



YEDİTEPE UNIVERSITY

INSTITUTE OF THE GRADUATE STUDIES IN SCIENCE & ENGINEERING

**IMPACT OF FORECASTING TECHNIQUE AND INVENTORY POLICY
SELECTION ON THE BULLWHIP EFFECT IN SUPPLY CHAINS: A SYSTEMS
DYNAMICS BASED SIMULATION MODEL**

by

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1. INTRODUCTION

In the past few decades the business world has been under some dramatic changes as globalization has combined individual market areas into one, forming a huge global market. Due to this transition, single companies have combined their forces and teamed up to form local and global business networks, which are called supply chains or supply networks. In today's global market, managing the entire supply chain became a key factor for the successful business. World-class organizations now perceived that non-integrated manufacturing processes, non-integrated distribution processes and poor relationships with suppliers and customers are inadequate for their success. They realized that the impact of an organization's plan on the other areas of the supply chain is important for success, and all elements of the supply chain is to be managed as a whole. By using supply chain management, firms gain the ability to produce the right products in the right quantities, at the right place, at the right moment with minimal cost. Although coordination across all members of a supply chain has recently received considerable attention, from both the academics and practitioners, modeling and controlling of the supply chain management (SCM) systems are still problematic today.

Changes in any one of the supply chain components usually creates waves of influences that propagate throughout the supply chain. These influences in the system determines the dynamics of a supply chain. Numerous inefficiencies can also occur such as excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation schedules, and missed production schedules. The main cause of to these problems is defined as the bullwhip effect which is well-known concept in supply chain management. It is an empirically observed phenomenon in which the variability of demand orders in a supply chain is magnified as the orders move up the supply chain. Lee et al. (1997 b) cited the case of Proctor and Gamble for diapers, and Hammond (1994) reported the case of an Italian pasta manufacturer (Barilla Co.) as examples where the demand at the factories was quite variable despite the fact that final demand for their products was consumed at a more or less steady rate.

In order to effectively manage any supply chain, the primary causes of the bullwhip effect must be understood. Different causes are revealed by many researchers in the supply chain management literature until now, and the general agreement given by Lee et al (1997) who identified four major causes of the bullwhip effect: demand signal processing, order batching, price fluctuations, and rationing & shortage gaming. Understanding the causes of the bullwhip effect can help managers or decision makers to find strategies to mitigate it. The various initiatives and possible remedies are proposed to avoid the bullwhip effect are as follows: information sharing, channel alignment and operation efficiency. The idea of business sharing information is introduced by Forrester (1958), is considered to be the best strategy when trying to reduce the bullwhip effect. However, it is impossible to completely eliminate the bullwhip effect from a supply chain (at least, in realistic supply chains).

Because of the complex structure of supply chain networks, understanding and reducing the bullwhip effect is a hard job to manage. The impact of an organization's plan on the whole supply chain is unpredictable before its execution. Simulation permits the evaluation of operating performance prior to the execution of a plan. For this reason, it was decided to develop a simulation model in this study. Simulation provides an effective pragmatic approach to detailed analysis and evaluation of supply chain design and management alternatives to mitigate the bullwhip effect. However, the utility of this methodology is prevented by the time and effort required to develop models with sufficient fidelity to the actual supply chain of interest. Some different simulation modeling techniques can be used for supply chain analysis as spreadsheets simulations, discrete events simulations and systems dynamics approach. Spreadsheets simulations are easy to calculate but they are often too simple and unrealistic. Discrete events simulations models are better at providing a detailed analysis of systems involving linear processes and modeling discrete changes in system behavior. The discrete models are also used when the goal is a statistically estimate of system performance. Systems dynamics methodology is best suited to problems associated with continuous processes where feedback significantly affects the behaviour of a system, and producing dynamic changes in it. In deciding which approach is best suited to model a particular problem, the key questions to be asked are: Which type of model best represents the system under study? What questions

does the decision-maker wish to address? What is the purpose the model will be used. In any supply chain network system, there are many different elements which are related with each other positively or negatively. These structural issues make systems dynamics approach more appropriate for modeling the system under study.

In this thesis, a systems dynamics based simulation model is developed to analyze the impact of forecasting techniques and inventory policy selection on the bullwhip effect under different demand processes. The goal is to follow the dynamic behaviour of placed orders under the several policies for each agent where orders fluctuations arise; this event worsens the performance of entire supply network. The information sharing strategy, named as the centralised case is applied to the model for mitigating the bullwhip effect; the decentralised case means that the end customer demand can only be seen by the downstream agent, but not the upstream agents.

The structure of this thesis is as follows. In Section 2, supply chain management is described and the reasons for the bullwhip effect is explained. This section also includes the review of the relevant literature. In Section 3, systems dynamics modeling approach is presented and the corresponding methodology is given. Here, stock – flow diagrams and systems dynamics modeling software packages are also presented. Furthermore, the modeling applications for supply chain management by using systems dynamics methodology is surveyed. In Section 4, the development steps of systems dynamics based simulation model are introduced. Conceptual modeling and its formulation is done using Powersim software. In Section 5, the simulation model is applied to a sample data for the decentralised and centralised cases. The actual simulation results are presented and the findings on the bullwhip effect are stated. The conclusions and recommendations are given in Section 6 and Section 7, respectively.

2. SUPPLY CHAIN MANAGEMENT AND THE BULLWHIP EFFECT

Supply chain management is nowadays seen as one of the most important areas that should be studied in industrial and systems engineering. The main effort in the supply chain management is dedicated to the interconnection of all subjects in the supply network, and related to the optimization of all flows that exist among these subjects. On the other hand, because of the fact that the firms are used to compete and not to cooperate, it isn't easy to manage the entire supply chain with a way that is acceptable for everyone. Firms do not want to share any information about their products, inventories, costs, and profits. This wrong comprehension in any supply network causes to a lot of pitfalls. The bullwhip effect is the most known trap in supply chain management; the demand is perceived by the upstream stages of supply network is more variable than the real demand of the downstream stages. Therefore, this distorted information from the end customer to the other agents of the supply chain can lead to tremendous inefficiencies as excessive inventory investments, poor customer service levels, lost revenues, misguided capacity plans, ineffective transportation and missed production schedules in the supply network.

Recently, the interest in the exploration and measurement of the bullwhip effect is grown. For achieving this purpose, first of all, it is obvious that the structure of the supply chain management philosophy should be clearly comprehended, and then the defined causes of the bullwhip effects and the suggested remedies in the literature should be openly scrutinized.

2.1 THE STRUCTURE OF SUPPLY CHAIN MANAGEMENT

Supply chain management is a set of approaches utilized to efficiently integrate suppliers, manufacturers, warehouses or distributors, and retailers as a one company, so that merchandise is produced and distributed at the right quantities, to the right locations, at the right time, in order to minimize systemwide costs while satisfying service level requirements. (D. Simchi Levi, P. Kaminsky, 2000)

This definition leads to several observations. First of all, the supply chain management takes into consideration for every facility that has an impact on cost, and plays a role in making the product conform to customer requirements; from the supplier and manufacturing facilities through warehouses and distribution centers to retailers and stores. Indeed, in some supply chain analysis, it is necessary to account for the suppliers' suppliers and customers' customers because they have an impact on supply chain performance. Secondly, the objective of the supply chain management is to be efficient and cost-effective across the entire system; total systemwide costs, from transportation and distribution to inventories of raw materials, work in process and finished goods, are to be minimized. Thus, the emphasis is not on simply minimizing transportation costs or reducing inventories, but rather, on taking a systems approach to supply chain management. Finally, because the supply chain management revolves around the efficient integration of suppliers, manufacturers, warehouses, and retailers, it encompasses the firm's activities at many level, from the strategic level through the tactical to the operational level.

A typical supply chain is depicted in Figure 2.1, which is a network of suppliers, manufacturers, distributors or warehouses, retailers, and customers. The demand information flows from downstream to the suppliers and products flow from upstream to the end customers. On the other hand, cash flows can occur in the both directions.

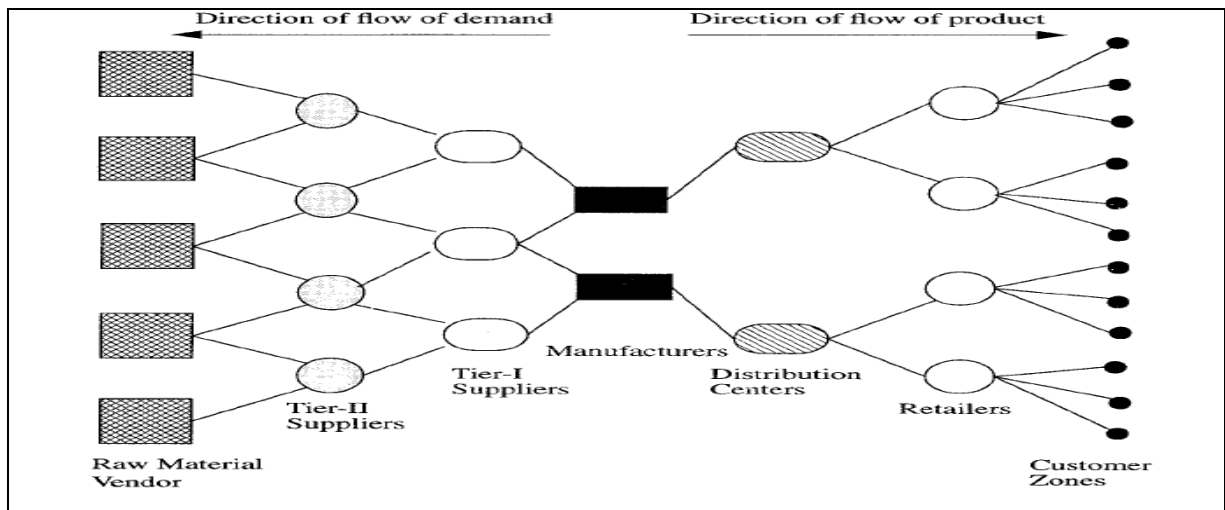


Figure 2.1 A supply chain network (Source: Swaminathan, Smith, and Sadeh, 1998)

2.1.1 A Historical Perspective for Supply Chain Management

In order to understand the significance of the changes taking place in supply chain initiatives, it would be prudent to review historical aspects of production and operations management activities (Bruce, 1997; Poirier and Reiter, 1996).

In the 1950s and 1960s, most of the manufacturers emphasized the mass production to minimize unit production cost as the primary operations strategy, with little product or process flexibility. New product development was slow and relied exclusively on in-house technology and capacity. Bottleneck operations were cushioned with inventory to maintain a balanced line flow resulting in huge investment in work in process (WIP) inventory. Sharing technology and expertise customers or suppliers was considered too risky, and unacceptable. Little emphasis is appeared to have been placed on cooperative and strategic buyer-supplier partnership. The purchasing function was generally regarded as being a service to production and managers paid limited attention to issues concerned with purchasing (Farmer, 1997).

During the period from 1960 to 1975, corporations had vertical organization structures and optimization of activities was focused on functions. Materials Resource Planning was introduced and managers realized the impact of huge WIP on manufacturing cost, quality, and new product development and delivery lead-time. Manufacturers resorted to new materials management concepts to improve performance within the four walls' of the company.

In the time frame from 1975 to 1990, corporations were still vertically aligned but several were involved in process mapping and analysis to evaluate their operations. There was a realization by organizations of the benefit of integration of functions such as product design and manufacturing. Various quality initiatives such as the TQM (total quality management) philosophies of Deming, Juran, and Crosby and ISO standards for quality measurement were initiated by many organizations. Manufacturing systems were focused on MRPII (Manufacturing Resource Planning) .

Starting in 1990, corporations all over the world have been experiencing increasing national and international competition. Strategic alliances among organizations have been growing. Organization structures were starting to align with processes. Manufacturing systems in organizations have been enhanced with information technology tools such as enterprise resource planning, distribution requirements planning, electronic commerce, product data management, collaborative engineering, etc. (Aberdeen, 1996). Design for disassembly, synchronous manufacturing, and agile manufacturing were some of the new paradigms in manufacturing. There has been a growing appreciation in many firms of total cost focus for a product from its source to consumption, as opposed to extracting lowest price from immediate vendors (Turbide, 1997). There has also been an increased reliance on purchased materials and outside processing with a simultaneous reduction in the number of suppliers and greater sharing of information between vendors and customers. A noticeable shift has taken place in the marketplace from mass production to customized products. This has resulted in the emphasis on greater organizational and process flexibility and co-

ordination of processes across many sites. More and more organizations were promoting the employee empowerment and the need for rule based, real time decision support systems to attain organizational and process flexibility, as well as to respond to competitive pressure to introduce new products more quickly, cheaply and with improved quality.

The underlying philosophy of managing the supply chains is evolved to respond to these changing business trends. The supply chain management phenomenon is received the attention of researchers and practitioners in various topics. In the earlier years, the emphasis was on material planning, utilizing materials requirements planning techniques, inventory logistics management with one warehouse multi-retailer distribution system, and push and pull operation techniques for production systems. In the last few years, however, there is a renewed interest in designing and implementing integrated systems, such as enterprise resource planning, multi-echelon inventory, and synchronous-flow manufacturing, respectively. A number of factors are contributed to this shift. First, there is a realization that better planning and management of complex interrelated systems, such as materials planning, inventory management, capacity planning, logistics, and production systems lead to overall improvement in enterprise productivity. Second, advances in information and communication technologies are complemented by sophisticated decision support systems enable designing, implementing and controlling strategic and tactical strategies essential to delivery of integrated systems. The availability of such systems has potential of fundamentally influencing enterprise integration issues.

As a result of these changes and developments, now, managers find that it is no longer enough to manage their organizations. They must also be involved in the management of the network of all upstream firms that provide inputs (directly or indirectly), as well as the network of downstream firms responsible for delivery and after-market service of the product to the end customer.

2.1.2 Key Issues for Effective Supply Chain Management

The primary purpose in establishing the supply chains is to minimize the flow of raw materials and finished products at every point in the pipeline in order to enhance productivity and cost saving (Cohen, 1996; Cooper and Ellram, 1993). The effective supply chain management can be reached by following the some critical key issues for individual business unit and the entire supply chain. These key issues are mentioned below.

2.1.2.1 Managing the Inventory Investment in the Chain

Each constituent of the supply chain desires to hold no more than its fair share of inventory. For instance, the distributor desires fewer inventories and would like to see inventory held by the manufacturer. As a result, the concept of vendor – managed inventory becomes a trend in the inventory management. This system allows the inventory to be pushed back to the vendor and as a result lowers the investment and risk for the other chain members (Donovan 1997; Mayer,1996).

As product life cycles are shortening, lower inventory investment in the chain has become important. Cycle times are being reduced as a result of the quick response inventory system. The quick response inventory system improves customer service because the customer gets the right amount of product, when and where it is needed (May, 1994).

2.1.2.2 Establishing the Supplier Relationship

It is important to establish strategic partnerships with suppliers for a successful supply chain. Corporations have started to limit the number of suppliers they do business with by implementing vendor review programs. These programs strive to find suppliers with operational excellence, so the customer can determine which supplier is serving it better. The ability to have a closer customer/supplier relationship is very important because these suppliers are easier to work with. With the evolution toward a sole supplier relationship, firms need full disclosure of information such as financial performance, gain sharing strategies, and plans for jointly designed works. They may establish a comparable culture and also implement compatible forecasting and information technology systems. This is because, their suppliers

must be able to link electronically into the customer's system to obtain shipping details, production schedules, and any other needed information (Copacino, 1996; Coyle et al., 1996; Keller, 1995).

2.1.2.3 Increasing the Customer Responsiveness

To remain competitive, firms focus on the improved supply chain efforts to enhance customer service through increased frequency of reliable product deliveries. Increasing demands on customer service levels are driving partnership between customers and suppliers. The ability to serve their customers with higher levels of quality service, including speedier delivery of products, is vital to partnering efforts. Having a successful relationship with a supplier results in trust and the ability to be customer driven, customer intimate and customer focused (Willis, 1995).

2.1.2.4 Building a Competitive Advantage for the Channel

Achieving and maintaining the competitive advantage in an industry is not easy undertaking for a firm. Many competitive pressures force a firm to remain efficient. Supply chain management is seen by some as a competitive advantage for firms that employ the resources to implement the process. It also serves to increase the clout in the channel because these firms are recognized as leading edge and are treated with respect. Attaining competitive advantage in the channel comes with top management support for decreased costs, waste management, and enhanced profits. Many firms want to push costs back to their supplier and take labor costs out of system. These cost reducing tactics tend to increase the competitive efficiency of the entire supply chain. Firms have become more market channel focused. They are observing how the entire channel's activities affect the system operation. In recent times, the channel power has shifted to the retailer. Retailer channel power in the distribution channel is driven by the shift to some large retail firms, such as Wal-Mart, Kmart, and Target. The large size of these retailers allows them the power to dictate exactly how they want their suppliers to do business with them. The use of point of sales data and increased efficiency of distribution also have been instrumental in improving channel power and competitive advantages (Magretta, 1998; Robinson, 1998; Ross, 1996).

2.1.2.5 Enabling Information Technologies

Information is vital to effectively operating the supply chain. The communication capability of an enterprise is enhanced by an information technology systems. However, information system compatibility among trading partners can limit the capability to exchange information. An improved information technology system that is user friendly, where partners in the channel have access to common databases that are updated in real-time, is needed. By using an effective information sharing technology, all agents in the chain can have a chance to reduce their material or information delays.



2.2 BULLWHIP EFFECT IN SUPPLY CHAINS

The bullwhip effect is the inherent variation of the demand that increases up in the supply chain from the customer to the supplier which is also one of the main reasons for inefficiencies in supply chains. It can be more clearly defined by considering a sample supply chain that is consisted of an OEM (original equipment manufacturer) and a 1st, 2nd and 3rd tier suppliers where the OEM faces the lowest and the 3rd tier supplier faces the largest variation of demand (as seen in the Figure 2.2), if bullwhip effect exists.

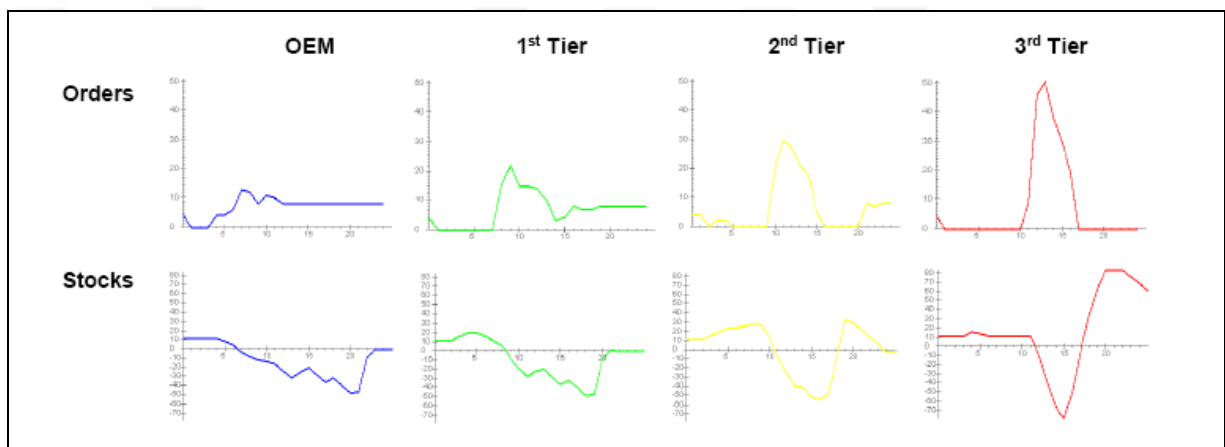


Figure 2.2 The bullwhip effect: Increasing demand variation in a supply chain (Source : Joerg Nienhaus, 2002)

Jay Forrester (1958) is among the first researchers to describe this phenomenon, who did not coin the term bullwhip, but used industrial dynamic approach to demonstrate the amplification in the demand variation. At that time, Forrester (1958) referred to this phenomenon as “Demand Amplification”. Forrester's work inspired to many researchers to quantify the bullwhip effect, to identify possible causes and consequences for it, and to suggest various countermeasures for taming or reducing it.

Procter and Gamble (P&G) first coined the phrase “bullwhip effect” to describe the ordering behaviour witnessed between the customers and the suppliers of one of their best-selling products which is Pampers disposal diapers. The logistics executives at Procter and Gamble (P&G) are examined that the order patterns for Pampers diapers where they noticed an

interesting situation. As expected, the retail sales of the product were fairly uniform; there is no particular day or month in which the demand is significantly higher or lower than any other. However, the executives noticed that the distributors' orders placed to factory fluctuated much more than the retail sales. In addition, P&G's orders to its suppliers, such as 3M, fluctuated even more. P&G called this phenomenon the "bullwhip effect" (in some industries, it known as the "whiplash" or the "whipsaw" effect). Another firm Hewlett-Packard (HP) is also faced with bullwhip effect too. HP's executives are examined the sales of one of its printers at major reseller, they found that there were, as expected, some fluctuations over time. However, when they examined the orders from the reseller, they observed much bigger swings. Also, to their surprise, they discovered that the orders from the printer division to the company's integrated circuit division had even greater fluctuation. Both of these two companies' situation is pictured in Figure 2.3.

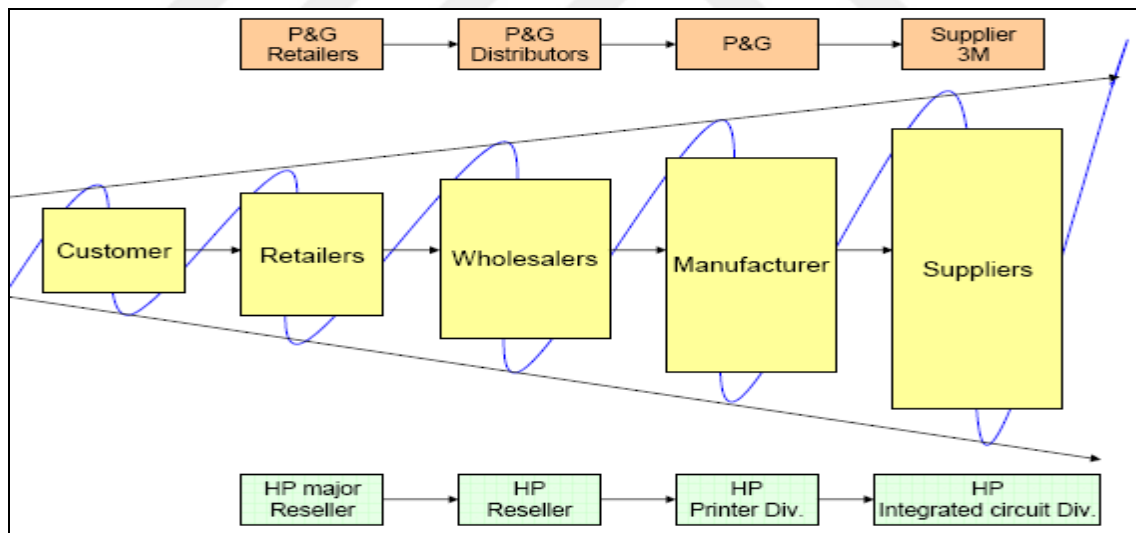


Figure 2.3 Increasing variability of orders for P&G and HP firms. (Source: MIT Lectures, 2006)

Furthermore, the bullwhip effect is also met into the many industries' supply chains by researchers as Holt, Modigliani and Shelton (1968) reported that the bullwhip effect in the TV-set industry, Hammond (1994) identified it in a pasta supply chain (Barilla Co.), and Lee, Padmanabhan and Whang (1997 b) observed it in a soup supply chain. Anderson, Fine and Parker (2000) attributed the substantial volatility in the machine tool industry to the bullwhip effect and Terwiesch, Ren, Ho and Cohen (2005) noted that the semiconductor equipment industry is more volatile than the personal computer industry. The main research about the bullwhip effect is found in the literature is classified into three broad classes as formal studies, empirical studies, and simulation-based studies.

2.2.1 Formal Studies on the Bullwhip Effect

Mathematical tools from different fields have been used in the formal studies for bullwhip effect researches. As mentioned above, firstly Forrester introduced the bullwhip effect in the field of System Dynamics in 1958, and other studies of this effect were next carried out in this field (Angerhofer and Angelides, 1999, Min and Bjornsson, 2000). Formal studies for bullwhip effect are started with focusing on inventory management which is the main field concerned with this effect, since it is strongly related with order placement. In particular, Lee and his colleagues (Lee et al., 1997b) proposed a formal description of the four main causes of the bullwhip effect as follows; (1) Demand signal processing, (2) Order batching, (3) Price fluctuation, (4) Rationing and shortage gaming.

In the same way, Simchi-Levi and his colleagues (Chen et al., 2000, Simchi-Levi et al., 2000) studied the first of those four causes (demand signal processing or in other words demand forecast updating) further by focusing on the impact of lead times and moving average forecasting and on how the bullwhip effect is reduced with information centralisation. In the same structure, Kelle and Milne (Kelle and Milne, 1999) wrote a work similar to Simchi-Levi and his colleagues' with the (s; S) ordering policy.

Economists (Kahn, 1987, Naish, 1994, Shen, 2001) have also studied how local optimizations done by companies without taking into account the rest of the supply chain cause the bullwhip effect. The difference with the previous approach is the fact that optimization is explicitly taken into account in economics models, while it disappears in classic inventory management models of the bullwhip effect.

Traffic Flow Theory was translated into supply chain management vocabulary by Daganzo (Daganzo, 2003) in order to study how ordering policies can stabilize flows in the supply chain. More precisely, this author represents the history of flow at each company with curves of cumulative count, i.e., the greater a flow is, the greater the gradient of the curve representing this flow is. With this representation of flows, he gave properties that the ordering policies ruling the order streams should have in order to avoid the bullwhip effect, and shows that all currently used policies lead to the bullwhip effect. In a similar approach to traffic flow theory, Dejonckheere, Disney, Lambrecht and Towill (Dejonckheere et al., 2002) have also focused on stabilizing streams in the supply chain, except that they used another formalism called Control Theory to verify the impact of exponential smoothing algorithms for forecasting in a similar way than the mentioned Simchi-Levi and his colleagues' (Chen et al., 2000, Simchi-Levi et al., 2000) and Kelle and Milne's (Kelle and Milne, 1999).

Finally, Zhang (Zhang, X., 2004) considered the impact of forecasting methods on the bullwhip effect for a simple replenishment system in which a first-order autoregressive process describes the customer demand and an order-up-to inventory policy characterizes the replenishment decision. A bullwhip effect measure is derived for the optimal forecasting procedure that minimizes the mean-squared forecasting error for the specified demand process. Similar measures are obtained for the moving average and exponential smoothing methods.

2.2.2 Empirical Studies on the Bullwhip Effect

Instead of focusing on mathematical representations of the bullwhip effect, many researchers have studied the bullwhip effect in an empirical way. For example, Lee and his colleagues (Lee et al., 1997a) gave a non-formal description of their paper (Lee et al., 1997b), in which the main five causes of the bullwhip effect are described. Similarly, Wilding (Wilding, 1998) explained in general terms that uncertainty in the supply chain is generated by three interacting sources: the bullwhip effect, deterministic chaos (chaos appears when the system is deterministic, i.e., chaos appears in the system when there is a definite rule with no random terms governing the dynamics of this system), and parallel interactions (interactions between companies in the same echelon may appear: a retailer has an influence not only on its suppliers, but also on other retailers). In a more practical way, Fransoo and Wouters (Fransoo and Wouters, 2000) proposed a method for the measurement of the bullwhip effect. In the same way, the LEAP (LEAn Processing) project (Hines and Holweg, 2000, Taylor, 1999) has focused on the bullwhip effect in three echelons of the automotive component supply chain in the U.K.

2.2.3 Simulation-based Studies on the Bullwhip Effect

Besides formal models and empirical approaches, simulation is increasingly seen as an efficient tool in supply chain management (Geoffrion and Krishnan, 2003, National Science Foundation). Undoubtedly, the most important contribution was proved by Forrester (1958) to understanding the bullwhip phenomenon with a simulation-based model. His contribution was based on his extensive knowledge of early computer systems, and supplemented by his understanding of differential equations, he was able to simulate the bullwhip effect on various models and suggest ways of reducing it. The resultant waveform propagation curves then yield “rich pictures” of likely system behaviour (van Aken, 1978). Forrester’s work is additionally outstanding for two other contributions. He developed DYNAMO, one of the early simulation languages specifically developed for modelling complex dynamic systems. The second, and arguably even more important step, was the use of influence diagrams to describe real-world enterprises in an explanatory and communicative manner. This is an ever extending field of investigation as more and more businesses and indeed socio-economic systems are modelled

in this way. By following Forrester, the Beer Game is developed by Sterman in 1989. The bullwhip effect has also been studied using the Beer Game, that can be defined as a simulation of a supply chain (composed of a retailer-a distributor-a warehouse-a beer factory) used to teach the bullwhip effect and it is by far the most popular simulation and the most widely used game in many business schools, supply chain electives and executive seminars. Simchi-Levi et al. (1998) developed a computerized version of the beer game, and several versions of the beer game are nowadays available, ranging from manual to computerized and even web-based versions (e.g. Machuca and Barajas 1997, Chen and Samroengraja 2000, Jacobs 2000). By Beer Game simulation, some researchers (Croson and Donohue, 2002, Sterman, 1989) have looked for the managers' cognitive limitations that cause this effect of demand variability. In fact, although there are mathematical tools to manage inventories, some people still use their intuition when placing orders in real supply chains. The problem lies in the fact that people have some difficulties understanding the dynamics of a supply chain, because there are complex feedback loops, time delays and past orders to consider together.

In the context of the bullwhip effect, Yung and Yang (Yung and Yang, 1999) represented each company as an Agent (i.e., as an autonomous, reactive and proactive software that can interact with other agents (Wooldridge, 2002)) that minimizes its costs subject to some constraints. Since these agents work in parallel, the optimization of the supply chain is done concurrently. In a similar approach based on agents, Carlsson and Fuller (Carlsson and Fuller, 2000) used Fuzzy Logic to estimate demand for the upcoming period. Like Chen and his colleagues (Chen et al., 2000) (mentioned above as a work in inventory management) but with the Agent paradigm, Yan (Yan, 2001) has studied the impact of lead-time distribution on the bullwhip effect.

Besides that, Kimbrough and his colleagues (Kimbrough et al., 2001) have gathered software Agents and the Beer Game by replacing human players by agents in order to find the best ordering scheme with a genetic algorithm. Next, some modifications have been proposed to the Beer Game: Chen and Samroengraja (Chen and Samroengraja, 2000) changed some parameters, Fjeld and Haartveit (Fjeld, 2001, Haartveit and Fjeld, 2002) adapted it to the

North European forest industry to study how the structure of the game can result in a mismatch between supply and demand, and FOR@C's researchers (FOR@C, 2003) at Universite Laval (Quebec, Canada), adapted this latter game in order to take Quebec forest industry specificities into account. This last game is called the Quebec Wood Supply Game (QWSG). FOR@C's researchers used the multi-agent paradigm to simulate this game (Moyaux et al., 2003a), and made it more realistic in (Moyaux et al., 2004). In particular, information sharing is studied as a decentralized coordination technique in (Moyaux et al., 2003b).

Chandra and Grabis (Chandra, C. and Grabis, J., 2005) suggested that the bullwhip effect, or increasing variability of inventory replenishment orders as one moves up a supply chain, illustrated inventory management inefficiencies. They quantified the bullwhip effect in the case of serially correlated external demand, if autoregressive models are applied to obtain multiple steps demand forecasts. A materials requirements planning (MRP) based inventory management approach is proposed to reduce the order variance. Simulation modeling is used to investigate the impact of the forecasting method selection on the bullwhip effect and inventory performance for the most downstream supply chain unit. The MRP based approach is shown to reduce magnitude of the bullwhip effect while providing the inventory performance comparable to that of a traditional order-up approach. The application of autoregressive models compares favorably to other forecasting methods considered according to both the bullwhip effect and inventory performance criteria.

Finally, Gündüz and Barlas (Y.Barlas, B.Gündüz, 2003) explained the supply chain inventories that are prone to fluctuations and instability. They found that small variations in end item demand create oscillations that amplify throughout the chain. In their paper they tried to understand the underlying structure that generates bullwhip effect, and explored the effectiveness information sharing to eliminate this type of behaviour, by using dynamic system simulation.

By following the literature survey, it is obvious that the bullwhip effect leads to disabilities in supply chains, since it increases the cost for logistics and reduces its competitive ability. But particularly, it negatively affects a supply chain in three respects:

- Dimensioning of capacities: A variation in demand causes variation in the usage of capacities. Here companies face a dilemma: If they dimension their capacities according to the average demand, they regularly have delivery difficulties in case of demand peaks. Adjusting their capacities to the maximum demand leads to poorly uses resources.
- Variation in inventory level: The varying demand leads to variation in inventory levels at each tier of the supply chain. If a company delivers more than the next tier passes on, the inventory level increases. Vice versa, the inventory is reduced in case a company delivers less than the next tier passes on. A high level of inventory causes costs for capital employed while a low level of inventory puts the delivery reliability at risk.
- High level of safety stock: The safety stock that is required to assure a sufficient service level increases with the variation of demand. Thus the stronger the bullwhip effect is in a supply chain, the higher is the safety stock required.

Hence, an important issue for supply chains is to cope with the bullwhip effect. For that purpose, the main factors contributing to the increase in variability in supply chain need to be identified and then remedies should be improved to avoid it.

2.3 CAUSES OF BULLWHIP EFFECT

In order to effectively manage the bullwhip effect, the primary causes of the bullwhip effect must be understood. A lot of contributors are discovered for fluctuations in the supply chain management but, the four main causes of the bullwhip effect are identified, and analytical proofs are constructed to show why these four causes contributed to the bullwhip effect by Lee, Padmanabhan, and Whang (1997) and is compromised. These four major causes of the bullwhip effect are demand signal processing, order batching, price fluctuations, and rationing & shortage gaming. In addition to them, misperception of feedback, local optimization without global vision, company processes, and lead times are other important causes of the bullwhip effect.

2.3.1 Demand Signal Processing

Every company in a supply chain usually makes product forecasting for its production scheduling, capacity planning, inventory control, and order requirements. Forecasting is often based on the orders history from the company's immediate customers. It means that the downstream agent in the supply chain does not know the exact form of the customer demand process. Instead, it uses historical data and some forecasting techniques to estimate the demand data. Similarly, the upstream manager does not know the downstream's demand data and so it processes the downstream's placed orders as a demand signal and it adjusts his or her demand forecast. Then in turn, the upstream operation places orders to its suppliers that perceives it as a new signal. This demand signal processing is a major contributor to the bullwhip effect. Figure 2.4 shows an example of such fluctuations in demand. As it can be seen from Figure 2.4 , the orders placed by the dealer to the manufacturer have much greater variability than the consumer demands.



Figure 2.4 Higher variability in orders from dealer to manufacturer than actual sales (Source: Lee, Padmanabhan, and Whang, 1997)

2.3.2 Order Batching

In a supply chain, each company places orders from an upstream organization by using some inventory monitoring and processing methods. Companies discretize orders in order to profit from economies of scales, and therefore, place orders for more or less products than what they actually need, is named as the order batching. The impact of the order batching is quite simple to understand. If the downstream uses the order batching, then the upstream will observe a large order, followed by several periods of no orders, followed by another large order, and so on. Thus, the upstream sees a distorted and highly variable pattern of orders which contributes to the bullwhip effect. It is useful to remind that firms use order batching for a number of reasons. First, a firm that is faced with ordering cost, needs to apply an inventory policy which leads to the order batching. Second, as transportation costs become more significant, downstream may order quantities that allow them to take advantage of transportation discounts (e.g., full truckload quantities). This may lead to some weeks with large orders, and some weeks no orders at all. Finally, the quarterly or yearly sales quotas or incentives observed in many business can also result in unusually large orders observed on a periodic basis.

2.3.3 Price Fluctuation

Customers are driven to buy in larger quantities by attractive offers on quantity discounts or price discounts. Every client (company or end-customer) profits from promotions by buying more products than what it really requires, and next, buying nothing when the promotion stops, because it has enough products in inventory. As a result, the customer's buying pattern does not reflect its consumption pattern, and the variation of buying quantities is much bigger than the variation of consumption rate. So, price fluctuation can lead to the bullwhip effect. The downstream often attempt to stock up when prices are lower. This is accentuated by the prevailing practices in many industries of offering promotions and discounts at certain times or for certain quantities. Figure 2.5 displays the structure of the price fluctuations reasons & remedies.

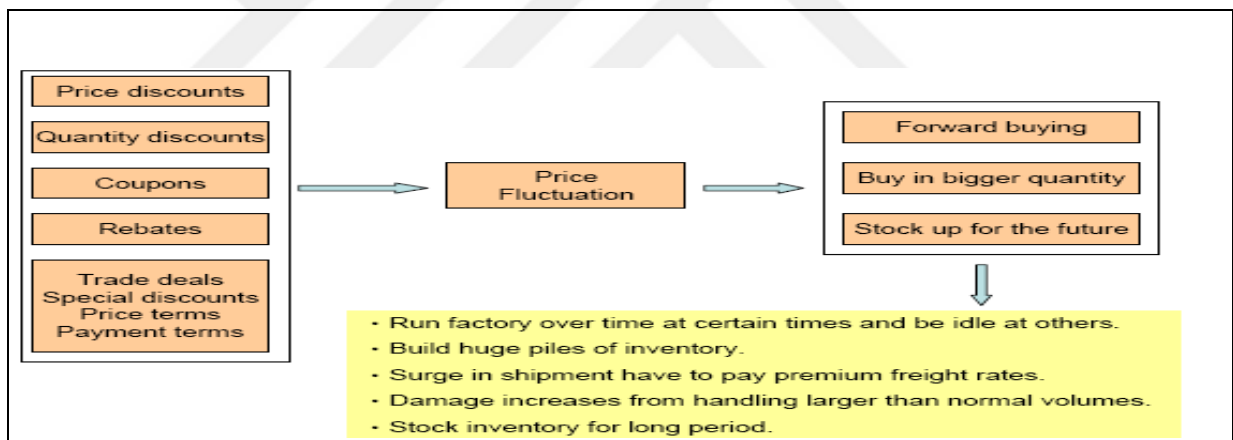


Figure 2.5 Price fluctuations: reasons & remedies (MIT Lectures, 2006)

2.3.4 Rationing and Shortage Gaming

This cause might be similar to the price fluctuation and occurs when the demand exceeds the supply or when the customers think that it may happen. When the product demand is greater than the product supply, an upstream agent often rations its product to the customers. In one scheme, the manufacturer allocates the amount in proportion to the amount ordered. For example, if the total supply is only 50 percent of the total demand, all customers receive 50 percent of what they order. This action is perceived as a shortage by the customers. Knowing

that the manufacturer has ration when the product is in short supply, the customers exaggerate their real needs when they order. After they started to exaggerate their real needs to be sure that the existing demand is satisfied, the demand amplification effect grows up even further if the customers are allowed to cancel their orders when their real demand is fulfilled. Customers place duplicate orders with multiple suppliers and buy from the first one that can deliver, then cancel all other duplicate orders, so this behaviour of the supply chain players causes the bullwhip effect.

