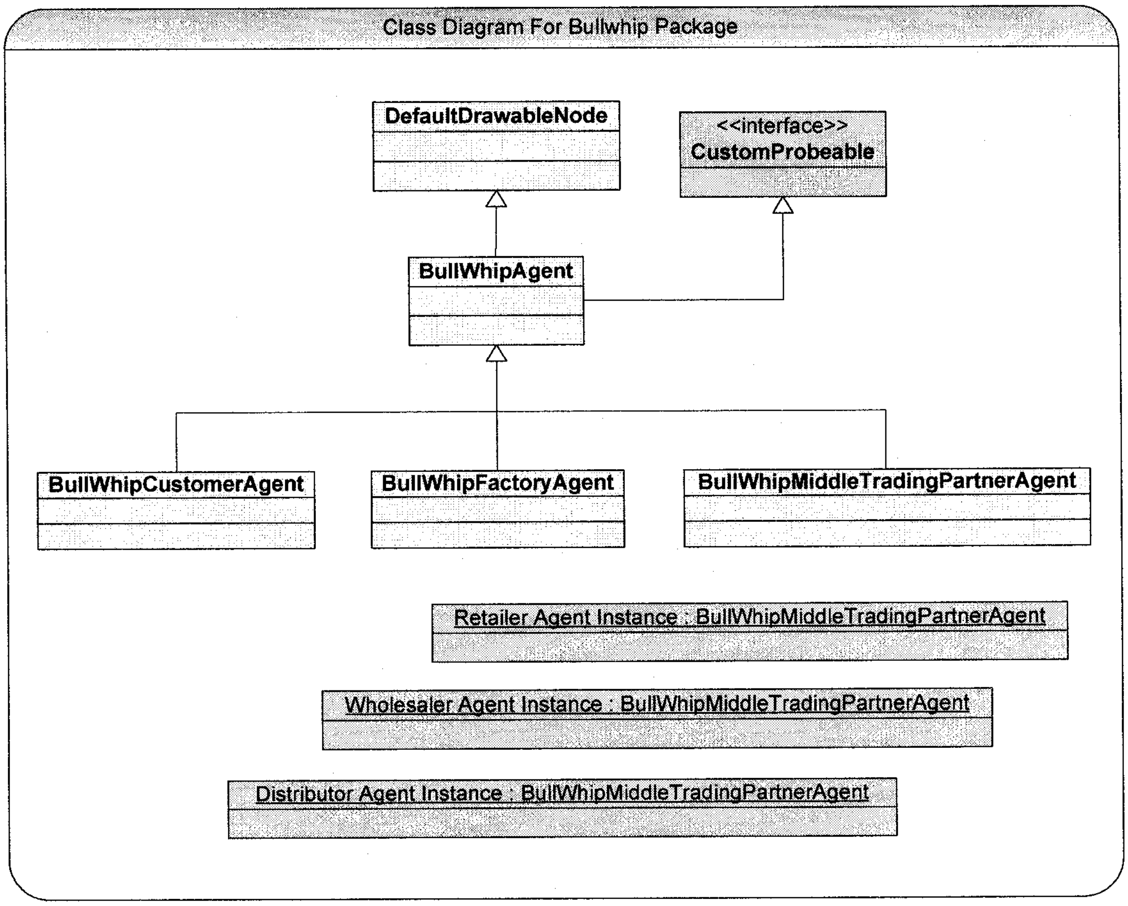


Figure 4-7: Class Diagram for Bullwhip Package

From the static structure diagram above (figure 4-7), we define 4 classes as our agents or trading partners. The basic one is BullwhipAgent, which extends from DefaultDrawableNode in REPAST and implements an interface named CustomProbeable. Only by this way, we can apply features in REPAST and plug our model in the REPAST framework. As is known, the behaviours in customer, factory, and middle trading partners (retailer, wholesaler, and distributor) are different. Therefore, we define three new classes extended from BullwhipAgent. However, for the trading partners like retailer, wholesaler, and distributor, they have the same behaviour, so we just put them there as an instances of class BullwhipMidlleTradingPartnerAgent.

4.3.3 Model structure and schedule mechanism

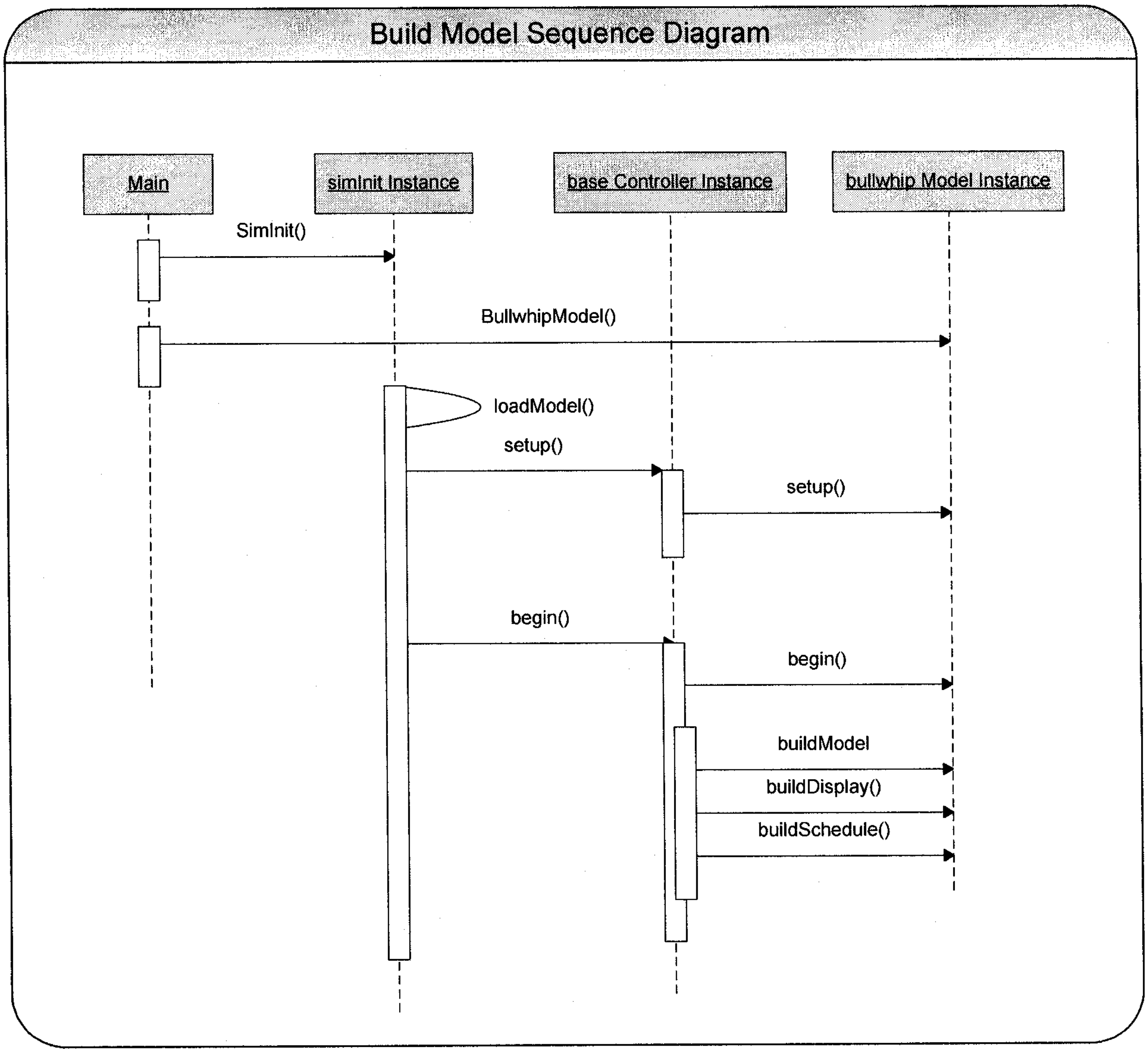


Figure 4-8: Model Sequence Diagram

According to REPAST framework, by three methods: buildDisplay(), buildModel(), and buildSchedule(), we can implement user interface, model structure, and schedule definition. In buildModel() method, we connect all the trading partners together. When the model runs its setup() method, it calls scheduler to decide time scale and diagram needed. Since in each agent, we have a method called step(), REPAST framework will invoke the step() method based on what we have already defined in method buildSchedule(). Figure 4-8 illustrates the functions invoking based on time sequence.

4.4 Minimum Mean Square Error optimal (MSE) for Holts and Double Exponential Smoothing Method (Browns Methods)

As is known, the Holts and the Double Exponential Smoothing (Browns) Method have their parameters. As a good decision support system, we cannot fix these parameters in a dynamic environment. Hence, for the Holts Method, we have to decide the values of λ (smoothing constant for the data) and γ (smoothing constant for trend estimate) before we forecast for the next time step; for the Double Exponential Smoothing (Browns) method, we have to decide the value of α_b (smoothing constant) before forecasting. In our design, we apply Minimum Mean Square Error optimal to find out these smoothing constants before forecasting in each time step. We called it optimal method, for trading partners can update their forecast policy through changing these constants based on minimum mean square error between the actual demand information and the forecasted value in the history. In figure 4-9, we illustrate demand (Diamond Icon) and forecasting data (Square Icon). For instance, if trading partner would like to forecast for time step 10, 9 sets of the history data will be used to identify a right smoothing constant; if trading partner would like to forecast for time step 16, 15 sets of the history data will be used to find out a right smoothing constant.

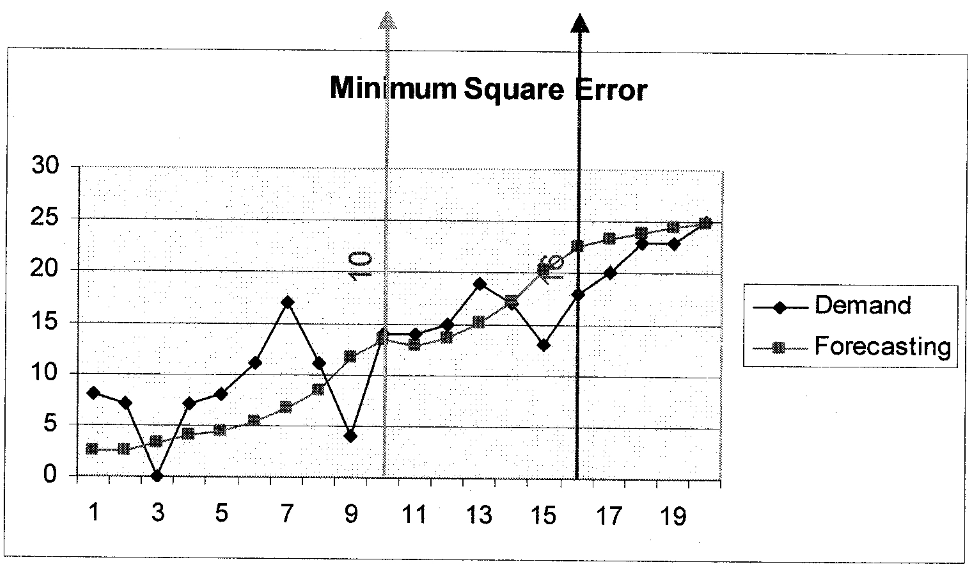


Figure 4-9: History data for MSE

For the Holts method, we divide λ (smoothing constant for the data) and γ (smoothing constant for trend estimate) into 10 grids respectively with value ranging from 0.1 to 1.0. Our arithmetic goes through 10*10=100 situations; and for each pair of λ and γ we calculate a mean square error with the formula $\frac{\sum_{t=1}^{n}(demand_t - forecast_t)^2}{n}$. For example, in figure above, if a trading partner wants to forecast for time step 10, the n is 9; if the trading partner wants to forecast for time step 16, the n is 15. Finally, in 100 results, the trading partner chooses the pair of α and γ that has a minimum mean square error.

For the Double Exponential Smoothing (Browns) method, we divide α_b (smoothing constant for the data) into 10 grids with values ranging from 0.1 to 1.0. Since the space of situations is only 10 a trading partner can loop these ten situations to find out an optimal value. Every mean square error is calculated by the same formula as the method used in the Holts method, which is $\frac{\sum_{t=1}^{n}(demand_t - forecast_t)^2}{n}$. At each time step, the trading partner chooses α_b that has a minimum mean square error in 10 results.

5 Results

In this chapter, experiment procedures and results are reported. In section 5.1, our simulation experiment procedure is described. The steps in our research involve simulations in ordering policy space or (α, β) space, experiments for optimal ordering policy identification, and boundary experiments. Since the volume of simulation observations is very big, we only choose one typical example $(\alpha, \beta) = (0.2, 0.3)$ in section 5.2 and we only list the summarized diagrams in this case; for detail experiment results, please refer to appendix 1. In appendix 2, we attach analysis data to identify the optimal ordering policy by KPI (key performance indicator).

5.1 Simulation Experiment Procedure

The purpose of our research is to discovery how different ordering policy and forecasting methods affect bullwhip effect. We plan to propose several managerial insights after simulation runs. Therefore, we group our simulation experiments by ordering policy at first level. Then in each ordering policy, we try four different forecast techniques in a row. We are interested in how the Holts and the Double Exponential Smoothing method affect local trend demands, so the input customers demands has a local trend feature. The period of our simulation is 100 time steps. The random disturbance in the pattern is a normal distribution with mean 0 and variance 4. Figure 5-1 shows customer demand pattern. Figure 5-2 shows the bullwhip effect that this data creates with parameter $\alpha = 0.4, \beta = 0.3$. Figure 5-2-0 to figure 5-2-4 show a separated view of the bullwhip effect based on figure 5-2.