More recently, Hewlett-Packard could not meet the demand for its LaserJet III printer and rationed the product. Orders surged, but HP managers could not discern whether the orders genuinely reflected real market demands or were simply phantom orders from resellers trying to get better allocation of the product. When HP lifted its constraints on resupply of the LaserJets, many resellers canceled their orders. HP's costs in excess inventory after the allocation period and in unnecessary capacity increases were in the millions of dollars (Lee, Padmanabhan, and Whang, 1997).

2.3.5 Other Causes

Sterman (Sterman, 1989) is noted that the players in the supply chain place orders in a non-optimal way because they do not understand the whole dynamics in their supply chain. For example, they do not correctly interpret their incoming orders, and in consequence, smooth their orders when they should order more, because they do not understand that market consumption is increased. This cause is named as misperception of feedback.

Several authors (Kahn, 1987, Naish, 1994, Shen, 2001) are noted that companies maximize their own profit without taking into account the effect of their decisions on the rest of the supply chain. For example, some companies use an ordering scheme, such as the (s; S) policy which optimizes only their own inventory. This cause is named as local optimization without global vision.

Taylor and his colleagues (Taylor, 1999) proposes two more causes of the bullwhip effect: the variability in machine reliability and output, and the variability in process capability and subsequent product quality. In these two causes, which are summarized as “Company processes”, production problems at each workstation are amplified from one workstation to another. This cause recalls that intracompany problems and uncertainties may affect each company's behavior, which in turn may make them change the way they place orders.

In addition to these explanations, it is obvious to consider more reasons that can influence each of the causes mentioned above. For instance, lead time increases, any information distortions, and material or information delays during the supply network which triggers the bullwhip effect. Any supply chain can be confronted with bullwhip effect and these fluctuations have several consequences on the entire supply chain. However, the common symptoms of the bullwhip effect can be summarize as:

- Excessive inventory.
- Poor product forecasts.
- Insufficient or excessive capacities.
- Poor customer service due to unavailable products or long backlogs.
- Uncertain production planning.
- High cost of correction.

2.4 COUNTERACTIONS FOR BULLWHIP EFFECT

Understanding the causes of the bullwhip effect can help managers to find strategies to avoid it. Information sharing, channel alignment and operational efficiency are main categories of remedies. With information sharing, the demand information at a downstream site is transmitted to upstream site. Channel alignment is the coordination of pricing, transportation, inventory planning and ownership between the upstream and downstream sites in a supply chain. Operational efficiency refers to activities that improve performance, such as reduced costs and lead time. Table 2.1 summarizes the causes and solutions of the bullwhip effect proposed in the literature, which are explained with details in the following part.

Table 2.1 Causes and Solutions of the bullwhip effect

Causes	Contributing Factors	Proposed Solutions	Authors
Demand forecast updating	* No concept of true demand * Multiple forecasts * Long lead time	Information sharing (e.g., VMI, CRP: :), echelon-based inventory and leadtime reduction	[Lee et al., 1997a, Lee et al., 1997b]
Order batching	* High fixed order costs * Random ordering * Correlated ordering	EDI (Electronic Data Interchange) and Internet Technologies, Synchronized ordering, Reducing lot sizes	[Lee et al., 1997a, Lee et al., 1997b] [Taylor, 1999]
Price fluctuation	* Fluctuation in prices * Promotions * Lot-size quantity discounts	EDLP (Every Day Low Pricing), Volume-based quantity discounts	[Lee et al., 1997a, Lee et al., 1997b]
Rationing and Shortage gaming	* Inflated orders * Free returns policies	Allocation based on past sales, Capacity reservation	[Lee et al., 1997a, Lee et al., 1997b]
Misperception of Feedbacks	* No understanding the supply chain dynamics	Giving a better understanding of the supply chain dynamics to managers	[Daganzo, 2003, Dejonckheere et al., 2002] [Forrester, 1958, Forrester, 1961] [Sternan, 1989]
Local optimization without global vision	* Unefficient management	Global optimization	[Chen et al., 2000, Kahn, 1987] [Naish, 1994, Shen, 2001] [Simchi-Levi et al., 2000]
Company processes	* Variability in machine reliability and output * Variability in process capability	Statistical analysis for machine and process variability	[Taylor, 1999]

By following Table 2.1, it can be seen that the key techniques are highlighted by Lee, Padmanabhan, and Whang (1997) on how to manage the four main causes of the bullwhip effect. In addition to this, some remedies are observed for other causes of the bullwhip effect by several researchers. All of the suggested remedies for each of the defined causes are explained in the next sections.

The first defined cause of the bullwhip effect is the demand forecast updating or the demand signal processing and its remedy is information sharing where each client provides complete information to its supplier to help the supplier to improve its forecasts. Nowadays, many firms can use point of sales (POS) data about their product demand process by using some new technologies such as EDI systems (electronic data interchange). Information sharing is already part of industry practices, such as VMI (Vendor-Managed Inventory), CRP (Continuous Replenishment Program), etc. In addition to this, Figure 2.6 summarizes all of the proposed solution alternatives for the demand forecast updating .

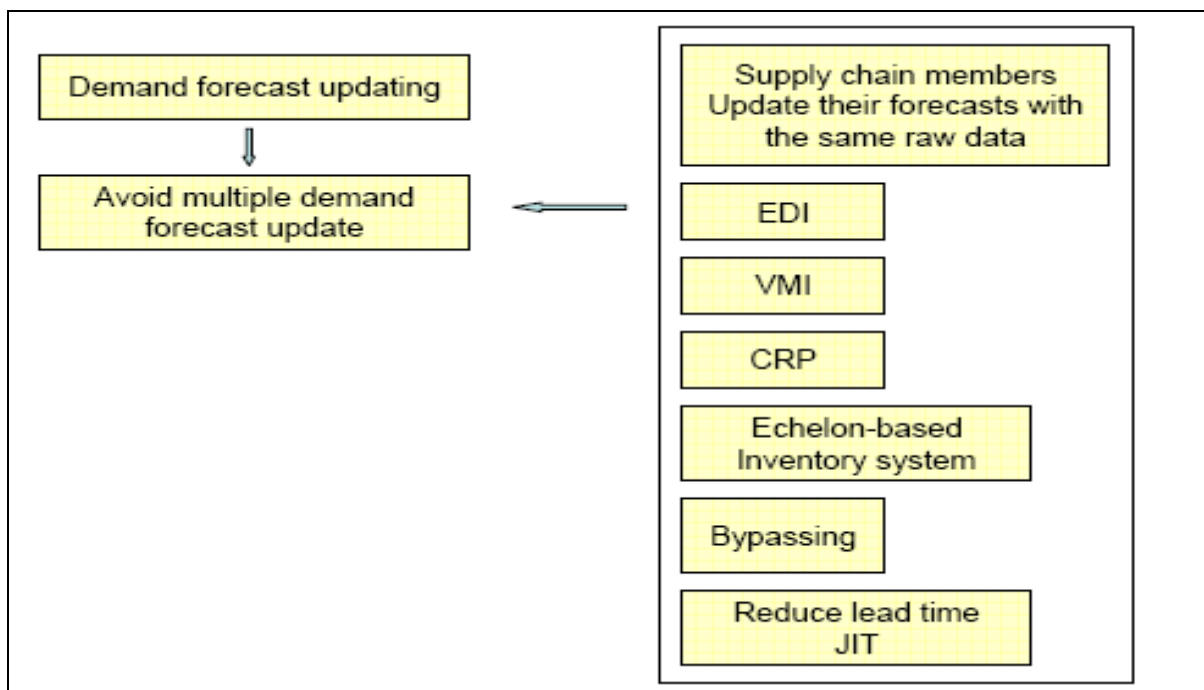


Figure 2.6 Demand forecast updating with remedies (MIT lecture notes, 2006)

“ IBM, HP, and Apple all requires sell-through data as part of their contract with resellers. In the consumer products industry, 20 percent of orders by retailers of consumer products is transmitted via EDI in 1990. In 1992, that figure is close to 40 percent and, in 1995, nearly 60 percent. The increasing use of EDI undoubtedly facilitate the information transmission and sharing among the chain members” (Lee, Padmanabhan, and Whang, 1997).

“ Many companies such as Campbell Soup, M&M/Mars, Nestle, Quaker Oats, Nabisco, P&G, and Scott Paper uses CRP with some or most of their customers. Inventory reductions of up to 25 percent are common in these alliances. P&G uses VMI in its diaper supply chain, starting with its supplier, 3M, and its customer, Wal-Mart. Even in the high-technology sector, companies such as Texas Instruments, HR Mototola, and Apple uses VMI with some of their suppliers and, in some cases, with their customers” (Lee, Padmanabhan, and Whang, 1997).

In addition to this, the solutions are proposed to the second defined cause of the bullwhip effect named as the order batching to decrease the ordering and the transportation costs. The ordering cost decrease can be achieved by using an ordering system as EDI or CAO (computer aided ordering) where the firms can decrease the costs of paperwork in generating an order. In addition to this, to reduce the transportation costs, firms can use order assortments of different products. Hence a truckload may contain different products from the same manufacturer (either a plant warehouse site or a manufacturer's market warehouse) instead of a full load of the same product. The effect is that, for each product, the order frequency is much higher, the frequency of deliveries to the distributors remains unchanged, and the transportation efficiency is preserved. Another remedy for reducing the tranportation cost is consolidation with 3rd party logistics company. By consolidating loads from multiple suppliers located near each other, a company can realize full truckload economies without the batches coming from the same supplier. Regular delivery appointments with customers is another alternative. Figure 2.7 displays all of the proposed solution alternatives for the order batching problems.

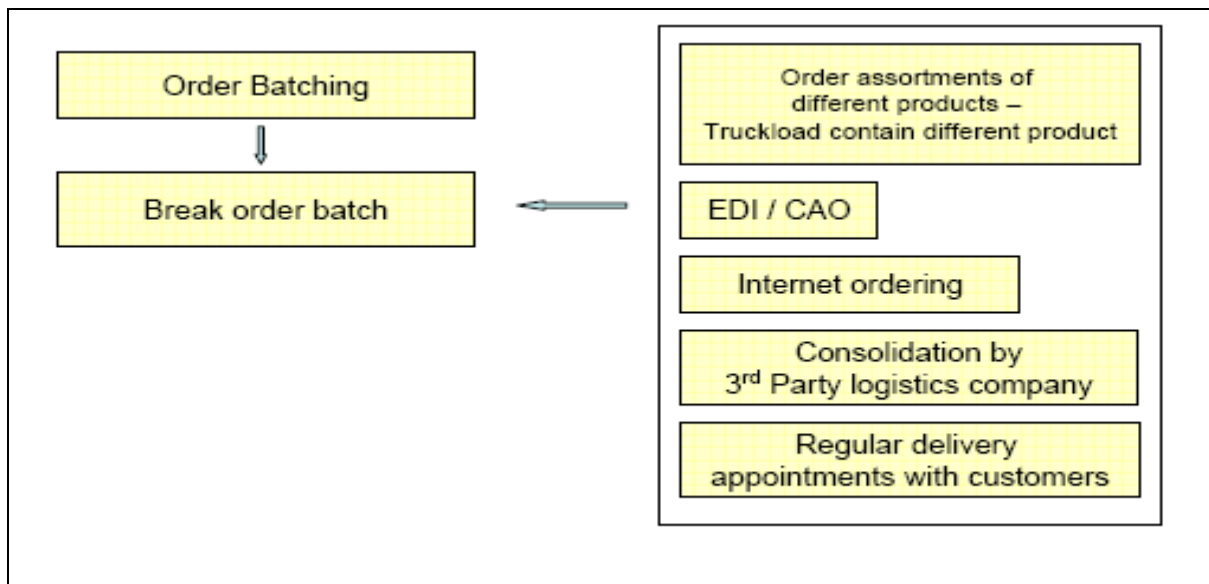


Figure 2.7 Order batching with remedies (MIT lecture notes, 2006)

“ Using EDI, companies such as Nabisco performs paperless, computer-assisted ordering (CAO), and consequently, customers orders more frequently. McKesson's Economost ordering system uses EDI to lower the transaction costs from orders by drugstores and other retailers. P&G is introduced standardized ordering terms across all business units to simplify the process and dramatically cut the number of invoices. And General Electric is electronically matching buyers and suppliers throughout the company. It expects to purchase at least \$1 billion in materials through its internally developed Trading Process Network. A paper purchase order that typically cost \$50 to process is now \$5” (Lee, Padmanabhan, and Whang, 1997).

“ P&G is given discounts to distributors that are willing to order mixed-SKU (stock-keeping unit) loads of any of its products. Manufacturers could also prepare and ship mixed SKUs to the distributors warehouses that are ready to deliver to the stores. British retailers like Tesco and Sainsbury use trucks with separate compartments at different temperatures so that they could transport many products on the same truck. In the United Kingdom, Sainsbury and Tesco are long used the National Freight Company for logistics” (Lee, Padmanabhan, and Whang, 1997).

However, for preventing the price fluctuations in the supply chains which is the third defined cause of the bullwhip effect, some stabilizations is needed to be applied on the prices. The proposed solutions are the uniform wholesale pricing policy, EDLP (Every Day Low Pricing) policy, EDLC (Every day low cost) policy, CRP (continuous replenishment policy), and ABC (activity-based costing) system. Figure 2.8 displays all of the proposed solution alternatives for the price fluctuations problems.

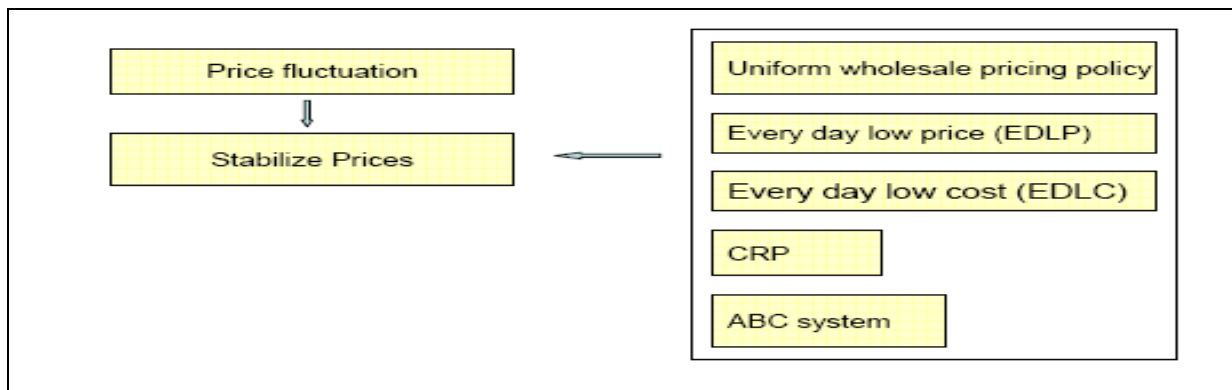


Figure 2.8 Price fluctuations with remedies (MIT lecture notes, 2006)

By establishing uniform wholesale pricing policy, the manufacturer can reduce the incentives for retail forward buying. However, by using the EDLP where price is set at the promotion level and does not change very frequently, firms can avoid from the price fluctuations. But the EDLP also has some drawbacks, e.g., always looking for the lowest price may put a stress on the supply chain that may eventually reduce profits. Similarly, retailers and distributors can aggressively negotiate with their suppliers to give them everyday low cost (EDLC). Practices such as CRP together with a rationalized wholesale pricing policy can help to control retailers' tactics, such as diversion. Activity-based costing (ABC) systems enable companies to recognize the excessive costs of forward buying and diversions.

“ In the grocery industry, major manufacturers such as P&G, Kraft, and Pillsbury move to an everyday low price (EDLP) or value pricing strategy. During the past three years, P&G is reduced its list prices by 12 percent to 24 percent and aggressively slashed the promotions it

offers to trade customers. In 1994, P&G reports its highest profit margins in twentyone years and shows increases in market share” (Lee, Padmanabhan, and Whang, 1997).

Finally, the solutions are proposed to the fourth defined cause of the bullwhip effect (Rationing and shortage gaming) can be defined as allocating the products in proportions to past sale records, offering a penalty cost, sharing of capacity inventory information, and working with customer to place order well in advance of the sales seasons. When supplied products are less than customers’ demand, supplier can allocate its products to customers according to their last orders and it can give the bigger portion to its more important or more faithful customers. In addition to this, supplier can offer a penalty cost against to customer if they cancel their ordered quantity. Without a penalty, retailers will continue to exaggerate their needs and cancel orders. The sharing of capacity and inventory information helps to alleviate customers' anxiety, and consequently, lessen their need to engage in gaming. Figure 2.9 displays all of the proposed solution alternatives to eliminate the rationing and shortage gaming from any supply chain.

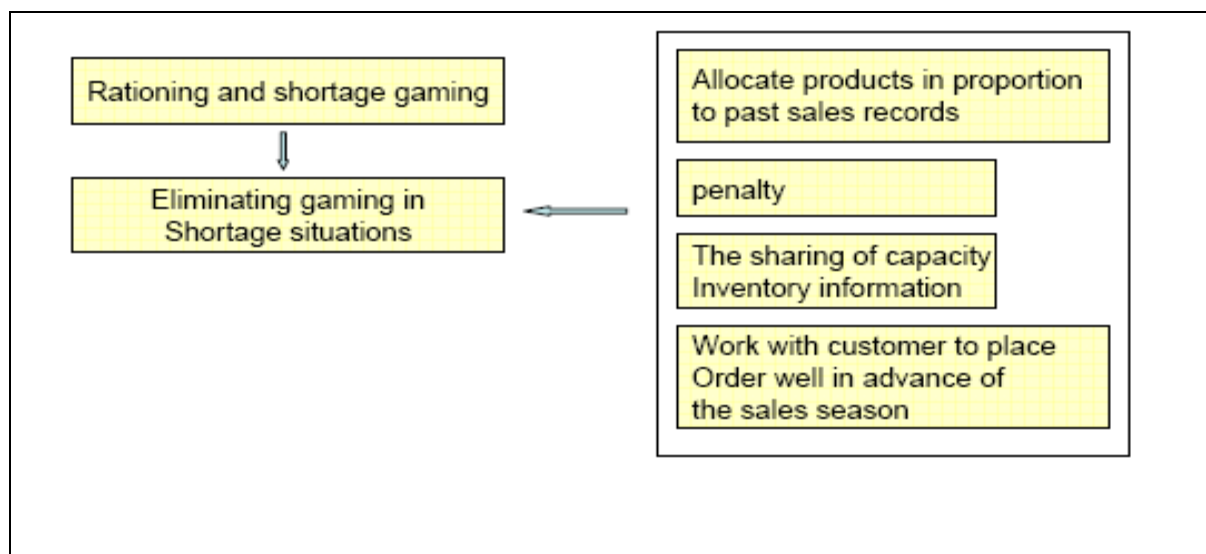


Figure 2.9 Rationing and shortage gaming with remedies (MIT lecture notes, 2006)

All of these remedies are also classified according to the main categories as information sharing, channel alignment and operational efficiency strategies by Lee, Padmanabhan, and Whang (1997) is shown in Figure 2.10.

Causes of Bullwhip	Information Sharing	Channel Alignment	Operational Efficiency
Demand Forecast Update	• Understanding system dynamics • Use point-of-sale (POS) data • Electronic data interchange (EDI) • Internet • Computer-assisted ordering (CAO)	• Vendor-managed inventory (VMI) • Discount for information sharing • Consumer direct	• Lead-time reduction • Echelon-based inventory control
Order Batching	• EDI • Internet ordering	• Discount for truck-load assortment • Delivery appointments • Consolidation • Logistics outsourcing	• Reduction in fixed cost of ordering by EDI or electronic commerce • CAO
Price Fluctuations		• Continuous replenishment program (CRP) • Everyday low cost (EDLC)	• Everyday low price (EDLP) • Activity-based costing (ABC)
Shortage Gaming	• Sharing sales, capacity, and inventory data	• Allocation based on past sales	

Figure 2.10 A Framework for supply chain coordination initiatives (Source: Lee, Padmanabhan, and Whang, 1997)

Some remedies are also proposed for the other defined causes of bullwip effect named as misperception of feedbacks, company process, and, local optimization which are listed, respectively. Giving a better understanding of the supply chain dynamics to managers by using simulation models is one eliminating cure for misperception of feedbacks, and similarly global optimization should be preferred against to local optimization and statistical analysis for machine and process variability can be used for company process.

3. SYSTEMS DYNAMICS MODELING FOR SUPPLY CHAINS

In system theoretical modelling, the models can be either static or dynamic. In the static models, the change on the input has a direct influence on the output, and they do not include any delays or time constants. On the other hand, the dynamic models are used to express and to model the behaviour of the entire system over time. They include the support of the activity diagrams, the state diagrams, the sequence diagrams, and the extensions including business process modeling.

If the systems under consideration are dynamic in nature, the descriptive equations are usually differential ones. In modelling the complex dynamic systems, first of all, the system and its components are defined. Then, the mathematical model is formulated and necessary assumptions are listed. Differential equations describing the model are written and solved for the desired output variables. After that, the solutions and assumptions are examined, reanalysed or redesigned. The transfer function of a system or element represents the relationship that describes the dynamics of the system.

A good example of a dynamic system is the ordinary domestic central heating system. The home owner sets a desired temperature on the thermostat, and the system does the rest by controlling itself as time passes and circumstances change. If the outside temperature falls, the room eventually cools down to the point where the heating is turned on until the house is comfortable again. If the weather is warm, the system turns itself off until the house cools down and heat is required again. Another system which is vastly more complex in operation but comparable in purpose is the automatic pilot on an airliner which is capable of accurately controlling the aircraft to follow a pre-set flight plan over great distances, despite the occurrence of unpredictable forces such as adverse headwinds.

These control systems have several important common features. First of all, all of them recognize or sense the effects of the external environment are produced on the actual state of the system, such as the temperature of the room in response to the outside weather. For this purpose, the control systems compare the actual state with the desired state and they employ

rules or policies for specifying what to do in given circumstances. As the given example, the room perhaps can be 2 degrees cooler than the required temperature, before the heating is turned on and 3 degrees warmer before it is turned off. Furthermore, secondly, all of these control systems always involve delays on their feedback loops. For example, when the house is sensed as having warmed up, the heating goes off. By following these common features, in the early 1960s, it is recognized that these control systems viewpoints could be very powerful if applied to the business firms. As a very simple example, if the demand for any firm's products starts to rise, the firm should quickly recruits more workers to increase production, and almost certainly a delay exists before the new staffs are recruited and trained. However, a significant danger exists as the work force overshoots the level required to meet the apparent increase in demand, and the delays in increasing production may mean that the demand can not be met and will go elsewhere. Even worse, the new staffs have to be paid even before they are productive and the resulting drain on the cash might mean cutting the marketing budget, which may be a very good way of killing off the demand. These and other management problems can be solved by applying the control theory. Because the problems can be so complicated, it is a necessity to have a methodology for dealing with them named as systems dynamics which can be interpreted as the branch of management science which deals with the dynamics and controllability of managed systems.

Systems dynamics methodology is also applied to the supply chain systems which are usually complex and include many cause-effect relationships, and a lot of uncertainties with many changes throughout the supply networks. The next section first gives an overview for the evolution of systems dynamics modeling methodology, and its tools. And then, it presents a taxonomy for the research and developments done in the supply chain management area by using System Dynamics modelling approach.

3.1 SYSTEMS DYNAMICS METHODOLOGY

In a world of growing complexity, many of the most boring problems facing by managers arise from the unanticipated side-effects of their own past actions. In response, organizations struggle to speed learning and adopt a more systemic approach. The challenge is to move past slogans about accelerating learning and “thinking systemically” to practical tools that help managers understand complexity, design better operating policies, and guide effective change. System dynamics is a powerful framework for identifying, designing, and implementing high-leverage interventions for sustained success in complex systems (MIT Lecture Notes, 2006).

Systems Dynamics is a computer-aided approach for analysing and solving complex problems with a focus on the policy analysis and design. The perspective is based on the information feedback and delays to understand the dynamic behaviour of the complex physical, biological and social systems. As mentioned, System Dynamics has its origin in control engineering and management science. It is used for finding out and forecasting the behaviour of the markets, establishing a structural framework for the decision making, challenging the industrial assumptions with applications which cover a very wide spectrum, including national economic problems, supply chains, project management, educational problems, energy systems, sustainable development, politics, psychology, medical sciences, health care, and many other areas. Some diverse industries and organizations are where the Systems Dynamics modeling is successfully applied as Airbus, Compaq, General Motors, Hewlett-Packard, Intel, and Merck (MIT Lecture Notes, 2006). Moreover, the interdisciplinary and systemic approach of Systems Dynamics modeling can be critical in dealing with the increasingly complex problems of our modern world in this new century.

3.1.1 Evolution of Systems Dynamics Approach

The field of Systems Dynamics is developed by Jay W. Forrester (1961) and others at the Massachusetts Institute of Technology in the late 1950s, based on developments following World War II in :

- The theory of information feedback systems
- The understanding decision making processes
- The use of mathematical models to simulate complex systems
- The development of high-speed electronic digital computers as a means of simulating mathematical models. (Maani and Cavana, 2000)

The first application area of the methodology is the strategic management of the industrial problems, and the main output of this research is the publication of Industrial Dynamics. Industrial Dynamics is the seminal book that introduces and illustrates the new methodology in the context of some classical industrial/business problems. The next major project is Urban Dynamics, presenting a dynamic theory of how the construction of housing and businesses determine the growth and stagnation in an urban area. With this application, the “Industrial Dynamics” method is moved to the larger domain of socio-economic problems and is eventually renamed “system dynamics”. The other application in the larger socio-economic domain is World Dynamics (and Limits to Growth). These models show how the population growth and the economic development policies can interact to yield overshoot and collapse dynamics, when crowding and overindustrialization exceed the finite capacity of the environment. In a short period of time since the late 1970s, applications are expanded to a very wide spectrum, including national economic modeling, supply chains, project management, educational problems, energy systems, sustainable development, politics, psychology, medical sciences, health care, and many other areas. In 1983, the International System Dynamics Society is founded. The current membership of the Society is over 1,000. The number of worldwide practitioners is probably much higher than this number.

Forrester (1961) defines Industrial Dynamics as the study of the information feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decision and actions) interact to influence the success of the enterprise. It treats the interactions between the flows of information, money, orders, materials, personnel, and capital equipment in a company, an industry, or a national economy.

Lane (1997) precisely summarises the Forrester's approach for modelling and understanding the management problems as social systems that should be modelled as flow rates and accumulations linked by information feedback loops involving delays and non-linear relationships. Computer simulation is then the means of inferring the time evolutionary dynamics endogenously created by such system structures. The purpose is to learn about their modes of behaviour and to design policies which improve performance.

R.G. Coyle (1996) defines Systems Dynamics as which deals with the time-dependent behaviour of managed systems with the aim of describing the system and understanding through qualitative and quantitative models, how information feedback governs its behaviour, and designing robust information feedback structures and control policies through simulation and optimization.

More recently, Systems Dynamics is explained by Eric Wolstenholme (1998) as a rigorous way to help thinking, visualising, sharing, and communication of the future evolution of complex organisations and issues over time for the purpose of solving problems and creating more robust designs, which minimizes the likelihood of unpleasant surprises and unintended consequences by creating operational maps and simulation models which externalise mental models and capture the interrelationships of physical and behavioural processes, organizational boundaries, policies, information feedback and time delays; and by using this architectures to test the holistic outcomes of alternative plans and ideas within a framework which respects and fosters the needs and values of awareness, openness, responsibility and equality of individuals and teams..

System Dynamics is also applied to a wide range of problem domains by different scientists. It includes work in corporate planning and policy design (Forrester 1961; Lyneis 1980), economic behaviour (Sterman et al. 1983), public management and policy (Homer and St. Clair 1991), biological and medical modelling (Hansen and Bie 1987), energy and the environment (Ford and Lorber 1977), theory development in the natural and social sciences (Dill 1997), dynamic decision making (Sterman 1989), complex non-linear dynamics (Mosekilde et al. 1991), software engineering (Abdel-Hamid 1984), and supply chain management (Towill 1996a; Barlas and Aksogan 1997; Akkermans et al. 1999).

3.1.2 Modeling Steps for Systems Dynamics

Some standard steps are defined for a typical System Dynamics study in the literature. The most general definitions for the classic Systems Dynamics processes are formed by System Dynamics Society is listed below.

- Identify a problem, puzzle, evaluation question, or issue
- Develop a dynamic hypothesis explaining the cause of the problem,
- Build a model of the system at the root of the problem
- Ensure the model reflects the behaviour seen in the real world, or explore similar models that have already been tested.
- Play around with the model to see what insights it gives you about the issue, problem, evaluation question or puzzle.
- Draw conclusions from these insights.

In addition to this, Maani and Cavana (2000) offers a general guideline to the Systems Dynamics approach. It involves five major phases (problem structuring, causal loop modeling, dynamic modeling, scenario planning and modeling, and implementation and organizational learning) and some detailed steps as seen in Table 3.1. However, it must be emphasised that not all of the phases and steps have to be undertaken which is listed. Rather, these phases and steps are presented as guidelines, and which are included in a particular Systems Dynamics

study depends on the issues or problems that are generated the systems enquiry and the degree of effort that the organisation is prepared to commit to the intervention.

Table 3.1 Systems Dynamics Methodology (Source : Maani and Cavana, 2000)

Phases	Steps
1. <i>Problem structuring</i>	1. Identify problems or issues of concern to management 2. Collect preliminary information & data
2. <i>Causal Loop modelling</i>	1. Identify main variables 2. Prepare behaviour over time graphs (reference mode) 3. Develop causal loop diagrams (influence diagrams) 4. Analyse loop behaviour over time 5. Identify system archetypes 6. Identify key leverage points 7. Develop intervention strategies
3. <i>Dynamic modelling</i>	1. Develop a systems map or rich picture 2. Define variable types and construct stock-flow diagrams 3. Collect detailed information and data 4. Develop a simulation model 5. Simulate steady-state / stability conditions 6. Reproduce reference mode behaviour (base case) 7. Validate the model 8. Perform sensitivity analysis 9. Design & analyse policies 10. Develop & test strategies
4. <i>Scenario planning and modelling</i>	1. Plan general scope of scenarios 2. Identify key drivers of change & keynote uncertainties 3. Construct forced & learning scenarios 4. Simulate scenarios with the model 5. Evaluate the robustness of the policies and strategies
5. <i>Implementation and organisational learning</i>	1. Prepare a report and presentation to management 2. Communicate results and insights of proposed intervention to stakeholders 3. Develop a microworld and learning lab based on the simulation model 4. Use learning lab to examine mental models and facilitate learning in the organisation

In the problem structuring phase, the situation or issue at hand is defined and the scope and boundaries of the study are identified. This is the common first step in most problem-solving approaches. The problem structuring phase consists of the following steps:

- (1) Identification of the problem area or policy issues of concern to management. This step requires that we clearly establish the objectives, taking into account multiple stakeholders and perspectives.
- (2) Collection of preliminary information and data including media reports, historical and statistical records, policy documents, previous studies, and stakeholder interviews (Maani and Cavana, 2000).

In the causal loop modelling phase, the conceptual models of the problem, known as causal loop diagrams (CLDs) are created. This is a major component and the most commonly used part of the Systems Dynamics approach. The following steps are used in causal loop modelling phase:

- (1) Identify main (key) variables.
- (2) Draw behaviour over time charts (or reference modes) for the main variables.
- (3) Develop causal loop diagrams (influence diagrams) to illustrate the relationships among the variables.
- (4) Discuss behaviour over time of the dynamics implied by the causal loop diagrams.
- (5) Identify system archetypes that would describe high-level causal patterns.
- (6) Identify key leverage points.
- (7) Develop intervention strategies (Maani and Cavana, 2000).

In the dynamic modelling phase, the dynamic relations between the system variables and the feedback loops are defined and pictured. After then, all relations are formulated with mathematical equations where commonly a Systems Dynamics simulation tools are used in this phase. Although it is possible to go into this phase directly after problem structuring, performing the causal loop modelling phase first enhance the conceptual rigour and learning

power of the systems approach. The completeness and wider insights of Systems Dynamics is generally absent from the other simulation modelling approaches, where causal loop modelling does not play a part. The following steps are generally followed in the dynamic modeling phase:

- (1) Develop a high-level map or systems diagram showing the main sectors of a potential simulation model, or a 'rich picture' of the main variables and issues involved in the system of interest.
- (2) Define variable types (e.g. stocks, flows, converters, etc.) and construct stock flow diagrams for different sectors of the model.
- (3) Collect detailed, relevant data including media reports, historical and statistical records, policy documents, previous studies, and stakeholder interviews.
- (4) Construct a computer simulation model based on the causal loop diagrams or stockflow diagrams. Identify the initial values for the stocks (levels), parameter values for the relationships, and the structural relationships between the variables using constants, graphical relationships and mathematical functions where appropriate. This stage involves using specialised computer packages like STELLA, ithink, POWERSIM, DYNAMO, DYSMAP, COSMIC or VENSIM.
- (5) Simulate the model over time. Select the initial value for the beginning of the simulation run, specify the unit of time for the simulation (e.g. hour, day, week, month, year, etc.). Select the simulation interval (DT) (e.g. 0.25, 0.5, 1.0) and the time horizon for the simulation run (i.e. the length of the simulation). Simulate model stability by generating steady state conditions.
- (6) Produce graphical and tabular output for the base case of the model. This can be produced using any of the computer packages mentioned above. Compare model behaviour with historical trends or hypothesised reference modes (behaviour over time charts).
- (7) Verify model equations, parameters and boundaries, and validate the model's behaviour over time. Carefully inspect the graphical and tabular output generated by the model.
- (8) Perform sensitivity tests to gauge the sensitivity of model parameters and initial values. Identify areas of greatest improvement (key leverage points) in the system.

(9) Design and test policies with the model, to address the issues of concern to management and to look for system improvement.

(10) Develop and test strategies (i.e. combinations of functional policies, for example operations, marketing, finance, human resources, etc.) (Maani and Cavana, 2000).

In the scenario planning and modelling phase, various policies and strategies are postulated and tested. Here 'policy' refers to changes to a single internal variable such as hiring, quality, or price. Strategy is the combination of a set of policies and as such deals with internal or controllable changes. When these strategies are tested under varying external conditions, this is referred to as scenario modelling. Scenario planning and modelling phase's steps are listed below.

(1) Develop general scope, time frame and boundaries of external environment for scenarios. Prepare stories of possible futures or theme scenarios.

(2) Identify key drivers of change, uncertainties and factors that could have a significant impact on the decisions, policies and strategies being evaluated. Determine ranges for external parameters and graphs.

(3) Construct forced scenarios by placing all the positive outcomes in an optimistic scenario and all the negative scenarios in a pessimistic scenario. Check the forced scenarios for internal consistency. Modify these scenarios as learning scenarios (based on Schoemaker, 1995).

(4) Simulate the scenarios (either the individual scenarios varying the key uncertainties or the learning scenarios) with the model. Redesign scenarios if necessary.

(5) Evaluate the performance of the policies and strategies with the model for each scenario. Assess the performance against a range of relevant performance measures for overall robustness. Select the policies or strategies that meet management's objectives for the investigation (Maani and Cavana, 2000).

One of the most beneficial and enduring outcomes of Systems Dynamics is implementation and organisational learning. Once the simulation models are developed, they can be enhanced by extending them into a microworld. Microworlds (also known as management flight simulators) provide an interactive and user-friendly interface for managers to experiment with

the model. The learning laboratory uses microworlds in a structured process, similar to a scientific environment, to test hypotheses and mental models designed to create individual and group learning. The following steps summarise this phase:

- (1) Prepare a report and presentation to the management team and other stakeholders. This should document the background and development of the systems thinking project, the challenges faced and lessons learned.
- (2) Communicate results and insights of the study and the reasons for the proposed intervention to all stakeholders.
- (3) Develop a microworld and design a learning lab for the simulation model. This involves adding necessary features (i.e. from computer software) to convert the simulation model into an interactive and user-friendly microworld. Then design a learning lab process for the microworld.
- (4) Use the learning lab process to diffuse and facilitate learning in the organisation (Maani and Cavana, 2000).

3.1.3 Modeling Tools for Systems Dynamics

Systems Dynamics is a computer based modeling approach as mentioned above, and uses computer simulation software such as Powersim, Stella, iThink, Vensim, Dynamo as a tool. All of them work basically with the same logic, but of course each of them has its own characteristics. The selected tool used in this study is Powersim Studio 7th edition which is chosen since its some practical and satisfactorily features as its ability to generate graphs, export and import data from/to Excel spreadsheet, possibility to create user-friendly interface. The graphs are essential attribute since they are the visual results of the simulation that can easily be understood by the users. However, the graphical results are also useful for the modeler to check the model errors. Exporting and importing data from/to Excel spreadsheet is another valuable feature. By exporting data from Excel, the statistical errors for generating data can be eliminated. In addition to this, by importing data to Excel, the results of the simulation study can be tabulated and extra analysis can be applied which are not supported by Powersim. Finally, since the model should be used by different users who are not familiar with

Powersim or System Dynamics modeling technique, an opportunity to create a user-friendly interface is precious.

Powersim and all of the other similar Systems Dynamics softwares have commonly four building blocks to construct a simulation model. These building blocks are named as the “stock” (represents the system state), the “flow” (represents the rate, filling or depleting the stock), the “auxiliary” (as converters), and the “connectors” (connecting the different blocks).

The “stocks” are reservoirs that accumulate the system flows and represent the state of the system at a given point in time. Their values are “levels” of the accumulations. They are also called “states” as they collectively represent the state of the system at time t . The standard symbolic shape for a stock is a rectangle and some stock examples can be as

- population
- cash balance
- inventory of goods
- weight
- anger level
- knowledge level
- temperature
- glucose in blood (BOUN Lecture Notes, 2003).

These examples show that the “stocks” can be physical entities as well as information entities; they can be managerial control variables as well as natural/biological variables. The “stocks” are universal, and represents the critical accumulations on which the very existence of all sorts of life forms depend (BOUN Lecture Notes, 2003).