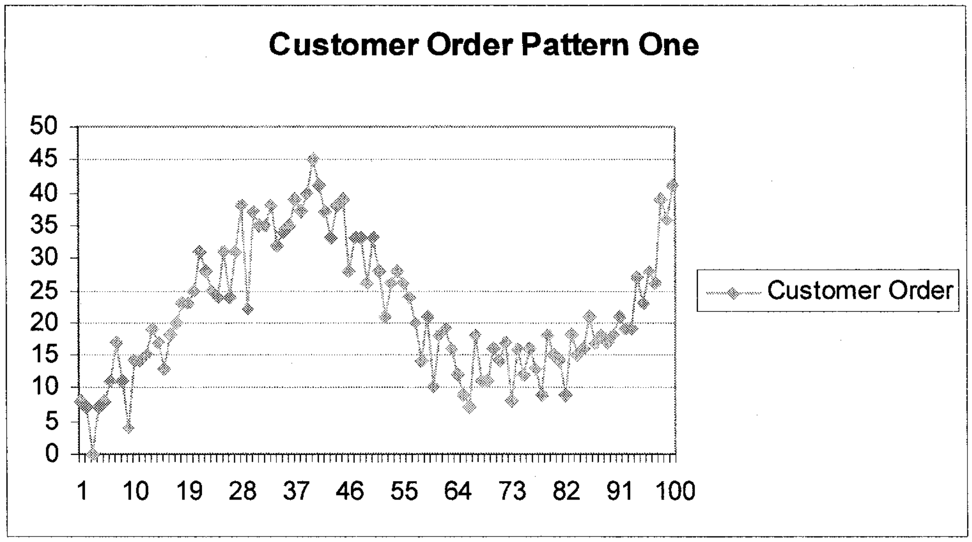


Figure 5-1: Customer Demand Pattern

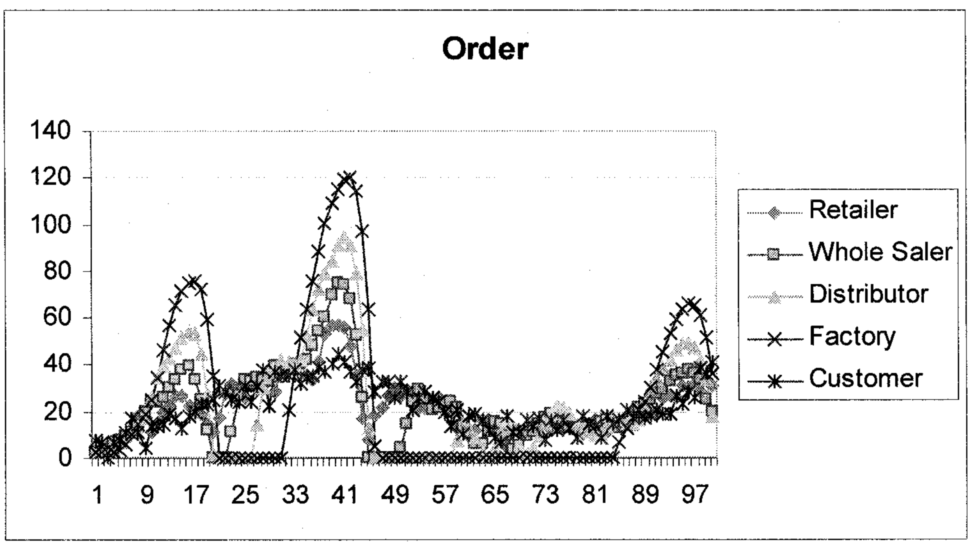


Figure 5-2: Bullwhip Effect Example

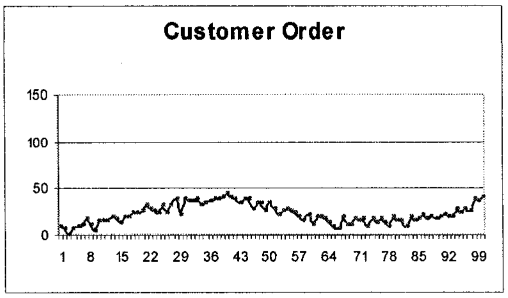


Figure 5-3-0: Retailer Order

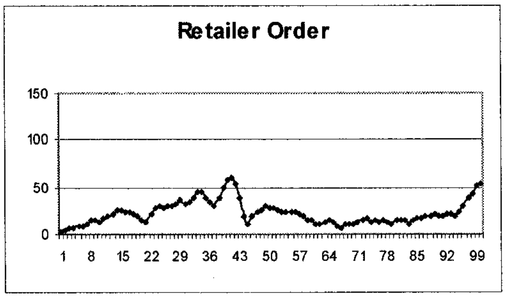


Figure 5-4-1: Retailer Order

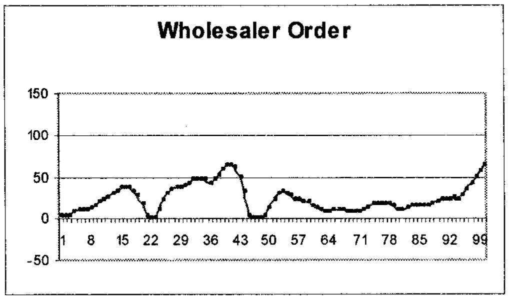


Figure 5-5-2: Wholesaler Order

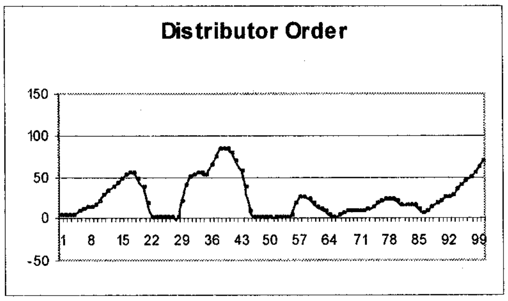


Figure 5-6-3: Retailer Order

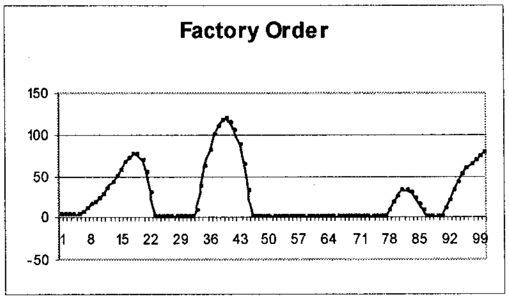


Figure 5-7-4: Retailer Order

We collect three types of datum from each simulation run: the quantity of order, inventory level, and cost. The quantity of the orders means the indicated order, which is the order the trading partners place from its upstream vendor, defined in the formula (8) section 4.2. The inventory means the quantity of goods available in the stock for each trading partner. The inventory is calculated by the current stock minus the backlog order, so it could be negative. The backlog order is the order placed by customer but can not be fulfilled because of lacking goods. The cost for each trading partner is defined by its inventory level and transaction volume. Table 5-1 below lists related cost definition. In the formula (1), *IsOrder* is 1 if there is a current order from its customer; otherwise, *IsOrder* equals 0.

Cost Name	Variable	Definition
Inventory cost	costI	Holding cost in units of dollars per unit item per unit time period
Shortage cost	costS	Penalty cost for lacking goods in units of dollars per unit item per unit time period
Fix cost for order	costF	Fixed cost for each order in units of dollars per order;
Purchase cost	costP	Transaction based cost for goods in units of dollars per unit.

Table 5-1: Cost definition

$$\cos t_t = \cos tI * Stock_t + \cos tS * backLogOrder_t + \cos tF * IsOrder + \cos tP * orderVolume_t$$

(1)

Where

$backLogOrder_t = backLogOrder_{t-1} + OR_t - S_t$

$backLogOrder_0 = 0$

$$TotalCost = \sum_{t=1}^{100} \cos t_t \qquad (2)$$

5.1.1 Simulations in ordering policy space

5.1.1.1 Criteria of simulations in ordering policy space

The space of ordering policy is 10*10=100 since there are two parameters (α, β) in the indicated order formula $IO_t = ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$. As we plan to do simulation experiments in ordering policy space systematically, the first step is to define a performance measure of the model. Generally, the performance measure for the bullwhip effect in previous literature includes order rate, inventory, and cost. The variance of order rate in each trading partners has already been used in many papers, for example, Chen, Drezener, Ryan, and Simchi-Levi (2000, 436-443) and Lee (2004, 1875-1886), so we keep it. Although variance can show us how the bullwhip effect happens, it is mainly to measure how spread out a distribution is. Therefore, we leverage the root mean square of the errors (RMSE) to get a more accurate analysis. The RMSE's formula is $\sqrt{\frac{\sum_{i=1}^{100} x_i^2}{100}}$ and x_i is the discrepancies between the trading partner's order and customer's original demands. Cost analysis comes at last but not the least, for one of destinations in our research is to cut the cost for the whole system. Because cost is based on the inventory performance in our model, we do not need choose inventory as a KPI again. In summary, we have variance of order rate, RMSE of order rate, and cost as criteria here.

5.1.1.2 Systematic procedure for simulations in ordering policy space

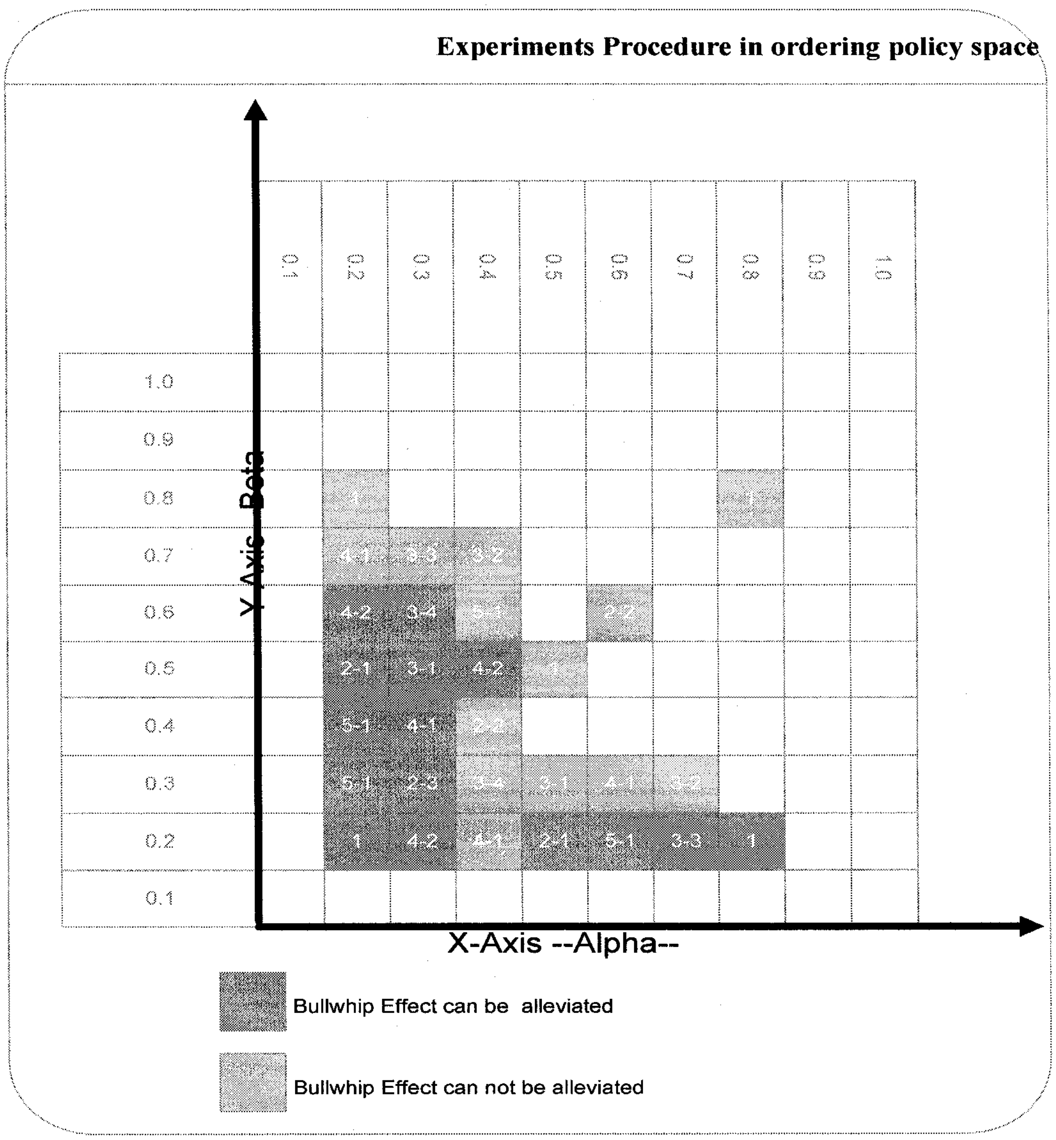
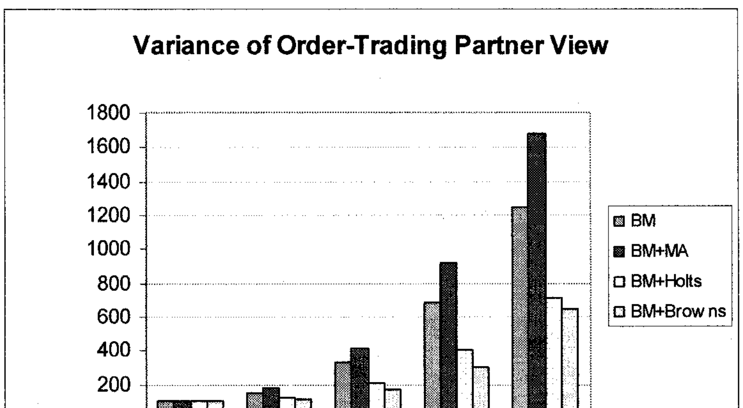


Figure 5-8: Experiments Procedure in ordering policy space

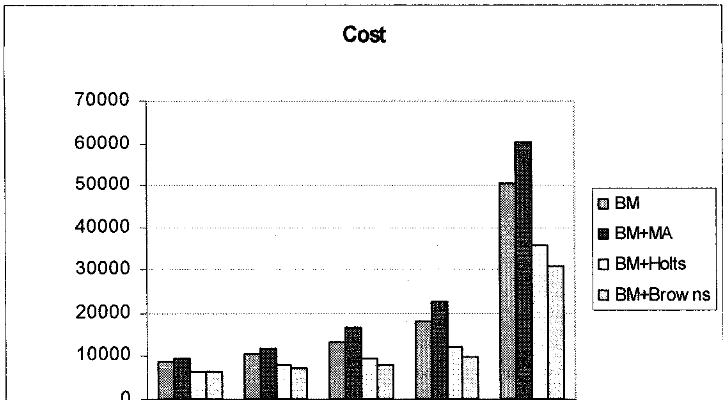
5.1.1.2.1 Legend Identification

Figure 5-3 illustrates the whole procedure in our simulation experiments. X-Axis stands for Alpha (α) while Y-Axis stands for Beta (β). Their ranges are both from 0.1 to 1.0. In the legend, we define two icons: dark shading and light shading. For each pair of (α, β), we do four experiments using Sterman's adaptive forecasting method, the moving average forecasting method, the Holts methods, and the double exponential smoothing method. The color of the square in figure 5-3 is based on analysis from experiment results. As we have the criteria for our simulation, for each pair of (α, β), we organize the datum by the three criteria in bar chart form. For example, figure 5-4 shows a bar chart of the variance of order rate; figure 5-5 shows a bar chart of the cost; and figure 5-6 shows a bar chart of the RMSE of the order rate. We mark the square as a dark shading (Legend: Bullwhip Effect can be alleviated in figure 5-3) if the Holts and the Double Exponential Smoothing (DES) methods both have smaller variance of the order rate, cost, and RMSE when comparing with the moving average and the Stermans's adaptive forecasting method. For example, if the results of the experiment look like figure 5-4, figure 5-5, and figure 5-6, we can mark the square dark shading. Hence, the dark shading square means forecasting techniques like the Holts and the DES can alleviate the bullwhip effect substantially in a local trend demand pattern under the right ordering policies. We mark the square as light shading if the Holts and the Double Exponential Smoothing (DES) methods both do not have a smaller variance of the order rate, or cost, or RMSE when comparing with the moving average and the Stermans's adaptive forecasting method. For instance, if the result looks like figure 5-7 and figure 5-8, the square should be colored as light shading. Therefore, the light shading square means the bullwhip effect cannot be reduced by the suitable forecasting methods and ordering policies.



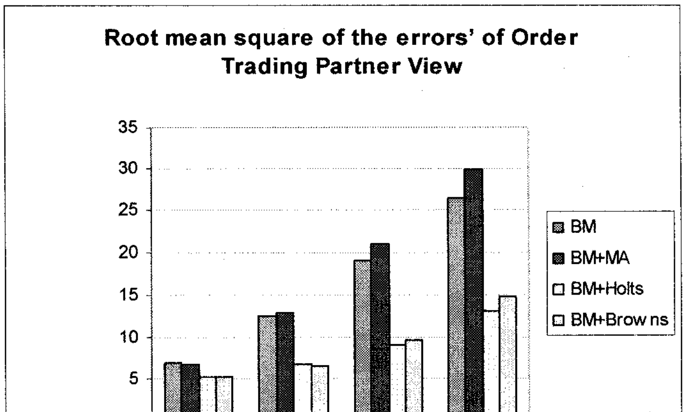
	Customer	Retailer	Whole Saler	Distributor	Factory
BM	104.64434	154.29241	324.10582	682.58813	1242.2515
BM+MA	104.64434	176.62013	414.86429	917.71057	1680.9153
BM+Holts	104.64434	122.07586	206.41552	402.59297	710.39112
BM+Brow ns	104.64434	112.0277	170.18905	296.26131	648.13194

Figure 5-9: Bar Chart of Variance of Order Rate for Dark shading Square Sample



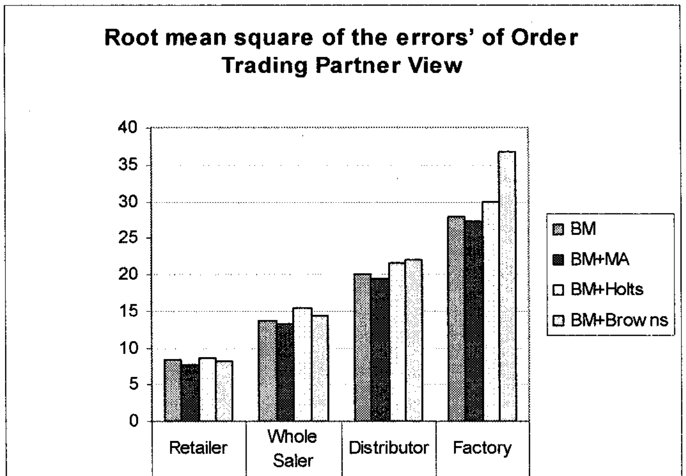
	Retailer	Whole Seller	Distributor	Factory	Total Cost
BM	8647.423	10443.46	13293.4	18182.39	50566.67
BM+MA	9227.132	11765.44	16711.86	22548.13	60252.57
BM+Holts	6482.859	7832.989	9543.482	11971.31	35830.64
BM+Brow ns	6307.833	6990.93	7988.306	9670.945	30958.01

Figure 5-10: Chart of Cost for Dark shading Square Sample



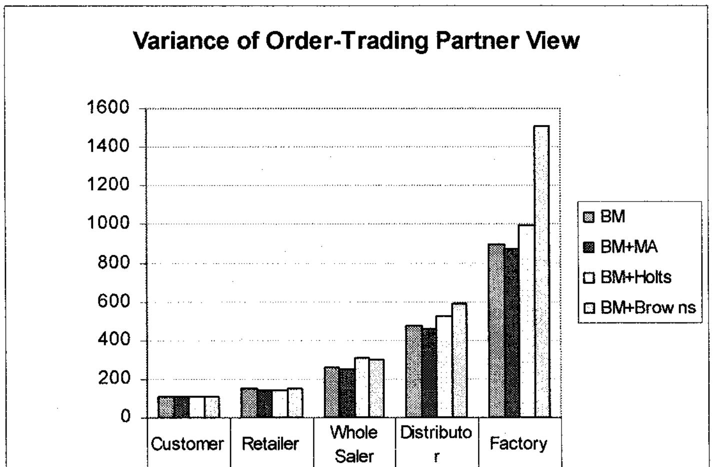
	Retailer	Whole Saler	Distributor	Factory
BM	6.8651361	12.518782	18.954215	26.314369
BM+MA	6.7864924	12.916412	20.953296	29.834746
BM+Holts	5.1964225	6.6818958	9.0248214	13.04399
BM+Brow ns	5.2073579	6.5601385	9.6028935	14.90265

Figure 5-11: Bar Chart of RMSE of Order for Dark shading Square Sample



	Retailer	Whole Saler	Distributor	Factory
BM	8.4356226	13.626147	20.082269	27.871921
BM+MA	7.7502976	13.273444	19.308048	27.181495
BM+Holts	8.5304987	15.420174	21.466532	29.862395
BM+Brow ns	8.1838319	14.271543	21.975295	36.664072

Figure 5-12: Bar Chart of RMSE for Light shading Square Sample



	Customer	Retailer	Whole Saler	Distributo r	Factory
BM	104.6443	145.2761	259.6024	473.5455	893.4555
BM+MA	104.6443	143.7752	252.174	454.0842	869.5164
BM+Holts	104.6443	143.5559	304.9846	524.6173	991.2392
BM+Brow ns	104.6443	149.9451	297.8614	590.258	1512.488

Figure 5-13: Bar Chart of Variance for Light shading Square Sample

5.1.1.2.2 Procedure Description

The procedure starts from five points for (α, β) at (0.2, 0.2), (0.2, 0.8), (0.8, 0.2), (0.8, 0.8), and (0.5, 0.5). The number "1" in these grids in figure 5-3 means it is the first step. We find out that the cases at grids (0.2, 0.2) and (0.8, 0.2) are dark shadings while other three are light shadings. As a result, a further investigation is necessary.

The step 2 includes the grids marked starting with number "2" and we divided step 2 into three sub-steps: "2-1", "2-2", and "2-3". Since (0.2, 0.2) and (0.2, 0.8) have the opposite result, the midpoint (0.2, 0.5) is selected in step "2-1". We are also interested in whether all the points for $\alpha = 0.2$ have a similar feature, so the midpoint (0.5, 0.2) between (0.2, 0.2) and (0.2, 0.8) belong to step "2-1" as well. In step "2-2", points (0.4, 0.4) and (0.6, 0.6) are experimented to see what happens around the central point (0.5, 0.5). After that, we try point (0.3, 0.3) at step "2-3", for we have the results that the points in step "2-2" are all light shading grids.

The step 3 has 4 sub-steps. After step 2, we identify several opposite points; for example, the pair of (0.2, 0.5) and (0.5, 0.5), the pair of (0.5, 0.2) and (0.5, 0.5). Hence, in step "3-1", points for (0.3, 0.5) and (0.5, 0.3) are tested. By using the similar logic, we experiment points for (0.7, 0.3) and (0.4, 0.7) at step "3-2"; (0.3, 0.7) and (0.7. 0.2) at step "3-3"; (0.3, 0.6) and (0.4, 0.3) at step "3-4".

For step 4 and step 5, we are trying to fill some empty grids among these points that we have already tried with opposite results. We do not try up-right triangle area since several points are light shadings and Sterman also mentioned that the production-distribution system with large α and large β was not stable. (Mosekilde, Larsen, and Sterman 1991, 199-229)

5.1.2 Optimal ordering policy identification

After the basic experiments in section 5.1.1, we screen all the dark shading grids to identify optimal ordering policies under which the Holts and DES method can play a good performance in reducing the bullwhip effect. In section 5.1.2.1, criteria are decided for filtering optimal ordering policies. In section 5.1.2.2, we describe the whole procedure.

5.1.2.1 Criteria for optimal ordering policy identification

The three basic criteria have been defined in section 5.1.1.1 including the variance of the order rate, cost, and RMSE of the order rate. For the cost, we consider the total cost for each trading partner. As the bullwhip effect is our research interest and the amplification on the Factory side would be more distinct than other trading partners, we choose the variance and RMSE in the Factory side. Based on these three criteria, we need to identify a function to evaluate the total performance of the ordering policy and forecasting methods on reducing the bullwhip effect.

The function to calculate the cost's performance is defined below and all the variables are specified in table 5-2. From the function, the smaller the costP is, the better the performance of BM+Holts and BM+Browns models over other two others is.

$$\cos tP = \frac{(\cos tHolts / \cos tBM + \cos tHolts / \cos tBMMA + \cos tBrowns / \cos tBM + \cos tBrowns / \cos tBMMA)}{4}$$

Variable Name	Variable Meaning
costP	Final performance for cost
costHolts	Total cost in Model BM+Holts
costBM	Total cost in Model BM
costBMMA	Total cost in Model BM+MA
costBrowns	Total cost in Model BM+Browns(DES)

Table 5-2: Cost Performance Function Definition

The function to calculate the variance's performance is listed below and the corresponding variables are defined in table 5-3. From the function, the smaller the varP is, the better the performance of BM+Holts and BM+Browns models over other two models is.

$$\mathrm{var}\,P = \frac{(\mathrm{var}\,Holts\,/\,\mathrm{var}\,BM + \mathrm{var}\,Holts\,/\,\mathrm{var}\,BMMA + \mathrm{var}\,Browns\,/\,\mathrm{var}\,BM + \mathrm{var}\,Browns\,/\,\mathrm{var}\,BMMA)}{4}$$

Variable Name	Variable Meaning
varP	Final performance for variance
varHolts	(Factory Variance) /(Customer Variance) in BM+Holts
varBM	(Factory Variance) /(Customer Variance) in BM
varBMMA	(Factory Variance) /(Customer Variance) in BM+MA
varBrowns	(Factory Variance) /(Customer Variance) in BM+Browns

Table 5-3: Definition of Factory Variance Performance Function

The function to calculate the RMSE's performance is showed below and the specification on the variables is listed in table 5-4. From the function, the smaller the rmseP is, the better the performance of BM+Holts and BM+Browns models over other two models is.

$$rmseP = \frac{(rmseHolts\,/\,rmseBM + rmseHolts\,/\,rmseBMMA + rmseBrowns\,/\,rmseBM + rmseBrowns\,/\,rmseBMMA)}{4}$$

Variable Name	Variable Meaning
rmseP	Final performance for RMSE
rmseHolts	Factory RMSE in Model BM+Holts
rmseBM	Factory RMSE in Model BM
rmseBMMA	Factory RMSE in Model BM+MA
rmseBrowns	Factory RMSE in Model BM+Browns(DES)

Table 5-4: Definition of Factory RMSE Performance Function

Total performance measure function is:

$$totalP = \frac{\cos tP + \operatorname{var} P + rmseP}{3} \qquad \text{(TP 1)}$$

From the function, the smaller the totalP is, the better the performance of BM+Holts and BM+Browns models over other two models is.

5.1.2.2 Procedure for identifying optimal ordering policy

Based on the function in section 5.1.2.1, we calculate all the dark shading grids in figure 5-3. The result is listed in figure5-9.

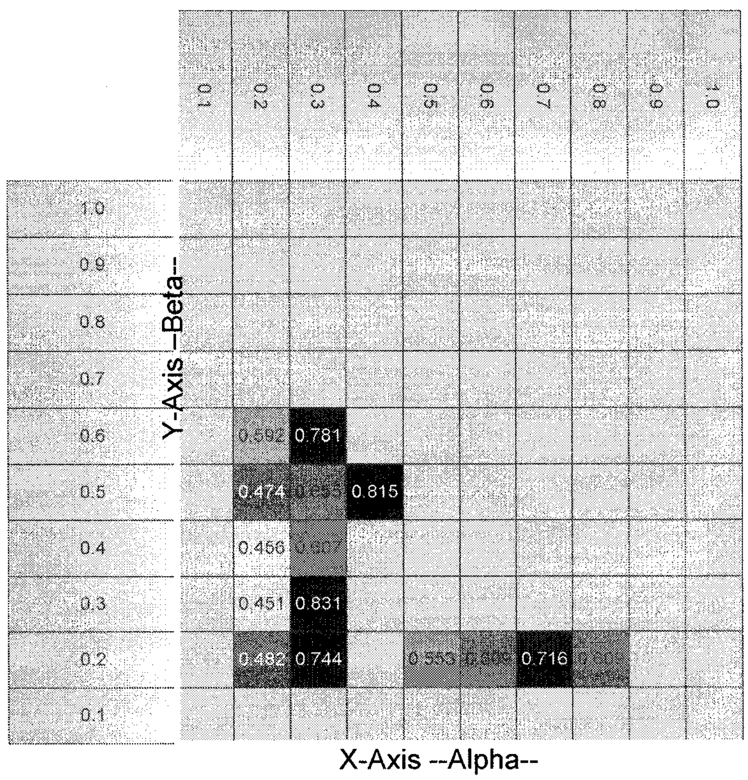


Figure 5-14: Optimal Ordering Policy Identification

From the performance measure functions, we calculate the cost ratio between BM+Holts and BM, BM+Browns and BM; between BM+Holts and BM+MA, BM+Browns and

BM+MA. As a result, the smaller the ration is, the better the performance of the ordering policy is. Similar conclusion happens to variance and RMSE performance function. Therefore, the smaller the total value is, the better the performance of the ordering policy is. From figure 5-9, the lighter the grid, the better the performance is; for instance, the value in the grid (0.2, 0.4) is 0.592 that is better than that of grid (0.4, 0.5), which is 0.815.

5.1.3 Boundary experiments

Our research is incomplete if we do not consider boundary experiments in our simulations. In chapter 4, 8 models are defined and 4 models are defined as the ordering policies without supply line support. As a result, the experiments with $\beta = 0$ can ensure the integrity of our simulations since it covers the ordering policies without supply line support. We test 7 points from $\alpha = 0.2$ to $\alpha = 0.8$ systematically.

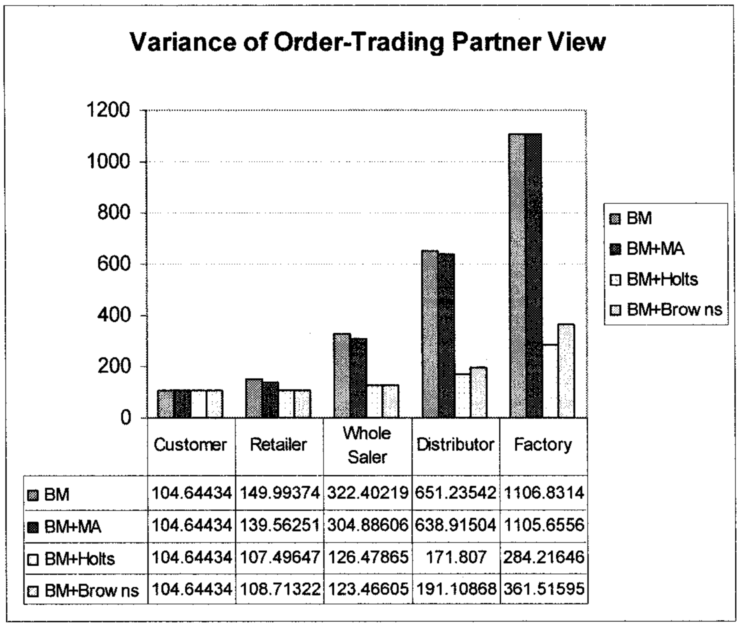
5.2 Simulation Results

In this section, sample simulation results are presented, including tables and graphs. We have 36 sets of experiments; each experiment has reports on order rate, inventory level, and cost; and each report includes 100 time series data. However, there is no enough space for us to list all the results in the thesis; as a result, we only choose one set of the most typical data here, that is, the case $\alpha = 0.2$ and $\beta = 0.3$. In this section, we list this experiment figures and attach all the total data for this case in appendix 1. As optimal ordering policies are important for the research, we present an example on how the criteria are applied.

5.2.1 Sample results in the case of $\alpha = 0.2$ and $\beta = 0.3$

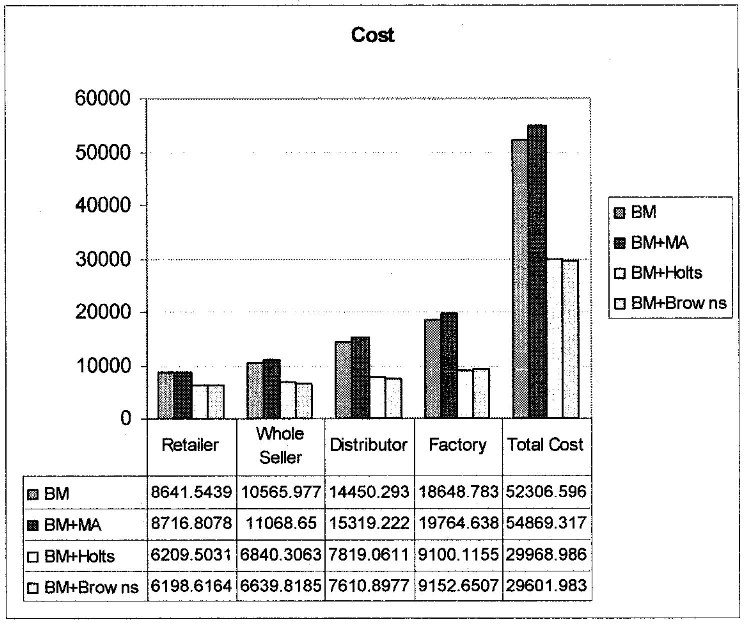
Figure 5-10 shows the variance of the order rate; figure 5-11 shows the cost; and figure 5-12 shows the RMSE in the case $\alpha = 0.2$ and $\beta = 0.3$. Figure 5-13 shows the order rate of BM; figure 5-14 shows the order rate of BM+MA; figure 5-15 shows the order rate of

BM+Holts; figure 5-16 shows the order rate of BM+Browns in the case and figure 5-16-0 to figure 5-16-4 shows a separated view of the order rate in BM+Browns. From the comparison in the diagram, we can see the obvious reduction on the bullwhip effect if Holts or Browns forecasting method is applied.