The “flows” represents the changes in the stock levels. For instance, the production rate or the shipment rate to the customer. They directly flow in and out of the stocks, thus changing their values. The symbol for the “flow” is double arrow line (representing the direction of flow) with valve flow into or out of the stock (representing the fact that the flow quantity is being regulated). If there is a cloud in the starting point of the “flow”, it represents the infinite source of material/resources. Some “flow” examples can be as

- births, deaths
- income, expenses
- production, sales
- caloric intake, calories burned
- increase and decrease in anger level
- learning and forgetting (or obsolescence rate)
- heat in, heat out
- glucose intake, glucose consumption (BOUN Lecture Notes, 2003).

The above “stock” and “flow” examples are related with each other in the ordered manner. For example “births” are inflow and “deaths” are outflow for the “population” stock variable or “income” is inflow and “expenses” is outflow for “cash balance” stock variable. The symbolic representations for these two examples are shown in Figure 3.1.

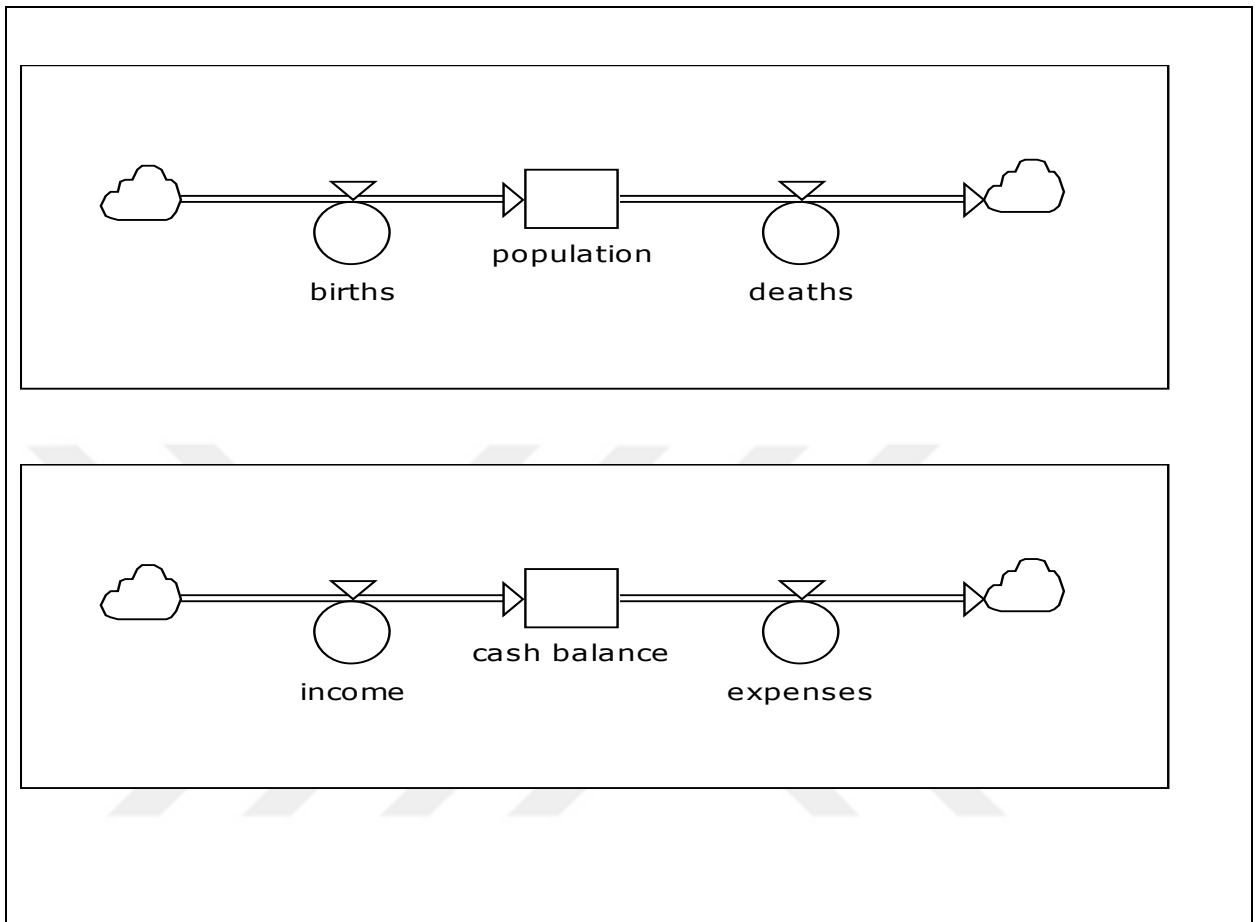


Figure 3.1 Stock – Flow representations for given examples

Mathematically, the above diagrams states that $dPop / dt = \text{births} - \text{deaths}$ and $dCash / dt = \text{income} - \text{expenses}$, in a continuous model or to stress the accumulation nature of a stock:

$$Pop(t) = Pop(0) + \int_0^t (\text{births} - \text{deaths})dt \quad (3.1)$$

$$\text{Cash Balance}(t) = \text{Cash Balance}(0) + \int_0^t (\text{income} - \text{expenses})dt \quad (3.2)$$

$Pop(0)$ and $\text{Cash Balance}(0)$ are initial values of these stock variables and the standard stock equation is a basic conservation equation over time.

Using only the stock-flow diagrams and their equations do not represent the complete models for any complex system. For this reason, some “auxiliary” variables and “connectors” are needed to be defined to reach the more beneficial models. The “auxiliary” variables can be in different form, as a graph function, or as delay function. The symbolic representation for an “auxiliary” variable is a circle. These converters are often computed and served as intervening variables in the close loops that connect stock to flow. However, the last building variable is “connectors” which provides the linkage between system components, and reflects the modeler’s assumptions about the causal relationships underlying the system. The representation for the “connectors” is an arrow line connecting different system components. In addition to this, it is meaningful to assume that the inflow and the outflow variables are functions of the other “auxiliary” variables with “connectors”. For instance, in the above simple population model, the simplest specification for the births and the deaths would be $\text{Births} = b * \text{Population}$ and $\text{Deaths} = d * \text{Population}$, where b is a constant birth fraction and d is a constant death fraction. The stock-flow diagram would then be as in Figure 3.2

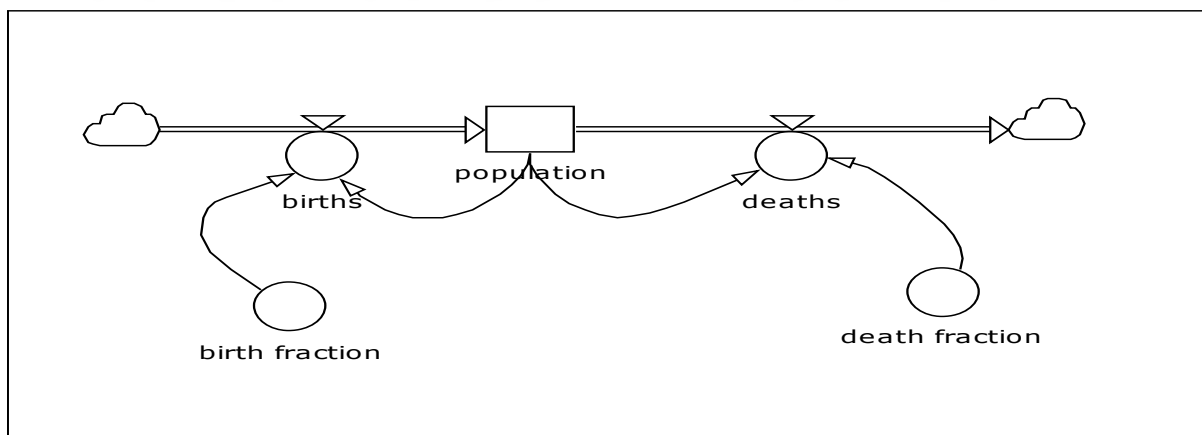


Figure 3.2 Stock-Flow diagram for the population model with converters and connectors

The “effect” arrows in this diagram show that $\text{Births} = f(\text{Population}, \text{Birth Fraction})$ and $\text{Deaths} = f(\text{Population}, \text{Death Fraction})$. In addition to this, the model can need several different variables for representing the real system. For example consider a situation where Birth Fraction is not constant, but depends on the “crowding level” of the population. To define the situation, the model needs to two more auxiliary variables as the “Crowding” and

the “Capacity” where $\text{Crowding} = \text{Population} / \text{Capacity}$. Birth Fraction would then be $f(\text{Crowding})$ where $f(.)$ is typically a monotonically decreasing function. A stock-flow diagram including such an auxiliary variable (Crowding and Capacity) is shown in Figure 3.3

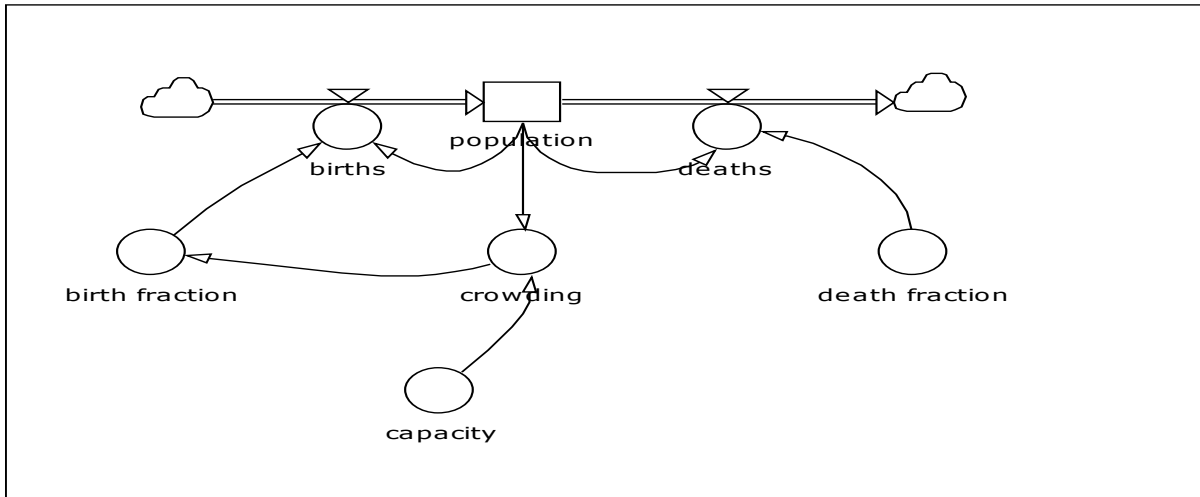


Figure 3.3 Stock-Flow diagram for the population model with auxiliary variables

The representations and formulations for any Systems Dynamics model with four basic building blocks can be generalized as in Figure 3.4. All of these variables can be time dependent functions or not time dependent. The $X(0)$ means the initial state of the stock value. The stock level $X(t)$ accumulates by integrating the flow rate (dX). Auxiliary variables (Y) control or convert other entities ($g(X(t))$).

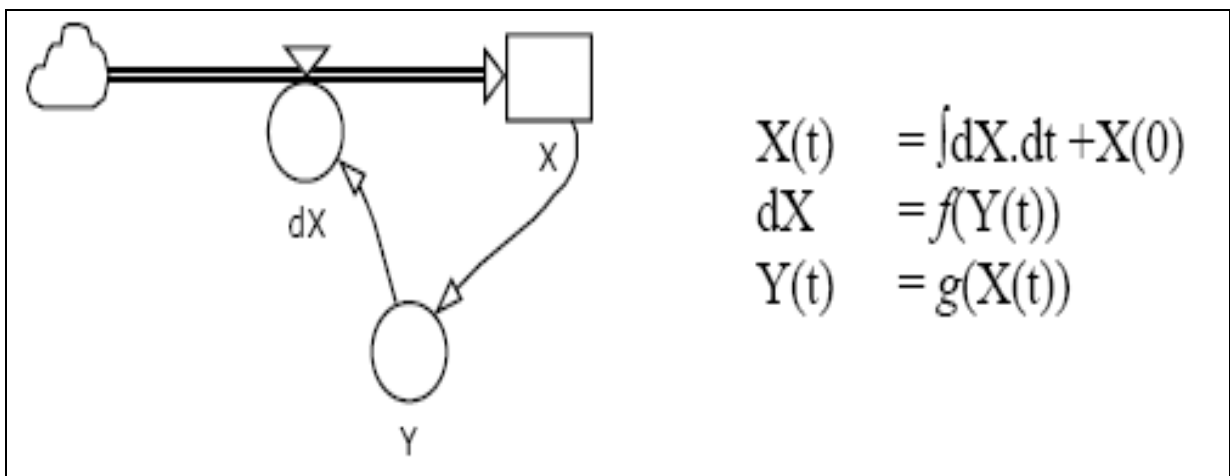


Figure 3.4 The basic building blocks and their formulations (Source : Lim, 2002)

3.1.4 Causal Effects and Feedback Loops

The main purpose of System Dynamics methodology is to understand the causes of the undesirable dynamics and to design the new policies to ameliorate/eliminate them. Managerial understanding, action and control are at the heart of the method. System Dynamics thus focuses on dynamic problems of systemic, feedback nature. Such problems arise from the interactions between system variables and from the feedbacks between the managerial actions and the system's reactions (BOUN Lecture Notes, 2003).

After the problem recognition and the variable definitions, the relations between variable should be carefully described to understand the real system structure, clearly. The influence diagrams are sometimes called “causal loop diagrams” are an essential tool for this purpose. They are not only the foundation on which the quantitative models are built, but are also a valuable device in their own right for describing and understanding to the systems. The causal relations between the two variables can be positive or negative directions. If one variable (x) has positive influence on the another variable (y) means that a change in x causes y to change in the same directions. Some examples for the positive causal effect can be seen as below. For example, if the population size increases, the demand for the new houses also increases. Similarly, if the births in any population increases, the size of the population also increases.

Population $\rightarrow$ + Housing Demand

Births $\rightarrow$ + Population

Pesticide $\rightarrow$ + Bird deaths

Motivation $\rightarrow$ + Productivity

On the other hand, if one variable (x) has negative influence on the another variable (y) means that a change in x causes y to change in the opposite directions. And some examples for the negative causal effect can be as below. For instance, if the price of the any product increases, the demand for that product decreases.

Unemployment → - Immigration

Deaths → - Population

Price → - Demand

Frustration → - Studying

Mapping the all relations between the system variables can help to understand the entire system as a whole. However, the feedback loops in the system can basically perceived. A feedback loop is a succession of the cause-effect relations that start and end with the same variable. It constitutes a circular causality, only meaningful dynamically, over time. The sign (or polarity) of a loop is the algebraic product of all signs around the loop. If the resulting sign is “+”, the loop is “positive” or “compounding” or “reinforcing”. If the resulting sign of the loop is “-“, then the loop is called “negative” or “balancing” or “goalseeking”. This type of feedback loop seeks a balance or a goal.

Figure 3.5 displays that more births means the higher population, which causes even more births, causing even higher population, and so on. The operation of this loop over time would create exponentially growing population. This feedback loop reinforces or compounds an initial change. Furthermore, not all the positive loops create the growth; some can create the collapse.

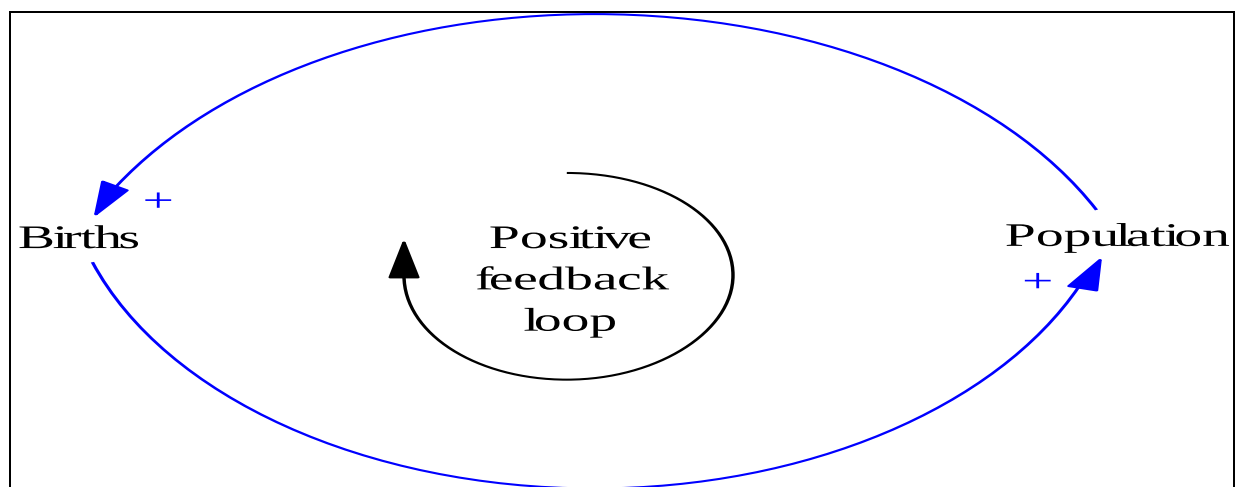


Figure 3.5 Positive feedback loop

In addition to this, Figure 3.6 states that the if more calories is taken, the more weight is gained by a person and when the weight increase is concerned, the person is lead to cut down on his / her caloric intake. This loop tries to keep the caloric intake (hence the weight) under control. The behaviour of this loop would be a convergent one, rather than a divergent one. In this example, the person tries to control his / her weight around some “desired” (“goal”) weight.

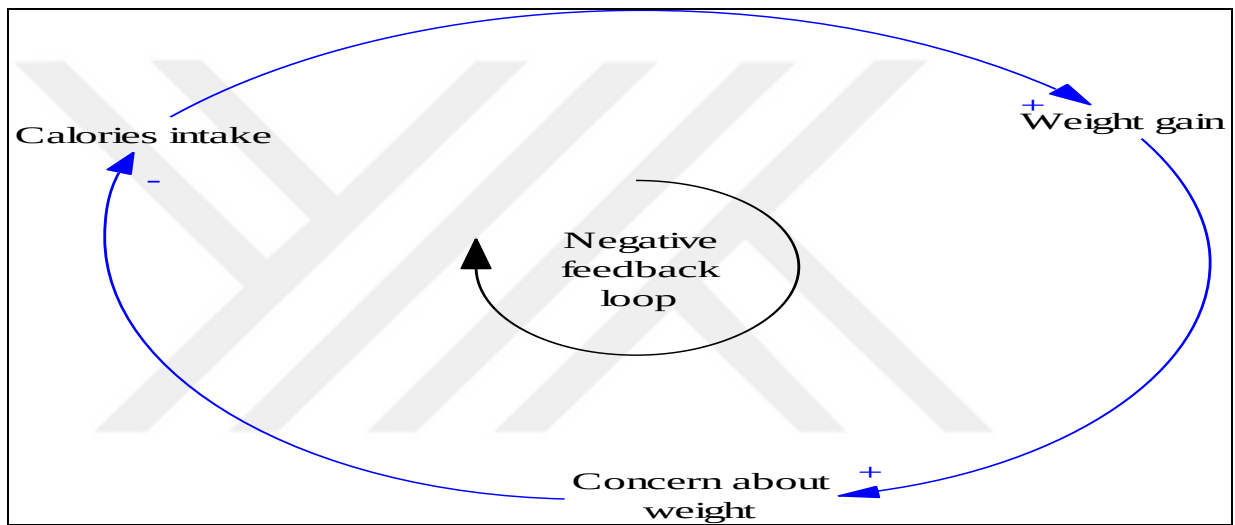


Figure 3.6 Negative feedback loop

3.2 SYSTEMS DYNAMICS MODELING APPLICATIONS TO SUPPLY CHAIN MANAGEMENT

The applications of System Dynamics modeling to supply chain management has its roots in Industrial Dynamics (Forrester 1958, 1961) which is a first published work in the area of System Dynamics modeling related to supply chain management. Industrial Dynamics is a model of a production-distribution system as a simple four level supply chain consisting of factories, a warehouse, a distributor and a retailer. It is described in terms of 6 interacting flow systems, namely the flows of information, materials, orders, money, manpower, and capital equipment. Figure 3.7 shows the classic supply chain model that is used by Forrester in simulation experiments.

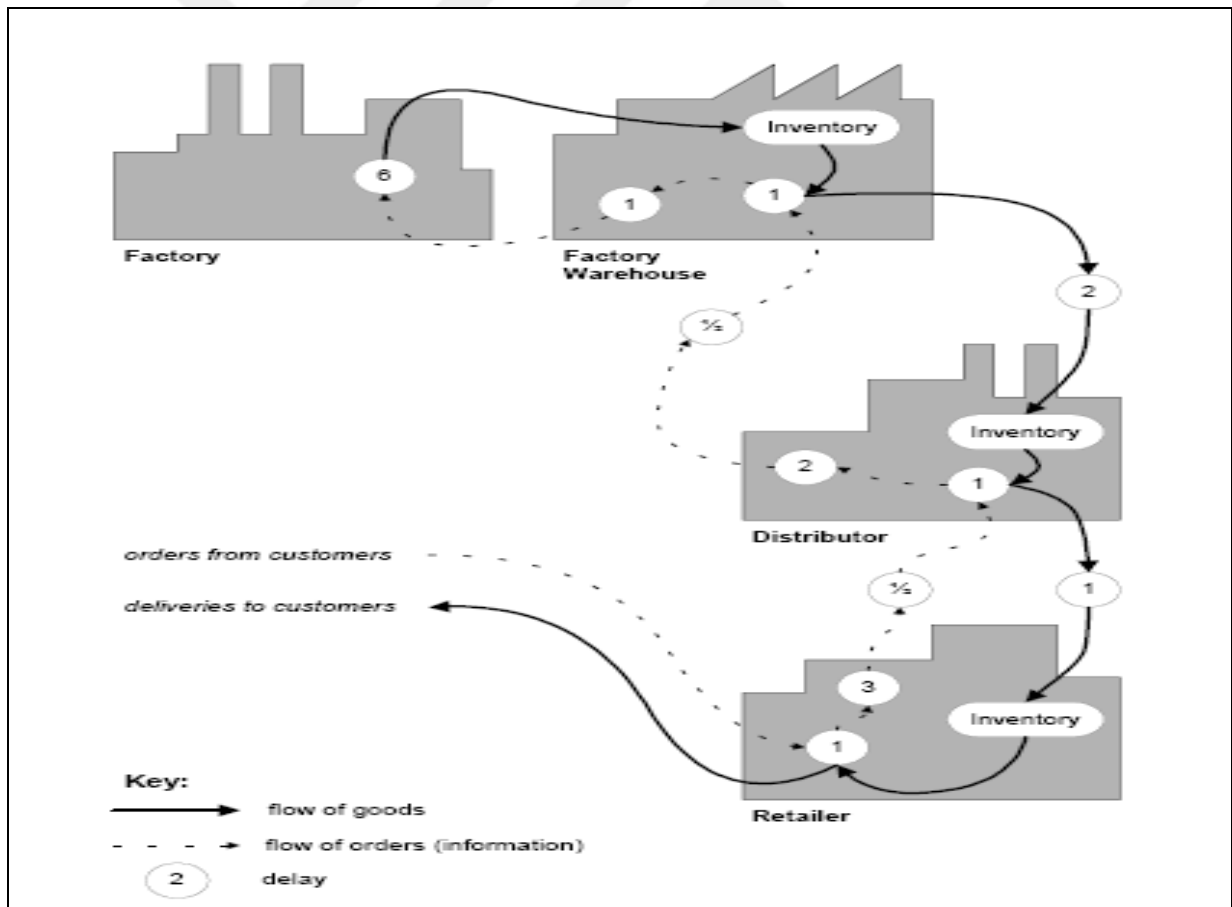


Figure 3.7 Forrester's supply chain model (Source : Forrester, 1961)

There is a downstream flow of material from the factory via the factory warehouse, the distributor and the retailer to the customer. Orders (information flow) flow upstream, and there is a delay associated with each echelon in the chain, representing, for instance, the production leadtime or delays for administrative tasks such as order processing.

Based on the development and usage of a System Dynamics simulation model, Forrester (1961) described, analysed, and explained issues evolving around the supply chain management as demand amplification, inventory swings, the effect of advertising policies on production variations, decentralised control, or the impact of the use of information technology on the management process. Despite its simplicity, Forrester model yielded important insights into the supply chain dynamics and he established the ground rules for the effective supply chain design, when he placed that the medium period demand amplification (bullwhip effect) is a system dynamics phenomenon, which could be tackled by reducing and eliminating delays, and the proper design of feedback loops.

After the Forrester (1961), many researchers are also interested with Systems Dynamics modeling for the supply chain management and some application works of Systems Dynamics modeling to the supply chain management are covered the following research areas in the literature. All of the researches about to these facets are explained with details in this section.

1. International supply chain management (ISCM)
2. Inventory management
3. Participate business modeling
4. Supply chain design
5. Demand amplification
6. Information visibility
7. Decision making in stock management
8. Supply chain reengineering
9. Integrated system dynamics approach

Angerhofer and Angelides (2000) summarizes all of the research and development works on Systems Dynamics modeling in supply chain management with a taxonomy. They divided the recent research into three groups as research for theory building, research for problem solving, and research for putting into practice for some above research areas. However, they also explained the key techniques and methods that are applied to the each research category as causal loop diagramming, continuous simulation, OR techniques, and discrete simulation. Table 3.2 gives their taxonomy of research and development on System Dynamics modeling in supply chain management with the key methods.

Table 3.2 A taxonomy of the research and development on System Dynamics modeling in the supply chain management (Source: Angerhofer and Angelides, 2000)

Category Research area	Research: Modeling for theory building	Practice: Modeling for Problem solving	Putting Research into practice: Improving the modeling approach
Inventory Management	Continuous simulation	Continuous simulation OR Techniques	
Demand Amplification		Continuous simulation	
Supply Chain Re-engineering		Causal loop diagramming Continuous simulation OR Techniques	Causal loop diagramming Continuous simulation OR Techniques
Supply Chain Design	Causal loop diagramming	Causal loop diagramming Continuous simulation OR Techniques	Causal loop diagramming Continuous simulation OR Techniques
International SCM		Causal loop diagramming Continuous simulation OR Techniques	Causal loop diagramming Continuous simulation OR Techniques Discrete Simulation

Akkermans et al. (1999) research is a typical example of the work in the use of System Dynamics Modelling in “International Supply Chain Management (ISCM)”. Akkerman, Vos and Paul (1999) proposes a theory of “Virtuous and Viscous cycles” in the ISCM through an exploratory causal model of goals, barriers, and enablers.

The roadblocks identified by them are:

- Local optimization
- Insufficient communication between supply chain partners
- Functional Silos
- Lack of top management support
- Self-fulfilling prophecies for management

The enablers of ISCM identified by them are:

- Demonstrating business success of ISCM by innovative new corners
- Customer demanding ISCM services
- Promoting cross-functional careers
- Leveraging the potential of information and communication technology (ICT) systems

Figure 3.8 shows a causal model of the ISCM. The core dynamics are straightforward, it means that all of the companies seemed to be caught in a reinforcing loop of either successes (a virtuous cycle) or failures (a vicious cycle), the later being considered more frequent than former.

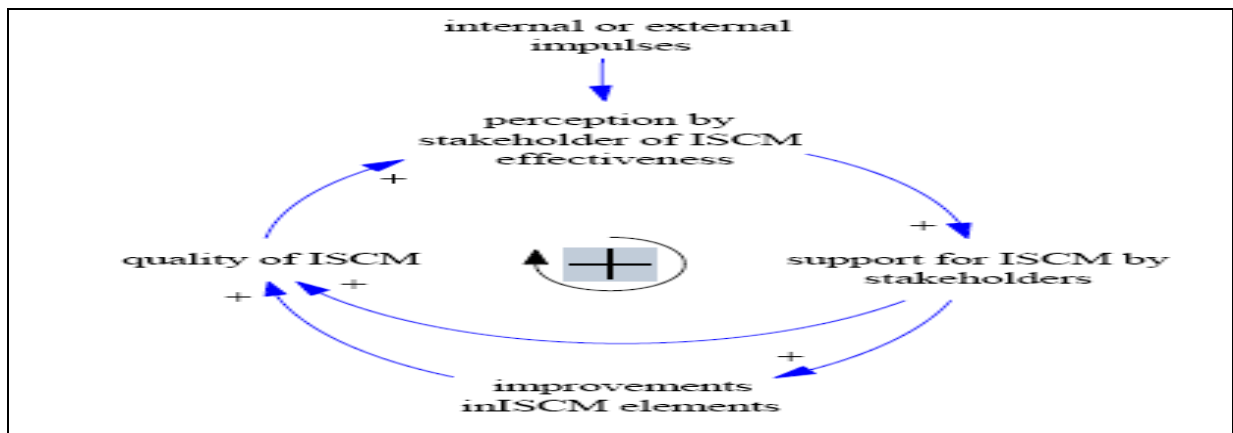


Figure 3.8 Virtuous and Vicious cycles in ISCM (Source: Akkermans et al., 1999)

“ Scenario of the vicious cycle state that if the current quality in managing a company’s ISCM is low, then main stake holders (top management, other company functions, external partners) will treat ISCM as a not very effective means of improving business performance. This will lead to a few immovements in elements such as training of staff, reliable and detailed information systems. This will then again result in a continuation of the existing dissatisfactory level of ISCM quality. Preciously the same dynamics apply in the virtuous cycle scenario; if the current quality level of ISCM is high, this will be observed by stockholders who will recognise its relevance and support it, thereby further boosting ISCM quality ” (Akkerman,Vos, and Paul, 1999).

Typical research on the development of “Inventory Management” policies is the work of Barlas and Aksogan (1997). Barlas and Aksogan (1997) developes the inventory management policies, where quick response supply chain management system is designed to meet the changing requirements of a competitive market. The textile and apparel industry is used for the study included from textile suppliers to final consumer. The primary focus of work is to build a system dynamics simulation model of the portion of the pipeline including the retailing and wholesaling processes to search for inventory decisions and policies that yield reduced costs / increased revenues in terms of the retailer particularly to examine the effectiveness of some quick response principles for this purpose.

“ Another purpose of the study is to examine the effect of diversification and the different assumptions about the effect of product diversity on customer demand, possible stockouts, and inventory levels. The simulation model of the apparel supply chain represented the physical structure of the system and also incorporated ordering and production decision rules. Simulation run is carried out, using different ordering and production policies under various inventory levels and demand patterns. The results highlighted, that order policies as used in continuous systems, are not adequate for partially discrete, partially continuous inventory systems. The outcome of the modeling effort led to the proposition of new ordering policies for particularly continuous, partially discrete inventory systems, which are robust in terms of fluctuations in demand ” (Bhushi, and Javalagi, 2004).

Akkermans (1995) proposes an approach labelled “Participative Business Modelling” (PBM) to address not only the technical, but also the organisational complexities inherent in the development of logistics strategies. Existing methods mainly focus on technical complexity, and although they are superior in tackling these issues, often the implementation success does not live up to the expectations. This is due to low management participation and the resulting lack of commitment towards the proposed strategies.

“ Participative Business Modelling combines intensive management participation with rigorous analysis and extensive modelling, aiming to facilitate learning about strategic issues and therefore the gaining of insights. Starting with qualitative analysis, the method gradually leads to more formal, quantitative modelling. PBM draws from several different methods, including System Dynamics Modelling, Operational Research, Social Sciences and process consultation, and aims to combine them for a greater benefit. It contains an implicit conceptual model (or theory) on effective strategic decision-making” (Angerhofer and Angelides, 2000).

Figure 3.9 shows the conceptual research model for the Participative Business Modelling (PBM).

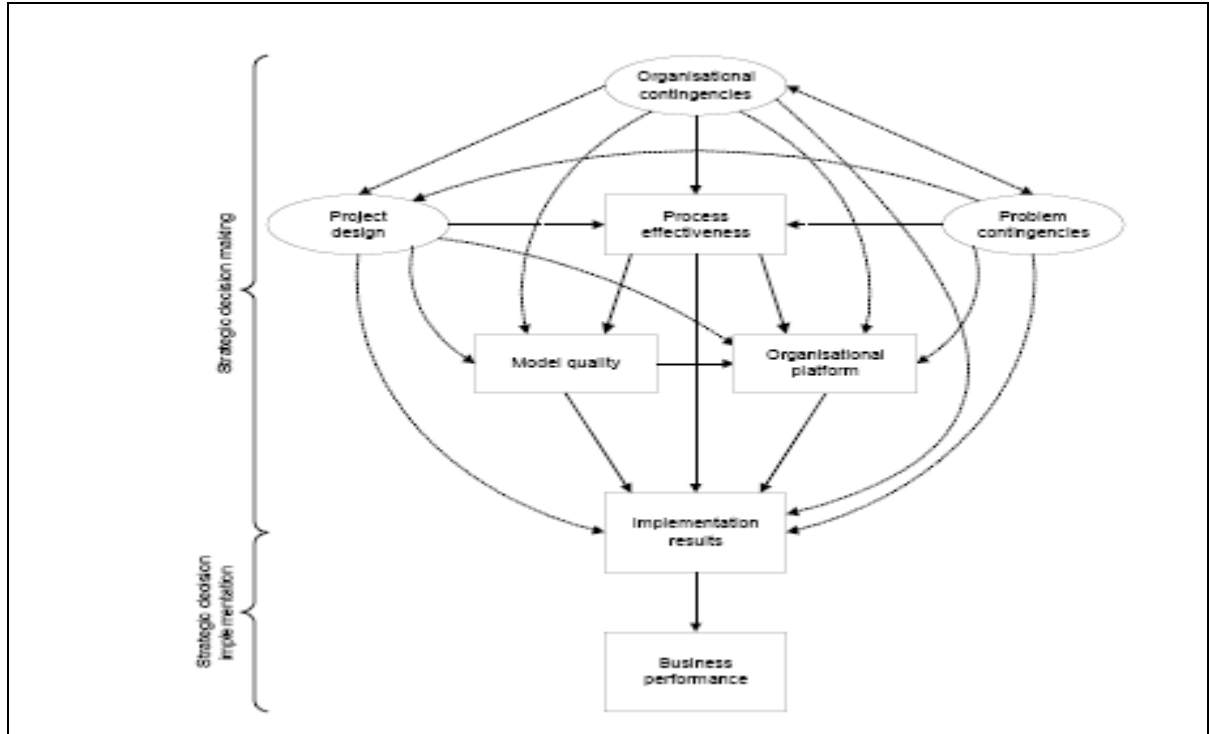


Figure 3.9 A Conceptual model of strategic decision-making (Source: Akkermans, 1995)

Participative Business Modelling is comprised of four project phases: (1) the project definition phase, using cognitive mapping; (2) the model conceptualisation phase, which is employing brainstorming, causal loop diagramming, and stock and flow diagramming; (3) the modelling formalisation phase, where System Dynamics Modelling as well as discrete event simulation may be applied; and (4) the knowledge dissemination phase, where the models are used for sensitivity and scenario analysis (Akkermans, 1995).

Main PBM project phases and techniques are listed in Figure 3.10. Akkermans (1995) demonstrates the application of PBM to facilitate the design of a logistics strategy through a case study, where an international company sets out to establish logistic operations in Europe.

PBM project phase	Steps in the strategy development	Main modeling techniques per phase	Main knowledge elicitation techniques
Project definition phase	Exploring of technical & organizational complexities Determining project scope & plan	Cognitive maps	Project kick-off meeting Pre-project questionnaire Structured interviews Issue clustering
Model conceptualization phase	Identifying strategic trade-offs and options Business process modelling Business process redesign	Hexagon brainstorming Causal, Stocks-and-flows, Graphical function diagramming Likert-scale propositions	Informal brainstorms Structured workshops Feedback workbooks In-house project design sessions
Modeling formalization phase	Fact finding Simulation modeling Model calibration and validation	Pareto-distributions, Graphical functions System dynamics simulation Discrete-event simulation	“Conventional” fact finding techniques (Pareto-analyses, time and method studies) Structured workshops
Knowledge dissemination phase	Designing of effective policies Policy evaluation Disseminating insights to wider audience	Sensitivity analyses Scenario analyses	“Learning Wheel” workshops Management presentations Formal reporting

Figure 3.10 Main PBM project phases and techniques (Source: Akkermans, 1995)

For the “Supply Chain Design”, Vos and Akkermans (1996) use a combination of Vos’ method and System Dynamics modeling to develop “ex ante” (based on prediction and extrapolation) models to support managerial decision-making.

Vos’ original method is based on three principles: (1) the identification and design phase of strategic decision-making; (2) the active participation of decision-makers; and (3) an integral chain approach as the underlying conceptual model. It is enhanced by the use of System Dynamics modelling to overcome the restrictions imposed by the static nature of the original

method. The extended model is represented in Figure 3.11. Vos and Akkermans (1999) applied this framework in the case of a European company considering expansion to Asia.

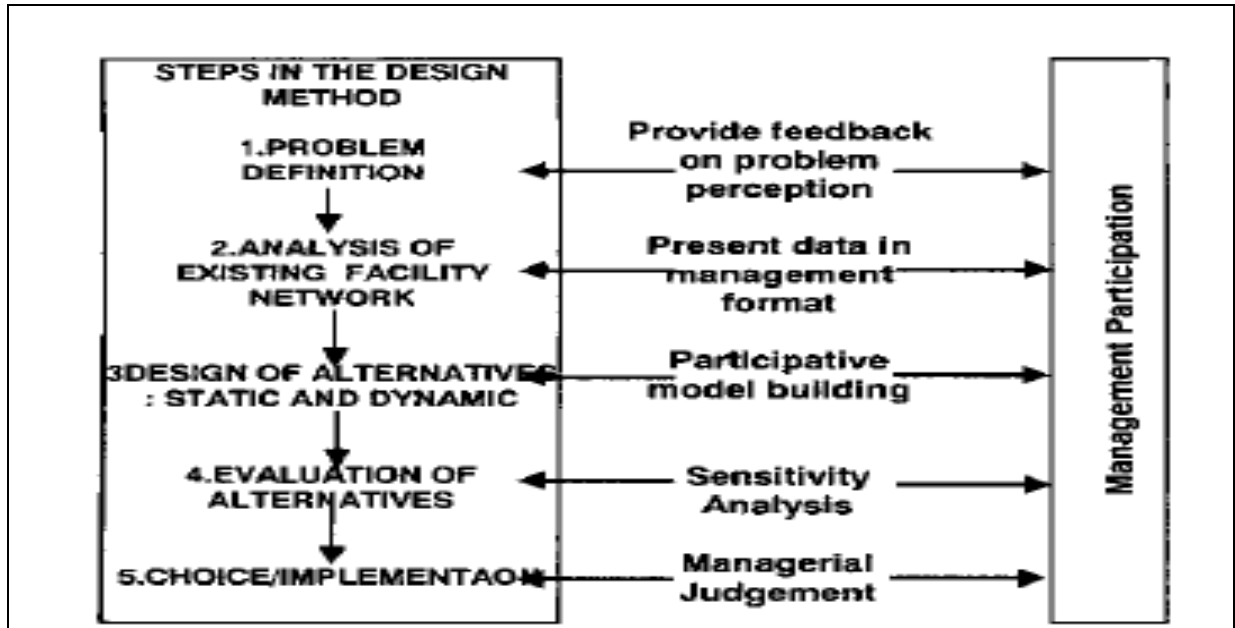


Figure 3.11 Vos extended design method (Source: Akkermans, 1995)

Vos's extended model offers the various advantages:

- Variables Dynamic behaviour can be incorporated.
- Model can be used for incremental implementation strategy for relocation, thus improving the fit with reality
- System dynamics model allows decision makers to obtain additional insight into critical cause-effect relationships.
- Rapid execution of various scenario analysis using system dynamics packages (Bhushi, and Javalagi, 2004).