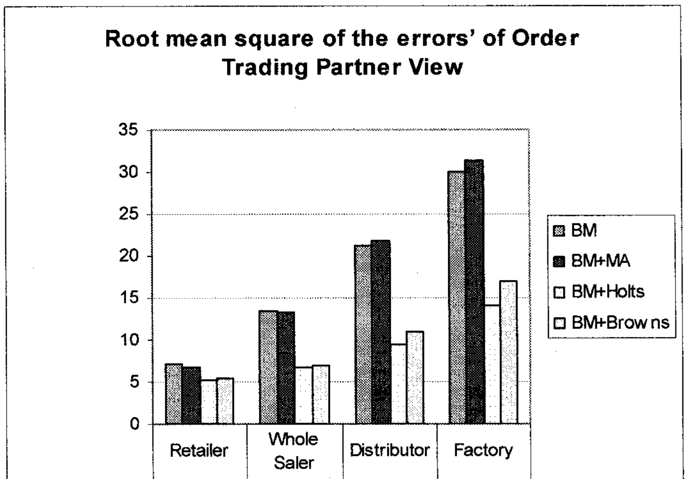
	Customer	Retailer	Whole Saler	Distributor	Factory
BM	104.64434	149.99374	322.40219	651.23542	1106.8314
BM+MA	104.64434	139.56251	304.88606	638.91504	1105.6556
BM+Holts	104.64434	107.49647	126.47865	171.807	284.21646
BM+Brow ns	104.64434	108.71322	123.46605	191.10868	361.51595

Figure 5-15: Variance of Order Rate for $\alpha = 0.2$ and $\beta = 0.3$



	Retailer	Whole Seller	Distributor	Factory	Total Cost
BM	8641.5439	10565.977	14450.293	18648.783	52306.596
BM+MA	8716.8078	11068.65	15319.222	19764.638	54869.317
BM+Holts	6209.5031	6840.3063	7819.0611	9100.1155	29968.986
BM+Brow ns	6198.6164	6639.8185	7610.8977	9152.6507	29601.983

Figure 5-16: Cost for $\alpha = 0.2$ and $\beta = 0.3$



	Retailer	Whole Saler	Distributor	Factory
BM	7.038542	13.423755	21.148637	29.970608
BM+MA	6.6784208	13.227441	21.818073	31.367546
BM+Holts	5.2482415	6.7339632	9.4617702	14.124073
BM+Brow ns	5.3108915	6.9778109	10.903824	16.997989

Figure 5-17: RMSE for $\alpha = 0.2$ and $\beta = 0.3$

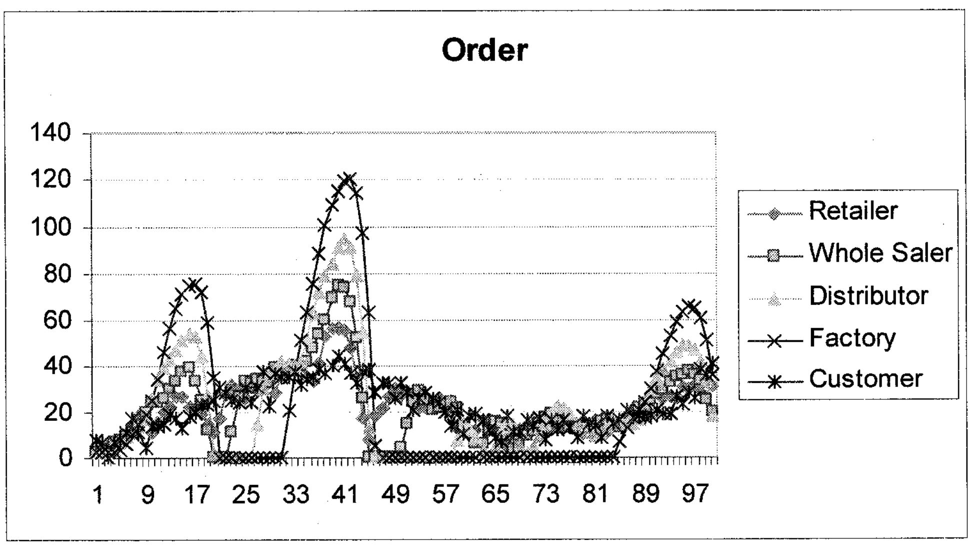


Figure 5-18: Order Rate using BM for $\alpha = 0.2$ and $\beta = 0.3$

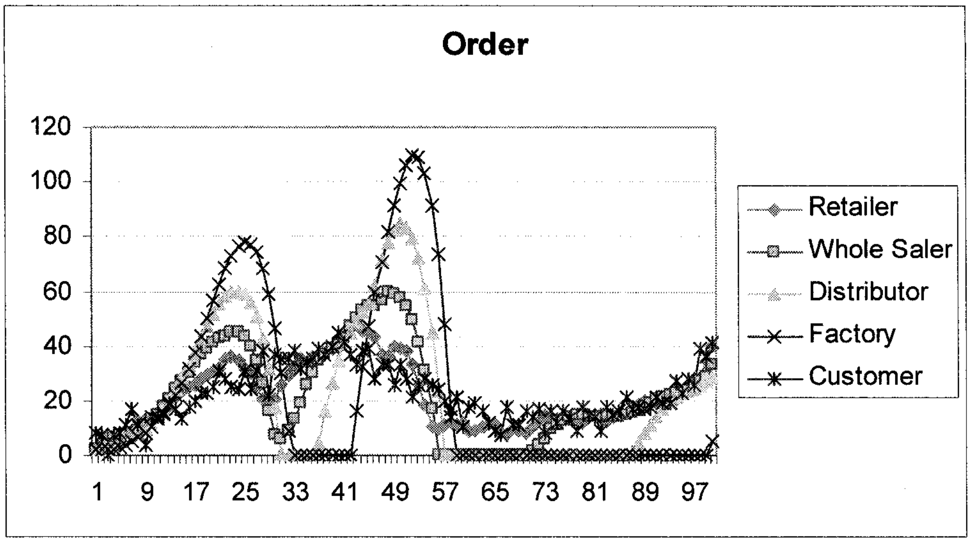


Figure 5-19: Order Rate using BM+MA for $\alpha = 0.2$ **and** $\beta = 0.3$

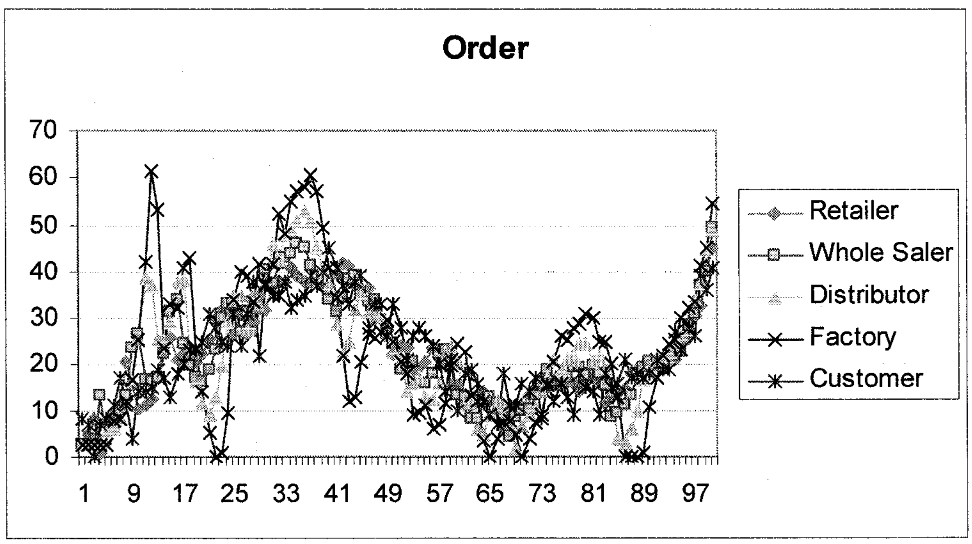


Figure 5-20: Order Rate using BM+Holts for $\alpha = 0.2$ **and** $\beta = 0.3$

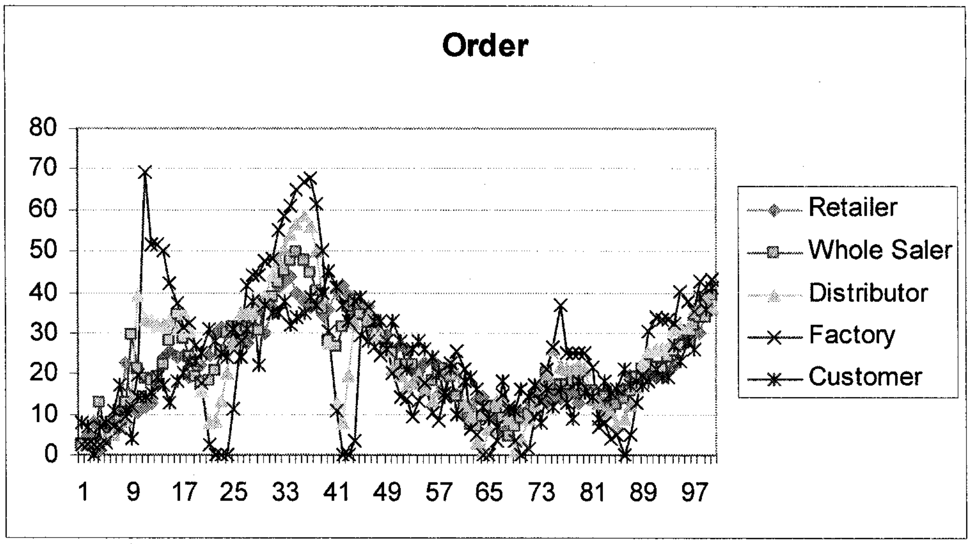


Figure 5-21: Order Rate using BM+Browns for $\alpha = 0.2$ and $\beta = 0.3$

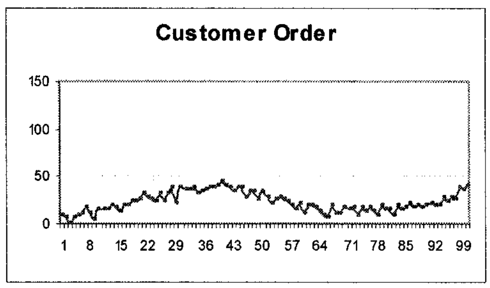


Figure 5-22-0: Customer Order

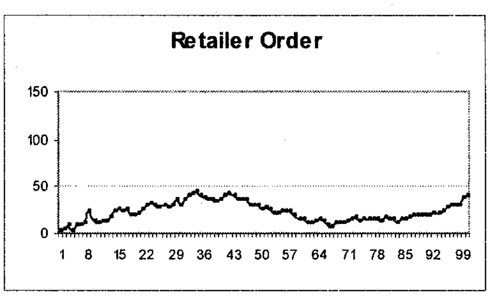


Figure 5-23-1: Retailer Order

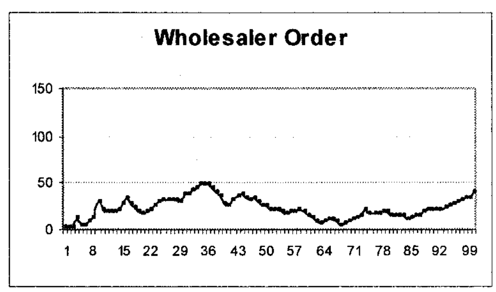


Figure 5-24-2: Wholesaler Order

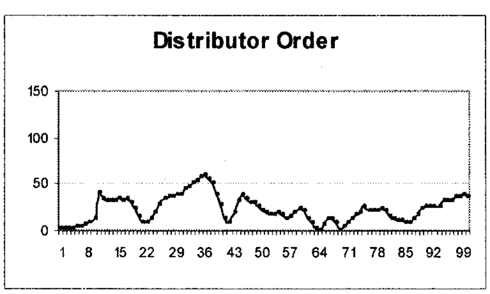


Figure 5-25-3: Distributor Order

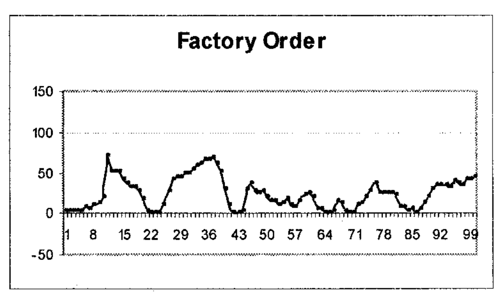


Figure 5-26-4: Factory Order

5.2.2 Sample on Criteria application

Table5-5 and table5-6 shows how to calculate the cost performance measure; table 5-7 and table 5-8 shows how to calculate the variance performance measure; and table 5-9 and table 5-10 shows how to calculate the RMSE performance measure.

Model	Total Cost
BM	52306.6
BM+MA	54869.32
BM+Holt	29968.99
BM+Browns	29601.98

Table 5-5: Cost for $\alpha = 0.2$ **and** $\beta = 0.3$

Models	/BM	/(BM+MA)
BM+Holt	0.572948	0.546188
BM+Browns	0.565932	0.5395
Total Mean	0.556142	

Table 5-6: Cost for $\alpha = 0.2$ **and** $\beta = 0.3$ **on Cost Performance Measure Computing**

Model	Variance(Factory/Customer)
BM	10.57708
BM+MA	10.56584
BM+Holt	2.716023
BM+Browns	3.454711

Table 5-7: Variance for $\alpha = 0.2$ **and** $\beta = 0.3$

Models	/BM	/(BM+MA)
BM+Holt	0.256784	0.257057
BM+Browns	0.326622	0.32697
Total Mean	0.291858	

Table 5-8: Variance for $\alpha = 0.2$ and $\beta = 0.3$ on Performance Measure Computing

Model	RMSE(Factory)
BM	29.97061
BM+MA	31.36755
BM+Holt	14.12407
BM+Browns	16.99799

Table 5-9: RMSE for $\alpha = 0.2$ and $\beta = 0.3$ on Performance Measure Computing

Models	/BM	/(BM+MA)
BM+Holt	0.471264	0.450277
BM+Browns	0.567155	0.541897
Total Mean	0.597468	

Table 5-10 RMSE for $\alpha = 0.2$ and $\beta = 0.3$ on Performance Measure Computing

Criteria Name	Value
Cost	0.556142
Variance	0.291858
RMSE	0.597468
Total Mean	0.451883

Table 5-11: Final Result for Performance Measure

5.2.3 Results of Boundary Experiments

Figure 5-17 shows the results of boundary experiments for $\beta = 0$. As defined in section 5.1.1.2, the dark shading square (Legend: Bullwhip Effect can be alleviated in figure 5-17) means forecasting techniques such as Holts and DES can alleviate the bullwhip effect substantially in local trend demand pattern; we mark the square as light shading (Legend: Bullwhip Effect can not be alleviated in figure 5-17) if Holts and Double Exponential Smoothing (DES) method both do not have smaller variance of order rate, or cost, or RMSE when comparing with moving average and Stermans's adaptive forecasting method. Hence, only the cases $\alpha = 0.2$ and $\alpha = 0.3$ are dark shading.

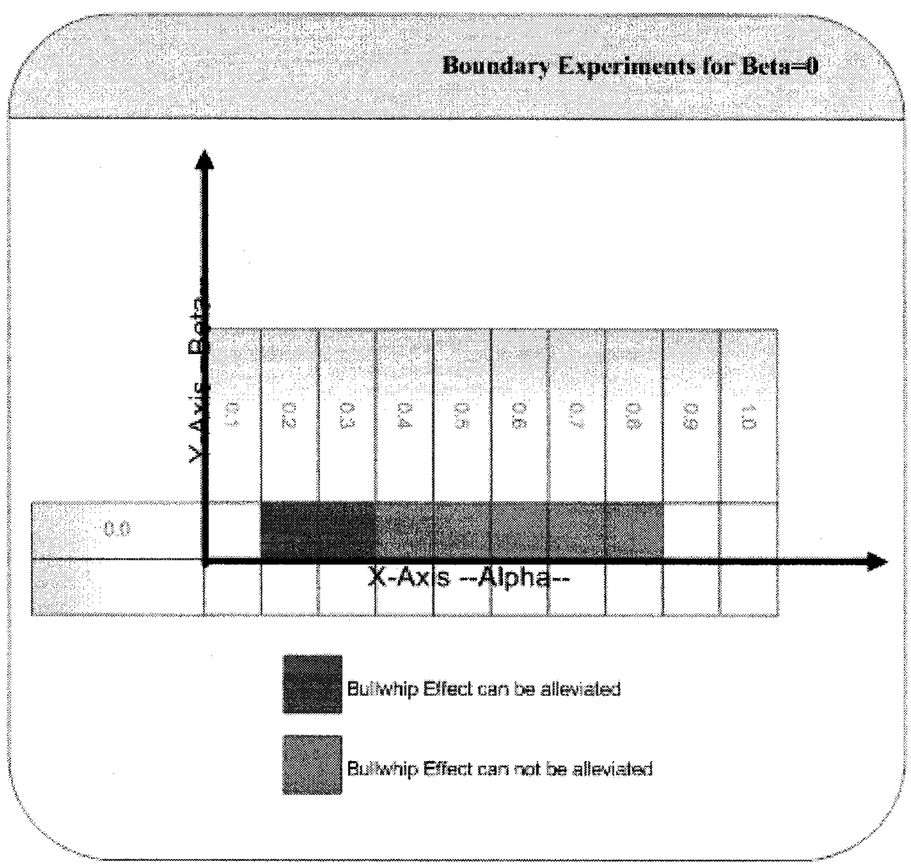


Figure 5-27: Results of Boundary Experiments

6 Discussion

In this chapter, we do further discussions based on the results from the simulations. Since system structure has an important role in systems dynamics, in the first section, we recap the difference among these 8 models. In the second section, detailed analysis on how forecasting techniques and ordering policy affect the bullwhip effect is presented. In the last section, we summarize our research contributions.