Anderson, Fine and Parker (1997) works on the “Demand Amplification” in supply chains. They explore the implication of demand amplification on lead-time, inventory, production, productivity and workforce machine tool industry. Capital equipment firms are subjected to large variances in demand, because a small change in end-product demand creates dramatic changes in the demand for capital equipment required to manufacture those products. They use System Dynamics model to explain demand amplification along capital equipment supply chains, and to test various strategies that could improve the functioning of the industry. The SD modelling methodology allows them to incorporate typical features of the capital equipment industry, such as feedback loops, delays and non-linearities.

Anderson, Fine and Parker (1997) demonstrates that: (1) the (observed and simulated) extreme amplification is primarily due to the machine tool industry production capacity in conjunction with the “investment accelerator” effect; (2) the machine maker’s employee productivity decreases with increasing volatility; (3) shorter production lead-time reduces supplier backlogs; and (4) smoothing machine maker employment policies and product maker order policies can improve machine maker operations. They also identify that the machine tool customers’ order forecast rules as an important leverage point for reducing volatility, which could be improved through closer collaboration between customers and suppliers in the machine tool industry (Angerhofer and Angelides, 2000).

Joshi (2000) develops a framework of “Information Visibility” for supply chains and explained the importance of information visibility in supply chains by developing a SD model. Taking the beer game as a realistic simplification of the supply chain, he uses System Dynamics model with SD software, and develops scenarios to demonstrate the importance of information visibility. He uses both “FORECAST” function and “SMOOTH” function for demand forecasting with / without information visibility. And in all the above, the scenarios with information visibility shows better results.

Sterman (1989) presents a generic model of a “Stock Management” system as shown in Figure 3.12, which is formed the basic structure in an environment for a decision-making experiment. This generic stock management structure is applicable to many different scenarios, including raw material ordering, production control, or at a macroeconomic level, the control of the stock of money. The model is consisted of two parts, the physical stock and flow structure of the system, and the decision rules used to control the system .

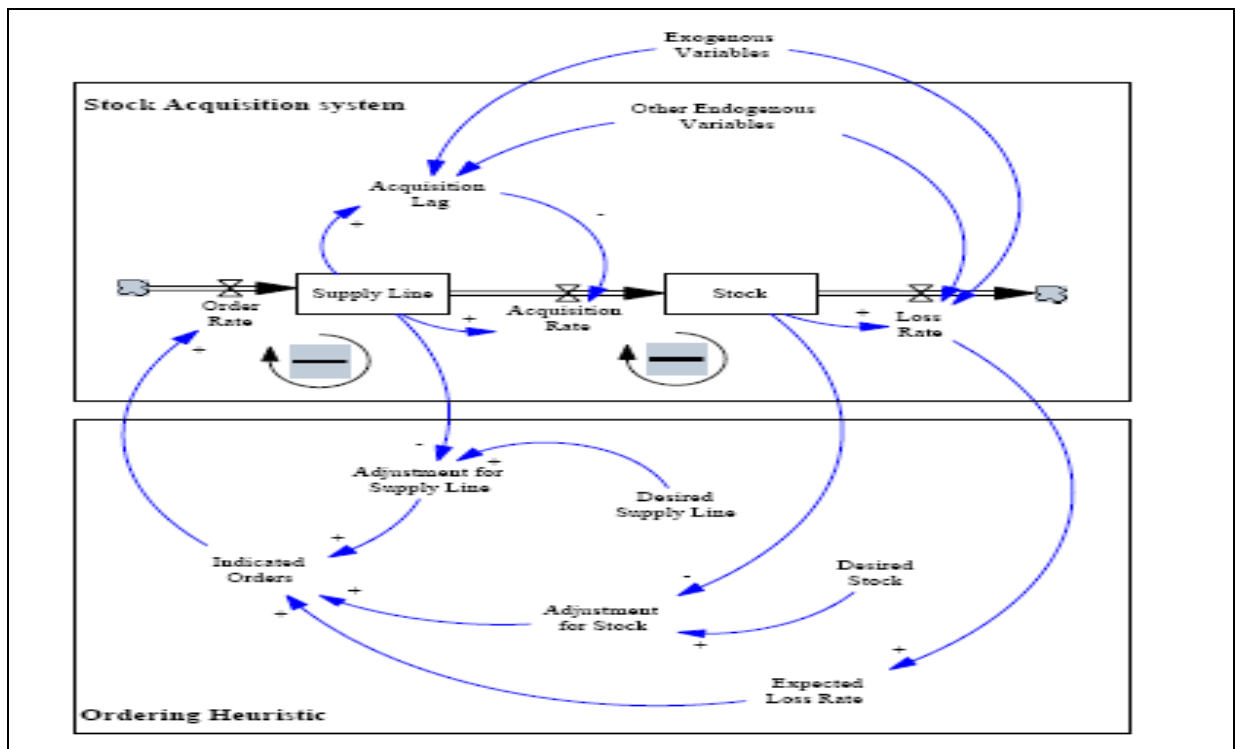


Figure 3.12 Generic stock management system (Source: Sterman, 1989)

Sterman’s model decision processes are based on anchoring and adjustment heuristic that is characterised by a mental simulation process, where an unknown quantity is estimated through recalling a known reference point (called the anchor), and then adjusting it according to other factors. Then Sterman (1989) uses the Beer Game to conduct an experiment on managing a simulated industrial production and distribution system. The Beer Game presents a multi-echelon production distribution system, containing multiple actors, non-linearities, feedbacks and time delays throughout the supply line. Sterman proposes that the decision-making process is dominated by locally rational heuristics, in form of an anchoring and adjustment

policy. This is due to the complexity of the system and time pressure, under which decisions are taken (Angerhofer and Angelides, 2000).

For “Supply Chain Re-engineering”, Towill (1996b) states that rapid, effective and efficient response to changes in the market is one of the main challenges in modern supply chains and time compression therefore is an answer to these challenges. He proposes that time compression strategies based on simulation is allowed to predict supply chain performance improvements. His case study is on the shipbuilding industry in Indonesia. Cakravastia and Diawata (1999) which describes a Systems Dynamics model that allows locating potential bottlenecks and forecasting the logistic performance in that particular industry. Based on his findings, then he proposes that the use of re-engineering strategies as follows: (1) reduction in all lead-times (material-, information- and cash-flows); (2) elimination of time delays in decision points; (3) provision of marked information to all upstream decision makers.

Hafeez et al. (1996) demonstrates the application of “systems engineering” to supply chains and describes an “Integrated System Dynamics” framework, with the aim of giving an example to “good total systems design” based on the case of a two-echelon steel industry supply chain, He defines the complex combination of “man” and “machine” as one of the major problems in modelling supply chains. By using his integrated system dynamics framework, Naim and Towill (1994), make an effort to take into consideration the complex details associated with modelling attitudinal, organisational and technological issues. Naim and Towill (1994) concludes that the combination of a “hard” systems approach with a “soft” systems analysis allows for a structured approach to supply chain design.

4. DEVELOPMENT OF A SYSTEMS DYNAMICS BASED SIMULATION MODEL FOR BULLWHIP EFFECT ANALYSIS IN SUPPLY CHAINS

A supply chain is a complex system which involves multiple entities encompassing activities of moving goods and adding value from the raw material stage to the final delivery stage. Along the chain, there exist various types of uncertainties, e.g., demand uncertainty, production uncertainty, and delivery uncertainty. Making decisions as to how much and when to replenish, often involves a feedback process triggering interaction between system entities, which may result in system nonlinearity (Hwarng et al., 2005)

The above-mentioned dynamics and complex behaviours which causes the bullwhip effect problem in any supply chain systems can be appropriately modeled by adopting the systems dynamics approach. Therefore, this study aims to identify the most important underlying reasons that generate the bullwhip effect as named the demand forecasting and the ordering policy selections with different demand processes. In addition to this, it explores how information sharing strategy can eliminate this type of behaviours for different model parameters. For this purpose, a systems dynamics based simulation model is developed using the Powersim software package for two stage supply chain. The intention is to understand how a series of inventory policy and the forecasting technique affect the demand fluctuations and how this demand fluctuation can be reduced by allowing information sharing throughout the supply chain.

4.1 MODEL CONCEPTUALIZATION

A two-stage supply chain system is composed for a single product that consists of identical agents (as one retailer and one manufacturer) where each agent orders only from its upper agent, and an agent ships goods immediately upon receiving the order if there is sufficient on-hand inventory. If there is not sufficient on hand inventory, orders may be partially fulfilled and unfulfilled orders are backlogged. Shipped goods arrive after a constant transit lead-time. Uppermost stage places orders to an infinite source (as a supplier with infinite capacity). This model represents an uncapacitated supplier-manufacturer-retailer settings.

External demand for a single item occurs at the retailer part is distinguished between an independent and identically distributed (IID) demand process and a first order autoregressive AR(1) demand process (Box and Jenkins, 1976). Each stage continuously observes its inventory position and gives orders according to two specific ordering policies (order up to S policy, Reorder point (r,Q) policy). Inventory Position of any stage is the sum of its Local Inventory and In Transit goods from upper stage minus Backlog at that stage.

$$(IP_i = LI_i + IT_i - BL_i) \quad (4.1)$$

IP_i shows inventory position of stage i and LI_i , IT_i , and BL_i are local inventory, in transit goods from upper stage and backlog inventory at that stage, respectively. The details of mentioned inventory policies (order up to S policy, Reorder point (r,Q) policy) are given in the next sections.

Before determining the parameters of the inventory control policy, one needs to forecast the that period's demand. The amount of information available for a company in the supply chain determines the accuracy of the forecast of the mean demand and the forecast of the standard deviation of the demand. There are two different information sharing strategy as named the decentralised and the centralised information sharing strategies in the supply chain management literature. If each stage in the supply chain forecasts its demand based on the orders it gets from the downstream stage (by downstream, it indicates the direction from supplier to the end customer), this means that they are using the decentralised information sharing strategy. However, in the centralised information sharing strategy, all stages have access to the data about actual end customer demand and can base the forecast of demand on the actual end customer demand data, instead of on the orders from the downstream stage.

In the simulation study, the demand at each stage is estimated by using the exponential smoothing or the moving average forecasting methods based on orders received from lower stage for decentralised information sharing strategy or based on orders received from the end

customer for the centralised information sharing strategy. The details of mentioned forecasting techniques are also given in the next sections.

This study compares the different strategies for each alternative scenario from the point of view of the bullwhip effect. All proposed selection alternatives for both of the ordering policy (order up to S policy, Reorder point (r,Q) policy) and the forecasting technique (exponential smoothing, moving average) is chosen because of their relative easiness and popularity. The developed conceptual model is shown in Figure 4.1 which includes the decentralised and the centralised supply chain management philosophies.

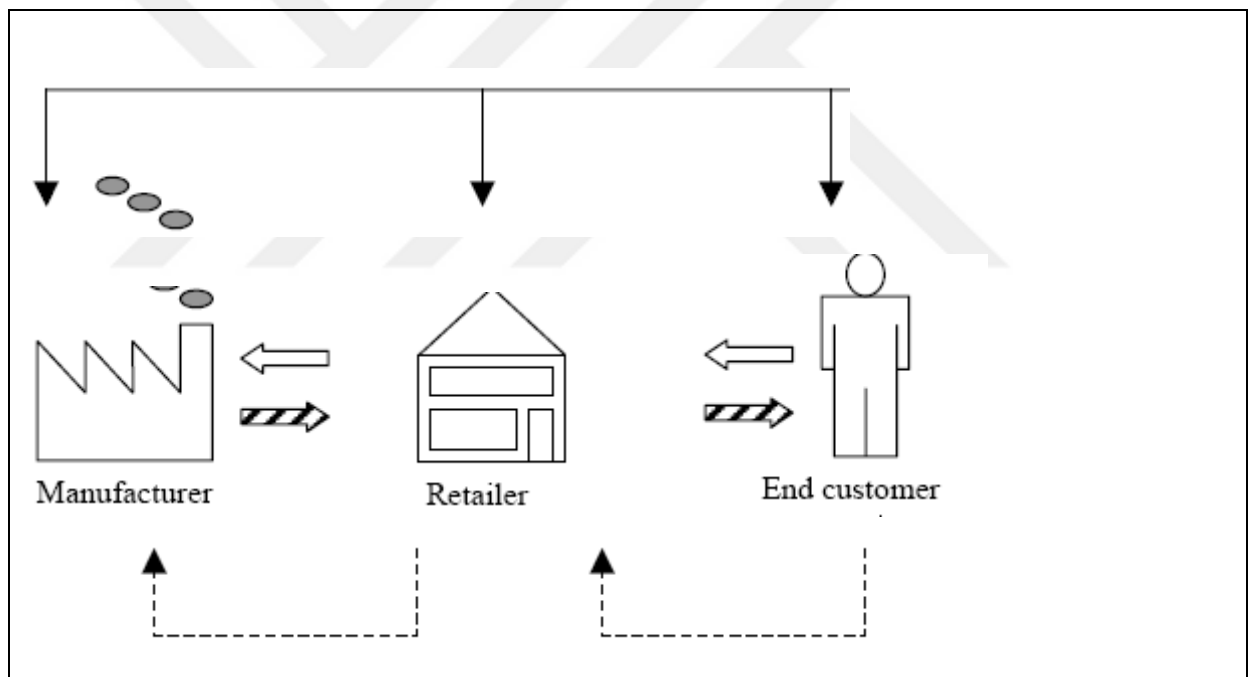


Figure 4.1 The Conceptual model

- ← Orders
- ▨→ Material flow
- Centralized information: all stages have access to end customer demand data
- - - - - Decentralized information: all stages base their forecast on the direct customer's demand

4.2 MODEL FORMULATION

In this section, the conceptual model mentioned in the last section is formulated quantitatively. The model is formulated using Powersim, one of the system dynamics software tools. A brief explanation on Powersim and the other systems dynamics software packages are available on Appendix A. This section starts with an explanation of the assumptions used in the model, continues with detailed formulation of all the stages involved. At the end of this section, the model verification and the validation procedure is presented.

4.2.1 Model Assumptions

Simulation models are normally built to simulate the real conditions, so that the models can be used to predict the behaviour of the systems if influenced by new decisions. However, not all real conditions can be simulated perfectly using simulation tools. Some assumptions or simplifications are needed to make models feasible to be built. These simplifications and assumptions may result in a slight difference in the exact value with the real condition but they can still show an acceptable behaviour of the systems. This is more important than searching the right models. (Lim, 2000).

The simulation model developed in this study also have several assumptions and simplifications as listed below.

- 1) Each agent in the supply chain continuously reviews its inventory position and places orders to other agents according to its selected inventory policy. For consistency with inventory literature, time is assumed to be discrete ($DT=1$ day) in the Powersim and each scenario is simulated for one year period (361 days in the Powersim). It is assumed that the end customer demand arrives with this fixed time interval and the arrival size is variable.
- 2) Each agent places the orders only from its upper agent and an agent ships goods immediately upon receiving the order if there is sufficient on-hand inventory. If there is not sufficient on hand inventory, orders may be partially fulfilled, and unfulfilled orders are backlogged. Any order cancelation is not allowed.

- 3) Shipped goods arrive after a constant transit lead-time, assumed to be two weeks for both of the retailer and the manufacturer.
- 4) No capacity constraints are assigned to the last stage of the supply chain.
- 5) No order processing delay is taken into account.
- 6) For identically independently distributed (IID) demand process, the end customer demand is assumed approximately normally distributed.
- 7) The model is assumed the full instant demand sharing is possible.
- 8) % 95 service level is commonly approved

4.2.2 Formulation of Demand Processes

External customer demand for a single product is formulated by borrowing the Box and Jenkins' (1976) simple first order autoregressive AR(1) demand process model as follows

$$D_t = \bar{D} + \rho (D_{t-1} - \bar{D}) + \varepsilon_t \quad (4.2)$$

where D_t represents the demand in period t , $\bar{D}$ is the average demand, ρ the autocorrelation coefficient and ε_t a normally distributed IID random error with mean 0 and variance σ_ε^2 . The demand variance equals $\sigma_D^2 = \sigma_\varepsilon^2 / (1 - \rho^2)$. When demand is IID, the autocorrelation coefficient $\rho = 0$. For $-1 < \rho < 0$, the process is negatively correlated and exhibits period-to-period oscillatory behavior. For $0 < \rho < 1$, the demand process is positively correlated which is reflected by a meandering sequence of observations.

The developed simulation model uses the above formula for formulating the demand processes where the user can select one of the two alternatives. For the first alternative, the simulation model generates the IID demand data for each time step by using the data generation function of Powersim. The end customer demand is assumed approximately normally distributed in the simulation study where the normal distribution is chosen since it is a well-known continuous distribution that can reflect the generalizations and continuity. Moreover, many inventory management models in the literature commonly uses this distribution.

Powersim has a function for normally distributed data generation as

$$\text{NORMAL}([\text{Mean}=0 [, \text{Deviation}=1 [\text{Seed}]]) \quad (4.3)$$

In this function, the “mean” shows the average value where the other values will be distributed. The “deviation” shows the variability measure of the data on the mean, and the “seed” is an initialization value for the random number generator. By specifying a value for the “Seed”, the random number generator will always produce the same series of numbers. The “Seed” is an optional parameter with a random value as default.

Powersim formula and the representation for the sample data generation by assuming the customer demand is normally distributed with mean 100 product / 1 day and standard deviation is 30 product is shown in Figure 4.2. Furthermore, Figure 4.3 shows the time series plot for the generated IID demand data set. The output values of this generated sample is tested for normality and autocorrelation (ρ = the autocorrelation coefficient which must be zero for IID demand process) for correction by using Minitab that is a statistical analysis software. The related results of these tests are displayed in Figure 4.4 and Figure 4.5, respectively.



Figure 4.2 The IID demand process data generation by using Powersim

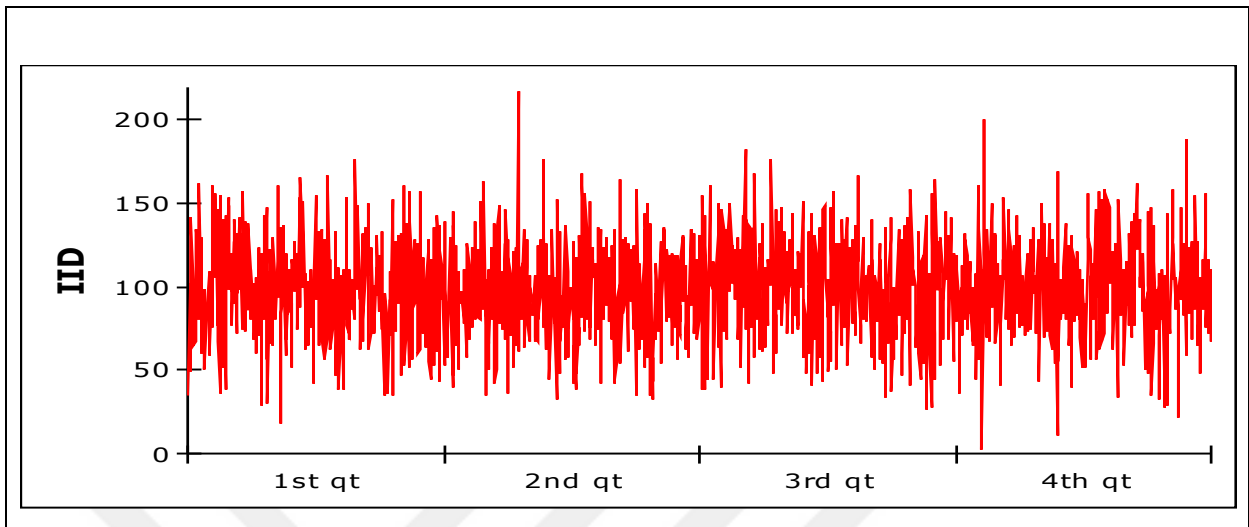


Figure 4.3 The time series plot for the generated IID demand process data by Powersim

It can be seen from Figure 4.4 that the generated data is normally distributed where the Pvalue = 0.391 is greater than the $\alpha = 0,05$ value (significance level). In addition to this, it can also be seen from Figure 4.5 that the generated data is stationary (no autocorrelation) since the correlation values on the output screen (cor columns on Figure 4.5) are approximately zero.

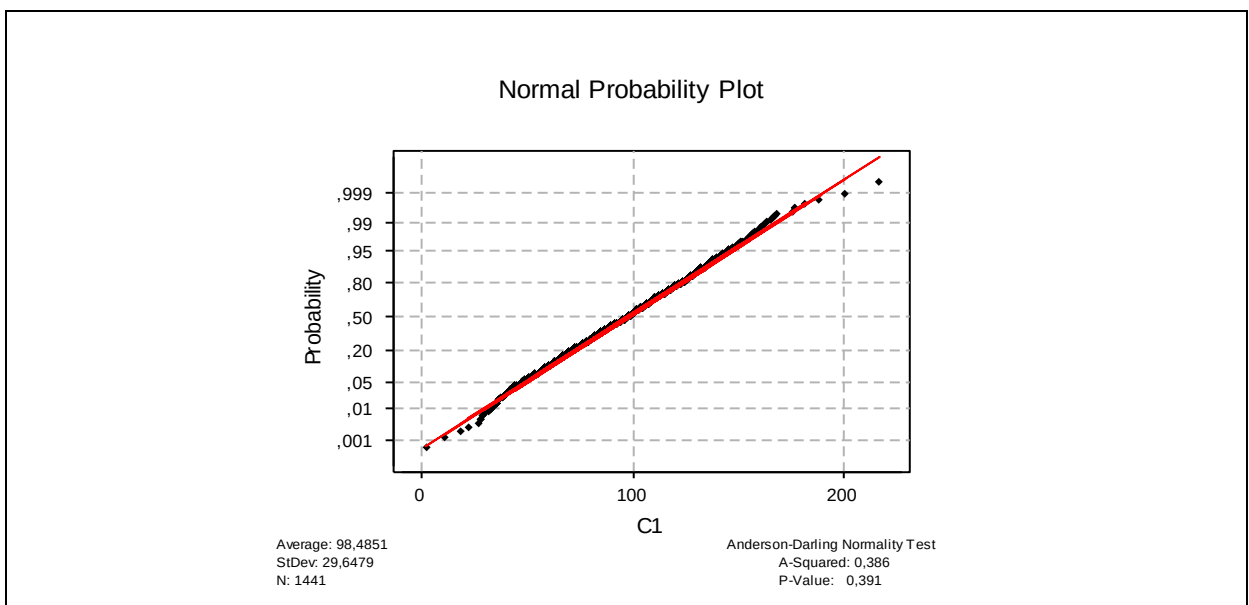


Figure 4.4 Normality test for the generated IID demand process data by Minitab

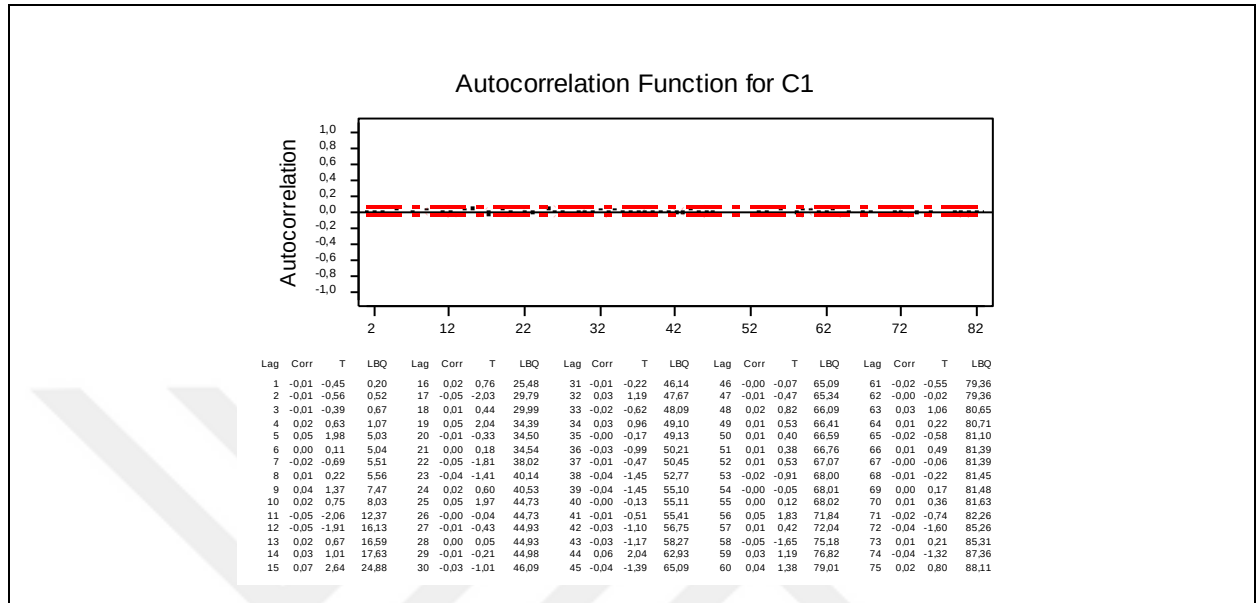


Figure 4.5 The Autocorrelation test for the generated IID demand process data by Minitab

The second demand processing alternative that is applied in the simulation model is the AR(1) demand process (first order autoregressive model), which is also called serially correlated demand process or nonstationary demand process. The simulation model uses a sub-systems dynamics model to generate the sample data in each time step for the AR(1) demand process. This submodel shown in Figure 4.6 generates demand data by using the equation 4.2. A sample data generation is evaluated with same assumptions where the average demand is assumed 100 product / 1 day and standard deviation is 30 product for the AR(1) demand process by using this submodel. But now, in addition to these inputs, the model needs to know ρ (the autocorrelation coefficient) where it is assumed as $\rho=0,7$ (positively autocorrelated). Figure 4.7 shows the time series plot for the generated AR(1) demand process data set. Moreover, this generated sample data is tested for autocorrelation correction by using Minitab again. Figure 4.8 shows correlogram or autocorrelation function graph for the generated AR(1) demand process data set.

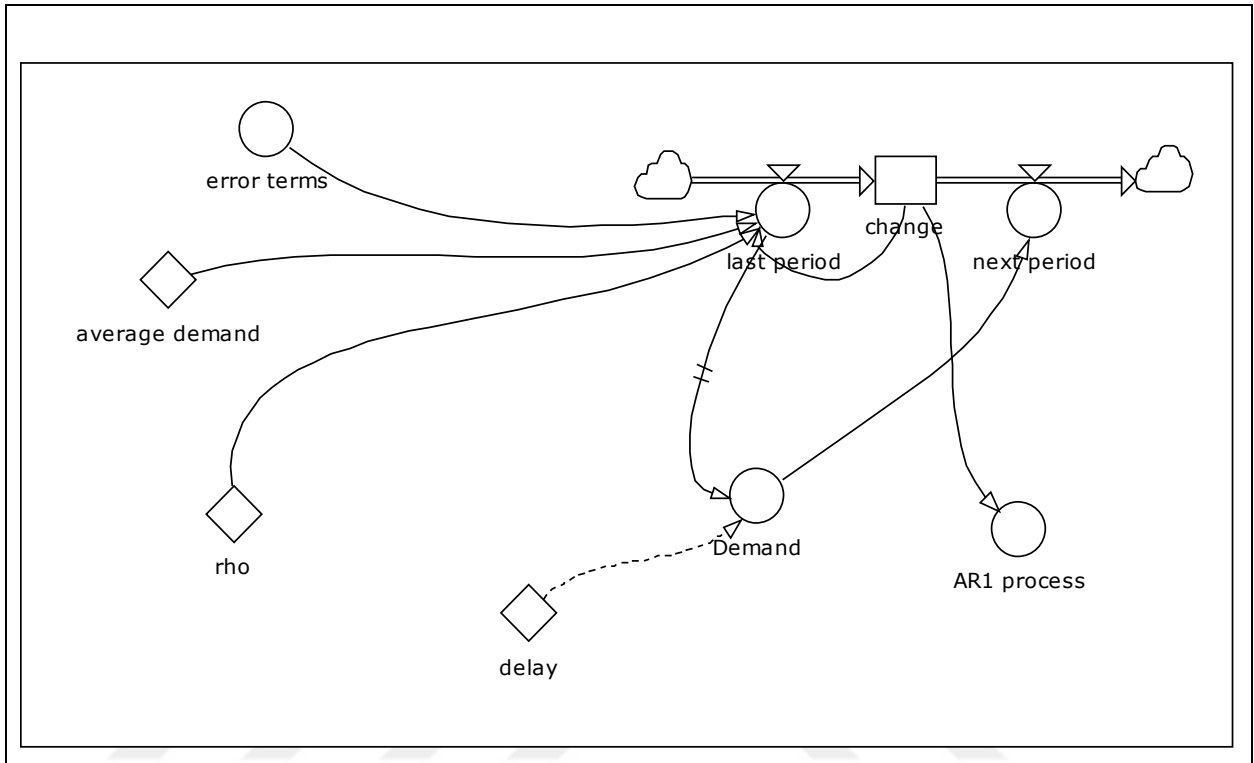


Figure 4.6 The AR(1) demand data generation by using Powersim

Formulation of the Figure 4.6 by Powersim is given as:

```

Change = 100 <<pd>>          /* Constant*/
Lastperiod = ((Rho*Change) + (Averagedemand * (1-Rho)) + (INTEGER (Errorterms
*1<<pd>>)))/1<<da>>
Next period=Demand
Demand= DELAYPPL(Lastperiod; Delay;100<<pd/da>>)
Delay = 1<<da>>              /* Constant*/
Rho=0.7                      /*positively correlation is assumed*/
Average demand=100 <<pd>>    /* Constant*/
Error terms = INTEGER(NORMAL(0;30))
AR 1 Process = Change

```

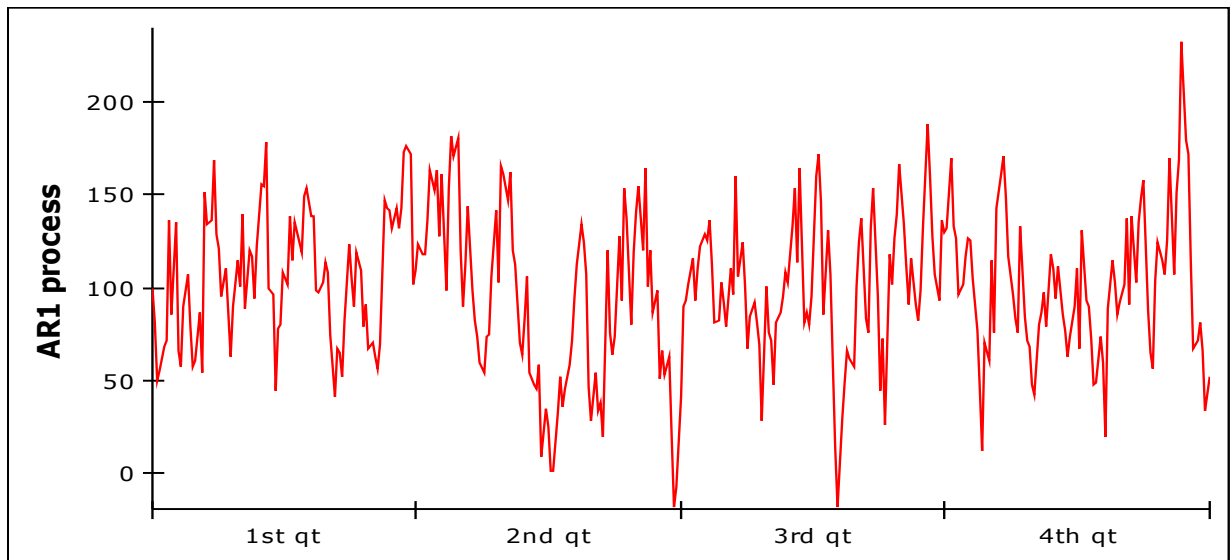


Figure 4.7 The time series plot for the generated AR(1) demand process data by Powersim

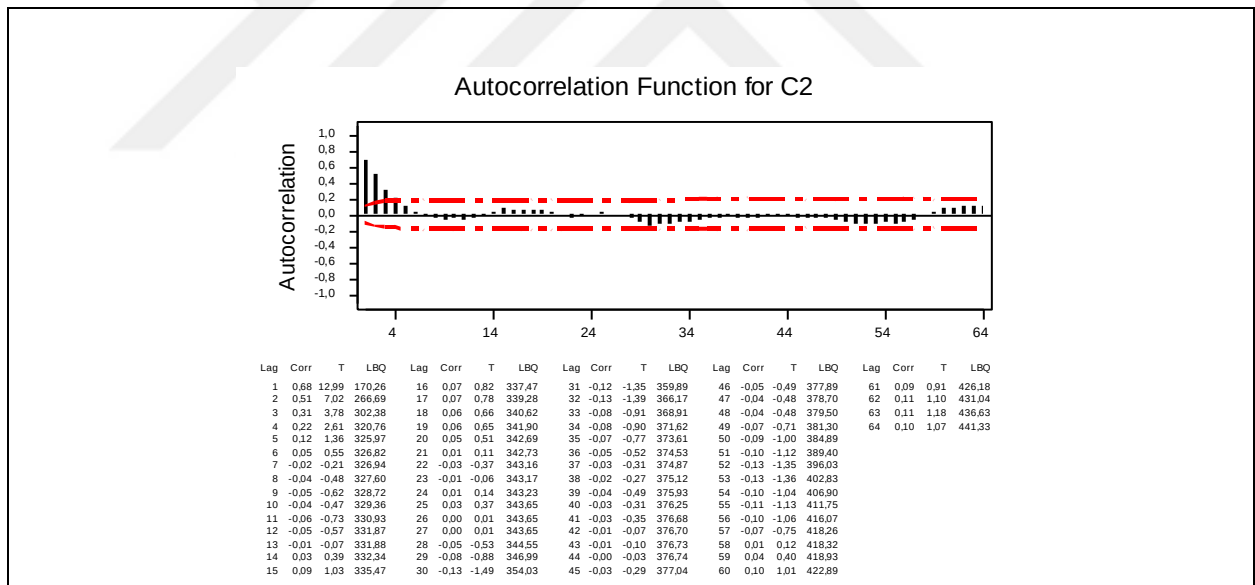


Figure 4.8 The Autocorrelation test for the generated AR(1) demand process data by Minitab

By following Figure 4.8 that shows the correlogram or the autocorrelation function graph for the AR(1) demand process, it can be seen that the generated data is positively correlated as assumed. Because, the correlation coefficient value in the first “Cor” value of Figure 4.8 is approximately 0,7 which shows the first order positively autocorrelation in the generated dataset is attained.

After forming the models of these two demand processing methods in Powersim, the user interface is developed to make the model user is able to select one of them automatically. For this purpose, the IID and the AR(1) demand process models are combined as a one model which is displayed in Figure 4.9. In addition to this, it can be seen in Figure 4.9 that the another variable named as “choice” is added to this combined model which uses this new variable as a decision variable. The “choice” variable can be 1 or 2 where the value 1 indicates that the user selects the IID demand process, and the value 2 means that the user selects the AR(1) demand process. The choice bar is added and displayed in the right hand side of the model diagram in Figure 4.9.

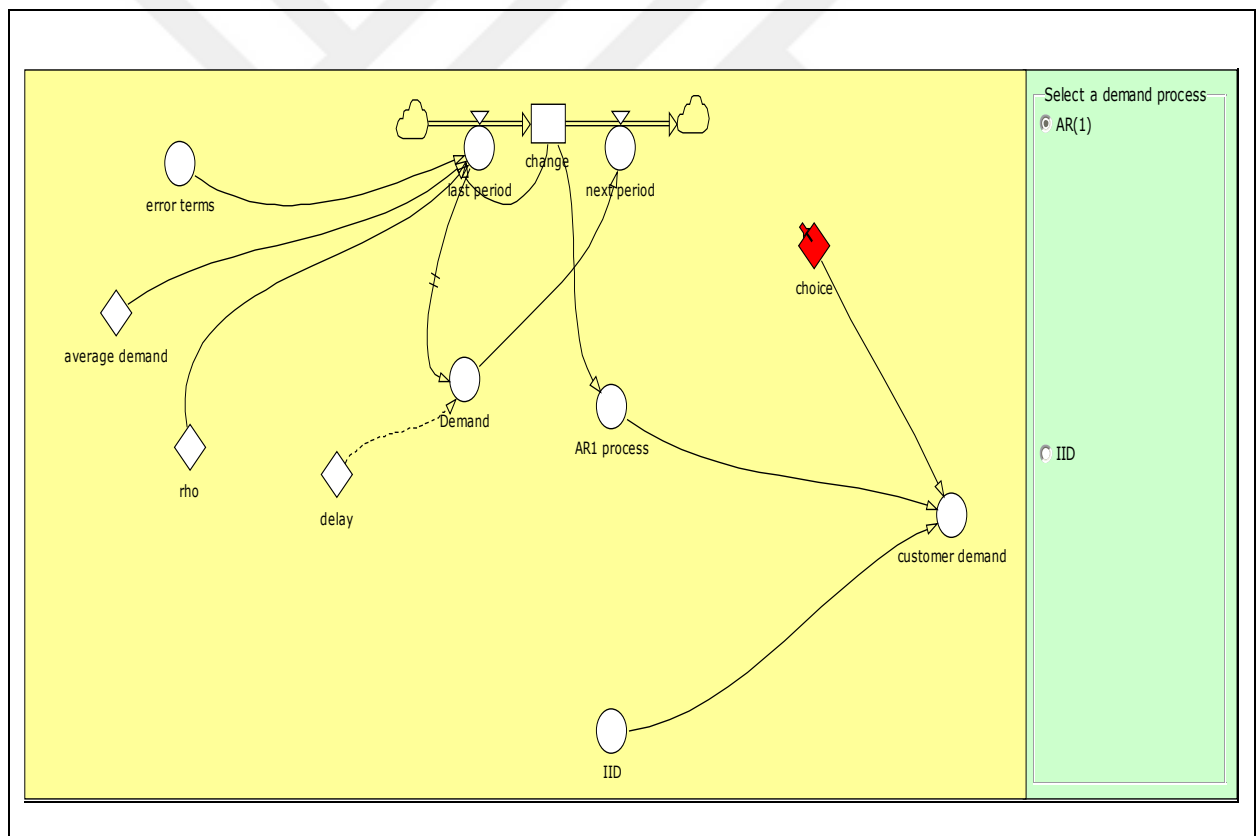


Figure 4.9 : The combined model for the demand processing with the user interface relations

Formulation for the combined model of the demand processing part with the user interface is shown below.

```

IID = INTEGER(NORMAL(100;30))*1<<pd/da>>
Change = 100 <<pd>>                                /* Constant*/
Lastperiod = ((Rho*Change) + (Averagedemand * (1-Rho)) + (INTEGER (Errorterms
*1<<pd>>)))/1<<da>>
Next period=Demand
Demand= DELAYPPL(Lastperiod; Delay;100<<pd/da>>)
Delay = 1<<da>>                                /* Constant*/
Rho=0.7                                            /* Constant*/
Average demand=100 <<pd>>                        /* Constant*/
Error terms = INTEGER(NORMAL(0;30))
AR 1 Process = Change
Choice = 1 (as integer), 1 = IID ; 2 = AR 1 Process
Customer Demand = {( IID);(AR 1 Process)}[INDEX(Choice)]

```

4.2.3 Formulation of Forecasting Policies

All of the agents in the supply chain systems are normally unaware from the exact demand patterns that they are facing with. More clearly, it means that the retailer does not know the exact form of the end customer demand process. Instead, the retailer uses the historical data and some forecasting techniques to estimate the demand for the next period. Moreover, the manufacturer does not know the retailer's demand data (in the decentralised case) or customer's demand data (in the centralised case), and it similarly needs a forecasting mechanism to forecast the future periods demands. For these reasons, all agents in the studied supply chain simulation model is able to use different forecasting methods to forecast the next period demands. These available different forecasting methods are named as the simple exponential smoothing and the moving average methods.

4.2.3.1 Exponential Smoothing Forecast

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

$$\check{D}_t = \check{D}_{t-1} + \alpha(D_{t-1} - \check{D}_{t-1}) \quad (4.4)$$

where $\check{D}_t$ is the forecasted value and D_t is the real demand, and $\check{D}_{t-1}$ is the forecast for the last period. This process can be modeled using Powersim as

$$E_{i,t} = E_{i,t-1} + (1/EAT_i) * (D_{i,t-1} - E_{i,t-1}) \quad (4.5)$$

where EAT_i is the expectation adjustment time used by stage i , $D_{i,t-1}$ is the demand faced by stage i for last period, $E_{i,t}$ is the forecast value, and $E_{i,t-1}$ is the forecast for the last period. Powersim diagram of the exponential smoothing process is displayed in the Figure 4.10.

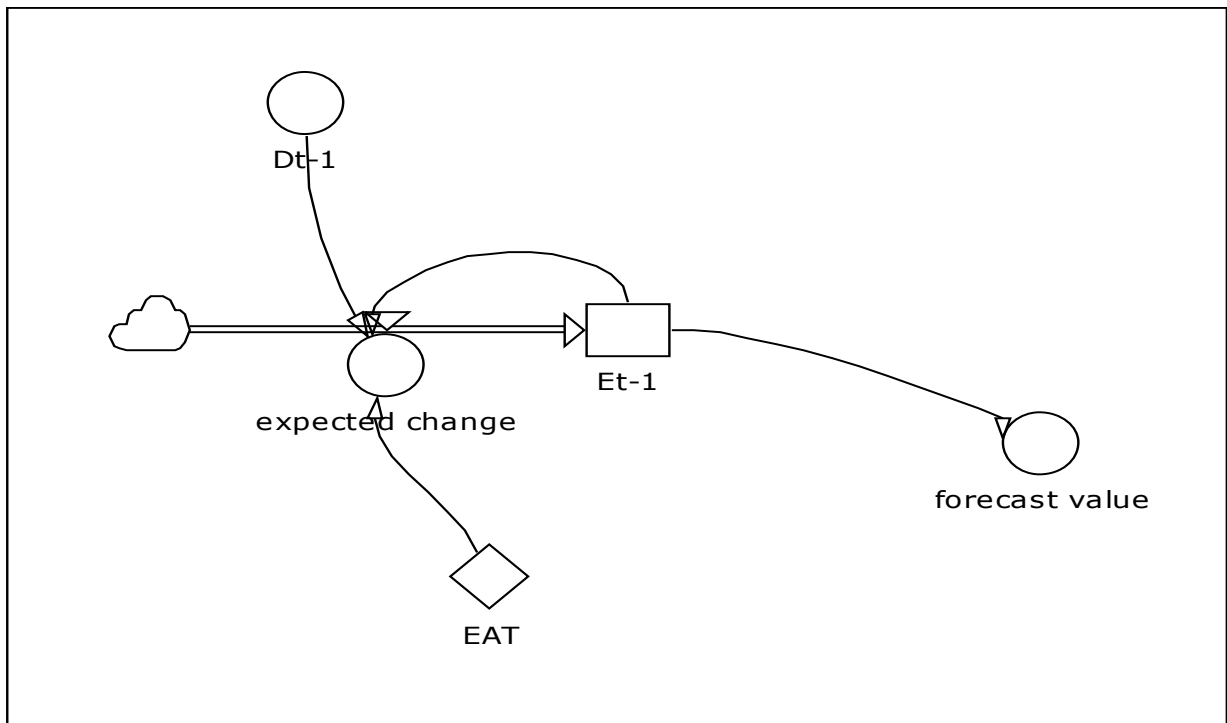


Figure 4.10 Stock – Flow diagram of the exponential smoothing forecasting method

Formulation for the exponential smoothing forecasting at Powersim shown in Figure 4.10 is given below:

```
Expected change = (1/EAT)*(Dt-1- Et-1)
Et-1 = 0 <<pd>> /* Constant*/
Dt-1 = INTEGER(NORMAL(100;30)) /* demand is assumed as normally distributed*/
EAT = 14 <<day>> /* expectation adjustment time is assumed 14 days*/
Forecast value = Et-1
```

4.2.3.2 Moving Average Forecast

The moving average forecast (MA) takes the average of the observed demand in the previous periods. The one-period ahead forecast is given by

$$\check{D}_t = \left(\sum_{i=0}^{T_m-1} D_{t-i} \right) / T_m \quad (4.6)$$

where T_m is the number of (historical) periods used in the forecast (is assumed 7 days for this study), D_t is the real demand and $\check{D}_t$ is the forecasted value. This process can also be modeled by using “SLIDINGAVERAGE” function of Powersim which returns the average of input (demand data) over the given time interval (T_m) as follows:

$$\text{SLIDINGAVERAGE}(\text{Input}, \text{Past } [, \text{Initial}=\text{Input}]) \quad (4.7)$$

The “Input” shows the historical data being evaluated in each time step, the “Past” shows the number of historical periods used in the forecast. Powersim diagram for the moving average forecasting is displayed in Figure 4.11 and its formulations are given in the following part.

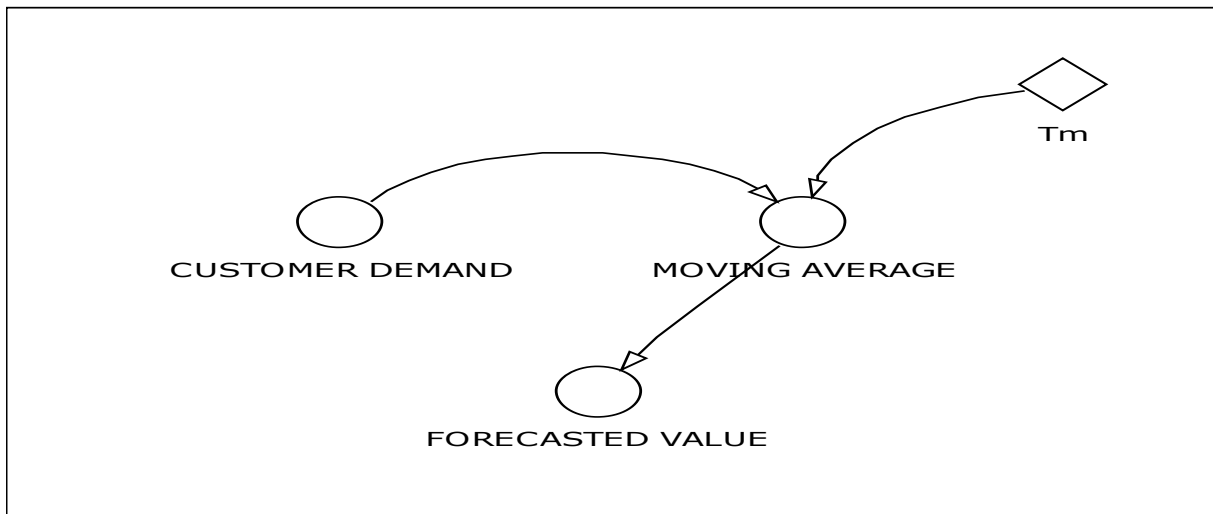


Figure 4.11 Stock – Flow diagram of the moving average forecasting method

Formulation for the moving average forecasting method shown in Figure 4.11 is given below:

```

Moving Average = INTEGER (SLIDINGAVERAGE ( Customer Demand * 1 <<da>>; Tm))
/1<<da>>
Customer Demand = INTEGER (NORMAL(100;30))      /* demand is assumed as
                                                    normally distributed*/
Tm = 7 <<day>>                                  /* Constant*/
Forecasted Value = Moving Average
  
```

Similar to the demand processing modeling part, the user interface is developed to make the model user is able to select one of these two forecasting methods automatically. For this purpose, the developed Powersim models for the exponential smoothing and the moving average forecasting methods are combined as a one model which is displayed in Figure 4.12. It can be seen in Figure 4.12 that the variable named as “choice” is again added to the combined model which is used as a decision variable. The “choice” variable can also be 1 or 2 in this case. The value 1 for the “choice” variable indicates that the user selects the exponential smoothing forecasting method. On the other hand the value 2 for the “choice” variable means that the user selects the moving average forecasting method. The choice bar is added and displayed in the right hand side of the model diagram in Figure 4.12.

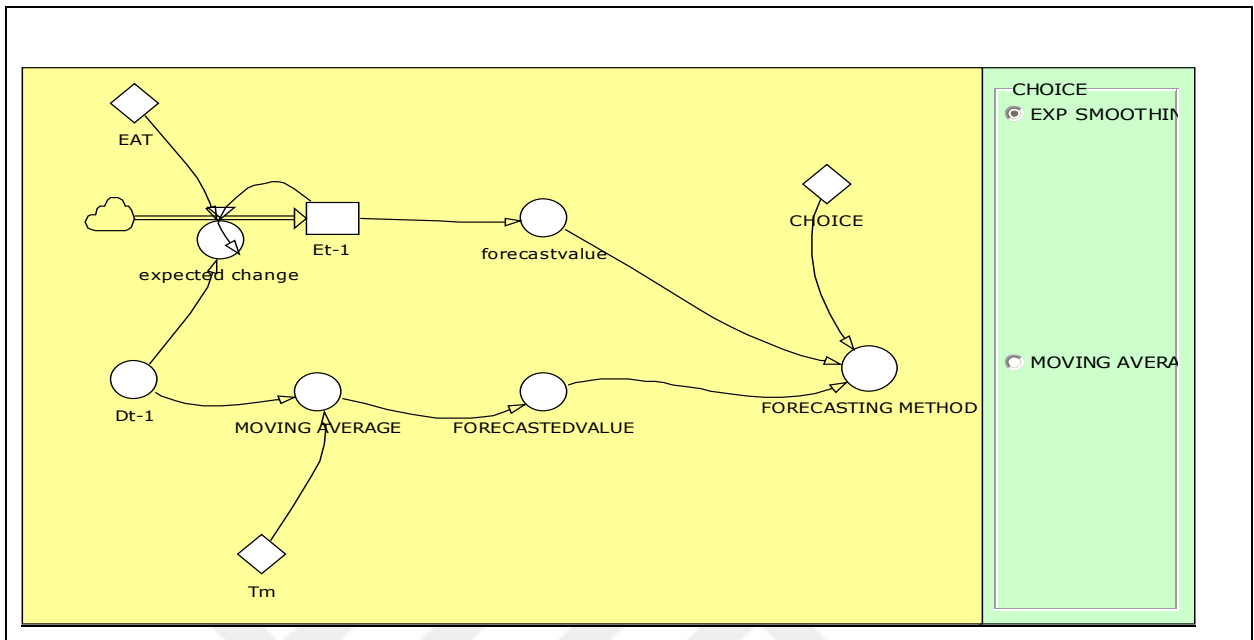


Figure 4.12 The combined model for the demand forecasting with the user interface relations

Formulation for the combined model of the demand forecasting part with the user interface is given below

```

Expected change = (1/EAT)*(Dt-1- Et-1)
Et-1 = 0 <<pd>>                                /* Constant*/
Dt-1 (customer demand) = INTEGER(NORMAL(100;30)) /* demand is assumed as
                                                    normally distributed*/
EAT = 14 <<day>>                                /* expectation adjustment
                                                    time is assumed 14 days*/

Forecast value = Et-1
Moving Average =INTEGER (SLIDINGAVERAGE ( Customer Demand * 1 <<da>>; Tm))
/1<<da>>
Tm = 7 <<day>>                                /* Constant*/
Forecasted Value = Moving Average
Choice = 1 (as integer), 1 = Exp. Smoothing ; 2 = Moving Average
Forecasting Method = { 'Forecast value'; 'forecasted value' }[INDEX(Choice)]

```

4.2.4 Formulation of Ordering Policies

The simulation model developed here follows the standard setup of the Beer Distribution Game (Sterman 1989) where a supply chain consisting of a beer retailer, wholesaler, distributor and factory is simulated with a constant one period review time. Analogous to the beer game setup, the review period in the model is assumed one period ($DT=1$ day in the Powersim simulation software), which implies that each agent can place an order in every period. Two basic single stage inventory management policies are tested with the supply chain model: Order up to S policy and Reorder point (r,Q) Policy. All stages are developed as identical in the simulation model to obtain the standardization. Its mean that the retailer or the manufacturer do not have any superiority over each other. In addition to this, the developed model is not a specific model for any firms' supply chain, it only reflects the general structure of any supply chain systems. But, it can also be applied to specific problems by some additions or subtractions . Thus, all stages use the same policy with the same parameters and each stage can select its ordering policy independent of the other without considering the whole supply chain. In other words, each agent applies a policy that locally optimizes its own inventory problem.

4.2.4.1 Reorder point (r,Q) Policy

In many inventory models where the item or items are purchased, the actual delivery of the orders may take several days after the execution of the purchase orders which is known as lead time. The presence of the lead time requires that the orders be placed several days in advance of reaching zero inventory to cover for the demand during this period. The inventory level at which the orders must be placed is referred to as Reorder Point (ROP). In the Reorder Point (r,Q) policy, a quantity Q is ordered whenever inventory position has reached to a reorder level r .

The ROP value is therefore given as

$$ROP = \mu * LT \quad (4.8)$$

where μ is the mean demand for each period and LT is the lead time. It is also possible that during the lead time period, the demand will not be constant and vary slightly. Therefore, one

may wish to carry an additional quantity to prevent the possibility of shortages. This additional amount is referred as the safety stock (SS) and its calculation requires that the stating the tolerable risk or probability of shortages that defines the service level which is the probability of satisfying the demand during the lead time. The equation for SS is

$$SS = z * \sigma * \sqrt{LT} \quad (4.9)$$

where z is the percentile from the standard normal distribution associated with the service level, and σ is the standard deviation of the demand. Adding SS to the expected demand during the lead time, the ROP equation is rewritten as

$$ROP = (\mu * LT) + (z * \sigma * \sqrt{LT}) \quad (4.10)$$

Different formulations for calculating the order quantity Q has been seen in the inventory management literature. Brown (1967) showed that for approximating the optimal order quantity Q value, the well known EOQ is usually acceptable unless $EOQ \leq \sigma_x$. Zipkin (2000) evaluated a dynamic programming algorithm and Nahmias (1993) put forward a recursive algorithm which found the optimal order quantity to minimize the expected average annual cost of the holding, the setup and the shortages. Wayne L. Winston (2004) supported Brown (1967) and found that the general EOQ formula gives a very close value for the optimal order quantity Q values. For this reason, he assumed that the optimal order quantity Q may be adequately approximated by the EOQ formula. For simplicity, Winston's approximation is adapted in this study to calculate the optimal order quantity Q as follows :

$$Q = EOQ = \sqrt{\frac{2C_o D}{C_h}} \quad (4.11)$$

where C_o is the ordering cost, C_h is the holding cost and D is the annual demand. The Reorder Point (r,Q) policy is modeled by using the Powersim is displayed in Figure 4.13.

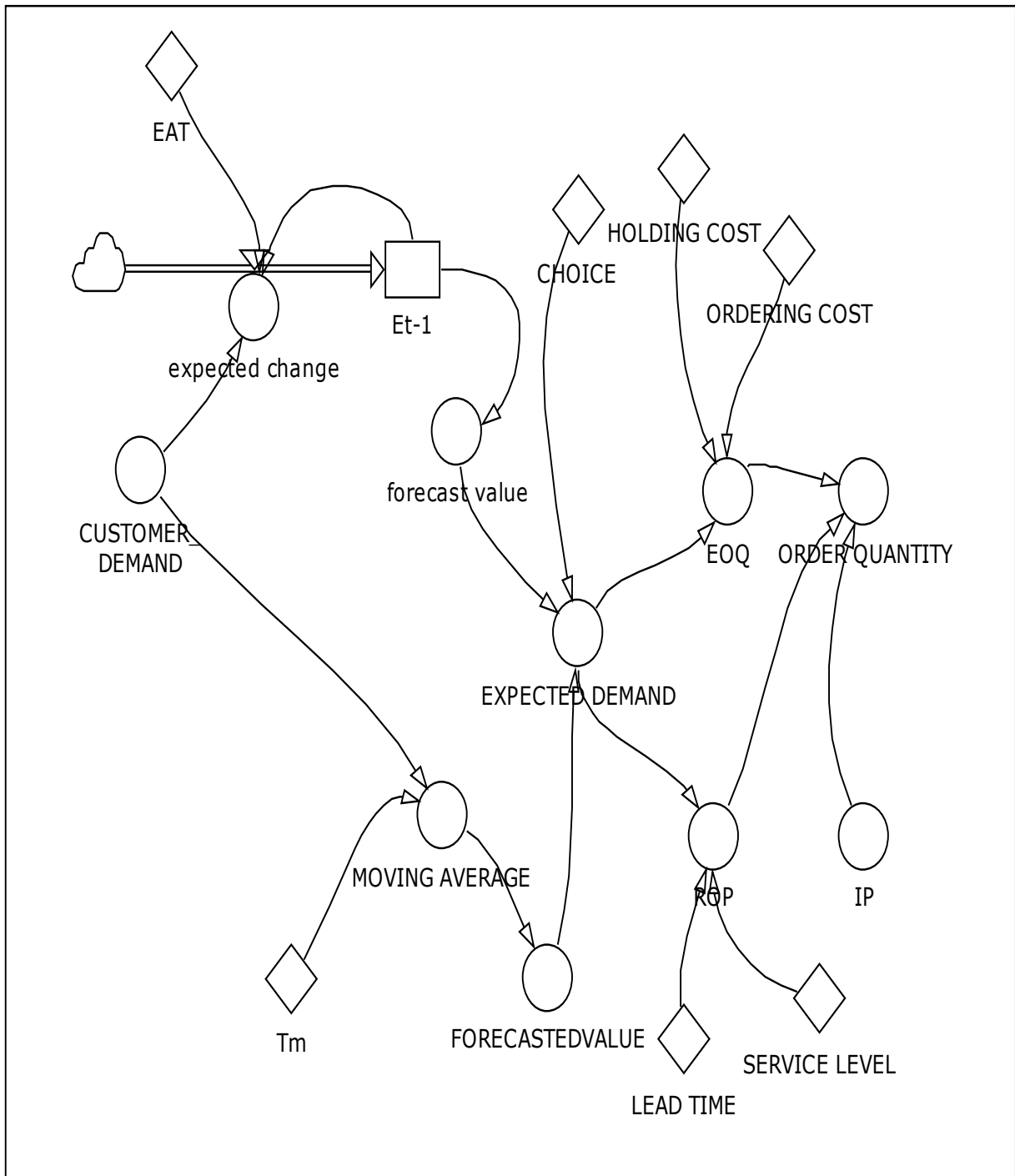


Figure 4.13 Stock – Flow diagram for the reorder point (r,Q) ordering policy

Formulations for the Figure 4.13 is given as

```

Expected change = (1/EAT)*(Dt-1 - Et-1)
Et-1 = 0 <<pd>> /* Constant*/
Customer Demand = (Dt-1) = INTEGER(NORMAL(100;30)) /* demand is assumed as
normally distributed*/
EAT = 14 <<day>> /* expectation adjustment
time is assumed 14 days*/

Forecast value = Et-1
Moving Average =INTEGER (SLIDINGAVERAGE ( Customer Demand * 1 <<da>>; Tm))
/1<<da>>
Tm = 7 <<day>> /* Constant*/
Forecasted Value = Moving Average
Choice = 1 (as integer), 1 = Exp. Smoothing ; 2 = Moving Average
Expected Demand = { 'Forecast value'; 'forecasted value' }[INDEX(Choice)]

EOQ =  $\sqrt{\frac{\text{Ordering cost} * \text{Expected Demand}}{\text{Holding cost}}}$ 
ROP = (Expected Demand*Lead Time)+(Service Level*σ* √Lead Time
σ = "Constant" <<pd>>
Holding Cost = "Constant"
Ordering Cost = 5 * Holding Cost
Lead Time = 14 <<day>> /* Constant*/
Service Level = 0.95 /* Constant*/
ORDER QUANTITY = (if (IP ≤ ROP ; EOQ ; 0 <<pd/day>>))/ IAT
IP = On Hand Inventory + Supply Line Inventory – Backlog Inventory
IAT = 1 <<day>> /* Constant*/

```

By following Figure 4.13, it can be seen that the combined model of the demand forecasting part is included in the stock-flow diagram for the re-order point (r,Q) ordering policy model. Because, the ordering policy uses the expected demand value is obtained from the demand forecasting part. In addition to the expected demand value, the model uses the holding cost, the ordering cost, the lead time, and the service level values for obtaining the EOQ and the ROP values. By using these two values and the inventory position value, the order quantity is evaluated for this ordering policy. The equations are formulated in Powersim as $ORDER\ QUANTITY = O_{i,t} = (if (IP_{i,t} \leq ROP_{i,t} ; EOQ_{i,t} ; 0)) / IAT_i$, where $O_{i,t}$ is the order decision, $IP_{i,t}$ is the inventory position, $ROP_{i,t}$ is the reorder point, $EOQ_{i,t}$ is the economic order quantity and IAT_i is the inventory adjustment time. In the standard reorder point policy, the discrepancy is immediately ordered, so the inventory adjustment time IAT is set to 1.

4.2.4.2 Order up to S Policy

Order-up-to-S Policy is the well-known base stock policy where an agent orders the quantity needed to bring its inventory position up to a base stock level S whenever it falls below S . Similarly to reorder point policy, there are different formulation for computing the maximum stock level S in the inventory management literature. One approach is to compute it by $S = \check{D}_L + k\sigma_L$, where $\check{D}_L$ is expected demand during lead time, $k\sigma_L$ is safety stock where σ_L is standard deviation of forecast errors of the lead time demand, and k is a constant selected according to a desired service level. In any case, the idea is to set S at a level greater than to account for the demand variation. A suitable constant S is another simple choice (Gündüz, 2003). The other practical formula suggested by Gündüz and Barlas (2003) for S is to ‘inflate’ the shipment lead time LT by a factor K , to account for the variation. The equation is $S_{i,t} = (LT_i + K_i) * E_{i,t}$ where LT_i is the transit lead time for stage i , K_i is the ‘lead time inflation constant’, and $E_{i,t}$ is the expected demand (or expected order of stage $i-1$) estimated by stage i . (Recall that $(\check{D}_{i,L} = (LT_i) (E_{i,t})$ anyway, so that the term $(K_i) E_i$ is the extra addition to $\check{D}_L$ to account for the variation). Another formulation for S is formed by Ballou (1999) where the order up to S point is calcuted as

$$\text{Order up to Point } S = ROP + EOQ \quad (4.12)$$

ROP and EOQ are the same parameters for the Re-order Point policy which is mentioned in the above part . In this work, Ballou's approximation is used to compute the order up to S point since it is easy to calculate and its relation with Re-order Point policy. The Order up to S policy is modeled by using Powersim simulation software that displayed in Figure 4.14 .

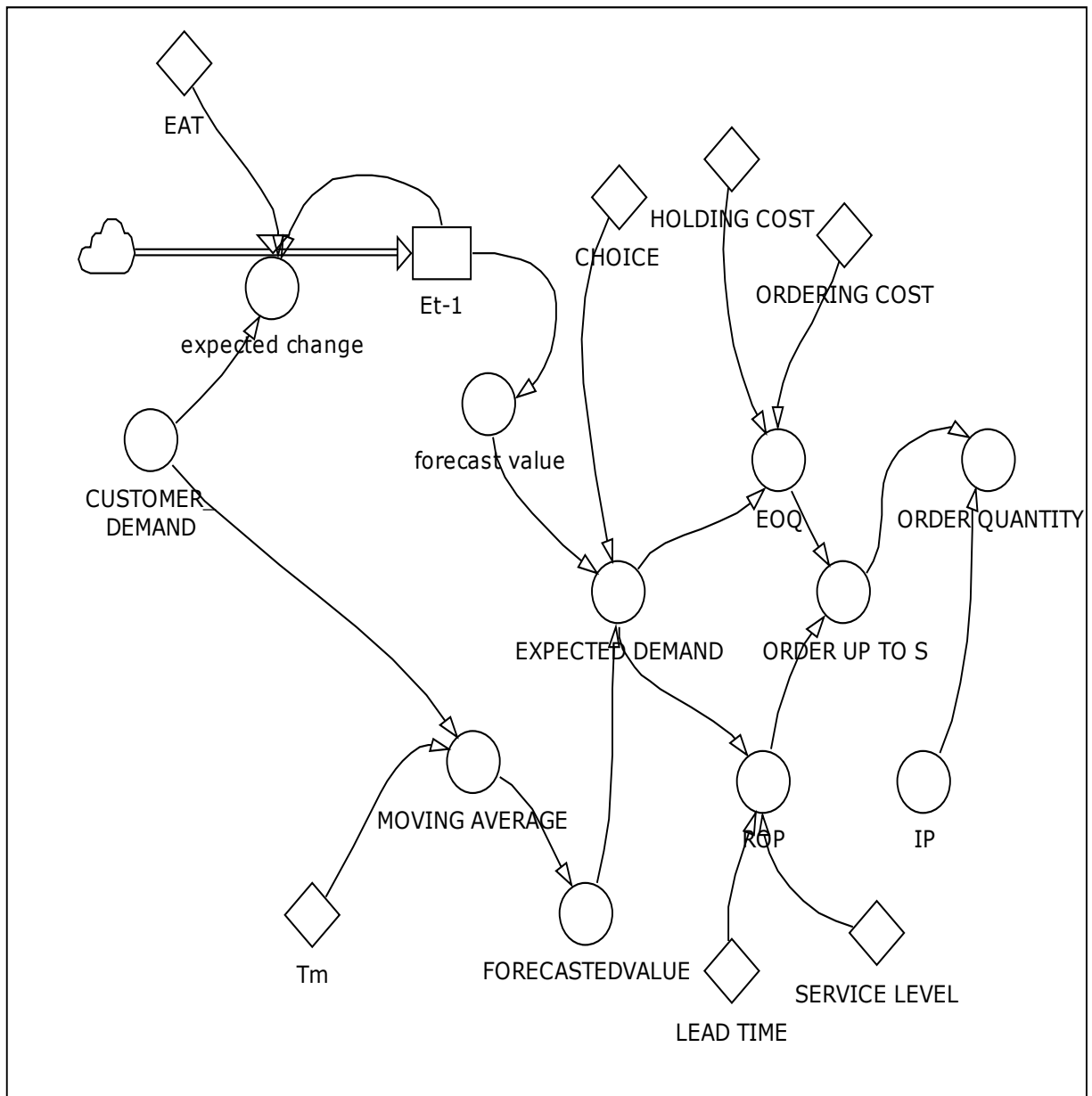


Figure 4.14 Stock – Flow diagram for the order up to S ordering policy

Formulations of Figure 4.14 at Powersim is given as:

```

Expected change = (1/EAT)*(Dt-1- Et-1)
Et-1 = 0 <<pd>>
Customer Demand (Dt-1) = INTEGER(NORMAL(100;30))      /* demand is assumed as
                                                         normally distributed*/
EAT = 14 <<day>>                                     /* expectation adjustment
                                                         time is assumed 14 days*/

Forecast value = Et-1
Moving Average =INTEGER (SLIDINGAVERAGE ( Customer Demand * 1 <<da>>; Tm))
/1<<da>>
Tm = 7 <<day>>                                         /* Constant*/
Forecasted Value = Moving Average
Choice = 1 (as integer), 1 = Exp. Smoothing ; 2 = Moving Average
Expected Demand = { 'Forecast value'; 'forecasted value' }[INDEX(Choice)]

EOQ =  $\sqrt{\frac{\text{Ordering cost} * \text{Expected Demand}}{\text{Holding cost}}}$ 
ROP = (Expected Demand*Lead Time)+(Service Level*σ* √Lead Time
σ = "Constant" <<pd>>
Holding Cost = "Constant"
Ordering Cost = 5 * Holding Cost
Lead Time = 14 <<day>>                                /* Constant*/
Service Level = 0.95                                  /* Constant*/
ORDER QUANTITY = INTEGER(MAX((Order Up to S - IP );0<<pd>>))
Order Up to S = ROP + EOQ
IP = On Hand Inventory + Supply Line Inventory – Backlog Inventory
IAT = 1 <<day>>                                       /* Constant*/

```

Similar to the ROP ordering policy, it can be seen by following Figure 4.14 that the combined model of the demand forecasting part is also included in the stock-flow diagram for the order up to S ordering policy model. In addition to this, the EOQ and the ROP values are obtained for the order up to S policy by using the same patterns as ROP policy model. By using these two values, the order up to S level is calculated with Ballou's approximation. And then by comparing the inventory position level and the order up to S level with each other, the order quantity is determined.

The equations are formulated for the order up to S level and the order quantity in Powersim as

$$\text{ORDER QUANTITY} = O_{i,t} = \max((S_{i,t} - IP_{i,t}) / IAT_i ; 0) \quad (4.13)$$

$$\text{ORDER UP TO } S_{i,t} = ROP_{i,t} + EOQ_{i,t} \quad (4.14)$$

where $O_{i,t}$ is the order quantity decision, $S_{i,t}$ is the order-up-to-level S, $IP_{i,t}$ is the inventory position, and IAT_i is the inventory adjustment time. In the standard order up-to-S policy, the discrepancy is immediately ordered, so the inventory adjustment time IAT is set to one.

The user interface is also developed to make the model user is able to select one of these two ordering policy, automatically. For this purpose, the developed stock-flow diagrams for the ROP and the order up to S ordering policies are merged as shown in Figure 4.15. All of the above formulations for the order up to S and the ROP policies are also the same in the user interface formulation part, except the variable "Order Quantity" that is changed to "ROP Policy" in the ROP policy model. In addition to this, "Orders" variable and the new "choice" variable are added to the merged model. The value 1 for the new "choice" variable indicates that the user selects the ROP policy. On the other hand the value 2 for the new "choice" variable means that the user selects order up to S ordering policy. The choice bar is also added and displayed in the right hand side of the model diagram in Figure 4.15.

Formulation for the combined model of the order processing part with the user interface is given below

```

Expected change = (1/EAT)*(Dt-1 - Et-1)
Et-1 = 0 <<pd>>
Customer Demand (Dt-1) = INTEGER(NORMAL(100;30))      /* demand is assumed as
                                                         normally distributed*/
EAT = 14 <<day>>                                       /* expectation adjustment
                                                         time is assumed 14 days*/

Forecast value = Et-1

Moving Average =INTEGER (SLIDINGAVERAGE ( Customer Demand * 1 <<da>>; Tm))
/1<<da>>
Tm = 7 <<day>>                                         /* Constant*/

Forecasted Value = Moving Average
Choice = 1 (as integer), 1 = Exp. Smoothing ; 2 = Moving Average
Expected Demand = { 'Forecast value'; 'forecasted value' }[INDEX(Choice)]

EOQ =  $\sqrt{\frac{\text{Ordering cost} * \text{Expected Demand}}{\text{Holding cost}}}$ 

ROP = (Expected Demand*Lead Time)+(Service Level*σ* √Lead Time
σ = "Constant" <<pd>>
Holding Cost = "Constant"
Ordering Cost = 5 * Holding Cost
Lead Time = 14 <<day>>                                /* Constant*/
Service Level = 0.95                                  /* Constant*/

ORDER QUANTITY = INTEGER(MAX((Order Up to S - IP );0<<pd>>))
Order Up to S = ROP + EOQ
IP = On Hand Inventory + Supply Line Inventory – Backlog Inventory
IAT = 1 <<day>>

ROP Policy = (if (IP ≤ ROP ; EOQ ; 0 <<pd/day>>))/ IAT
Choice 2 = 1 (as integer), 1 = ROP Policy ; 2 = Order up to S
Orders = {ROP Policy,Order Quantity}[INDEX(Choice 2)]

```

4.2.5 Formulation of Retailer and Manufacturer

The structure of the supply chain considered here corresponds to a two stage (retailer-manufacturer), and a single item supply chain which is similar to the well known “beer distribution game”. Both of the retailer and the manufacturer agents are formed identically, and the simulation model has the following sequence of events arranged in the order for each period: (1) incoming orders (demand) are received from the downstream decision-maker and either filled (if inventory is available) or backlogged, (2) the last period demand is used to forecast the next period demand and a new order is placed according to the selected ordering policy and passed to the upstream echelon, and (3) incoming shipments from the upstream decision-maker are received and placed into the inventory. The inventory position is reviewed every time period ($DT = 1$ day) and shipments are received with a delay. However, the formulations for the retailer and the manufacturer are clearly explained in the next sections.

4.2.5.1 Retailer

The retailer agent of the supply chain is modeled using Powersim and its stock–flow diagram is displayed in Figure 4.16.

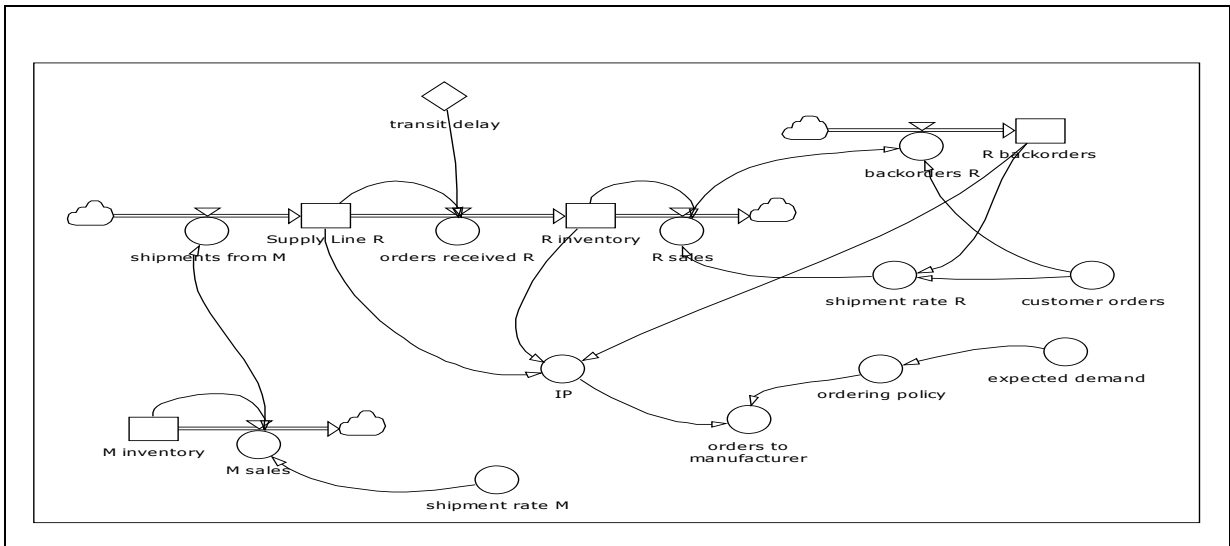


Figure 4.16 Stock – Flow diagram for the retailer agent

By following Figure 4.16, it can be seen that the retailer receives orders from the end customer. If the retailer on-hand inventory level is enough to fulfill this received orders, it satisfies the end customer needs. On the other hand, if the retailer on-hand inventory level is not enough, the retailer adds the unfulfilled orders to its backorder inventory. And then, the retailer checks its inventory position by controlling the on-hand, backordered, and the supply line inventories for each time periods. The retailer forecasts the next period expected demand value with a suitable forecasting method. Then by using the this value, it determines the amounts of the order quantity is placed to the manufacturer by using the preferred ordering policy.