6.1 Comparison of formula

In this section, we use two tables to compare these 8 models by their ordering policies and forecasting methods. From the two tables (Table 6-1 and Table 6-2), we have a clear vision on the difference among these 8 models. The footnotes indicate the related references. In table 6-1, we use ordering policy in the Basic Model to obtain the "indicated order" in the first four models; in the last four models, we remove the adjustment to the supply line from the indicated order formula. Table 2 shows the forecasting methods used in different models.

IO_t / Model	Ordering Policy	
	$ED_t + \alpha_S * (S' - S_t - \beta * SL_t)$ Section 4.2.1 formula (8)	$ED_t + \alpha_S * (S' - S_t)$ chapter 4.2.5, formula(16)
BM	√	
BM+MA	√	
BM+Holts	√	
BM+Browns	√	
BM-SL		√
BM-SL+MA		√
BM-SL+Holts		√
BM-SL+Browns		√

Table 6-1: Model formula comparison-1 (Order Policy)

ED_t / Model	Forecasting Methods			
	$\theta * OR_{t-1} + (1-\theta) * ED_{t-1}$ section 4.2.1, formula(7)	$M_t(Order)$ section 4.2.2, formula (12)	$H_t(Order)$ section 4.2.3, formula (14)	$B_t(Order)$ section 4.2.4, formula (15)
BM	√			
BM+MA		√		
BM+Holt			√	
BM+Browns				√
BM-SL	√			
BM-SL+MA		√		
BM-SL+Holts			√	
BM-SL+Browns				√

Table 6-2: Model formula comparison-2 (Forecasting Method)

6.2 Results Discussion

6.2.1 General Discussion

The input customer demand pattern (figure 5-1) in our simulations includes four local trends: 3 slopes and 1 horizontal. Starting from time step 0 with 8 units, at time step 40, it reaches its peak value: 45 units. From all the order rate diagrams, we can find that the bullwhip effect occurred. For example, in figure 6-1, at time step 47, the order rate of the retailer is 21 units; the order rate of the wholesaler is 43 units; the order rate of the distributor is 62 units; and the order rate of the factory is 112 units. We can also find that a time delay on peak value in the figure 6-1: the retailer reaches its peak order at time step 41 with 52 units; the wholesaler reaches its peak order at time step 43 with 63 units; the distributor reaches its peak order at time step 44 with 79 units; and the factory reaches its peak order at time step 47 with 112 units. If we define such kind fluctuations as "waves", we can find that "waves" can not be eliminated entirely in all our experiments. However, in figure 5-15 and figure 5-16, the amplification of order rate in all trading partners is reduced and their order rate is close to the original customer demands, which means the bullwhip effect can be controlled or alleviated by the right combination between the ordering policies and the forecasting methods.

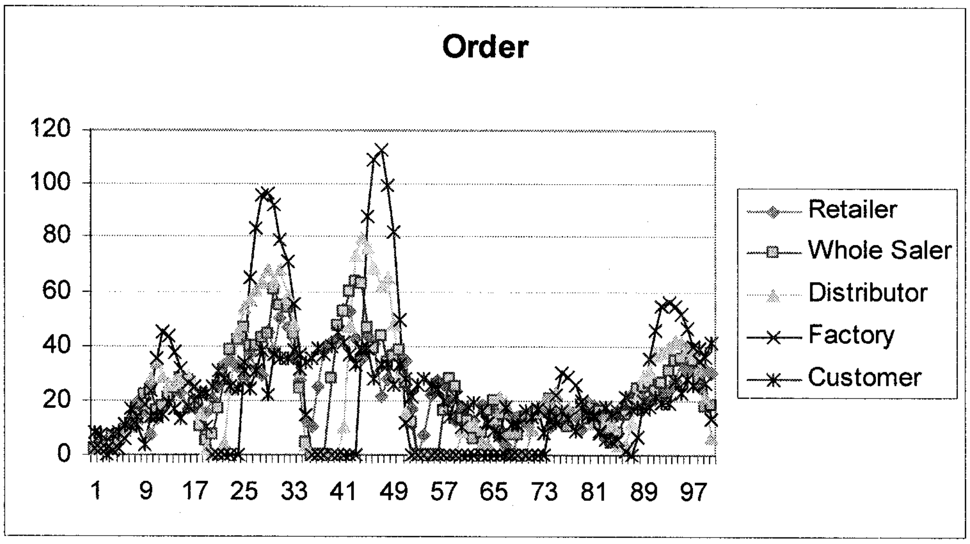


Figure 6-1: Bullwhip Effect Sample for BM with $\alpha = 0.6$ **and** $\beta = 0.6$

6.2.2 Forecasting Methods Analysis

Many previous literatures discussed how demand forecasting affected the bullwhip effect. Paik in the PhD dissertation (Paik 2003) identified one of the statistically significant main-effect variables was demand forecast updating after reviewing nine causes from previous literature. Hence, we start to discuss how forecasting methods affect the bullwhip effect.

In our simulation experiments, we have 4 forecasting methods: Sterman's adaptive forecast (Exponential Smoothing Method, or ES), the moving average, the Holts method, and the double exponential smoothing (DES) method. The reason we choose last two techniques is that we hope to focus our research on the customer demands with local trends. As mentioned in section 5.1, we have 36 ordering policies and each includes 4 forecasting methods for a total of 144 scenarios. In 29 experiments in section 5.1.1, we identify 15 dark shading squares and in 7 boundary experiments in section 5.1.3, we find 2 dark shading squares. For recapitulation, we color the square as dark shading if Holts and DES method both have smaller variance of the order rate, cost, and RMSE when comparing with the moving average and the Sterman's adaptive forecasting (ES) method. Hence, the dark shading square means forecasting techniques like the Holts and the DES can alleviate the bullwhip effect substantially under the local trend demand pattern. The data we discuss in the remainder of this section is in the dark shading areas. From the figure 5-3, we find that the dark shading squares cover two main areas: one for small alpha $\alpha = 0.2$ and $\alpha = 0.3$; another for beta $\beta = 0.2$ and $0.5 \leq \alpha \leq 0.8$. There are about 50% results (17 results) that show the bullwhip effect can be cut down significantly by suitable forecasting techniques, which is not a contingency.

varP at	Value	varP at	Value
(0.2,0.2)	0.329	(0.3,0.5)	0.519
(0.2,0.3)	0.292	(0.3,0.6)	0.675
(0.2,0.4)	0.293	(0.4,0.5)	0.745
(0.2,0.5)	0.318	(0.5,0.2)	0.454
(0.2,0.6)	0.466	(0.6,0.2)	0.499
(0.3,0.2)	0.699	(0.7,0.2)	0.659
(0.3,0.3)	0.810	(0.8,0.2)	0.494
(0.3,0.4)	0.475		

Table 6-3: Variance Performance Measure Report

In figure 5-10, we find that the variance of the order rate in the factory side is alleviated around 2/3 if the Holts or the DES method is applied. The variance of the DES is higher than that of the Holts method. In figure 5-10, the variance of order rate is 284 for the Holts method while the variance of order rate is 361 for the DES method in the factory side. The result from figure 5-10 is not a peculiar phenomenon. Table 6-3 shows all the variance performance measure "varP" defined in section 5.1.2.1. From the table, we find that all the values are less than 1, which means the Holts and the DES have a distinct affection on reducing the bullwhip effect from the variance viewpoint.

In figure 5-12, we notice that the RMSE of the order in the factory side is alleviated around 1/2 if the Holts or the DES method is applied. The variance of the DES is higher than that of the Holts method. In figure 5-12, the RMSE of the order rate is 14 for the Holts method while the variance of order rate is 16 for the DES method. The result from figure 5-12 is not a peculiar phenomenon too. Table 6-4 shows all the RMSE performance measure defined in section 5.1.2.1. From the table, we find that all the values are less than 1, which means Holts and DES have a distinct affection on reducing the bullwhip effect from the perspective of RMSE.

In figure 5-11, we find that the total cost is alleviated around 2/5 if the Holts or the DES method is applied. Table 6-5 shows all the cost performance measure defined in section 5.1.2.1. From the table, we find that all the values are less than 1, which means the Holts and the DES have a distinct affection on reducing bullwhip effect in the cost performance measure.

rmseP at	Value	rmseP at	Value
(0.2,0.2)	0.543	(0.3,0.5)	0.791
(0.2,0.3)	0.508	(0.3,0.6)	0.899
(0.2,0.4)	0.499	(0.4,0.5)	0.957
(0.2,0.5)	0.501	(0.5,0.2)	0.692
(0.2,0.6)	0.618	(0.6,0.2)	0.723
(0.3,0.2)	0.849	(0.7,0.2)	0.793
(0.3,0.3)	0.911	(0.8,0.2)	0.685
(0.3,0.4)	0.737		

Table 6-4: RMSE Performance Measure Report

costP at	Value	costP at	Value
(0.2,0.2)	0.573	(0.3,0.5)	0.653
(0.2,0.3)	0.556	(0.3,0.6)	0.769
(0.2,0.4)	0.575	(0.4,0.5)	0.741
(0.2,0.5)	0.604	(0.5,0.2)	0.513
(0.2,0.6)	0.691	(0.6,0.2)	0.605
(0.3,0.2)	0.683	(0.7,0.2)	0.695
(0.3,0.3)	0.773	(0.8,0.2)	0.648
(0.3,0.4)	0.607		

Table 6-5: Cost Performance Measure Report

The total performance measure, totalP, can be found in figure 5-9, without exception, all the values are less than 1. For the boundary experiments, we have 2 dark shading squares out of 7 simulations. For these two experiments, their varP, rmseP, costP, and totalP are all smaller than 1.

In summary, in total 36 ordering policy space, the bullwhip effect can be alleviated by the Holts and the DES forecasting techniques in half of the ordering policies.

6.2.3 Ordering Policy Analysis

In our simulation experiments, we have 36 ordering policies and 17 ordering policies out of them are colored dark shading, which implies that forecasting techniques like the Holts and the DES can alleviate the bullwhip effect substantially fed with the local trend demand pattern. From the figure 5-2, the dark shading squares can be divided into two areas: one for small alpha $\alpha = 0.2$ and $\alpha = 0.3$; another for beta $\beta = 0.2$ and $0.5 \le \alpha \le 0.8$. Additionally, in boundary experiments, we have two dark shading squares. In this section, we will discuss how different ordering policies affect the bullwhip effect. We start to evaluate the result with three system performance measures. Then how ordering policies perform under specific forecasting techniques is analyzed.

6.2.3.1 Evaluation based on three system performance measures

The result of the variance performance measure, varP, which is defined in section 5.1.2.1, is listed in figure 6-2. From the figure, smaller alpha like $\alpha = 0.2$ shows good performance on reducing the bullwhip effect; in the same alpha $\alpha = 0.2$ or $\alpha = 0.3$, medium beta like $\beta = 0.4$ shows good performance.

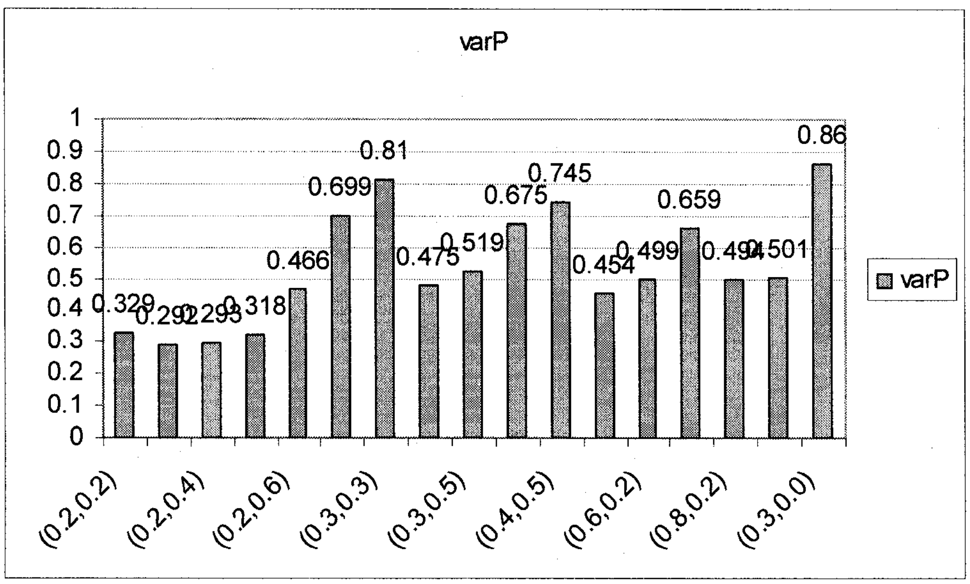


Figure 6-2: Variance Performance Measure

The result of the RMSE performance measure, rmseP, which is defined in section 5.1.2.1, is listed in figure 6-3. From the figure, smaller alpha like $\alpha = 0.2$ shows good performance on alleviating the bullwhip effect; in the same alpha $\alpha = 0.2$ or $\alpha = 0.3$, medium beta like $\beta = 0.4$ shows good performance.

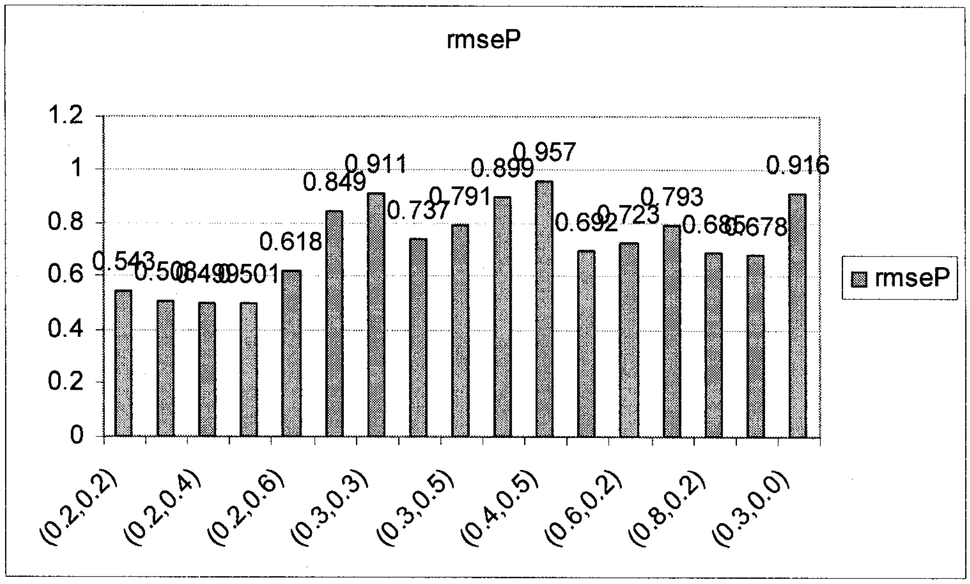


Figure 6-3: RMSE Performance Measure

The result of the cost performance measure, costP, which is defined in section 5.1.2.1, is listed in figure 6-4. From the figure, smaller alpha like $\alpha = 0.2$ shows good performance when comparing with $\alpha = 0.3$. However, there is no significant difference among all the costP in all the dark shading areas.