Formulations for the retailer agent shown in Figure 4.16 is given as:

Supply LineR = 0 <<pd>>	/* Initial value*/
R inventory = 3000 <<pd>>	/* Initial value*/
R backorders = 0 <<pd>>	/* Initial value*/
M inventory = 3000 <<pd>>	/* Initial value*/
Customer Order = Customer Demand	/*(AR(1) or IID process)*/
Shipment Rate R = Customer order +('R backorder'/1<<da>>)	
Backorders R = Customer order - R sales	
R sales = MAX(0<<pd/da>>;(MIN('R inventory'/1<<da>>;'shipment rate R'))	
Order Received R = DELAYMTR('Supply line R'/1<<da>>; Transit delay; 1; 0<<pd/da>>)	
Transit delay = 14<<da>>	/*Constant*/
Shipment from M = M sales	
IP = 'R inventory'+ 'Supply line R' - 'R backorder'	
Orders to Manufacturer = Ordering Policy	
Ordering Policy = Expected Demand	
Expected Demand = { 'Forecast value'; 'forecasted value' }[INDEX(Choice)]	

4.2.5.2 Manufacturer

Since the all agents of the supply chain model is assumed to be identical, the manufacturer agent follows the same patterns with the retailer agent that is explained in the last section. On the other hand, it is known that the two information sharing strategy named as the decentralised and the centralised cases can be used in the supply chain management. The information sharing strategy does not give the significant results for the retailer agent, but it can be very beneficial for the manufacturer agent. For this reason, the manufacturer agent of the supply chain is modeled with respect to both of these information sharing strategies. The first model is constructed for the decentralised supply chain strategy where the manufacturer only knows the retailer's demand, and it is shown in Figure 4.17.

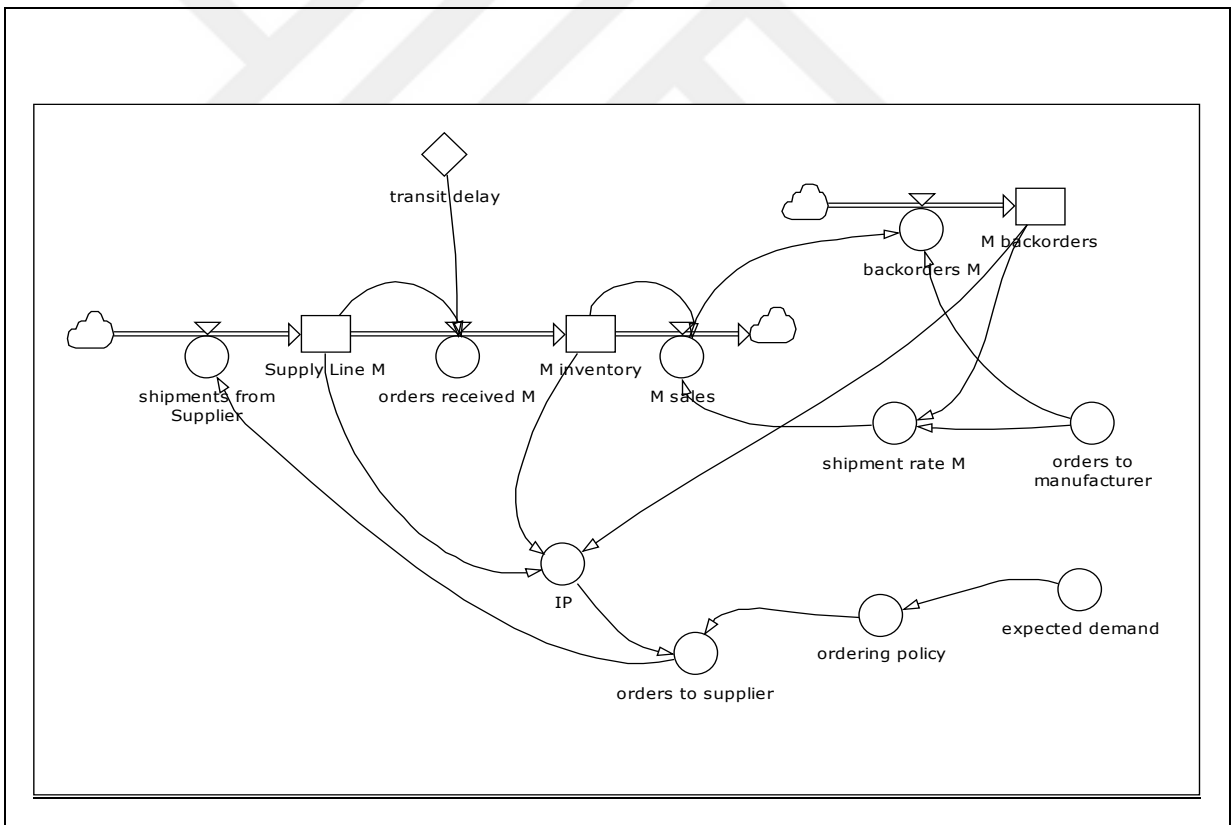


Figure 4.17 : Stock – Flow diagram for the manufacturer agent in the decentralised case

By following Figure 4.17, it can be perceived that the manufacturer receives orders from the retailer agent. If the manufacturer on-hand inventory level is enough to fulfill this received orders, it satisfies the retailer needs. On the other hand, if the manufacturer on-hand inventory level is not enough, the manufacturer adds the unfulfilled orders to its backorder inventory. And then, the manufacturer checks its inventory position by controlling the on-hand, backordered, and the supply line inventories for each time periods. The manufacturer forecasts the next period expected demand value with a suitable forecasting method by using the historical data that is received from the retailer's orders. Then by using the this value, it determines the amounts of the order quantity is placed to the supplier by using the preferred ordering policy.

Formulations for the manufacturer agent in the decentralised case shown in Figure 4.17 is given as:

Supply LineM = 0 <<pd>>	/* Initial value*/
M inventory = 3000 <<pd>>	/* Initial value*/
M backorders =0 <<pd>>	/* Initial value*/
Orders to Manufacturer = Retailer Demand	/*(ROP or Order up to S policies)*/
Shipment Rate M = Orders to Manufacturer +('M backorder'/1<<da>>)	
Backorders M = Orders to Manufacturer - M sales	
M sales = MAX(0<<pd/da>>;(MIN('M inventory'/1<<da>>;'shipment rate M'))	
Order Received M= DELAYMTR('Supply line M'/1<<da>>; Transit delay; 1; 0<<pd/da>>)	
Transit delay = 14<<da>>	/*Constant*/
Shipment from Supplier = Orders to Supplier	
Orders to Supplier = Ordering Policy	
Ordering Policy = Expected Demand	
Expected Demand = { 'Forecast value'; 'forecasted value' }[INDEX(Choice)]	
IP = 'M inventory'+ 'Supply line M' - 'M backorder'	

The second model is formed for the centralised supply chain management strategy where the manufacturer is allowed to know the end customer demand data instead of the retailer's orders information. In the centralised case, the manufacturer forecasts its next period expected demand by using the end customer demand information against to the retailer demand information. The corresponding stock – flow diagram of the manufacturer agent in the centralised case is shown in Figure 4.18.

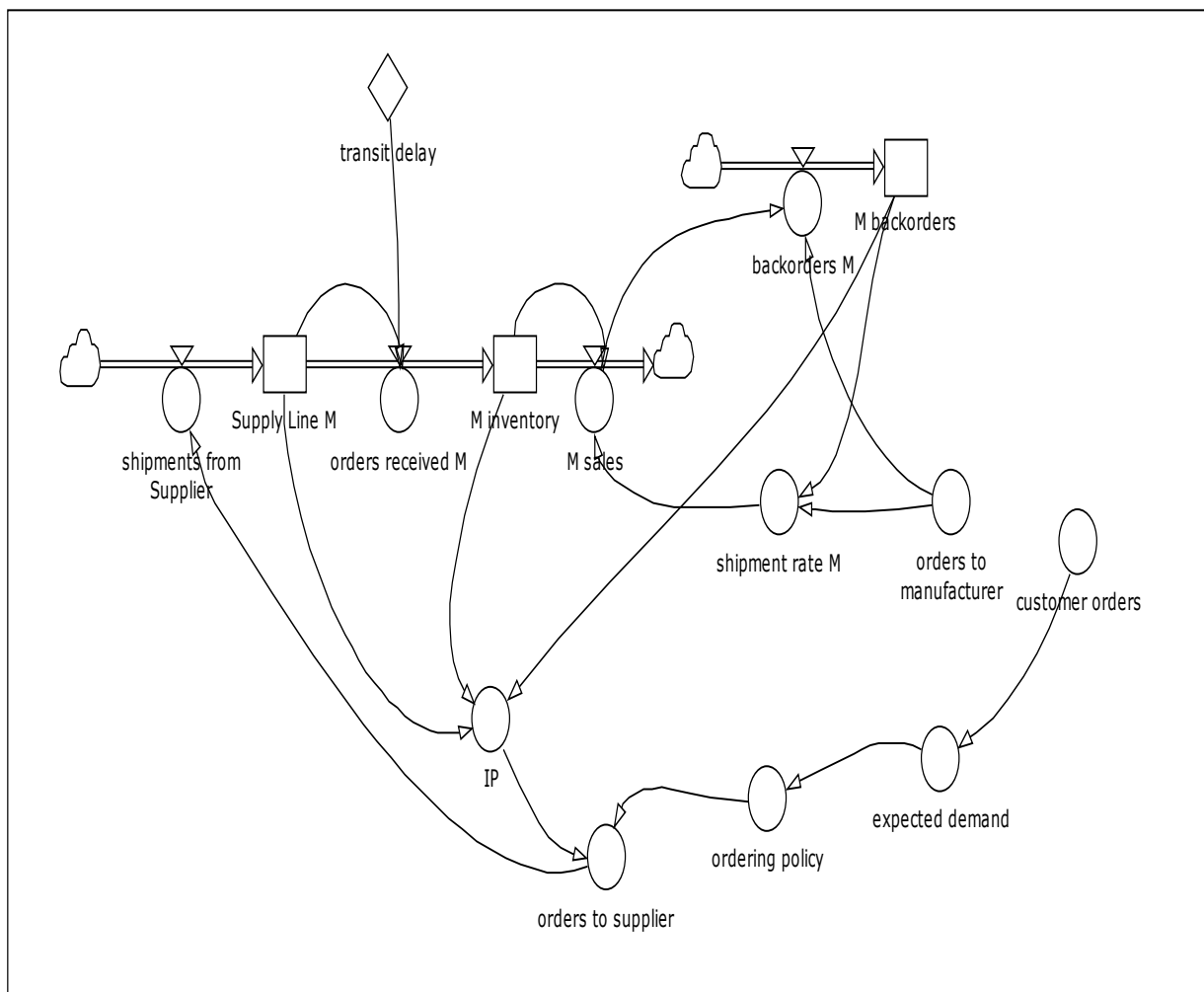


Figure 4.18 : Stock–Flow diagram for the manufacturer agent in the centralised case

Formulations for the manufacturer agent in the centralised case shown in Figure 4.18 is given as:

Supply LineM = 0 <<pd>>	/* Initial value*/
M inventory = 3000 <<pd>>	/* Initial value*/
M backorders =0 <<pd>>	/* Initial value*/
Orders to Manufacturer = Retailer Demand	/*(ROP or Order up to S policies)/*
Shipment Rate M = Orders to Manufacturer +('M backorder'/1<<da>>)	
Backorders M = Orders to Manufacturer - M sales	
M sales = MAX(0<<pd/da>>;(MIN('M inventory'/1<<da>>;'shipment rate M')	
Order Received M= DELAYMTR('Supply line M'/1<<da>>; Transit delay; 1; 0<<pd/da>>)	
Transit delay = 14<<da>>	/*Constant*/
Shipment from Supplier = Orders to Supplier	
Orders to Supplier = Ordering Policy	
Ordering Policy = Expected Demand	
Expected Demand =Customer order	/* Forecast value by using end customer demand history*/
IP = 'M inventory'+ 'Supply line M' - 'M backorder'	

For constructing the full supply chain model, all of the developed parts are combined and the stock-flow diagrams of the whole simulation model in the decentralised and the centralised cases are shown in Figure 4.19 and 4.20, respectively. The upper stage in the figures represent the retailer agent and the lower stage in the figures represent the manufacturer agent that places orders to the uncapacitated supplier.

In Figure 4.19, the retailer receives orders from the end customer according to the IID or the AR (1) demand process, then controls its inventory position, forecasts the next period demand, and places orders to the manufacturer agent according to its ordering policy. The manufacturer agent uses this order as a customer demand, then forecasts the next period demand and places orders to its supplier.

In addition to this, in Figure 4.20, the flows indicate a little but important change where the retailer and the manufacturer are able to reach to the end customer demand at the same time, and they can forecast the next period demand and determine their order quantity by using the this information. All of the variable names and their formulations for the entire supply chain simulation model for the decentralised, and the centralised cases listed in Appendix B.



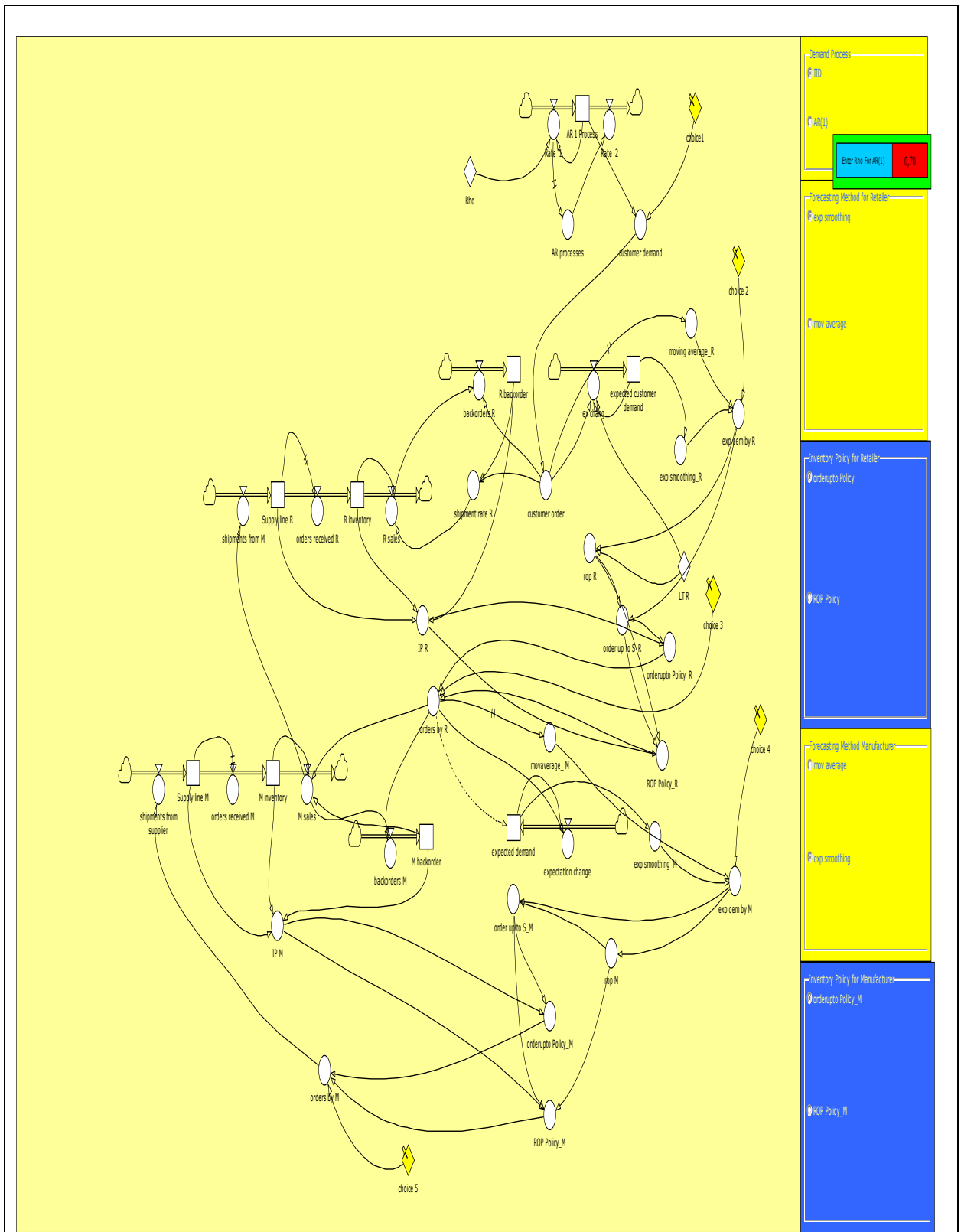


Figure 4.19 The stock–flow diagram for the whole simulation model in the decentralised case

The combined user interface is composed of four parts where first three parts is developed to take information from the user and last part is developed to show the simulation model's output, displayed in Figure 4.21 and Figure 4.22. First three parts give user a test chance by turning the simulation model parameters and constants. User can select a demand process for customer demand as identically independently distributed IID or AR (1) serially correlated demand processing alternatives. User can also choose a suitable demand forecasting method from the exponential smoothing or the moving average forecasting techniques to forecast the next period demand. In addition to these, user can decide the desired ordering policy for each agent in the supply network from the standard order up to S or the ROP Policy. The simulation model may also be worked for both decentralised or centralised information sharing strategies. Furthermore, model needs some constant values from the user as autocorrelation coefficient, lead time, customer service level, ordering and holding costs. The last part is developed to show the simulation model's output which gives the graph of customers orders to the retailer (retailer's demand), the retailer orders to the manufacturer (manufacturer's demand) and the manufacturer orders to the supplier (supplier's demand) , respectively. Besides these graphs, it shows all of them in a one graph which give user to chance to see the bullwhip effect more clearly. In addition to these graphs, the output part displays the performance measure of simulation analysis for the variance amplification ratios named as 'bullwhip effect measure' that is simply defined in literature as:

$$\text{Bullwhip Effect Measure} = [\text{Standard deviation of Orders}] / [\text{Standard deviation of Demands}] \quad (4.15)$$

A bullwhip measurement equal to one implies that the order variance is equal to the demand variance or in other words, there is no variance amplification. A bullwhip measurement larger than one indicates that the bullwhip effect is present (amplification), whereas a bullwhip measurement smaller than one is referred to as a "smoothing" scenario, meaning that the orders are smoothed (less variable) compared to the demand pattern (dampening). In the present study, the BEM for retailer is calculated by using above formula as variance of retailer orders is divided to variance of retailer demand and similarly, the BEM for manufacturer is calculated as variance of manufacturer orders is divided to variance of manufacturer demand.

7TEPE (SUPPLY CHAIN SIMULATOR)

PART 1 : DEMAND PROCESS AND INFORMATION SHARING STRATEGIES

SELECT THE DEMAND PROCESS :

SELECT THE DEMAND PROCESS
☒ I I D
☐ AR (1) PROCESS

ENTER RHO FOR AR(1)

0,00

SELECT THE INFORMATION SHARING STRATEGY :

SELECT INFORMATION SHARING STRATEGY
☒ DECENTRALIZED
☐ CENTRALIZED

PART 2 : RETAILER INPUTS

ENTER THE RETAILER INPUTS TO BELOW PART :

LEAD TIME (IN DAYS)	0,00
SERVICE LEVEL (BETWEEN 0-1)	0,00
Co (ORDERING COST)	0,00
Ch (HOLDING COST)	0,00

FORECASTING METHOD FOR RETAILER
☒ EXP SMOOTHING
☐ MOVING AVERAGE

INVENTORY POLICY FOR RETAILER
☒ ORDER UP TO S
☐ ROP POLICY

PART 3 : MANUFACTURER INPUTS

ENTER THE MANUFACTURER INPUTS TO BELOW PART :

LEAD TIME (IN DAYS)	0,00
SERVICE LEVEL (BETWEEN 0-1)	0,00
Co (ORDERING COST)	0,00
Ch (HOLDING COST)	0,00

FORECASTING METHOD FOR MANUFACTURER
☒ EXP SMOOTHING
☐ MOVING AVERAGE

INVENTORY POLICY FOR MANUFACTURER
☒ ORDER UP TO S
☐ ROP POLICY

Figure 4.21 User interface for simulation model's inputs part

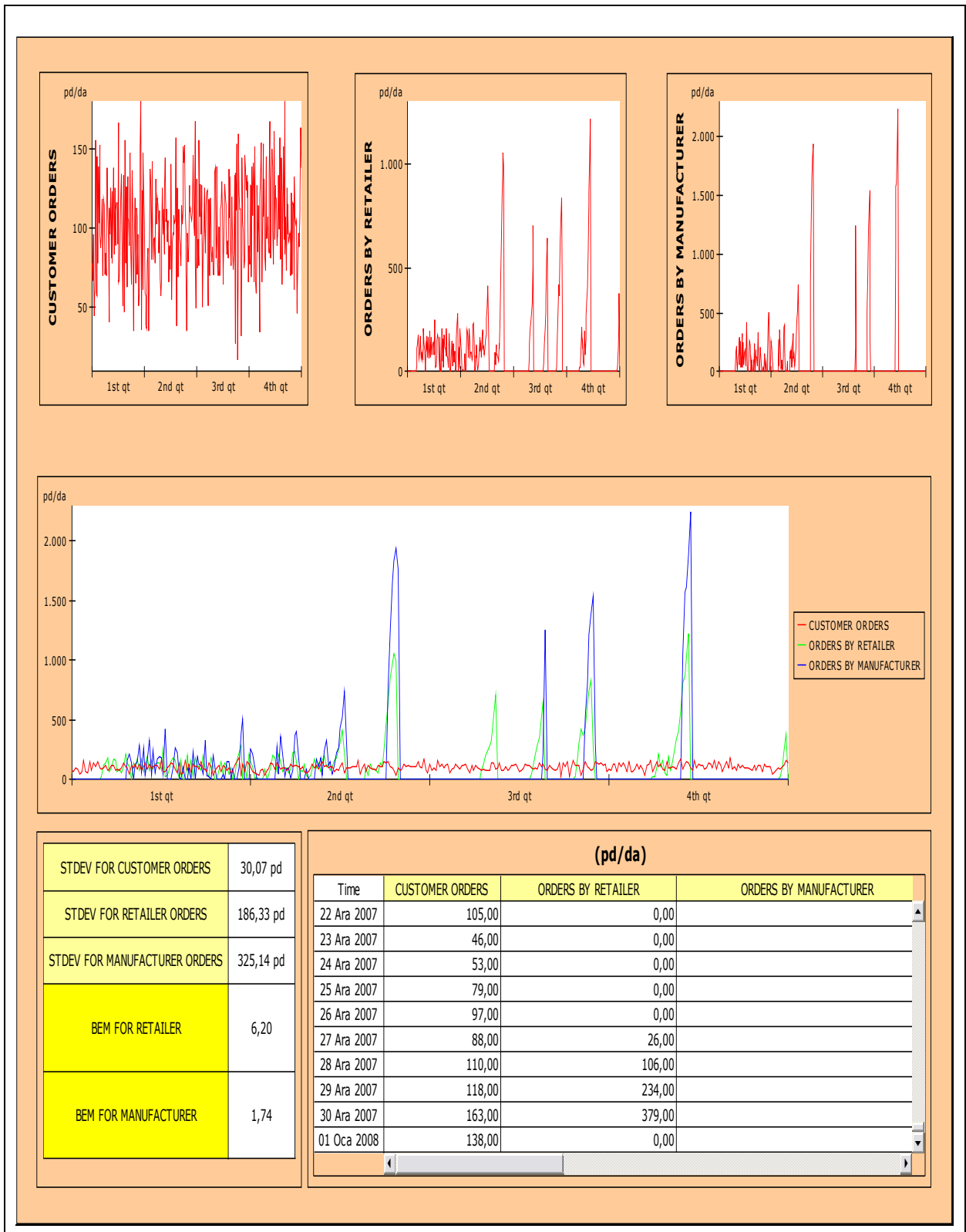


Figure 4.22 User interface for simulation model's outputs part

4.2.6 Model Verification and Validation

“ Simulation models are increasingly being used in problem solving and to aid in decision-making. The developers and users of these models, the decision makers using information obtained from the results of these models, and the individuals affected by decisions based on such models are all rightly concerned with whether a model and its results are “correct”. This concern is addressed through model validation and verification” (Sargent, R. G. 1994) .

“ Model verification is substantiating that the model is transformed from one form into another, as intended, with sufficient accuracy. Model verification deals with building the model right. Model validation is substantiating that the model, within its domain of applicability, behaves with satisfactory accuracy consistent with the M&S (modeling & simulation) objectives. Model validation deals with building the right model” (Balci, O. 1997).

The review of the academic literature on the validation of system dynamics models suggests two things. One is that the attitude of authors to this subject is by no means consistent. Some treat it in detail, others more cursorily. In addition to this, System dynamicists commonly believe that it is meaningless to judge the validity of a model without a clear view of model purpose (Richardson and Pugh,1981). The appropriate level of detail, i.e. system boundaries, system variables, and the assumed system interaction among the variables, is determined depending on the purpose and objectives that are set beforehand.

According to system dynamicists, model validation can not be totally formal and quantitative, because it signifies usefulness with respect to a purpose. Therefore, it is important to test the validity, or usefulness, of the purpose and objectives, which are subjective entities. So objective, quantitative, and formal tools go together with subjective, qualitative, and informal tools. The subjective, qualitative ones are those that are dispersed throughout the modeling process, whereas the quantitative tools are used at the end of model construction, immediately before policy design simulations (Barlas, 1996).

The validation tests of system dynamics models are grouped into two classes, namely structural and behavioral. Structural validity tests check whether the structure of the model matches the structure of the system being modeled (Shreckengost, 1985). Form of each equation, selection of system boundaries, variables and relationships between the variables must be tested (Forrester, 1961). All important factors of the real system must be represented in the model, and all elements of the model must have counterparts in the real system. Barlas (1989, 1996) partitions the structural validity into two groups: direct structure tests and structurally-oriented behavior tests. Direct structure tests are strong tests since they evaluate the model structure directly. These tests do not use simulation. Basically, they take each relationship (mathematical equation or any form of logical relationship) individually and compare it with the available knowledge (empirical or theoretical) about the real system (Barlas, 1996). Structure-oriented behaviour tests assess the validity of the structure indirectly, by applying certain behaviour tests on model-generated behaviour patterns. They do involve simulation, and can be applied to the whole model as well as to its isolated sub-models. Once the structure of the model is believed to be adequate, one can pass on to behaviour validity tests. These tests check if the model is capable of producing an acceptable output behaviour. Output validation involves demonstrating that the model is able to reproduce the dynamic time patterns that have been observed in the behaviour of the real system (Barlas, 1989). So, the crucial point is the emphasis on pattern prediction rather than point prediction. Barlas (1989) mentions five components present in complex behaviour patterns: trends, periods of oscillations, phases of oscillations, average values, and amplitudes (variations). He also develops a multi step behaviour validation procedure (Barlas 1989, 1996).

On the other hand, verification of system dynamics models can be obtained by using the similar ways of other simulation modeling tools. However, all of the available softwares also include model verification toolboxes. In this thesis' simulation model, Powersim software verification toolbox, and some of the validation tests proposed by Barlas (1989, 1996) is applied for model verification&validation which are explained in the next section.

4.2.6.1 Model Verification

The first verification is the dimensional consistency check. In this test, the units of all variables are checked so that the relations between them are logical and meaningful. This test is carried out automatically by Powersim Studio. It will automatically detect inappropriate units and cannot run the simulation. Checking the numerical integration method and step size has also been done as the second verification method. The integration method is Euler with 1 day as step size because lower step size will also generate the same result. Higher step size will result in differences in model's result (compared to consecutive runs).

4.2.6.2 Model Validation

Some direct structure tests and structure-oriented behaviour tests are used for thesis model validation. Theoretical structure and parameter confirmation, and face validation tests are used for direct structure testing where these are checked without running any simulation but studied each relation in the model. In addition to this, extreme condition tests are used for structure-oriented behaviour testing where these test are evaluated indirectly by running the model.

4.2.6.2.1 Direct Structure Tests

Both of the model structure and the parameters correspond to the relevant descriptive knowledge of the real system's theoretical structure and parameter are confirmed. Although supply chain management, that is the interested real system in the simulation model, is a management philosophy not a concrete system, the theory of it is completely comprehended and this comprehension is reflected to the developed model. In addition to this, the parameters are also checked on the basis of any numerical knowledge. This check is done simultaneously while building the model.

Face validation means that checking the model with experts that know the system in study very well. Assumptions and equations used in this model are checked together with people from the different industry sectors, and universities who works on supply chain management philosophy and bullwhip effect in academical or consultancy levels.

4.2.6.2.2 Structure-Oriented Behaviour Tests

In this test, the model is run under three extreme conditions. The simulated behaviour is then compared to the expected behaviour of the system under those conditions. The first extreme condition is applying a “PULSE” increase in the end customer demand. The second extreme condition is applying a “STEP” increase in the end customer demand. In addition to these, the third extreme condition is applying a “RAMP” increase in the end customer demand. In response of these extreme conditions, the orders fluctuation behaviour is expected for each agent in real supply chains. The simulation model outputs also support these expectation where orders for the retailer, and the manufacturer fluctuates. The simulation model outputs for each of three extreme conditions are displayed on the Appendix C.

5. SIMULATION MODEL APPLICATION AND ANALYSIS

The generic systems dynamics based simulation model is applied to a sample data to explore how a series of replenishment policies and the forecasting techniques selection, under the different demand patterns, induces or reduces the bullwhip effect. Furthermore, it is desired to make a comparison between the centralised and the decentralised supply chain management strategies as far as the bullwhip effect is concerned. For this purpose, each agent in the supply chain is able to select one forecasting technique and one ordering policy for the different end customer demand processing methods. In addition to this, the model user is able to test the all of the scenarios under the decentralised or the centralised cases. The combination of selection alternatives reached to 32 scenarios for each strategy, making 64 scenarios altogether.

Figure 5.1 briefly shows the tree diagram for all possible scenarios are analysed. By following the each branch of Figure 5.1, the parameters of each scenario can be determined. For example, the parameters of the first scenario can be reached by following the first branch of the tree diagram where both of the retailer and the manufacturer uses the exponential smoothing method (ES1,ES2) for demand forecasting, and the order up to S policy (OUT1,OUT2) for inventory management.

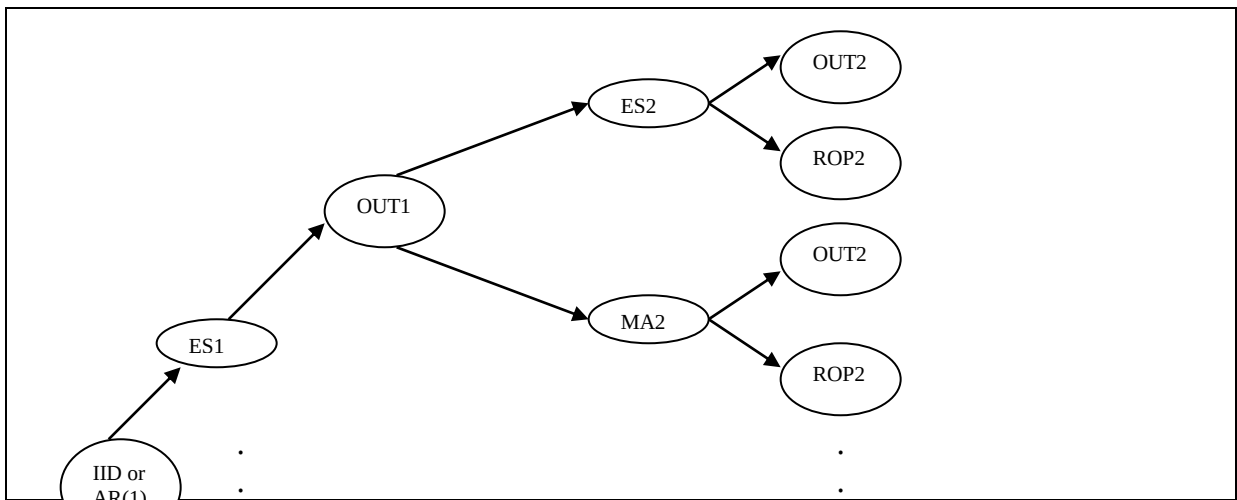


Figure 5.1 Tree diagram for all scenarios

A sample analysis is performed with an illustrative example for all of the 64 different scenarios to observe how changing the parameters of supply chain agents affect on the order

fluctuations. All of the findings are also valid for selected parameters of the sample data set. Therefore, any user can choose his / her own preferences to observe their interested simulation model results. Moreover, some constant values are used in the simulation model listed at Table 5.1 where the ordering and the holding costs are not directly given, but their mathematical relation is predicted according the general inventory management theory. So, it is assumed that the ordering cost of each agent is five times greater than the holding cost of them in the simulation study.

Table 5.1 Sample input data for simulation model

LEAD TIME	14 DAYS (2 WEEKS)
SERVICE LEVEL	% 95
Co (ORDERING COST)	$\sim 5 * Ch$ (ASSUMED BY PREDICTION)
Ch (HOLDING COST)	ASSUMED A CONSTANT

For the IID demand process, the end customer demand is assumed as normally distributed with mean 100 products / day and standard deviation 30 products. For the AR(1) demand process, again the average of the end customer demand is assumed to be 100 products / day with $\rho = 0,7$ (positively correlated). All of the output graphs of the Powersim models for each scenario is adopted to Excel and they are shown in the Appendix D. Moreover, some important findings as the average of the standard deviations for the placed orders by each agent, and the BEM's (bullwhip effect measure) values are summarized for each scenario under the decentralised and the centralised cases, respectively. These findings are also dealt with to clarify clearly how a series of replenishment policies and the forecasting techniques selection, under the different demand patterns, induces or reduces the bullwhip effect for each information sharing strategy. For this purpose, the "what if analysis" are made for each possible selection alternative to observe is there any significant difference on the order fluctuation, if the user alters his or her preferences on the forecasting technique or the ordering policy selection alternatives.

5.1 ANALYSIS OF THE BULLWHIP EFFECT UNDER THE DECENTRALISED INFORMATION SHARING STRATEGY

The decentralised information sharing strategy means that the demand information of the end customer is not shared by each agent throughout the whole supply chain. In this case, the end customer places orders to the retailer, and the retailer places orders to the manufacturer. The manufacturer does not have any information about the end customer demand and it is only able to know the retailer's order informations. For the sample data set, the first finding from the simulation model analysis is the average of the standard deviations for placed orders by the retailer and the manufacturer agents that are shown in Table 5.2. These results are obtained for each possible scenario by running the simulation model with 10 replications and getting average values of these 10 observation results.

Table 5.2 The average of the standard deviations for placed orders in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV. FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.547	65.001	112.562
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	30.177	64.053	220.595
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.248	64.614	95.580
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	29.834	64.240	221.963
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.495	221.868	233.122
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	29.942	221.894	230.455
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	30.159	219.912	232.863
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	29.969	221.297	223.088
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.978	52.986	97.139
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.797	52.558	222.642
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.255	51.149	85.140
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	30.254	52.240	223.268
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.287	221.577	229.791
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	30.485	220.427	228.915
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	29.745	220.132	232.735
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.676	221.659	224.581
Min.					29.255	51.149	85.140
Max.					30.676	221.894	233.122
Average					30.053	139.725	194.652

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV. FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to	Order up to S	40.157	79.142	133.656

			S				
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.012	81.633	225.095
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	40.426	80.773	121.305
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.170	80.180	217.993
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	40.078	225.343	262.829
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	41.031	221.816	235.206
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.024	219.941	250.429
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.252	218.406	222.033
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	41.302	69.637	119.250
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.164	70.320	232.436
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.577	67.906	108.831
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	39.458	68.158	221.683
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	40.775	220.059	248.598
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	41.763	222.972	236.297
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	40.536	223.099	256.005
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.153	219.421	224.392
Min.					39.458	67.906	108.831
Max.					41.763	225.343	262.829
Average					40.492	148.050	207.252

Total Min.	29.255	51.149	85.140
Total Max.	41.763	225.343	262.829
Total Average	35.273	143.888	200.952

As shown in Table 5.2, the average of the standard deviations for the retailer orders are larger than the end customer orders and similarly, the average of the standard deviations for the manufacturer orders are also larger than retailer orders in all 32 scenarios. This increase can also be followed by looking the “Total Average” values of the average of standard deviations where the total average value of the end customer orders’ deviations is 35.273. On the other hand, the total average values for the retailer and the manufacturer orders are 143.888 and 200.952, respectively. The average of average placed orders for the end customer, retailer, and manufacturer are approximately 100 products / day in each scenario.

Again by following Table 5.2, it can be seen that Scenario 11 gives the best result for the retailer, and the manufacturer agents with the minimum average standard deviation values, under the assumption of the customer demand is the IID demand process as normally

distributed with the mean demand 100 products / day and the standard deviation 30 products. In this scenario, both of the agents uses the moving average forecasting method, and the order up to S ordering policy. Furthermore, under the assumption of the customer demand is AR(1) demand process, Scenario 27 gives the best result for both of the agents where they use the moving average forecasting method, and the order up to S ordering policy. However, both of these results presents worse values than results obtained in the IID demand process. In addition to these findings, a paired t-test which is a statistical analysis tool, applied to the sample output to receive is there any significant difference on the order fluctuation for the retailer and the manufacturer agents, under the IID, and the AR(1) demand processes. The paired t-test method requires that observations drawn from each population (simulated system) are normally distributed and independent within a population. However, the paired t-test method does not require that the observation between populations be independent. In this study, simulation results are evaluated based on the average of the standard deviations for placed orders of the retailer, and the manufacturer agents by using the different stream of random numbers in each replication, so the independency within a population is satisfied. In addition to this, the normality is assumed for each observation. Moreover, for making a comparison on two different demand processes, simulation model results are classified into two groups. The first group results between Scneraio 1 and Scenario 16 are evaluated under the IID demand process, and the second group results between Scenario 17 and Scenario 32 are evaluated under the AR (1) demand process. Since, all of these scenarios uses the same parameters for the demand forecasting and the ordering decisions, it is assumed that observations between population are not fully independent. But it is not a requirement for the paired t-test, so it is chosen for this analysis with $\alpha = 0.05$ level of significance to compare the two candidate strategy results using the following hypothesis.

$H_0 : \mu_1 - \mu_2 = 0$ or using the new “paired” notation $\mu_{(1-2)} = 0$

$H_1 : \mu_1 - \mu_2 \neq 0$ or using the new “paired” notation $\mu_{(1-2)} \neq 0$

where the subscripts 1 and 2 denote strategy 1 (the end customer demand process is IID), and strategy 2 (the end customer demand process is AR(1)), respectively. Results of the paired t-

test for analysing the effect of the demand processes on order fluctuation for each agent is displayed below, respectively.

The test result for the retailer agent is shown below indicates that there is a significant difference on the order fluctuations when the end customer changes its demand process between the IID and the AR (1) demand processes. This is obtained because, the calculated P – value statistic (0.001) is less than the $\alpha = 0.05$ level of significance. In addition to this, by following the given confidence interval in the test result, where both of the upper and lower bounds have negative values, indicates that the order fluctuation increases when the end customer demand is AR(1) demand process against to the IID demand process for the retailer agent.

Paired T-Test and CI: DC_iid_Ret; DC_ar1_Ret

Paired T for DC_iid_Ret - DC_ar1_Ret

	N	Mean	StDev	SEMean
DC_iid_Ret	16	139.7	84.2	21.0
DC_ar1_Ret	16	148.1	75.9	19.0
Difference	16	-8.32	8.51	2.13

95% CI for mean difference: (-12.86; -3.79)

T-Test of mean difference = 0 (vs not = 0): T-Value = -3.91 P-Value = 0.001

However, the test result for the manufacturer agent is shown below indicates that there is also a significant difference on the order fluctuations when the end customer changes its demand process between the IID and the AR (1) demand processes.. Because, the calculated P – value statistic is approximately 0 which is again less than the $\alpha = 0.05$ level of significance. Similar to the retailer agent, by following the given confidence interval in the test result, where both of the bounds have negative values, indicates that the order fluctuation also increases when the

end customer demand is AR(1) demand process against to the IID demand process for the manufacturer agent.

Paired T-Test and CI: DC_iid_Man; DC_ar1_Man

Paired T for DC_iid_Man - DC_ar1_Man

	N	Mean	StDev	SE Mean
DC_iid_Man	16	194.7	58.2	14.6
DC_ar1_Man	16	207.3	53.3	13.3
Difference	16	-12.60	11.30	2.83

95% CI for mean difference: (-18.62; -6.58)

T-Test of mean difference = 0 (vs not = 0): T-Value = -4.46 P-Value = 0.000

In addition to these findings about the average of the standard deviations for the placed orders by each agent, the BEM's (bullwhip effect measure) values are the other important and basic measures for analysing the order fluctuation's behaviours. The BEM's values can basically reflect the which scenario is affected or not affected by the bullwhip effect. Table 5.3 lists the BEM's values for all of the possible scenarios under the decentralised information sharing strategy for the sample data set. The BEM's values are also calculated between the retailer-customer agents, the manufacturer-retailer agents, and the manufacturer-customer agents.

Table 5.3 BEM's values for the decentralised information sharing strategy

DECENTRALISED CASE

IID process	FORECASTING METHOD		ORDERING POLICY		THE BULLWHIP	EFFECT	MEASURES
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Retailer&Customer	Manf. & Retailer	Man & Customer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	2.128	1.732	3.685
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	2.123	3.444	7.310
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	2.136	1.479	3.160
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	2.153	3.455	7.440
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	7.522	1.051	7.904
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	7.411	1.039	7.697
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	7.292	1.059	7.721
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	7.384	1.008	7.444
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	1.768	1.833	3.240
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	1.764	4.236	7.472
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	1.748	1.665	2.814
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	1.727	4.274	7.380
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	7.316	1.037	7.587
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	7.231	1.039	7.509
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	7.401	1.057	7.824
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	7.226	1.013	7.321
				Min.	1.727	1.008	2.814
				Max.	7.522	4.274	7.904
				Average	4.646	1.901	6.469

AR(1) process	FORECASTING METHOD		ORDERING POLICY		THE BULLWHIP	EFFECT	MEASURES
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Retailer&Customer	Manf. & Retailer	Man & Customer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	1.971	1.689	3.328
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	1.990	2.757	5.488
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	1.998	1.502	3.001
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	1.996	2.719	5.427
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	5.623	1.166	6.558
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	5.406	1.060	5.732
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	5.495	1.139	6.257
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	5.426	1.017	5.516
AR(1) process	FORECASTING METHOD		ORDERING POLICY		THE BULLWHIP	EFFECT	MEASURES
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Retailer&Customer	Manf. & Retailer	Man & Customer

scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	1.686	1.712	2.887
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	1.751	3.305	5.787
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	1.716	1.603	2.750
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	1.727	3.252	5.618
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	5.397	1.130	6.097
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	5.339	1.060	5.658
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	5.504	1.147	6.315
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	5.332	1.023	5.453
Min.					1.686	1.017	2.750
Max.					5.623	3.305	6.558
Average					3.647	1.705	5.117

Total Min.	1.686	1.008	2.750
Total Max.	7.522	4.274	7.904
Total Average	4.145	1.803	5.793

By following Table 5.3, it can be perceived that all of the BEM's values of each 32 scenario for both of the retailer and the manufacturer agents are greater than one. It is concluded that the bullwhip effect exists for all of the possible scenarios under the decentralised case. Moreover, by using Table 5.3, it can be seen that the BEM's values for the manufacturer – customer branch is greater than the retailer-customer branch, meaning that the manufacturer is faced with the bullwhip effect more fatally than the retailer. For more clearly perceiving the bullwhip effect, the visual dynamic response plot of the best scenario for the retailer and the manufacturer are obtained from the simulation study and given in Figure 5.2. These types of animations are commonly used in place of statistical output analysis tools in the SD simulation modeling to provide considerable insight into the dynamic behaviour of a system.



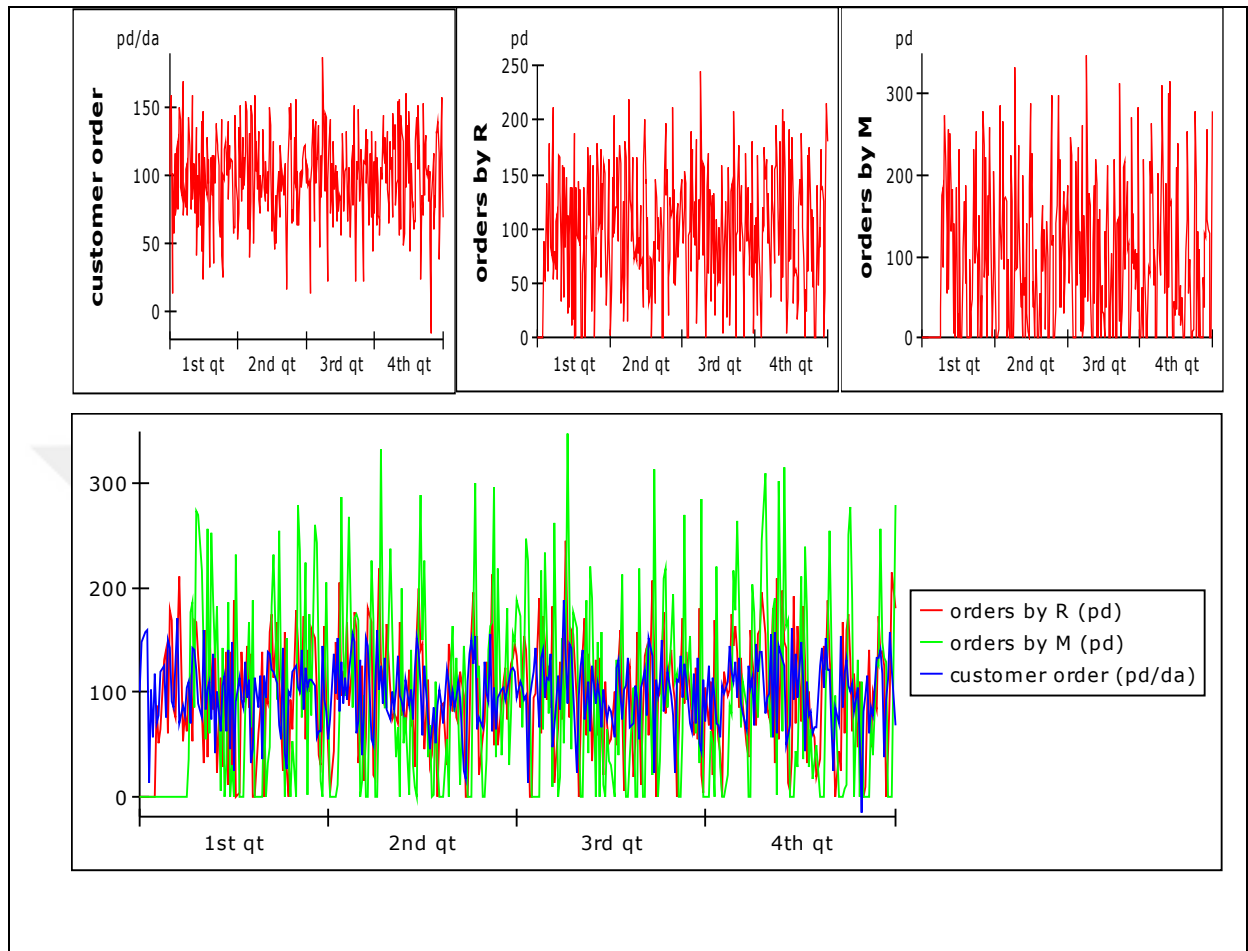


Figure 5.2 The dynamic response plots of Scenario 11 under the decentralised case

Figure 5.2 shows the time series plots of the placed orders by each agent for Scenario11 which is the best scenario for the retailer, and the manufacturer under the decentralised case. In this scenario, the retailer and the manufacturer uses the moving average forecasting method , and they use the order up to S ordering policy. It can be followed from Figure 5.2 where the amount of the average of the standard deviation for the placed orders by the end customer to the retailer, and the amount of the average of the standard deviation for the placed orders by the retailer to the manufacturer are very near to each other. On the other hand, the amount of the average of the standard deviation for the placed orders by the manufacturer to the supplier is extremely larger than these two placed orders' deviations.

It can be obviously seen that the average of the standard deviation values displayed in Table 5.2 are close to each other for some scenarios, and this makes it hard to obtain a conclusion about the best scenario selection. The given best scenario result is only an illustrative result and it may change according to the other user's possible different parameter choices. In addition to these general findings about the bullwhip effect, it is a good idea to make some "what if analysis" based on the results of how the order fluctuations are affected, when one of the model parameters is changed. More clearly, it states that while all other conditions are same, what happens to the bullwhip effect if the retailer or the manufacturer changes its forecasting method from the "Exponential Smoothing" to the "Moving Average" or converts its ordering policy from the "Order up to S" to the "ROP". There are 4 possible alternatives for the retailer which can make two alteration on the forecasting method selection and two alterations on the ordering policy selection. Similarly, there are also four possible alternatives for the manufacturer, altogether eight alternatives for the whole supply chain in the decentralised case. All of the grouping "what if analysis" results based on the average values of the placed orders' standard deviations by each agent are displayed during Table 5.4 to Table 5.11, and each one is tested with statistical methods to obtain a conclusion about is there any significant difference between these alternative scenarios, respectively.

The first "what if analysis" is made based on the forecasting method selection for both of the retailer and the manufacturer. Table 5.4 shows the list of all scenario results based on the average of order standard deviations where the retailer uses the exponential smoothing method to forecast the next period demand. It can be seen that there is not any condition for other model parameters and there are eight scenarios for the IID demand process and eight scenarios for the AR(1) demand process in this case.

Table 5.4 The average of order standard deviations if the retailer uses the exponential smoothing method in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV. FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.547	65.001	112.562
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	30.177	64.053	220.595
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.248	64.614	95.580
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	29.834	64.240	221.963
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.495	221.868	233.122
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	29.942	221.894	230.455
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	30.159	219.912	232.863
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	29.969	221.297	223.088
Average						142.860	196.278
Standard Dev.						83.798	57.299

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV. FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.157	79.142	133.656
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.012	81.633	225.095
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	40.426	80.773	121.305
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.170	80.180	217.993
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	40.078	225.343	262.829
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	41.031	221.816	235.206
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.024	219.941	250.429
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.252	218.406	222.033
Average						150.904	208.568
Standard Dev.						75.367	52.340

Total Average	146.882	202.423
Total St Dev.	77.103	53.393

Nevertheless, Table 5.5 shows the list of all scenario results based on the average of order standard deviations where the retailer uses the moving average forecasting method as opposed to the exponential smoothing method. There are also eight scenarios for the IID demand process and eight scenarios for the AR(1) demand process in this case too.

Table 5.5 The average of order standard deviations if the retailer uses the moving average method in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD DEV.FOR ORDERS		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.978	52.986	97.139
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.797	52.558	222.642
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.255	51.149	85.140
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	30.254	52.240	223.268
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.287	221.577	229.791
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	30.485	220.427	228.915
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	29.745	220.132	232.735
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.676	221.659	224.581
Average						136.591	193.026
Standard Dev.						90.185	63.062

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD DEV.FOR ORDERS		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	41.302	69.637	119.250
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.164	70.320	232.436
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.577	67.906	108.831
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	39.458	68.158	221.683
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	40.775	220.059	248.598
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	41.763	222.972	236.297
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	40.536	223.099	256.005
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.153	219.421	224.392
Average						145.197	205.936
Standard Dev.						81.465	57.921

Total Average	140.894	199.481
Total St Dev.	83.141	58.872

It can also be seen by jointly following Table 5.4 and Table 5.5 that the total average value of the order fluctuations in the case where the retailer uses the moving average method is less than the case where the retailer uses the exponential smoothing method for both of the agents. The total average value for the retailer is 146.882, and for the manufacturer is 202.423 in Table 5.4 where the retailer uses the exponential smoothing method .

On the other hand, when the retailer changes its demand forecasting method from exponential smoothing to the moving average method, the total average value of the order fluctuations for the retailer is 140.894 and for the manufacturer is 199.481. The standard deviation values of these average statistics are also close each other, but making a conclusion by following these average statistics can cause a mistake. For avoiding from this mistake, the output results of these possible scenarios are tested with a well-known statistical test method named as “two sample t-test” or “Welch confidence interval method” which can compare two possible alternative system design with desired significance level. This statistical testing method also requires that the observations drawn from each population (simulated system) are normally distributed and independent each other. Recall that the observations in Table 5.1 are independent and are assumed normal. Additionally, this testing method does not require that two populations have equal variances as do other approaches. This is useful because the true value of the variance of a population is seldomly known. The two sample t-test is applied to all “what if analysis” results by using the statistical analysis software Minitab with $\alpha = 0.05$ level of significance to compare the two candidate strategy results using the following hypothesis.

$$H_0 : \mu_1 - \mu_2 = 0$$

$$H_1 : \mu_1 - \mu_2 \neq 0$$

where the subscripts 1 and 2 denote Strategy 1 (the retailer/manufacturer uses exponential smoothing method/order up to S), and Strategy 2 (the retailer/manufacturer uses moving average/ROP), respectively.

The two sample t-test result for the first “what if analysis” case where the retailer changes its forecasting method between the exponential smoothing and the moving average methods are displayed below, respectively. It is tested that this change makes any significant effect on the average of the standard deviations for placed orders by the retailer or the manufacturer agents.

Two-Sample T-Test and CI: ret_exp; ret_mav

Two-sample T for ret_exp vs ret_mav

	N	Mean	StDev	SE Mean
ret_exp	16	146.9	77.1	19
ret_mav	16	140.9	83.1	21

Difference = mu ret_exp - mu ret_mav

Estimate for difference: 6.0

95% CI for difference: (-52.0; 64.0)

T-Test of difference = 0 (vs not =): T-Value = 0.21 P-Value = 0.834 DF = 29

The above test result supports that there is not a significant difference on the average order fluctuation values for the retailer agent, when the retailer changes its forecasting method between exponential smoothing and the moving average methods. This is obtained because, the “P - value statistic for this test is 0.834 which is greater than the $\alpha = 0.05$ level of significance. Furthermore, the two sample t-test result for the manufacturer agent when the retailer changes its forecasting method between exponential smoothing and the moving average methods is shown below where it can be seen that there is also not a significant difference on the average order fluctuation values for the manufacturer agent. Because the “P - value statistic for this test is 0.883 which is also greater than the $\alpha = 0.05$ level of significance.

Two-Sample T-Test and CI: man 1; man 2

Two-sample T for man 1 vs man 2

	N	Mean	StDev	SE Mean
man 1	16	202.4	53.4	13
man 2	16	199.5	58.9	15

Difference = mu man 1 - mu man 2

Estimate for difference: 2,9

95% CI for difference: (-37.7; 43.6)

T-Test of difference = 0 (vs not =): T-Value = 0.15 P-Value = 0.883 DF = 29

Similar to the retailer agent, the manufacturer can also have a chance to vary its forecasting method by selecting one from the two alternatives. From this point of view, the “what if analysis” for this case where the manufacturer changes its forecasting method is also analysed. Table 5.6 and Table 5.7 shows the scenario lists and the results for the cases where the manufacturer uses the exponential smoothing and the moving average forecasting methods, respectively.

Table 5.6 The average of order standard deviations if the manufacturer uses the exponential smoothing method in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD DEV.FOR ORDERS		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.547	65.001	112.562
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	30.177	64.053	220.595
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.495	221.868	233.122
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	29.942	221.894	230.455
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.978	52.986	97.139
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.797	52.558	222.642
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.287	221.577	229.791
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	30.485	220.427	228.915
Average						140.045	196.902
Standard Dev.						87.131	57.114

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD DEV.FOR ORDERS		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.157	79.142	133.656
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.012	81.633	225.095
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	40.078	225.343	262.829
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	41.031	221.816	235.206
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	41.302	69.637	119.250
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.164	70.320	232.436
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	40.775	220.059	248.598
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	41.763	222.972	236.297
Average						148.865	211.671
Standard Dev.						78.884	53.958
Total Average						144.455	204.287
Total St Dev.						80.421	54.214

Table 5.6 shows the list of all scenario results where the manufacturer uses the exponential smoothing method to forecast the next period demand. There are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process. Furthermore, Table 5.7 shows the list of all scenario results where the manufacturer uses the moving average forecasting method against to the exponential smoothing method. Again there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process for this case too.

It can be seen by jointly following Table 5.6 and Table 5.7 that the average value of the order fluctuations increases with a little amount for both of the retailer, and the manufacturer, if the manufacturer uses the exponential smoothing method against moving average method. The total average values of the order fluctuations in the case where the manufacturer uses the exponential smoothing method are 144.455 for the retailer and 204.287 for the manufacturer, respectively. On the other hand, if the manufacturer changes its demand forecasting method from the exponential smoothing to the moving average method, the total average values of the order fluctuations decreases to 143.320 for the retailer and to 197.618 for the manufacturer, respectively.

In addition to these, the two sample t-test is applied for this new “what if analysis” case where the manufacturer changes its forecasting method between the exponential smoothing and the moving average methods. It is tested that is this change makes any significant difference on the average of the standard deviations for placed orders by the retailer or the manufacturer agents. The two sample t-test results of Minitab for the retailer and the manufacturer agents are displayed below, respectively.

Table 5.7 The average of order standard deviations if the manufacturer uses the moving average method in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.248	64.614	95.580
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	29.834	64.240	221.963
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	30.159	219.912	232.863
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	29.969	221.297	223.088
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.255	51.149	85.140
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	30.254	52.240	223.268
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	29.745	220.132	232.735
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.676	221.659	224.581
Average Standard Dev.						139.405	192.402
						87.096	63.186

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	40.426	80.773	121.305
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.170	80.180	217.993
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.024	219.941	250.429
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.252	218.406	222.033
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.577	67.906	108.831
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	39.458	68.158	221.683
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	40.536	223.099	256.005
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.153	219.421	224.392
Average Standard Dev.						147.235	202.834
						78.173	56.054

Total Average	143.320	197.618
Total St Dev.	80.051	57.952

The following two sample t-test result displayed below implies that any significant difference is obtained for the retailer agent, if the manufacturer changes its forecasting method between the exponential smoothing and the moving average methods. Because, the evaluated P-value statistics for this case is 0.968 which is greater than the $\alpha = 0.05$ level of significance.

Two-Sample T-Test and CI: ret 1; ret 2

Two-sample T for ret 1 vs ret 2

	N	Mean	StDev	SE Mean
ret 1	16	144.5	80.4	20
ret 2	16	143.3	80.1	20

Difference = mu ret 1 - mu ret 2

Estimate for difference: 1.1

95% CI for difference: (-56.9; 59.2)

T-Test of difference = 0 (vs not =): T-Value = 0.04 P-Value = 0.968 DF = 29

Similar to the above result, the following two sample t-test result displayed below implies that any significant difference is also obtained for the manufacturer agent, if the manufacturer changes its forecasting method between the exponential smoothing and the moving average methods. This is concluded that since the evaluated P-value for this case is 0.739 also greater than the $\alpha = 0.05$ level of significance.

Two-Sample T-Test and CI: man_exp; man_mov

Two-sample T for man_exp vs man_mov

	N	Mean	StDev	SE Mean
man_exp	16	204.3	54.2	14
man_mov	16	197.6	58.0	14

Difference = mu man_exp - mu man_mov

Estimate for difference: 6.7

95% CI for difference: (-33.9; 47.2)

T-Test of difference = 0 (vs not =): T-Value = 0.34 P-Value = 0.739 DF = 29

These findings about the “what if analysis” results based on the forecasting method selection indicates that there is not a significance difference in order fluctuations neither for retailer nor for manufacturer. This result can be understood by explaining the parameters selected for each forecasting techniques. Both methods depend on the specification of a single parameter. For moving averages the parameter is N , the number of periods in the moving average, and for exponential smoothing the parameter is α , the smoothing constant. Small values of N or large values of α result in forecast that put greater weight on current data, and large values of N and small values of α put greater weight on past data. Small N and large α may be more responsive to changes in the demand process, but will result in forecast errors with higher variance. When $\alpha = 2 / (N+1)$, both methods have the same distribution of forecast error. This means that they should have roughly the same level of accuracy, but it does not mean that they will give the same forecast.

For the sample analysis, α and N values are selected by using the above relation to reach the same distribution of forecast error. By adjusting the values of N and α , it can be made that two methods are more or less responsive to underlying pattern of the data. Analysis of the simulation results of the decentralised case reveals that the major cause of the bullwhip effect is the independent sequential demand forecasting performed at each agent of the supply chain, making use of previous stage’s orders. Experiments with different α and N values also reveal that the bulwhip effect decreases with the decrease in α and with the increase in N values (see Appendix D). The large values of N and small values of α means that demand forecast is less responsive to changes in the demand process.

In addition to the forecasting method selection, another “what if analysis” are made based on the ordering policy selection for both of the retailer and the manufacturer where the retailer and the manufacturer can also chance to select two different ordering policies. The “what if analysis” for answering to how these changes make an effect on the order fluctuation is studied and related outputs are listed in Table 5.8 through Table 5.11.

Table 5.8 The average of order standard deviations if the retailer uses the order up to S policy in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.547	65.001	112.562
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	30.177	64.053	220.595
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.248	64.614	95.580
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	29.834	64.240	221.963
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.978	52.986	97.139
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.797	52.558	222.642
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.255	51.149	85.140
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	30.254	52.240	223.268
Average						58.355	159.861
Standard Dev.						6.570	66.969

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.157	79.142	133.656
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.012	81.633	225.095
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	40.426	80.773	121.305
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.170	80.180	217.993
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	41.302	69.637	119.250
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.164	70.320	232.436
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.577	67.906	108.831
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	39.458	68.158	221.683
Average						74.719	172.531
Standard Dev.						6.193	55.891

Total Average	66.537	166.196
Total St Dev.	10.462	59.946

Table 5.8 shows the list of all scenarios where the retailer uses the order up to S policy for ordering decision. There are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process for this case. However, Table 5.9 shows the list of all scenarios where the retailer uses the ROP ordering policy against to the order up to S ordering policy. Again, there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process.

Table 5.9 The average of order standard deviations if the retailer uses the ROP policy in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV. FOR ORDERS	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.495	221.868	233.122
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	29.942	221.894	230.455
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	30.159	219.912	232.863
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	29.969	221.297	223.088
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.287	221.577	229.791
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	30.485	220.427	228.915
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	29.745	220.132	232.735
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.676	221.659	224.581
Average Standard Dev.						221.096	229.444
						0.811	3.808

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV. FOR ORDERS	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	40.078	225.343	262.829
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	41.031	221.816	235.206
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.024	219.941	250.429
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.252	218.406	222.033
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	40.775	220.059	248.598
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	41.763	222.972	236.297
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	40.536	223.099	256.005
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.153	219.421	224.392
Average Standard Dev.						221.382	241.974
						2.326	14.794

Total Average	221.39	235.709
Total St Dev.	1.689	12.279

Under the IID demand process, if the retailer uses the ROP policy against the order up to S policy, the average value of the order fluctuation increases for the retailer from 58.355 to 221.096, and for the manufacturer from 159.861 to 229.444. In addition to this, under the AR(1) demand process, the average value of the order fluctuation also increases from 74.719 to 221.382 for the retailer, and again increases from 172.531 to 241.974 for the manufacturer at the same time.

Furthermore, the total average value of the order fluctuations also increases for the retailer (66.537 for the order up to S, 221.239 for the ROP), and for the manufacturer (166.196 for the order up to S, 235.709 for the ROP) in this case where the retailer uses the ROP policy against to the order up to S policy. These average statistics support that the order up to S inventory policy has more advantages against to the ROP inventory policy for bullwhip effect reduction. The two sample t-test is also applied for this “what if analysis” case to investigate is there any significant difference on the retailer and the manufacturer orders fluctuations. Results of the two sample t-test analysis for this “what if analysis” case is given below for the retailer and the manufacturer agents, respectively.

The following two sample t-test result indicates that a significant difference occurs in order fluctuation for the retailer agent when the retailer makes a selection between the order up to S, and the ROP inventory policies. Because the P-value statistic is approximately 0 which is smaller than the $\alpha = 0.05$ level of significance. In addition to this. it can be seen from the given confidence interval result of the two sample t-test, where both of the limits are negative, indicates that the average order fluctuation for the retailer increases when the retailer uses ROP policy against to the order up to S policy.

Two-Sample T-Test and CI: ret_ouS; ret_ROP

Two-sample T for ret_ouS vs ret_ROP

	N	Mean	StDev	SE Mean
ret_ouS	16	66.5	10.5	2.6
ret_ROP	16	221.24	1.69	0.42

Difference = μ ret_ouS - μ ret_ROP

Estimate for difference: -154.70

95% CI for difference: (-160.35; -149.06)

T-Test of difference = 0 (vs not =): T-Value = -58.39 P-Value = 0.000 DF = 15

Therefore, the two sample t-test result shown below also indicates that a significant difference also occurs in order fluctuation for the manufacturer agent when the retailer makes selection between the order up to S, and the ROP inventory policies. Because, again in this case, the P-value statistic is approximately 0 which is smaller than the $\alpha = 0.05$ level of significance. Similar to the retailer agent, the given confidence interval result of the two sample t-test, where both of the limits are negative, indicates that the average order fluctuation for the manufacturer increases when the retailer uses ROP policy against to the order up to S policy.

Two-Sample T-Test and CI: man_1; man_2

Two-sample T for man_1 vs man_2

	N	Mean	StDev	SE Mean
man_1	16	166.2	59.9	15
man_2	16	235.7	12.3	3.1

Difference = mu man_1 - mu man_2

Estimate for difference: -69.5

95% CI for difference: (-101.9; -37.1)

T-Test of difference = 0 (vs not =): T-Value = -4.54 P-Value = 0.000 DF = 16

In addition to these results of the “what if analysis” is made based on the retailer’s ordering policy selection alternatives, Table 5.10 and Table 5.11 shows the scenario lists and the “what if analysis” results for the manufacturer ordering policy selection alternatives. Table 5.10 and Table 5.11 display the results of the cases where the manufacturer uses the order up to S and the ROP policy, respectively.

Table 5.10 The average of order standard deviations if the manufacturer uses the order up to S policy in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.547	65.001	112.562
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.248	64.614	95.580
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.495	221.868	233.122
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	30.159	219.912	232.863
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.978	52.986	97.139
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.255	51.149	85.140
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.287	221.577	229.791
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	29.745	220.132	232.735
					Average	139.655	164.866
					Standard Dev.	86.962	72.292

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.157	79.142	133.656
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	40.426	80.773	121.305
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	40.078	225.343	262.829
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.024	219.941	250.429
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	41.302	69.637	119.250
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.577	67.906	108.831
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	40.775	220.059	248.598
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	40.536	223.099	256.005
					Average	148.238	187.613
					Standard Dev.	79.108	71.901
					Total Average	143.946	176.240
					Total St Dev.	80.431	70.636

Table 5.10 displays the list of all scenario results where the manufacturer uses the order up to S ordering policy. Similar to the all other cases, it can be seen that there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process. Moreover, Table 5.11 shows the list of all scenario results where the manufacturer uses the ROP ordering policy against to the order up to S ordering policy. There are also 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process for this case too.

Table 5.11 The average of order standard deviations if the manufacturer uses the ROP policy in the decentralised case

DECENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD DEV.FOR ORDERS		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	30.177	64.053	220.595
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	29.834	64.240	221.963
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	29.942	221.894	230.455
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	29.969	221.297	223.088
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.797	52.558	222.642
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	30.254	52.240	223.268
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	30.485	220.427	228.915
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.676	221.659	224.581
Average						139.796	224.438
Standard Dev.						87.266	3.455

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD DEV.FOR ORDERS		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.012	81.633	225.095
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.170	80.180	217.993
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	41.031	221.816	235.206
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.252	218.406	222.033
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.164	70.320	232.436
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	39.458	68.158	221.683
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	41.763	222.972	236.297
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.153	219.421	224.392
Average						147.863	226.892
Standard Dev.						77.956	6.843
Total Average						143.830	225.665
Total St Dev.						80.045	5.388

For the IID demand process, if the manufacturer uses the ROP ordering policy against the order up to S ordering policy, it can be seen by following Table 5.10 and Table 5.11 that the average value of the order fluctuations increases for the manufacturer (164.866 for the order up to S and 224.438 for the ROP policy), but it does not cause an important change on the average order fluctuation of the retailer agent (139.655 for the order up to S and 139.796 for the ROP policy). In addition to this, for the AR(1) demand process, if the manufacturer uses the ROP ordering policy against the order up to S ordering policy, the average value of the order fluctuations also increases for the manufacturer (187.613 for the order up to S and 226.892 for the ROP policy), but again it does not cause an important change on the average order fluctuation of the retailer agent (148.238 for the order up to S and 147.863 for the ROP policy). In addition to these, the total average values of the order fluctuations support these results which are 143.830 for the retailer, and 225.665 for the manufacturer for the case where the manufacturer uses the ROP policy, and the same values for the case where the manufacturer uses the order up to S policy are 143.946 for the retailer, and 176.240 for the manufacturer.

These average statistics support that if the manufacturer prefers the order up to S inventory policy against to the ROP inventory policy, it has more advantages for bullwhip effect reduction. It is seen that the retailer agent is not effected from the manufacturer ordering policy decision in this case. This is caused since the starting inventory level for each agent is selected as a huge level and the retailer is not faced with any backorder inventory in both of the different inventory policy is used by the manufacturer. Because of this, the manufacturer inventory policy selection is only effected itself. The two sample t-test is also applied for this “what if analysis” case to investigate is there any significant difference on the retailer and the manufacturer orders fluctuations. And the results is given below for each agent, respectively.

The following two sample t-test result indicates that a significant difference does not occurs for the retailer order fluctuation when the manufacturer makes selection between the order up to S, and the ROP inventory policies. Because, the P-value statistic is 0.997 which is greater than the $\alpha = 0.05$ level of significance in this case.

Two-Sample T-Test and CI: ret_1; ret_2

Two-sample T for ret_1 vs ret_2

	N	Mean	StDev	SE Mean
ret_1	16	143.9	80.4	20
ret_2	16	143.8	80.0	20

Difference = μ ret_1 - μ ret_2

Estimate for difference: 0.1

95% CI for difference: (-57.9; 58.1)

T-Test of difference = 0 (vs not =): T-Value = 0.00 P-Value = 0.997 DF = 29

On the other hand, the two sample t-test result shown below also indicates that a significant difference occurs in order fluctuation for the manufacturer agent, when the manufacturer makes selection between the order up to S, and the ROP inventory policies. Because the P-value statistic is 0.014 which is smaller than the $\alpha = 0.05$ level of significance in this case. In addition to this, the given confidence interval result of the two sample t-test, where both of the limits are negative values, indicates that the average order fluctuation for the manufacturer increases when the manufacturer uses ROP policy against to the order up to S policy.

Two-Sample T-Test and CI: man_ouS; man_ROP

Two-sample T for man_ouS vs man_ROP

	N	Mean	StDev	SE Mean
man_ouS	16	176,2	70,6	18
man_ROP	16	225,67	5,39	1,3

Difference = μ man_ouS - μ man_ROP

Estimate for difference: -49,4

95% CI for difference: (-87,2; -11,7)

T-Test of difference = 0 (vs not =): T-Value = -2,79 P-Value = 0,014 DF = 15

By following the findings given in Table 5.8 through Table 5.11, among the scenarios tested, it can be concluded that orders are batched in ROP inventory policy (since they are not placed in each period) that caused to an increase in bullwhip effect.

These findings are compatible with the results given in the supply chain management literature where it is stated that the decentralised decision making can lead to poor supply chain performance, and information asymmetry is one of the most powerful sources of the bullwhip effect (Lee et al, 1997). However, using the strategic partnership is a mostly approved suggestion for purifying the supply chain from the effect of the decentralised decision making. In the strategic partnership, the cooperation is based on the customer demand information sharing throughout the supply chain, so it leads to increased information flows, reduced uncertainty, and a more profitable supply chain performance. For realizing to these benefits, all of the 32 scenarios simulated in the decentralised case are also simulated in the centralised case for making a comparison between the decentralised and the centralised cases. In addition to this, the behaviour of the supply chain with the bullwhip effect and the influences of a series of replenishment policies and the forecasting techniques selection, under the different demand patterns are observed for the end customer demand information sharing strategy. Similar to the decentralised case, some important findings as the average of the standard deviations of placed orders by each agent and the BEM's (bullwhip effect measure) values are summarized for each scenario and explained in the next part. These results are also studied to clarify how a series of replenishment policies and the forecasting techniques selection, under different demand patterns induces or reduces the bullwhip effect. In addition to this, the gained amount of improvement for each scenario by passing from decentralised case to centralised case is also examined.

5.2 ANALYSIS OF THE BULLWHIP EFFECT UNDER THE CENTRALISED INFORMATION SHARING STRATEGY

In the centralised case, all of the agents are allowed to reach the demand information of the end customer. As mentioned above, the reduction in the bullwhip effect is expected in this case. Table 5.12 shows the results of the average of the standard deviations for placed orders by the retailer and the manufacturer in the centralised information sharing strategy.

Table 5.12 The average of the standard deviations of placed orders in the centralised case

CENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV. FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.556	63.400	69.771
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	31.128	63.728	216.545
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.325	63.159	68.070
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	30.357	63.320	216.897
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.974	219.746	202.769
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	30.819	221.231	218.077
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	31.223	219.959	204.958
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	30.218	220.732	216.578
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.868	51.028	61.647
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.693	51.783	217.501
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.551	50.895	58.125
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	31.347	51.312	216.807
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.682	219.214	200.376
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	31.248	219.239	216.041
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	30.152	219.984	205.600
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.965	219.590	215.905
Min.					29.551	50.895	58.125
Max.					31.347	221.231	218.077
Average					30.507	138.645	175.354

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	39.804	78.975	100.883
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	39.984	79.680	218.402
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	39.765	78.618	92.645
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	39.461	78.815	214.503
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	41.495	219.379	204.230
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	42.654	219.989	218.744
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.094	218.174	204.105
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	39.378	217.225	213.716
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	39.120	66.541	88.896

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.339	66.923	219..891
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.069	64.881	82.621
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	40.014	67.107	215.154
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	42.199	217.634	198.894
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	42.441	215.254	215.544
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	39.982	219.118	203.975
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.861	218.951	217.680
				Min.	39.069	64.881	82.621
				Max.	42.654	219.989	219.891
				Average	40.479	145.454	181.868

Total Min.	29.551	50.895	58.125
Total Max.	42.654	221.231	219.891
TotalAverage	35.493	142.049	178.611

As shown in Table 5.12, in the centralised case, the average of the standard deviations for the placed orders by the retailer and the manufacturer closes to each other. Furthermore, the retailer orders' deviations exceed the manufacturer orders' deviations for some scenarios. Under the IID demand process, the best policy which has a minimum average order fluctuation value for both of the retailer and the manufacturer is Scenario 11 where each agent uses the moving average forecasting method and the order up to S policy. Under the AR(1) demand process, the best results are in Scenario 27 for the retailer and the manufacturer where each agent also uses the moving average forecasting method and the order up to S policy. Both of these results are again worse than the IID demand process ones and it can be seen in Table 5.12 that the average value of the order fluctuations is hardly greater enough in the AR(1) demand process than the IID demand process. In addition to this, similar to the decentralised case, the paired t-test is also made for the centralised case to analysis the effect of the demand processes on order fluctuation. The paired t-test results for the retailer, and the manufacturer agents are displayed below, respectively.

The test result for the retailer agent is shown below indicates that there is a significant difference on the order fluctuations when the end customer demand changes between the IID and the AR (1) demand processes. Because, the calculated P – value statistic (0.008) is less than the $\alpha = 0.05$ level of significance in this case. However, by following the given confidence interval of the test result, where both of the bounds have negative values, indicates that the order fluctuation increases when the end customer demand is AR(1) demand process against to the IID demand process for the retailer agent.

Paired T-Test and CI: C_iid_Ret; C_ar1_Ret

Paired T for C_iid_Ret - C_ar1_Ret

	N	Mean	StDev	SE Mean
C_iid_Ret	16	138.6	84.1	21.0
C_ar1_Ret	16	145.5	75.3	18.8
Difference	16	-6.81	8.89	2.22

95% CI for mean difference: (-11.55; -2.07)

T-Test of mean difference = 0 (vs not = 0): T-Value = -3.06 P-Value = 0.008

Furthermore, the test result for the manufacturer agent is shown below indicates that there is also a significant difference on the order fluctuations when the end customer demand changes between the IID and the AR (1) demand processes. Because again, the calculated P – value statistic is 0.048 which is less than the $\alpha = 0.05$ level of significance. Similar to the retailer agent, by following the given confidence interval of the test result, where both of the bounds have negative values, indicates that the order fluctuation increases when the end customer demand is AR(1) demand process against to the IID demand process for the manufacturer agent.

Paired T-Test and CI: C_iid_Man; C_ar1_Man

Paired T for C_iid_Man - C_ar1_Man

	N	Mean	StDev	SE Mean
C_iid_Man	16	175.4	66,5	16.6
C_ar1_Man	16	181.9	54,5	13.6
Difference	16	-6.51	12,31	3.08

95% CI for mean difference: (-13.07; -0.05)

T-Test of mean difference = 0 (vs not = 0): T-Value = -2.12 P-Value = 0.048

By following jointly Table 5.12 and Table 5.2, it can be seen that the average of the standard deviations of the placed orders for each agent decreases in every scenario for the centralised case, as predicted. On the other hand, the decrease for the retailer agent occurs with a little amount, occurs with a meaningful improvement for the manufacturer agent. In other words, for the decentralised case, the total average values of the orders deviations are 143.888 for the retailer, and 200.952 for the manufacturer. On the other hand, for the centralised case, the total average values of the orders deviations decreases to 142.049 for the retailer, and to 178.611 for the manufacturer, respectively.