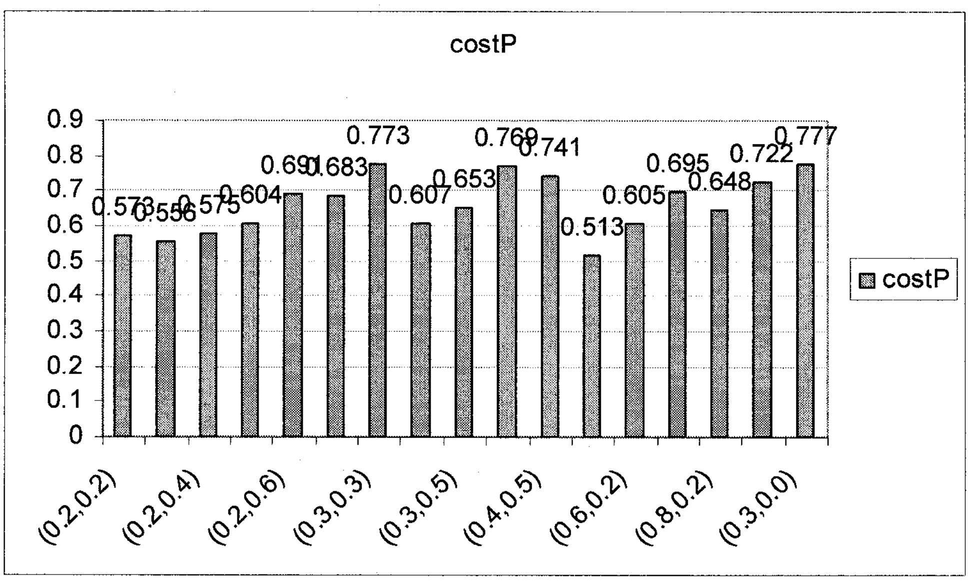


Figure 6-4: Cost Performance Measure

From the figure 5-9, we can find out that the total performance measure keep the consistent result as that from varP, rmseP, and costP. Smaller alpha like $\alpha = 0.2$ shows good performance when comparing with $\alpha = 0.3$; in the same alpha $\alpha = 0.2$ or $\alpha = 0.3$, medium beta like $\beta = 0.4$ shows good performance. Therefore, slowly adjustment on the discrepancy of the stock with a relative large adjustment on the discrepancy of the supply line is a best practice; for example, ordering policies like cases $(\alpha = 0.2, \beta = 0.3)$, or $(\alpha = 0.2, \beta = 0.4)$, or $(\alpha = 0.3, \beta = 0.4)$, or $(\alpha = 0.3, \beta = 0.5)$. In the variance (figure 6-2) and the RMSE (figure 6-3) performance measure, the diagram fluctuates more than that in cost performance measure (figure 6-4).

6.2.3.2 Ordering policy analysis under specific forecasting methods

In this section, we analyze how ordering policy performs under specific forecasting techniques.

In figure 6-5, we can see how different ordering policies perform under the Holts forecasting method. With a small alpha $\alpha = 0.2$, system has a relative lower RMSE; as alpha increases, the RMSE reach up to 66 at (0.8, 0.2). Beta β does not have a big affection on the RMSE.

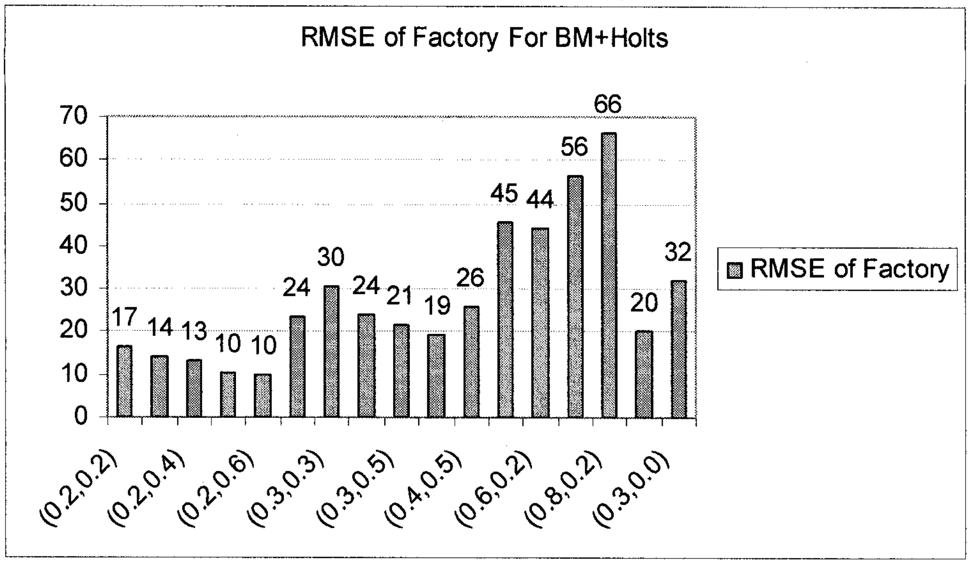


Figure 6-5: RMSE of Factory for Holts Method

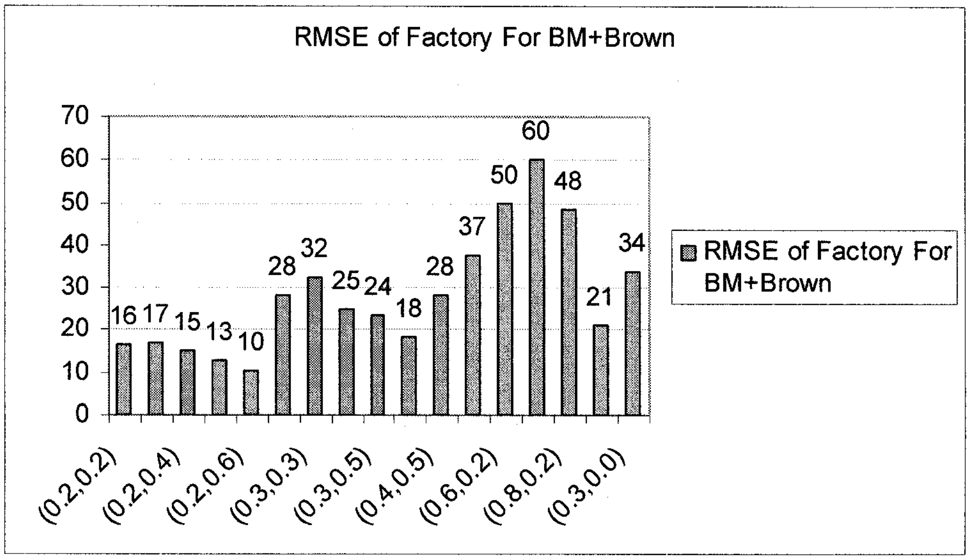


Figure 6-6: RMSE of Factory for DES (Browns) Method

In figure 6-6, we have the similar result as in figure 6-5. Under the DES (Brown) forecasting method, with small alpha $\alpha = 0.2$, system has a relative lower RMSE; as alpha increases, RMSE reach up to 60 at (0.7, 0.2). The same as figure 6-5, Beta β does not have a big affection on the RMSE.

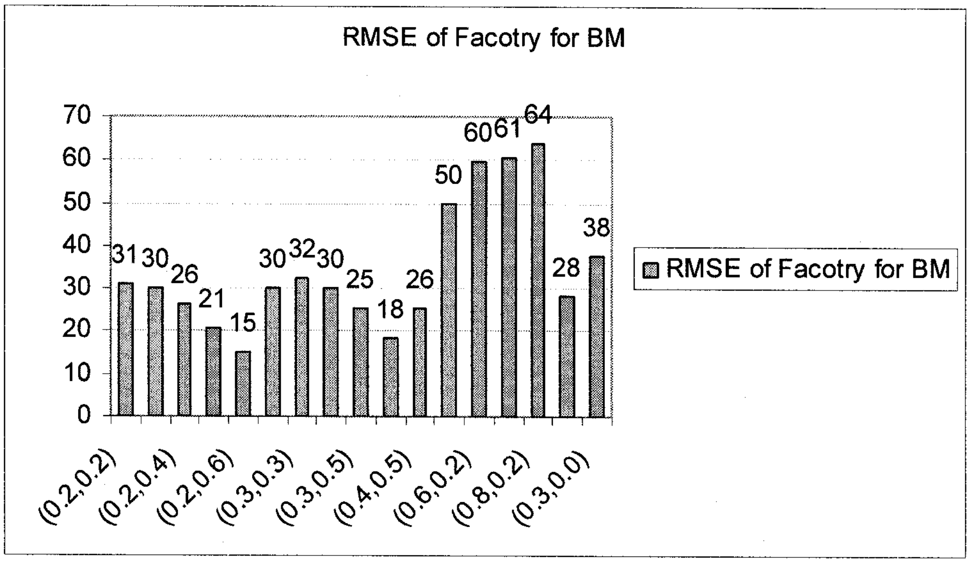


Figure 6-7: RMSE of Factory for BM

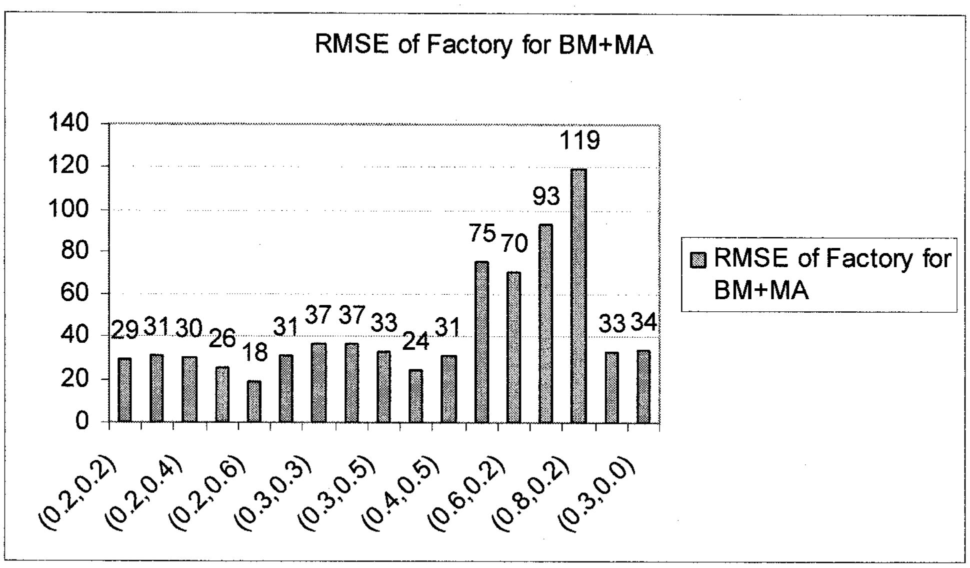


Figure 6-8: RMSE of Factory for Moving Average Method

Figure 6-7 and figure 6-8 have the similar distribution pattern. There is no significant difference on the RMSE of the order rate between the ordering policy $\alpha = 0.2$ and the ordering policy $\alpha = 0.3$. Relative smaller alpha like $\alpha = 0.2$ or $\alpha = 0.3$ has smaller RMSE. As alpha increases, the RMSE reaches up to their peak value.

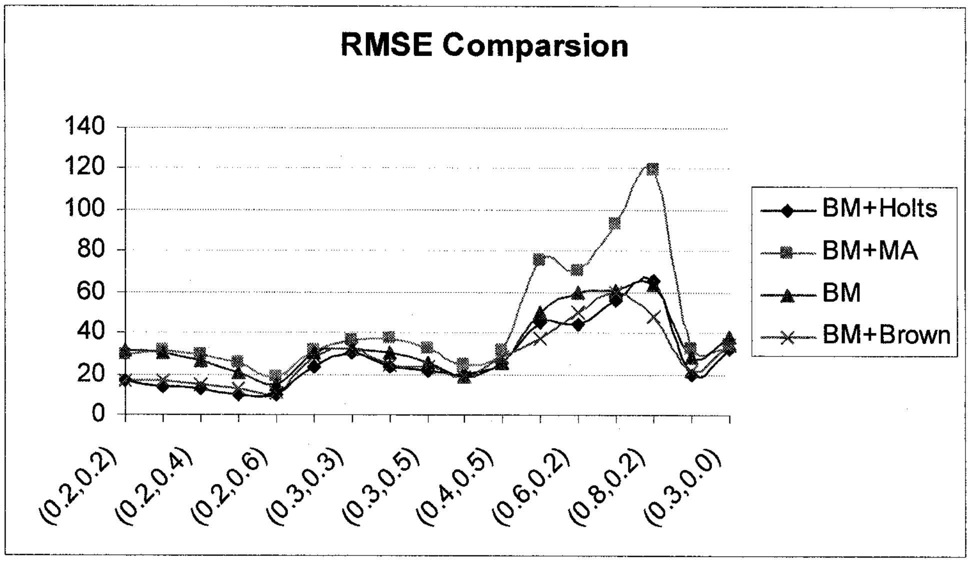


Figure 6-9: RMSE Comparison

Figure 6-9 shows a summary based on the figures from 6-5 to 6-8. When alpha is smaller, for example, $(\alpha = 0.2)$ or $(\alpha = 0.3)$, there is no big difference on the RMSE under the Holts and the DES (Browns) forecasting methods; however, the RMSE using Sterman's adaptive or the moving average forecasting method is relative larger than that using the Holt or the DES method. When alpha increases, the RMSE under the moving average gets more fluctuation. Therefore, the slow adjustment on the discrepancy of the stock is better than other ordering policies.

In conclusion, in total 36 ordering policy spaces, from three system performance measures and the RMSE comparison, the bullwhip effect can be alleviated in half of the ordering policies by the right forecasting methods (the Holts and the DES). Besides the statement in section 6.2.2, in the figure 6-9, we also can find that BM+Holts and BM+Brown have a more stable curve than other two forecasting techniques. Under the same ordering policy, the Holts and the DES (Brown) method keep a lower fluctuation. In these ordering policies, smaller alpha shows good performance. As a result, slow adjustment on the discrepancy of the stock is one managerial insight, which is rational since partial noise led by other decision maker has already been filtered out by the right forecasting method. In the small alpha area, we have relative large beta, for instance $0.4 \le \beta \le 0.6$, which means that the adjustment on the supply line could be quiet large.

7 Conclusion, contributions, and future research

7.1 Conclusion

This section summarizes the major conclusions of the study with reference to our research motives.

Through our research, we have achieved our modeling goal: to analyze the effect of additional forecasting techniques (Holts method and Double Exponential Smoothing method) in the bullwhip effect model and to present a more vivid demonstration by using system dynamics and agent-based modelling (ABM). The total model and research framework can be used in future study.

The aim of this research is to increase our understanding on how the varied combinations of ordering policies and forecasting methods affects the bullwhip effect. Through the simulation and the analysis, several managerial insights were obtained. They are as follows.

First, the experiments show us the bullwhip effect; that is, the variance or RMSE value continues to increase from retailer to factory and their peak order is delayed correspondingly. We show that the bullwhip effect happened in 36 ordering policies and each included 4 forecasting methods – a total of 144 scenarios. From all the inventory and order rate figures, there is no notable change in the "wave" number of inventory and order rate, which means that fluctuation cannot be eliminated entirely by these 36 ordering policies combined with the 4 forecasting methods.

Furthermore, a good way to control or reduce the bullwhip effect is to choose a suitable forecasting method. In our research, we feed local trends customer order pattern. We noticed that the: Holts and double exponential smoothing forecasting methods can contribute to mitigate the bullwhip effect very well when compared with the other forecasting methods, for these two forecasting techniques do well in local trend data. After going through 36 ordering policies, half of them show the same result; hence, our study is statistically significant. Therefore, we can say that the stability of the whole supply chain system relies on choosing the right forecasting method.

Finally, the ordering policy has a notable effect on the bullwhip effect. We watch how different ordering policies perform on reducing the bullwhip effect by the 4 forecasting methods individually. They all have the same result: a smaller alpha value shows good performance. As a result, slow adjustment on the discrepancy of the stock is another managerial insight. Since first our experiments present an aggregation effect from varied factors including forecasting methods and ordering policies, and second the fluctuation led by other trading partners has already been filtered out by the right forecasting method, this managerial insight is rational. Moreover, in the small alpha area, we have a relatively large beta value, for instance $0.4 \le \beta \le 0.6$, which means that the adjustment on the supply line could be quite large. Therefore, the insight for us to alleviate the bullwhip effect is to apply a slow adjustment on the discrepancy of the stock and a relatively large adjustment on the difference of the supply line.

In summary, this thesis exemplifies how forecasting methods and ordering policies affect the bullwhip effect by the ABM and the system dynamics method. We find that fed with local trend customer order pattern, the bullwhip effect can be mitigated significantly if the suitable forecasting method like Holts or DES is applied under the right ordering policy that has a slow adjustment on the discrepancy of the stock.

7.2 Contributions

The contributions in our study are grouped according to the reviewed literature.

Comparing with previous research, we have unique contributions. Forrester (1961) mentioned using a "smoothing" method to filter out short-period noise. In our research we extend the smoothing method from the moving average and the exponential average, which was in Forrester's study, to the Holts and the DES methods.

Sterman (1989, 321-339) modeled the Beer Distribution Game to show misperceptions of the feedback account for the poor performance in dynamic systems. We extend his model to investigate other managerial behaviours, including additional forecasting methods.

CDRS (Chen, Drezener, Ryan, and Simchi-Levi 2000, 436-443) and CRS (Chen, Ryan, and Simchi-Levi 2000, 269-286) concluded that the variability of order depended on both "*the nature of the customer demand and on the forecasting technique*". They also pointed out that under certain demand processes the exponential smoothing forecasting method generated a larger variability than the moving average method. However, our study shows that the right forecasting technique can control or reduce the bullwhip effect. The variance or RMSE of order rate using the Holts or DES methods is smaller than that using Sterman's adaptive (exponential smoothing) or moving average methods. We also identify that ordering policies have big impact on system behaviour.

Yao (2001) applied order-up-to policy that is the same as CDRS and CRS, but an optimal forecast scheme was used to prove how the bullwhip effect can be reduced or made to disappear. Differing from Yao, we extend the conclusion to a heuristic ordering policy. In the heuristic ordering policy, using the right forecasting methods the bullwhip effect can be reduced. We prove that about half of the ordering policies of the total 36 can alleviate the bullwhip effect.

Information sharing is an important method which reduces the bullwhip effect; however, it may lead to other problems, like mutual trust or additional cost. Our research has another important managerial insight: through the right ordering policy and forecasting method, trading partners can reduce the bullwhip effect without sharing their private information.

7.3 Future Research

The thesis would be incomplete if we do not mention the limitations of our research. Our model clearly does not cover many complex situations in the real world; for example, we have not considered the supply network; and we only include a single finished product. We do not identify the right forecasting methods and ordering policies for other customer demand patterns except for the local trends.

Our future research will touch on these areas by building a relatively complex supply network model; inducing bill of material (BOM) to fulfill a multi-products environment in our model; and identifying the right forecasting method and ordering policies for other customer demand patterns. Fortunately, as we have applied agent based modeling, so extending our model to the supply network is not so hard. The object oriented implementation can ease the work to induce the BOM.

Just like the great scientist Newton said: *"If I saw further than other men, it was because I stood on the shoulders of giants"*. If our research has been even a little bit successful, it was because we built on the work of authors to whom we have referred.

Publications resulted from This Work

David Wright and Xin Yuan, "Mitigating the Bullwhip Effect by Ordering Policies and Forecasting Methods", Production and Operations Management, submitted, 2006.

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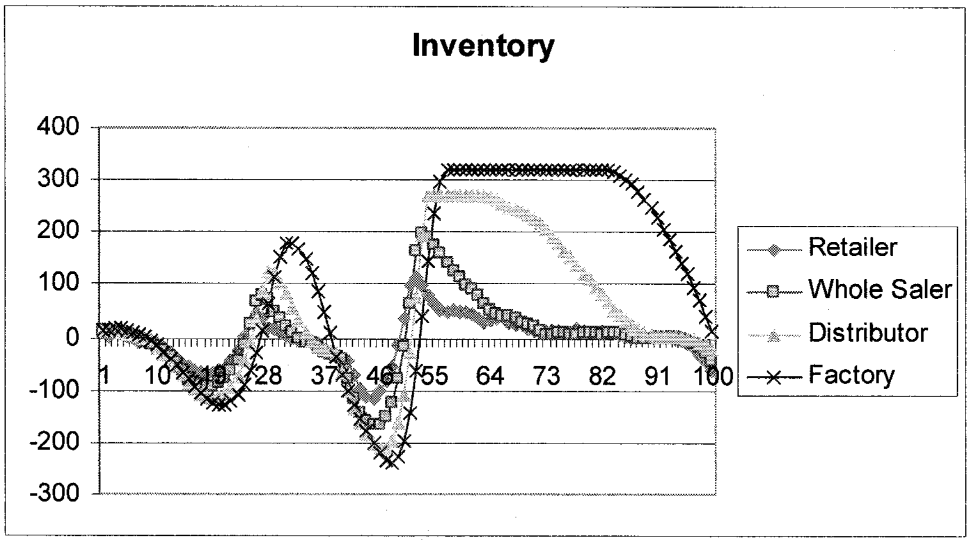
Appendices

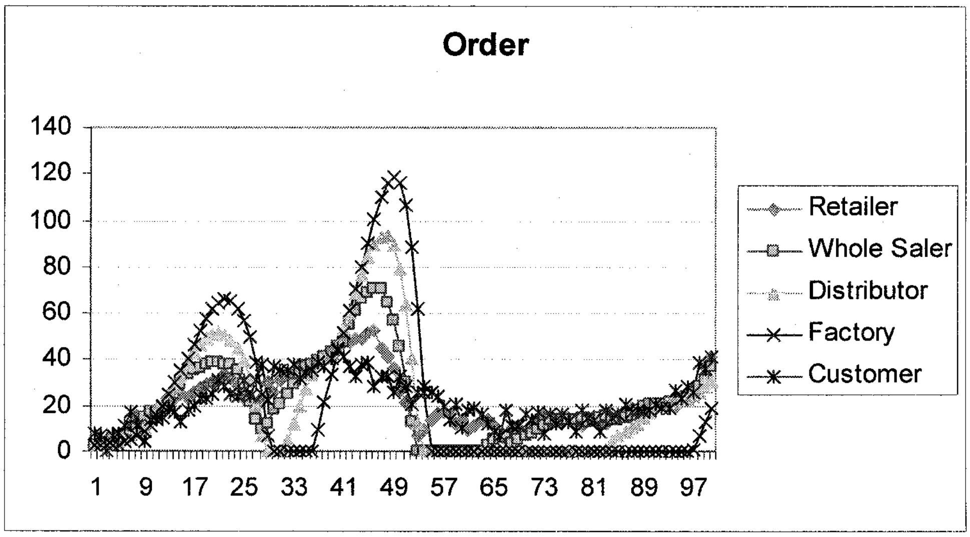
Appendix 1: Simulation results in the case of $\alpha = 0.2$ and $\beta = 0.3$

We list the simulation results from BM, BM+MA, BM+Holts, and BM+Browns.

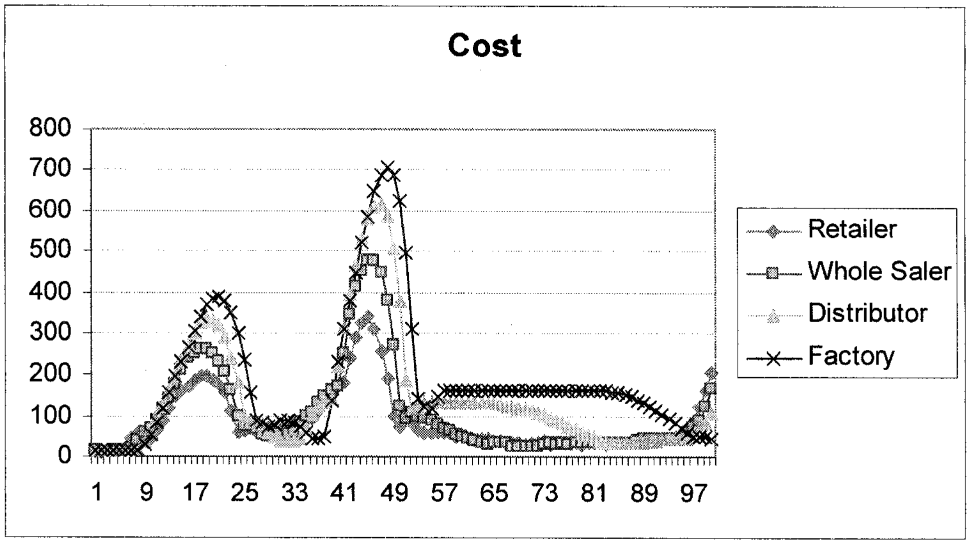
BM:



Appendix Figure 1: Inventory of BM

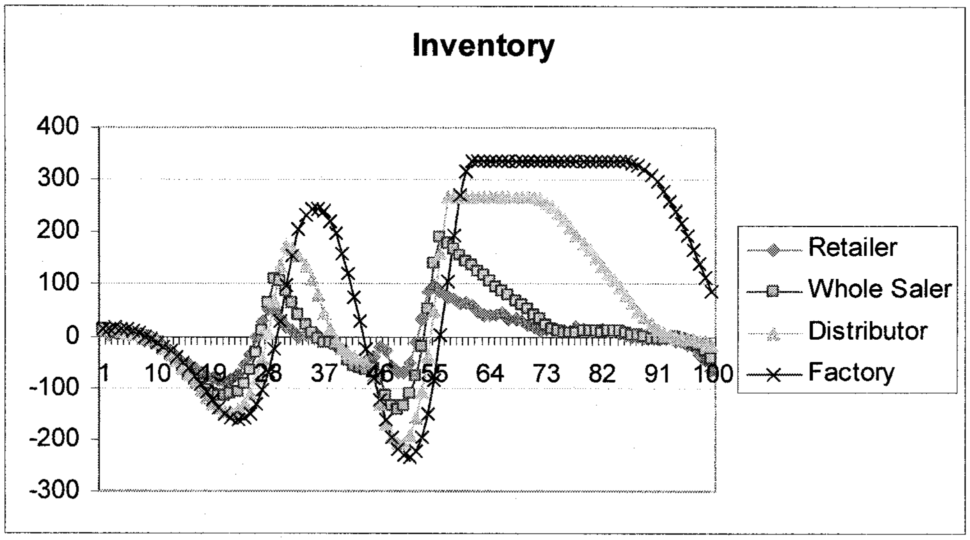


Appendix Figure 2: Order Rate of BM

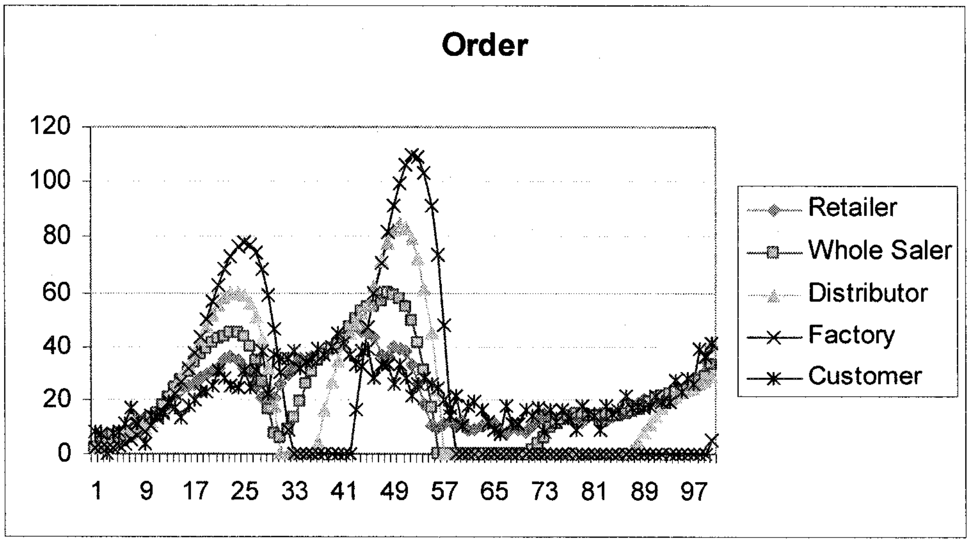


Appendix Figure 3: Cost of BM

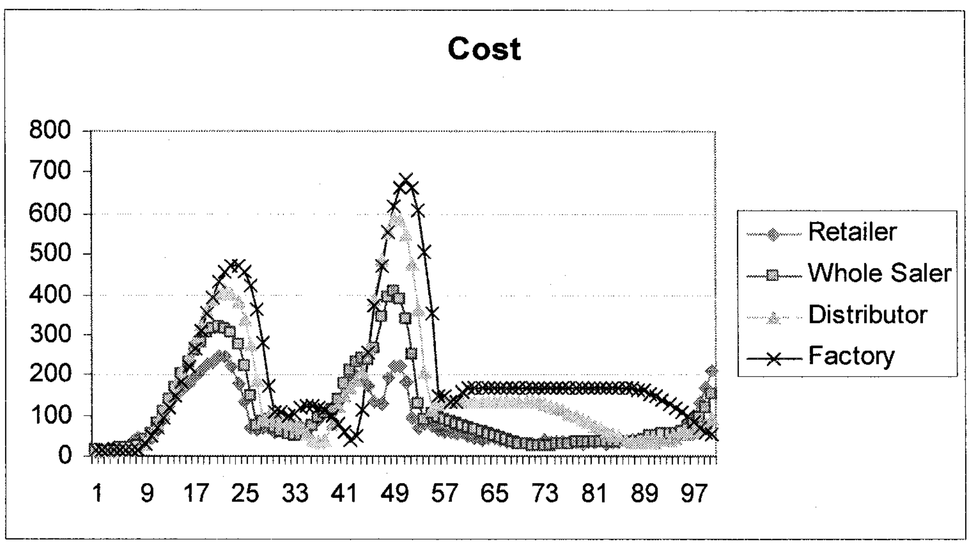
BM+MA:



Appendix Figure 4: Inventory of BM+MA

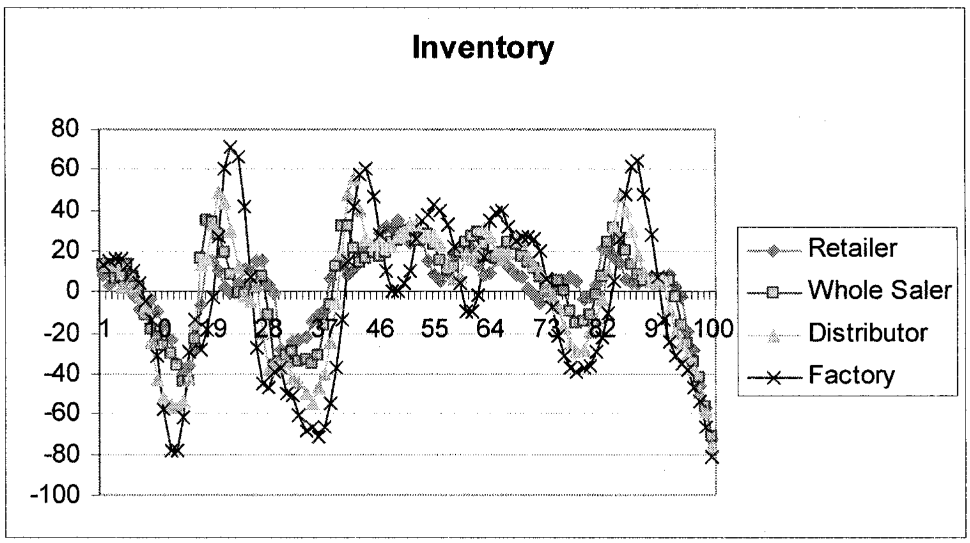


Appendix Figure 5: Order Rate of BM+MA

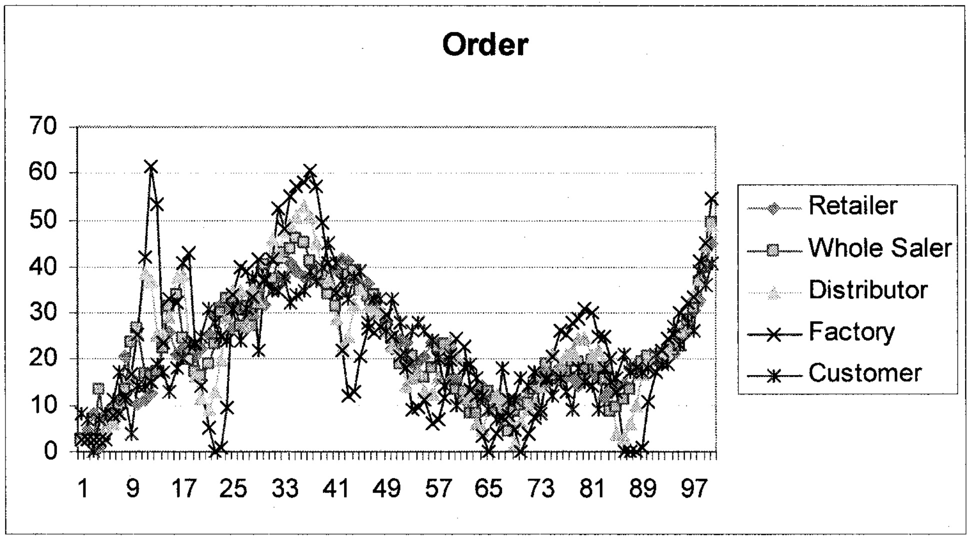


Appendix Figure 6: Cost of BM+MA

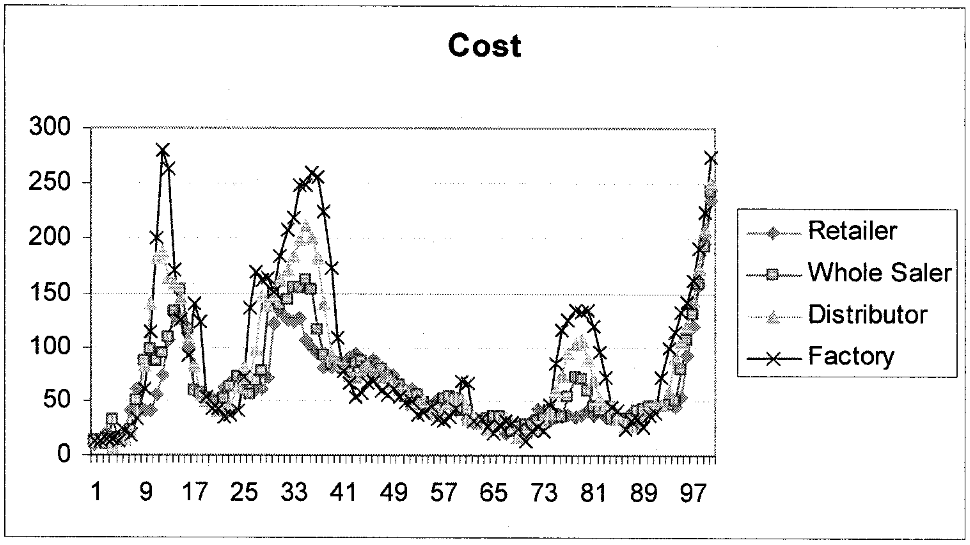
BM+Holts:



Appendix Figure 7: Inventory of BM+Holts

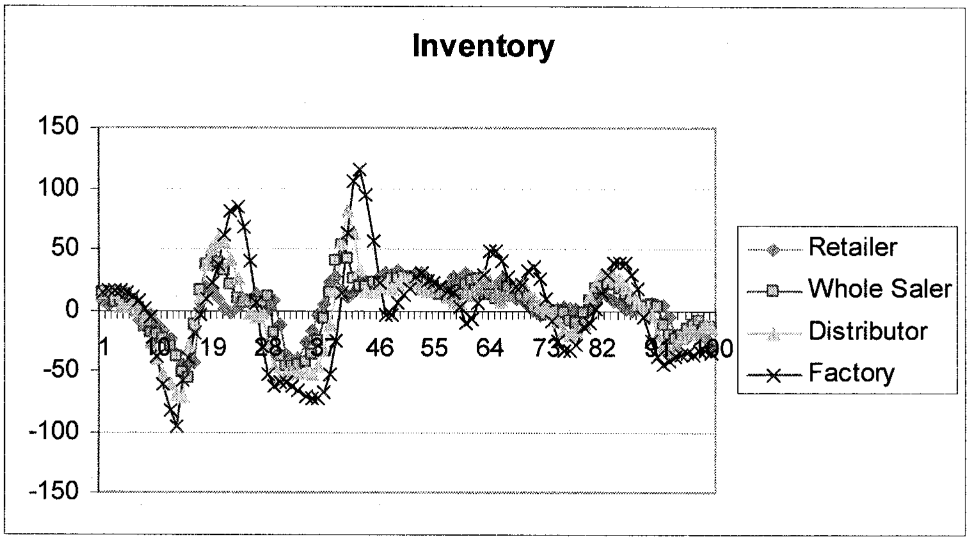


Appendix Figure 8: Order Rate of of BM+Holts

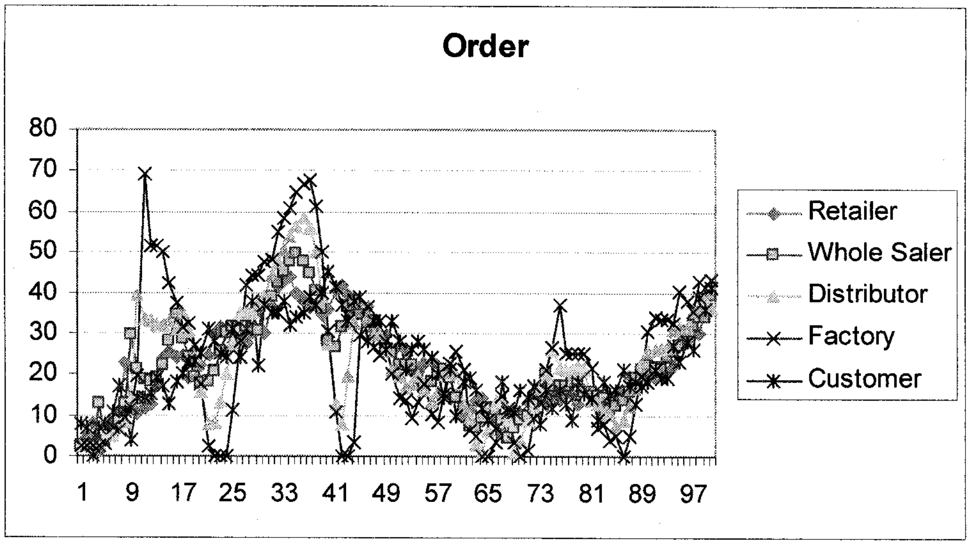


Appendix Figure 9: Cost of BM+Holts

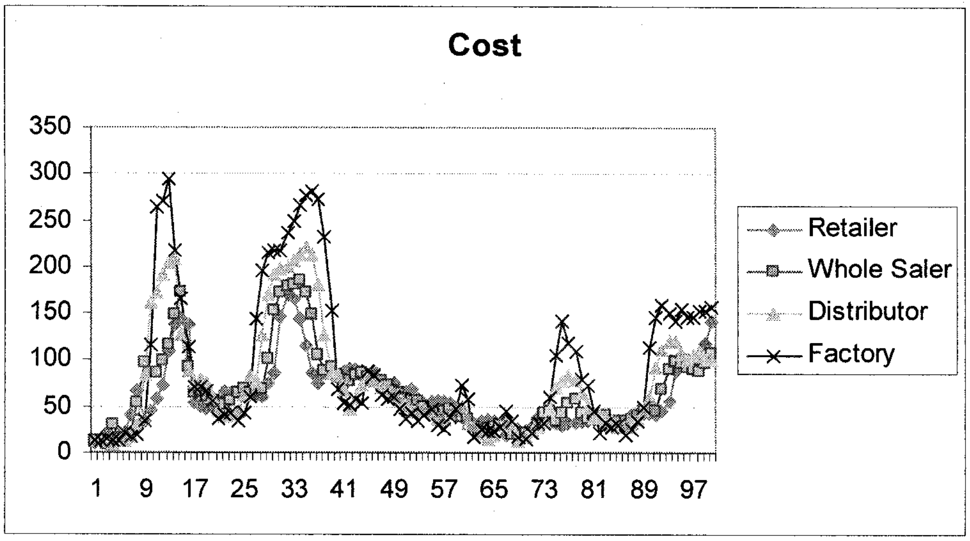
BM+Browns:



Appendix Figure 10: Inventory of BM+Browns



Appendix Figure 11: Order Rate of BM+Browns



Appendix Figure 12: Cost of BM+Browns

Appendix 2: Optimal ordering policy identification

$\alpha = 0.2$ and $\beta = 0.2$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.577322	0.606805	
	BM+Browns	0.540192	0.56778	
			Cost Mean	0.573025
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.317259	0.369579	
	BM+Browns	0.292061	0.340226	
			Variance Mean	0.329781
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.531477	0.562888	
	BM+Browns	0.524107	0.555082	
			RMSE Mean	0.0543388
Total Mean				0.482605

Appendix Table 1: $\alpha = 0.2$ **and** $\beta = 0.2$ **on Performance Measure Computing**

$\alpha = 0.2$ and $\beta = 0.3$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.572948	0.546188	
	BM+Browns	0.565932	0.5395	
			Cost Mean	0.556142
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.256784	0.257057	
	BM+Browns	0.326622	0.32697	
			Variance Mean	0.291858
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.471264	0.450277	
	BM+Browns	0.567155	0.541897	
			RMSE Mean	0.597468
Total Mean				0.451883

Appendix Table 2: $\alpha = 0.2$ **and** $\beta = 0.3$ **on Performance Measure Computing**

$\alpha = 0.2$ and $\beta = 0.4$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.617736	0.55866	
	BM+Browns	0.589784	0.533381	
			Cost Mean	0.57489
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.289695	0.258679	
	BM+Browns	0.330484	0.295101	
			Variance Mean	0.29349
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.495698	0.437208	
	BM+Browns	0.566331	0.499507	
			RMSE Mean	0.499686
Total Mean				0.456002

Appendix Table 3: $\alpha = 0.2$ **and** $\beta = 0.4$ **on Performance Measure Computing**

$\alpha = 0.2$ and $\beta = 0.5$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.635506	0.575169	
	BM+Browns	0.632425	0.572381	
			Cost Mean	0.60387
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.316026	0.24929	
	BM+Browns	0.395834	0.312246	
			Variance Mean	0.318349
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.495296	0.398705	
	BM+Browns	0.614116	0.494353	
			RMSE Mean	0.500618
Total Mean				0.474279

Appendix Table 4: $\alpha = 0.2$ **and** $\beta = 0.5$ **on Performance Measure Computing**

$\alpha = 0.2$ and $\beta = 0.6$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.741301	0.675748	
	BM+Browns	0.703974	0.641721	
			Cost Mean	0.690686
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.521119	0.414935	
	BM+Browns	0.516337	0.411127	
			Variance Mean	0.46588
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.674211	0.547799	
	BM+Browns	0.690438	0.560984	
			RMSE Mean	0.618358
Total Mean				0.591641

Appendix Table 5: $\alpha = 0.2$ **and** $\beta = 0.6$ **on Performance Measure Computing**

$\alpha = 0.3$ and $\beta = 0.2$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.671202	0.64412	
	BM+Browns	0.722121	0.692985	
			Cost Mean	0.682607
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.575376	0.556307	
	BM+Browns	0.847581	0.819491	
			Variance Mean	0.699689
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.780504	0.758767	
	BM+Browns	0.940781	0.914579	
			RMSE Mean	0.848658
Total Mean				0.743651

Appendix Table 6: $\alpha = 0.3$ **and** $\beta = 0.2$ **on Performance Measure Computing**

$\alpha = 0.3$ and $\beta = 0.3$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.823474	0.726316	
	BM+Browns	0.820162	0.723394	
			Cost Mean	0.773337
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.835988	0.703031	
	BM+Browns	0.923973	0.777023	
			Variance Mean	0.810004
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.938336	0.827556	
	BM+Browns	0.998173	0.880328	
			RMSE Mean	0.911098
Total Mean				0.831479

Appendix Table 7: $\alpha = 0.3$ **and** $\beta = 0.3$ **on Performance Measure Computing**

$\alpha = 0.3$ and $\beta = 0.4$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.708582	0.594674	
	BM+Browns	0.612222	0.513804	
			Cost Mean	0.607321
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.571858	0.422622	
	BM+Browns	0.52174	0.385583	
			Variance Mean	0.47545
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.796246	0.646255	
	BM+Browns	0.830759	0.674266	
			RMSE Mean	0.736881
Total Mean				0.606551

Appendix Table 8: $\alpha = 0.3$ **and** $\beta = 0.4$ **on Performance Measure Computing**

$\alpha = 0.3$ and $\beta = 0.5$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.756208	0.644492	
	BM+Browns	0.654734	0.558009	
			Cost Mean	0.653361
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.592968	0.41078	
	BM+Browns	0.634507	0.439556	
			Variance Mean	0.519453
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.844725	0.658572	
	BM+Browns	0.933032	0.727419	
			RMSE Mean	0.790937
Total Mean				0.654583

Appendix Table 9: $\alpha = 0.3$ **and** $\beta = 0.5$ **on Performance Measure Computing**

$\alpha = 0.3$ and $\beta = 0.6$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.900806	0.734859	
	BM+Browns	0.792131	0.646205	
			Cost Mean	0.7685
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.882297	0.566017	
	BM+Browns	0.761577	0.488572	
			Variance Mean	0.674616
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	1.049139	0.799282	
	BM+Browns	0.993661	0.757016	
			RMSE Mean	0.899775
Total Mean				0.780963

Appendix Table 10: $\alpha = 0.3$ **and** $\beta = 0.6$ **on Performance Measure Computing**

$\alpha = 0.4$ and $\beta = 0.5$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.883126	0.724732	
	BM+Browns	0.744943	0.611333	
			Cost Mean	0.741034
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.897344	0.563562	
	BM+Browns	0.942441	0.591884	
			Variance Mean	0.748808
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	1.005062	0.820849	
	BM+Browns	1.101252	0.899409	
			RMSE Mean	0.956643
Total Mean				0.815495

Appendix Table 11: $\alpha = 0.4$ **and** $\beta = 0.5$ **on Performance Measure Computing**

$\alpha = 0.5$ and $\beta = 0.2$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.688198	0.443757	
	BM+Browns	0.55997	0.361074	
			Cost Mean	0.51325
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.759741	0.351637	
	BM+Browns	0.482099	0.223134	
			Variance Mean	0.454153
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.915302	0.602811	
	BM+Browns	0.754514	0.496917	
			RMSE Mean	0.692386
Total Mean				0.553263

Appendix Table 12: $\alpha = 0.5$ **and** $\beta = 0.2$ **on Performance Measure Computing**

$\alpha = 0.6$ and $\beta = 0.2$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.654476	0.513447	
	BM+Browns	0.700893	0.549862	
			Cost Mean	0.604669
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.490553	0.358868	
	BM+Browns	0.662581	0.484716	
			Variance Mean	0.499179
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.736168	0.625307	
	BM+Browns	0.828306	0.703569	
			RMSE Mean	0.723338
Total Mean				0.609062

Appendix Table 13: $\alpha = 0.6$ **and** $\beta = 0.2$ **on Performance Measure Computing**

$\alpha = 0.7$ and $\beta = 0.2$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.8712	0.509771	
	BM+Browns	0.88278	0.516547	
			Cost Mean	0.695075
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.851667	0.3649	
	BM+Browns	0.994543	0.426115	
			Variance Mean	0.659306
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.926418	0.60608	
	BM+Browns	0.99234	0.649208	
			RMSE Mean	0.793511
Total Mean				0.715964

Appendix Table 14: $\alpha = 0.7$ **and** $\beta = 0.2$ **on Performance Measure Computing**

$\alpha = 0.8$ and $\beta = 0.2$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	1.049632	0.493764	
	BM+Browns	0.713831	0.335797	
			Cost Mean	0.648256
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.996199	0.287318	
	BM+Browns	0.539276	0.155535	
			Variance Mean	0.494582
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	1.030418	0.553389	
	BM+Browns	0.752019	0.403874	
			RMSE Mean	0.684925
Total Mean				0.609254

Appendix Table 15: $\alpha = 0.8$ **and** $\beta = 0.2$ **on Performance Measure Computing**

$\alpha = 0.2$ and $\beta = 0.0$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.764981	0.683612	
	BM+Browns	0.759818	0.678999	
			Cost Mean	0.721852
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.532971	0.439049	
	BM+Browns	0.564956	0.465398	
			Variance Mean	0.500594
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.704021	0.613352	
	BM+Browns	0.74528	0.649298	
			RMSE Mean	0.677988
Total Mean				0.633478

Appendix Table 16: $\alpha = 0.2$ **and** $\beta = 0.0$ **on Performance Measure Computing**

$\alpha = 0.3$ and $\beta = 0.0$ on Performance Measure Computing				
Cost	Models	/BM	/(BM+MA)	
	BM+Holt	0.757589	0.795298	
	BM+Browns	0.758312	0.796056	
			Cost Mean	0.776814
Variance	Models	/BM	/(BM+MA)	
	BM+Holt	0.735548	0.913473	
	BM+Browns	0.799108	0.992408	
			Variance Mean	0.860314
RMSE	Models	/BM	/(BM+MA)	
	BM+Holt	0.842714	0.935155	
	BM+Browns	0.893517	0.99153	
			RMSE Mean	0.915729
Total Mean				0.850892

Appendix Table 17: $\alpha = 0.3$ **and** $\beta = 0.0$ **on Performance Measure Computing**