Similar to decentralised case, in addition to these findings about the average of the standard deviations of the placed orders, the BEM's (bullwhip effect measures) values are obtained in the centralised case. Table 5.13 lists the findings of the simulation study based on the BEM's values for all of the possible scenarios, under the centralised information sharing strategy. BEM's values are also calculated between the retailer-customer, the manufacturer-retailer, and the manufacturer-customer agents branches.

Table 5.13 BEM's values for the centralised information sharing strategy

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	THE BULLWHIP	EFFECT	MEASURES
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Retailer& Customer	Manf. & Retailer	Man & Customer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	2.075	1.100	2.283
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	2.047	3.398	6.957
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	2.083	1.078	2.245
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	2.086	3.425	7.145
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	7.331	0.923	6.765
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	7.178	0.986	7.076
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	7.045	0.932	6.564
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	7.305	0.981	7.167
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	1.708	1.208	2.064
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	1.744	4.200	7.325
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	1.722	1.142	1.967
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	1.637	4.225	6.916
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	7.145	0.914	6.531
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	7.016	0.985	6.914
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	7.296	0.935	6.819
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	7.092	0.983	6.973
				Min.	1.637	0.914	1.967
				Max.	7.331	4.225	7.325
				Average	4.532	1.714	5.732

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	THE BULLWHIP	EFFECT	MEASURES
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Retailer& Customer	Manf. & Retailer	Man & Customer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	1.935	1.277	2.472
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	1.898	2.741	5.202
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	1.977	1.178	2.330
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	1.943	2.722	5.288
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	5.287	0.931	4.922
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	5.157	0.994	5.128
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	5.442	0.936	5.091
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	5.366	0.984	5.280
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	1.659	1.336	2.216
scenar26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	1.659	3.286	5.451

AR(1) process	FORECASTING METHOD		ORDERING POLICY		THE BULLWHIP EFFECT MEASURES		
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Retailer & Customer	Manf. & Retailer	Man & Customer
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	1.661	1.273	2.115
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	1.677	3.206	5.377
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	5.157	0.914	4.713
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	5.072	1.001	5.079
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	5.480	0.931	5.102
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	5.230	0.994	5.200
Min.					1.659	0.914	2.115
Max.					5.480	3.286	5.451
Average					3.538	1.544	4.435

Total Min.	1,637	0,914	1.967
Total Max.	7,331	4,225	7.325
Total Average	4,035	1,629	5.084

In the centralised case, the manufacturer also knows the amount of the end customer demand and it can adjust its demand forecasting, and the ordering policy parameters by using this information. By following Table 5.13, it can be seen that the bullwhip effect also exists for all 32 scenarios in the centralised case where the BEM's values for the retailer-customer branch, and the manufacturer-customer branch are greater than one. On the other hand, in the centralised case, some of the BEM's values for the manufacturer-retailer branch are less than one which implies that the bullwhip effect between the retailer and the manufacturer does not exist for these scenarios. In addition to this, Table 5.3 and Table 5.13 can jointly be used for making a comparison for answering to how the bullwhip effect changes in the decentralised and the centralised cases. So, the average value of the BEM's values for both of the retailer and the manufacturer in the centralised case are less than the decentralised case. The total average value of the BEM's values for the centralised case are 4.035 for the retailer-customer branch, and 5.084 for the manufacturer-customer branch. On the other hand, the total average values of the BEM's values for the decentralised case are 4.415 for the retailer-customer branch, and 5.793 for the manufacturer-customer branch.

By using Table 5.12, the best scenario for the centralised case is indicated again as Scenario 11 which gives the minimum order fluctuation values for both of the retailer and the manufacturer agents at the same time. Both of the retailer and the manufacturer uses the moving average as a forecasting method, and the order up to S as an ordering policy in this scenario. The visual dynamic response plots of the best scenario (Scenario 11) of the retailer and the manufacturer for the centralised case is given in Figure 5.3. It is repeated that the average of the standard deviation values displayed in Table 5.12 are close to each other for some scenarios, and this makes it hard to obtain a conclusion about the best scenario selection. The given best scenario result is only an illustrative results.

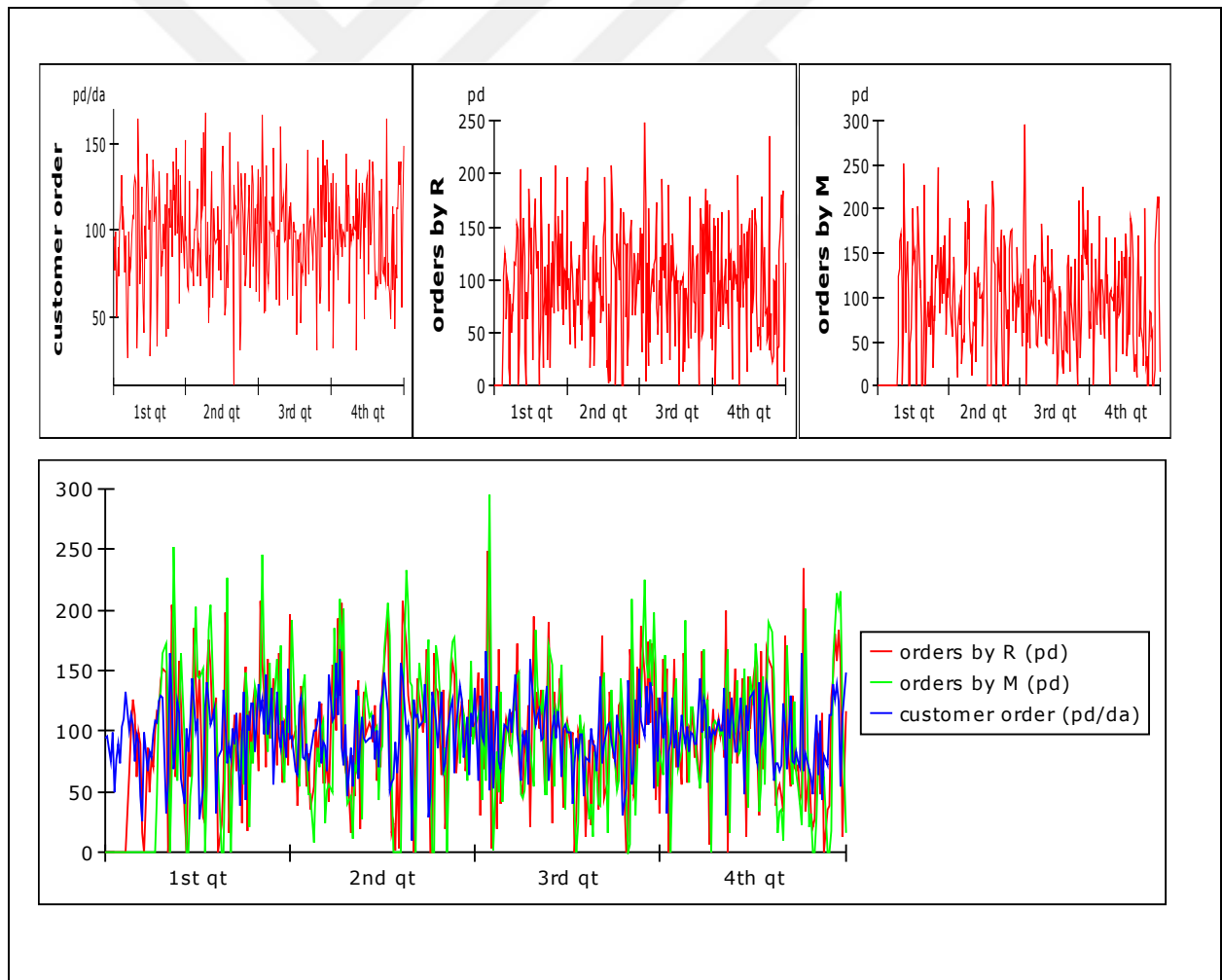


Figure 5.3 The dynamic response plots of Scenario 11 under the centralised case

In Scenario 11, the bullwhip effect is simultaneously reduced to a minimum value for both of the retailer and the manufacturer according to the sample data set. By following Figure 5.3, it can be seen that the customer's placed orders, the retailer's placed orders, and the manufacturer's placed orders come closer to each other. Since the starting inventory level for both agents are chosen as a huge value (as 3000 products), the benefits of passing from the decentralised case to the centralised case can not be seen with an enormous improvement for the retailer agent, but it can be followed for the manufacturer agent. Moreover, as a conclusion, it is found that managing the supply chain in the centralised case against to the decentralised case gives better results for the bullwhip effect reduction for all of the supply chain agents. It is clear that decisions of each agent for the entire supply chain make some effects on this reduction level.

Similar to the decentralised case, the same “what if analysis” are made for the centralised case based on the results of how the order fluctuations are affected, if one of the model parameters is changed. The results of the possible 8 alternatives are displayed throughout Table 5.14 to Table 5.21, and each one is tested with statistical methods to obtain a conclusion about is there any significant difference between these alternative scenarios, respectively.

The first “what if analysis” for the centralised case is again made based on the forecasting method selection for the retailer and the manufacturer agents. Table 5.14 shows the list of all scenario results where the retailer uses the exponential smoothing method to forecast the next period demand. It can be seen that there is not any condition for the other model parameters, and similar to decentralised case, there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process for this case too.

Table 5.14 The average of order standard deviations if the retailer uses the exponential smoothing method in the centralised case

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.556	63.400	69.771
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	31.128	63.728	216.545
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.325	63.159	68.070
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	30.357	63.320	216.897
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.974	219.746	202.769
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	30.819	221.231	218.077
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	31.223	219.959	204.958
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	30.218	220.732	216.578
Average						141.909	176.708
Standard Dev.						83.930	66.781

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEVIATIONS	FOR ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.804	78.975	100.883
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.984	79.680	218.402
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	39.765	78.618	92.645
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.562	78.815	214.503
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	41.495	219.379	204.230
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	42.654	219.989	218.744
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.094	218.174	204.105
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.478	217.225	213.716
Average						148.857	183.404
Standard Dev.						74.662	53.810
Total Average						145.383	180.056
Total St Dev.						76.821	58.689

In addition to this, Table 5.15 shows the list of all scenarios where the retailer uses the moving average forecasting method against to the exponential smoothing method. Again, there are 8 scenarios for the IID demand process and 8 scenarios for AR(1) demand process..

Table 5.15 The average of order standard deviations if the retailer uses the moving average method in the centralised case

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.868	51.028	61.647
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.693	51.783	217.501
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.551	50.895	58.125
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	31.347	51.312	216.807
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.682	219.214	200.376
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	31.248	219.239	216.041
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	30.152	219.984	205.600
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.965	219.590	215.905
Average						135.381	174.000
Standard Dev.						89.935	70.703

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	40.120	66.541	88.896
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.339	66.923	219.891
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.069	64.881	82.621
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	40.014	67.107	215.154
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	42.199	217.634	198.894
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	42.441	215.254	215.544
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	39.982	219.118	203.975
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.861	218.951	217.680
Average						142.051	180.332
Standard Dev.						80.925	58.826

Total Average	138.716	177.166
Total St Dev.	82.720	62.916

For both of the agents, the total average value of the order fluctuations for the case where the retailer uses the moving average method is a little less than the case where the retailer uses the exponential smoothing method. When the retailer uses the exponential smoothing method, the total average value of the order fluctuations for the retailer is 145.383 and for the manufacturer is 180.056. On the other hand, when the retailer changes its demand forecasting method from

the exponential smoothing to the moving average method, the total average value of the order fluctuations decreases for the retailer to 138.716 and for the manufacturer to 177.166.

In addition to these average statistics, the two sample t-test is applied to this “what if analysis” results of the centralised case where the retailer changes its forecasting method between the exponential smoothing and the moving average methods. It is tested that is this change makes any significant effect on the average of standard deviations for the retailer and the manufacturer agents. The two sample t-test result of Minitab for the retailer and the manufacturer agents are displayed below, respectively

Two-Sample T-Test and CI: ret_exp; ret_mav				
Two-sample T for ret_exp vs ret_mav				
	N	Mean	StDev	SE Mean
ret_exp	16	145.4	76.8	19
ret_mav	16	138.7	82.7	21
Difference = mu ret_exp - mu ret_mav				
Estimate for difference: 6.7				
95% CI for difference: (-51.1; 64.4)				
T-Test of difference = 0 (vs not =): T-Value = 0.24 P-Value = 0.815 DF = 29				

The above two sample t-test result supports that there is not a significant difference on the order fluctuation values of the retailer agent when the retailer changes its forecasting method between exponential smoothing and the moving average methods in the centralised case. Because the “P - value statistic for this test is 0.815 which greater than the $\alpha = 0.05$ level of significance.

Moreover, the two sample t-test result for the manufacturer agent shows that there is also not a significant difference on the order fluctuation values of the manufacturer agent, when the retailer changes its forecasting method between exponential smoothing and the moving

average methods in the centralised case. Because the “P - value statistic for this test is 0.894 which also greater than the $\alpha = 0.05$ level of significance.

Two-Sample T-Test and CI: man 1; man 2

Two-sample T for man 1 vs man 2

	N	Mean	StDev	SE Mean
man 1	16	180.1	58.7	15
man 2	16	177.2	62.9	16

Difference = μ man 1 - μ man 2

Estimate for difference: 2.9

95% CI for difference: (-41.1; 46.9)

T-Test of difference = 0 (vs not =): T-Value = 0.13 P-Value = 0.894 DF = 29

Similar to the retailer agent, the manufacturer can choose one forecasting method from the two alternatives, so the behaviour of the order fluctuations for the cases where the manufacturer changes its forecasting method are also analysed. Table 5.16 and Table 5.17 shows the scenario lists and the results for the cases where the manufacturer uses the exponential smoothing and the moving average forecasting methods, respectively

Table 5.16 The average of order standard deviations if the manufacturer uses the exponential smoothing method in the centralised case

CENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.556	63.400	69.771
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	31.128	63.728	216.545
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.974	219.746	202.769
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	30.819	221.231	218.077
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.868	51.028	61.647
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.693	51.783	217.501
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.682	219.214	200.376
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	31.248	219.239	216.041
Average						138.671	175.341
Standard Dev.						86.916	68.042

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.804	78.975	100.883
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.984	79.680	218.402
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	41.495	219.379	204.230
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	42.654	219.989	218.744
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	40.120	66.541	88.896
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.339	66.923	219.891
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	42.199	217.634	198.894
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	42.441	215.254	215.544
Average						145.547	183.186
Standard Dev.						77.682	55.101

Total Average	142.109	179.263
Total St Dev.	79.713	59.949

Table 5.16 shows the list of all scenarios where the manufacturer uses the exponential smoothing method to forecast the next period demand. There are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process. Furthermore, Table 5.17 shows the list of all scenarios where the manufacturer uses the moving average forecasting method against to the exponential smoothing method. Again, there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process for this case too.

Table 5.17 The average of order standard deviations if the manufacturer uses the moving average method in the centralised case

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.325	63.159	68.070
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	30.357	63.320	216.897
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	31.223	219.959	204.958
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	30.218	220.732	216.578
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.551	50.895	58.125
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	31.347	51.312	216.807
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	30.152	219.984	205.600
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.965	219.590	215.905
Average Standard Dev.						138.619	175.367
						87.192	69.521

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEVI.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	39.765	78.618	92.645
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.562	78.815	214.503
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.094	218.174	204.105
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.478	217.225	213.716
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.069	64.881	82.621
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	40.014	67.107	215.154
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	39.982	219.118	203.975
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.861	218.951	217.680
Average Standard Dev.						145.361	180.550
						78.199	57.632

Total Average	141.990	177.959
Total St Dev.	80.085	61.746

The total average values of the order fluctuations for both agents are a little less in the case where the manufacturer uses moving average method than the case where the manufacturer

uses the exponential smoothing method. When the manufacturer uses the exponential smoothing method, the total average value of the order fluctuations for the retailer is 142.109 and for the manufacturer is 179.163. On the other hand, when the manufacturer changes its demand forecasting method from the exponential smoothing to the moving average, the total average value of the order fluctuations for the retailer and the manufacturer decreases to 141.990 and to 177.959, respectively.

In addition to these average statistics, the two sample t-test is applied for this new “what if analysis” case, and the results are explained below. The following two sample t-test result displayed below implies that any significant difference on orders fluctuations are obtained for the retailer agent, if the manufacturer changes its forecasting method between the exponential smoothing and the moving average methods. Because, the evaluated P-value for this case is 0.997 which greater than the $\alpha = 0.05$ level of significance.

Two-Sample T-Test and CI: ret 1; ret 2

Two-sample T for ret 1 vs ret 2

	N	Mean	StDev	SE Mean
ret 1	16	142.1	79.7	20
ret 2	16	142.0	80.1	20

Difference = mu ret 1 - mu ret 2

Estimate for difference: 0.1

95% CI for difference: (-57.7; 57.9)

T-Test of difference = 0 (vs not =): T-Value = 0.00 P-Value = 0.997 DF = 29

Similar to the above result, the following two sample t-test result displayed below implies that any significant difference on orders fluctuations are obtained for the manufacturer agent, if the manufacturer changes its forecasting method between the exponential smoothing and the moving average methods. Because, the evaluated P-value for this case is 0.952 which again greater than the $\alpha = 0.05$ level of significance.

Two-Sample T-Test and CI: man_exp; man_mov

Two-sample T for man_exp vs man_mov

	N	Mean	StDev	SE Mean
man_exp	16	179.3	59.9	15
man_mov	16	178.0	61.7	15

Difference = μ man_exp - μ man_mov

Estimate for difference: 1.3

95% CI for difference: (-42.7; 45.3)

T-Test of difference = 0 (vs not =): T-Value = 0.06 P-Value = 0.952 DF = 29

By following the findings between Table 5.14 to Table 5.17, it can be concluded that for both of the retailer and the manufacturer, the usage of the exponential smoothing forecasting method or the moving average forecasting method does not have any superiority over each other for bullwhip effect reduction in the centralised case. These findings are similar to the decentralised case, because parameters of these two forecasting method are selected with the same forecasting error. In addition to this, experiments with different α and N values also reveal that the bulwhip effect decreases with the decrease in α and with the increase in N values (see Appendix D). The large values of N and small values of α means that demand forecast is less responsive to changes in the demand process.

As decentralised case, another “what if analysis” is made for the centralised case based on the ordering policy selection by each agent. The retailer and the manufacturer agents have also chance to select two different ordering policies. The effect of these changes on the order fluctuation is analysed and related findings are listed in Table 5.18 to Table 5.21.

Table 5.18 The average of order standard deviations if the retailer uses the order up to S policy in the centralised case

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.556	63.400	69.771
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	31.128	63.728	216.545
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.325	63.159	68.070
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	30.357	63.320	216.897
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.868	51.028	61.647
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.693	51.783	217.501
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.551	50.895	58.125
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	31.347	51.312	216.807
						Average	57.328
						Standard Dev.	6.500
							140.670
							81.612

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.804	78.975	100.883
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41.984	79.680	218.402
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	39.765	78.618	92.645
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40.562	78.815	214.503
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	40.120	66.541	88.896
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40.339	66.923	219.891
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.069	64.881	82.621
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	40.014	67.107	215.154
						Average	72.692
						Standard Dev.	6.806
							154.124
							67.410

Total Average	65.010	147.397
Total St Dev.	10.212	72.643

Table 5.18 shows the list of all scenarios and results where the retailer uses the order up to S policy for the ordering decision. There are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process. Moreover, Table 5.19 shows the list of all scenarios and results where the retailer uses the ROP ordering policy against to the order up to S ordering policy. Again, there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process.

Table 5.19 The average of order standard deviations if the retailer uses the ROP policy in the centralised case

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.974	219.746	202.769
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	30.819	221.231	218.077
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	31.223	219.959	204.958
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	30.218	220.732	216.578
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.682	219.214	200.376
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	31.248	219.239	216.041
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	30.152	219.984	205.600
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.965	219.590	215.905
						Average	
						Standard Dev.	
						219.962	210.038
						0.704	7.266

AR(1) process	FORECASTING	METHOD	ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	41.495	219.379	204.230
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	42.654	219.989	218.744
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.094	218.174	204.105
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40.478	217.225	213.716
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	42.199	217.634	198.894
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	42.441	215.254	215.544
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	39.982	219.118	203.975
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41.861	218.951	217.680
						Average	
						Standard Dev.	
						218.215	209.611
						1.509	7.620

Total Average	219.089	209.825
Total St Dev.	1.452	7.196

For the IID demand process, if the retailer uses the ROP policy against the order up to S policy, the average value of the order fluctuations increases for the retailer from 57.328 to 219.962, and for the manufacturer from 140.670 to 210.038. In addition to this, for the AR(1) demand process, the average value of the order fluctuations also increases for the retailer from 72.692 to 218.215, and for the manufacturer from 154.124 to 209.611. Moreover, the total average value of the order fluctuations increases for the retailer (65.010 for the order up to S,

219.089 for the ROP) and the manufacturer (147.397 for the order up to S, 209.825 for the ROP).

These average statistics support that the order up to S inventory policy has more advantages against to the ROP inventory policy for bullwhip effect reduction. In addition to this, the two sample t-test is also applied for this “what if analysis” case to investigate is there any significant difference on the orders fluctuations for the retailer and the manufacturer agents. The results of the two sample t-test analysis for this “what if analysis” case is given below for the retailer and the manufacturer, respectively.

The following two sample t-test result indicates that a significant difference occurs for the retailer order fluctuation when the retailer makes selection between the order up to S, and the ROP inventory policies in the centralised case. Because the P-value statistic is approximately 0 which is smaller than the $\alpha = 0.05$ level of significance in this case. In addition to this. it can be seen from the given confidence interval result of two sample t-test, where both of the limits are negative values, indicates that the average order fluctuation for the retailer increases when the retailer uses ROP policy against to the order up to S policy.

Two-Sample T-Test and CI: ret_ouS; ret_ROP

Two-sample T for ret_ouS vs ret_ROP

	N	Mean	StDev	SE Mean
ret_ouS	16	65.0	10.2	2.6
ret_ROP	16	219.09	1.45	0.36

Difference = μ ret_ouS - μ ret_ROP

Estimate for difference: -154.08

95% CI for difference: (-159.57; -148.58)

T-Test of difference = 0 (vs not =): T-Value = -59.75 P-Value = 0.000 DF = 15

However, the two sample t-test result shown below also indicates that a significant difference occurs for the manufacturer order fluctuation when the retailer makes selection between the order up to S, and the ROP inventory policies in the centralised case. Because the P-value statistic is 0.004 which is again smaller than the $\alpha = 0.05$ level of significance. Similar to the retailer agent, the given confidence interval result of the two sample t-test, where both of the limits are negative values, indicates that the average order fluctuation for the manufacturer agent increases when the retailer uses the ROP policy against to the order up to S policy.

Two-Sample T-Test and CI: man_1; man_2

Two-sample T for man_1 vs man_2

	N	Mean	StDev	SE Mean
man_1	16	147.4	72.6	18
man_2	16	209.82	7.20	1.8

Difference = mu man_1 - mu man_2

Estimate for difference: -62.4

95% CI for difference: (-101.3; -23.5)

T-Test of difference = 0 (vs not =): T-Value = -3.42 P-Value = 0.004 DF = 15

In addition to the retailer agent, the manufacturer agent can also have a chance to select an ordering policy from the two alternatives. Table 5.20 and Table 5.21 shows the scenario lists of the “what if analysis” results for the manufacturer where it uses the order up to S and the ROP policy, respectively.

Table 5.20 The average of order standard deviations if the manufacturer uses the order up to S policy in the centralised case

CENTRALISED CASE							
IID process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	30.556	63.400	69.771
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	30.325	63.159	68.070
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	29.974	219.746	202.769
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	31.223	219.959	204.958
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	29.868	51.028	61.647
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	29.551	50.895	58.125
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	30.682	219.214	200.376
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	30.152	219.984	205.600
Average						138.423	133.914
Standard Dev.						87.041	74.412

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	40.804	78.975	100.883
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	39.765	78.618	92.645
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	41.495	219.379	204.230
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	40.094	218.174	204.105
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	40.120	66.541	88.896
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	39.069	64.881	82.621
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	42.199	217.634	198.894
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	39.982	219.118	203.975
Average						145.415	147.031
Standard Dev.						78.372	59.854

Total Average	141.919	140.473
Total St Dev.	80.093	65.588

Table 5.20 displays the list of all scenarios where the manufacturer uses the order up to S ordering policy. Similar to all other cases, it can be seen that there are 8 scenarios for the IID demand process and 8 scenarios for the AR(1) demand process for this case. Furthermore, Table 5.21 shows the list of all scenarios where the manufacturer uses the ROP ordering policy against to the order up to S ordering policy. Again, there are 8 scenarios for the IID demand process and 8 scenarios for AR(1) demand process.

Table 5.21 The average of order standard deviations if the manufacturer uses the ROP policy in the centralised case

CENTRALISED CASE							
IID process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	31.128	63.728	216.545
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	30.357	63.320	216.897
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	30.819	221.231	218.077
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	30.218	220.732	216.578
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	29.693	51.783	217.501
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	31.347	51.312	216.807
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	31.248	219.239	216.041
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	30.965	219.590	215.905
Average						138.867	216.794
Standard Dev.						87.067	0.720

AR(1) process	FORECASTING METHOD		ORDERING POLICY		STANDARD	DEV.FOR	ORDERS
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	Customer	Retailer	Manufacturer
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	41,984	79.680	218.402
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	40,562	78.815	214.503
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	42,654	219.989	218.744
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	40,478	217.225	213.716
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	40,339	66.923	219.891
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	40,014	67.107	215.154
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	42,441	215.254	215.544
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	41,861	218.951	217.680
Average						145.493	216.704
Standard Dev.						77.508	2.258
Total Average						142.180	216.749
Total St Dev.						79.705	1.619

For the IID demand process, if the manufacturer uses the ROP ordering policy against the order up to S ordering policy, it can be seen by jointly following Table 5.20 and Table 5.21 that the average value of the order fluctuations increases for both of the retailer (138.423 for the order up to S and 138.867 for the ROP policy) and the manufacturer (133.914 for the order up to S and 216.794 for the ROP policy). Moreover, for the AR(1) demand process, if the manufacturer uses the ROP ordering policy against the order up to S ordering policy, the

average value of the order fluctuations also increases for both of the retailer (145.415 for the order up to S and 145.493 for the ROP policy) and the manufacturer (147.031 for the order up to S and 216.704 for the ROP policy).

In addition to this, the total average values of the order fluctuations support these results where those values are 141.919 for the retailer, and 140.473 for the manufacturer in the case where the manufacturer uses the order up to S policy. On the other hand, same values for the case where the manufacturer uses the ROP policy are 142.180 for the retailer, and 216.749 for the manufacturer.

These average statistics also support that if the manufacturer uses the order up to S inventory policy against to the ROP inventory policy, advantages for the bullwhip effect reduction will increase. But, it is seen that gained benefits for the retailer agent is less than the manufacturer agent in according to the manufacturer ordering policy decision. This is caused since the starting inventory level for each agent is selected as a huge level and the retailer is not faced with any backorder inventory in both of the different inventory policy is used by the manufacturer. Because of this, the manufacturer inventory policy selection is only affected itself. In addition to these average statistics, the two sample t-test is also applied for this “what if analysis” case to investigate is there any significant difference on the orders fluctuations of the retailer and the manufacturer agents. Results of the two sample t-test analysis for this “what if analysis” case is given below for the retailer and the manufacturer, respectively.

The following two sample t-test result indicates that a significant difference does not occur on the order fluctuation for the retailer agent, when the manufacturer makes selection between the order up to S, and the ROP inventory policies in the centralised case. Because the P-value statistic is 0.993 which is greater than the $\alpha = 0.05$ level of significance in this case.

Two-Sample T-Test and CI: ret_1; ret_2

Two-sample T for ret_1 vs ret_2

	N	Mean	StDev	SE Mean
ret_1	16	141.9	80.1	20
ret_2	16	142.2	79.7	20

Difference = mu ret_1 - mu ret_2

Estimate for difference: -0.3

95% CI for difference: (-58.0; 57.5)

T-Test of difference = 0 (vs not =): T-Value = -0.01 P-Value = 0.993 DF = 29

Furthermore, the two sample t-test result shown below also indicates that a significant difference occurs on the order fluctuation for the manufacturer agent when the manufacturer makes selection between the order up to S, and the ROP inventory policies in the centralised case. Because, the P-value statistic is now approximately 0 which is smaller than the $\alpha = 0.05$ level of significance. In addition to this, the given confidence interval result of the two sample t-test, where both of the limits are negative values, indicates that the average order fluctuation for the manufacturer increases when the manufacturer uses the ROP policy against to the order up to S policy.

Two-Sample T-Test and CI: man_ouS; man_ROP

Two-sample T for man_ouS vs man_ROP

	N	Mean	StDev	SE Mean
man_ouS	16	140.5	65.6	16
man_ROP	16	216.75	1.62	0.40

Difference = mu man_ouS - mu man_ROP

Estimate for difference: -76.3

95% CI for difference: (-111.2; -41.3)

T-Test of difference = 0 (vs not =): T-Value = -4.65 P-Value = 0.000 DF = 15

By following the findings between Table 5.18 to 5.21, similar to the decentralised case, among the scenarios tested in the centralised case, it can be concluded that orders are batched in ROP inventory policy (since they are not placed in each period) that caused to an increase in bullwhip effect. This is also a significant result, because it is known that the ROP ordering policy allows the order batching which is the one of the important defined reason of the bullwhip effect in supply chains. In addition to these results, the next section analysis the the amount of the improvements is reached by passing from the decentralised case to the centralised case for each scenario according to the sample data set.



5.3 ANALYSIS OF THE BULLWHIP EFFECT REDUCTIONS

The improvements obtained in the BEM value by passing from the decentralised case to the centralised case for the bullwhip effect reduction is evaluated and displayed with percentages in this part. The BEM's (bullwhip effect measures) values are used to calculate the amount of improvement for each scenario. Table 5.22 gives the improvement percentages for the retailer, and Table 5.23 gives the improvement percentages for the manufacturer, respectively.

Table 5.22 The amount of improvements in the bullwhip effect by passing from decentralised case to centralised case for the retailer

RETAILER							
IID process	FORECASTING METHOD		ORDERING POLICY		DECENT.CASE	CENT.CASE	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	BE Measure for Retailer	BE Measure for Retailer	IMPROVEMENT (%)
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	2.128	2.075	2.492
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	2.123	2.047	3.545
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	2.136	2.083	2.500
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	2.153	2.086	3.130
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	7.522	7.331	2.539
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	7.411	7.178	3.136
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	7.292	7.045	3.388
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	7.384	7.305	1.078
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	1.768	1.708	3.344
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	1.764	1.744	1.133
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	1.748	1.722	1.474
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	1.727	1.637	5.202
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	7.316	7.145	2.340
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	7.231	7.016	2.966
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	7.401	7.296	1.415
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	7.226	7.092	1.859
Min.					1.727	1.637	1.078
Max.					7.522	7.331	5.202
Average					4.646	4.532	2.596

AR(1) process	FORECASTING METHOD		ORDERING POLICY		DECENT.CASE	CENT.CASE	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	BE Measure for Retailer	BE Measure for Retailer	IMPROVEMENT (%)
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	1,971	1,935	3,328
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	1,990	1,898	5,488
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	1,998	1,977	3,001
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	1,996	1,943	5,427
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	5,623	5,287	6,558
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	5,406	5,157	5,732
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	5,495	5,442	6,257
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	5,426	5,366	5,516
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	1,686	1,659	2,887
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	1,751	1,659	5,787
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	1,716	1,661	2,750
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	1,727	1,677	5,618
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	5,397	5,157	6,097
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	5,339	5,072	5,658
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	5,504	5,480	6,315
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	5,332	5,230	5,453
Min.					1,686	1,659	2,750
Max.					5,623	5,480	6,558
Average					3,647	3,538	5,117

Total Min.	1,686	1,637	1,078
Total Max.	7,522	7,331	6,558
Total Average	4,146	4,035	3,857

It can be seen in Table 5.22 that the biggest improvement in the bullwhip effect reduction under the IID demand process is reached in Scenario 12 for the retailer with a decrease in the BEM value from 1.727 to 1.637 and totally with a % 5.202 improvement. The second and the third best scenarios for the retailer are Scenario 2 with % 3.545 improvement, and Scenario 7 with % 3.388 improvement. The last three scenarios where the worst improvement is obtained under the IID demand process listed as Scenario 8 with % 1.078 improvement, Scenario 10 with % 1.133 improvement, and Scenario 15 with % 1.415 improvement.

In addition to these, the biggest improvement in the bullwhip effect reduction under the AR(1) demand process is reached in Scenario 21 for the retailer with a decrease in the BEM value from 5.623 to 5.287 and totally with a % 6.558 improvement. The second and the third best scenarios under the AR(1) demand process are Scenario 31 with % 6.315 improvement, and Scenario 23 with % 6.257 improvement. The last three scenarios where the worst improvement is obtained under the AR(1) demand process listed as Scenario 27 with % 2.750 improvement, Scenario 25 with % 2.887 improvement, and Scenario 19 with % 3.001 improvement.

The total average improvement value for the retailer 3.857. It is obvious that changing the information sharing strategy in the supply chain management can cause more advantages for the retailer agent, but it can not be clearly followed from the studied sample data. Because the initial inventory level is arbitrarily chosen a huge value, benefits of information sharing strategy is limited in this sample study. However, it can be pointed out by changing the parameter of the studied model. In addition to the retailer agent, the amount of improvements in the bullwhip effect by passing from decentralised case to centralised case for the manufacturer is displayed in Table 5.23.

Table 5.23 The amount of improvements in the bullwhip effect by passing from decentralised case to centralised case for the manufacturer

MANUFACTURER							
IID process	FORECASTING	METHOD	ORDERING	POLICY	DECENT.CASE	CENT.CASE	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	BE Measure for Manf.	BE Measure for Manf.	IMPROVEMENT (%)
scenario 1	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	3.685	2.283	38.034
scenario 2	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	7.310	6.957	4.833
scenario 3	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	3.160	2.245	28.963
scenario 4	Exp.Smoothing	Moving Avg.	Order up to S	ROP	7.440	7.145	3.965
scenario 5	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	7.904	6.765	14.410
scenario 6	Exp.Smoothing	Exp.Smoothing	ROP	ROP	7.697	7.076	8.064
scenario 7	Exp.Smoothing	Moving Avg.	ROP	Order up to S	7.721	6.564	14.984
scenario 8	Exp.Smoothing	Moving Avg.	ROP	ROP	7.444	7.167	3.719
scenario 9	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	3.240	2.064	36.304
scenario 10	Moving Avg.	Exp.Smoothing	Order up to S	ROP	7.472	7.325	1.970
scenario 11	Moving Avg.	Moving Avg.	Order up to S	Order up to S	2.910	1.967	32.409
scenario 12	Moving Avg.	Moving Avg.	Order up to S	ROP	7.380	6.916	6.281
scenario 13	Moving Avg.	Exp.Smoothing	ROP	Order up to S	7.587	6.531	13.923
scenario 14	Moving Avg.	Exp.Smoothing	ROP	ROP	7.509	6.914	7.927
scenario 15	Moving Avg.	Moving Avg.	ROP	Order up to S	7.824	6.819	12.851
scenario 16	Moving Avg.	Moving Avg.	ROP	ROP	7.321	6.973	4.761
				Min.	2.910	1.967	1.970
				Max.	7.904	7.325	38.034
				Average	6.475	5.732	14.587

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	DECENT.CASE	CENT.CASE	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	BE Measure for Manf.	BE Measure for Manf.	IMPROVEMENT (%)
scenario 17	Exp.Smoothing	Exp.Smoothing	Order up to S	Order up to S	3.328	2.472	25.717
scenario 18	Exp.Smoothing	Exp.Smoothing	Order up to S	ROP	5.488	5.202	5.220
scenario 19	Exp.Smoothing	Moving Avg.	Order up to S	Order up to S	3.001	2.330	22.357
scenario 20	Exp.Smoothing	Moving Avg.	Order up to S	ROP	5.427	5.288	2.551
scenario 21	Exp.Smoothing	Exp.Smoothing	ROP	Order up to S	6.558	4.922	24.949
scenario 22	Exp.Smoothing	Exp.Smoothing	ROP	ROP	5.732	5.128	10.538
scenario 23	Exp.Smoothing	Moving Avg.	ROP	Order up to S	6.257	5.091	18.640

AR(1) process	FORECASTING	METHOD	ORDERING	POLICY	DECENT.CASE	CENT.CASE	
Scenario No.	Retailer	Manufacturer	Retailer	Manufacturer	BE Measure for Manf.	BE Measure for Manf.	IMPROVEMENT (%)
scenario 24	Exp.Smoothing	Moving Avg.	ROP	ROP	5.516	5.280	4.284
scenario 25	Moving Avg.	Exp.Smoothing	Order up to S	Order up to S	2.887	2.216	23.258
scenario 26	Moving Avg.	Exp.Smoothing	Order up to S	ROP	5.787	5.451	5.807
scenario 27	Moving Avg.	Moving Avg.	Order up to S	Order up to S	2.750	2.115	23.095
scenario 28	Moving Avg.	Moving Avg.	Order up to S	ROP	5.618	5.377	4.292
scenario 29	Moving Avg.	Exp.Smoothing	ROP	Order up to S	6.097	4.713	22.693
scenario 30	Moving Avg.	Exp.Smoothing	ROP	ROP	5.658	5.079	10.241
scenario 31	Moving Avg.	Moving Avg.	ROP	Order up to S	6.315	5.102	19.220
scenario 32	Moving Avg.	Moving Avg.	ROP	ROP	5.453	5.200	4.630
				Min.	2.750	2.115	2.551
				Max.	6.558	5.451	25.717
				Average	5.117	4.435	14.218

Total Min.	2.750	1.967	1.970
Total Max.	7.904	7.325	38.034
TotalAverage	5.796	5.084	14.403

As shown in Table 5.23, under the IID demand process, the greatest improvement in the bullwhip effect reduction is reached in Scenario 1 for the manufacturer agent. The BEM's value decreases from 3.685 to 2.283 for this scenario, with a % 38.034 improvement. The second and the third best scenarios are Scenario 9 with % 36.304 improvement, and Scenario 9 with % 32.409 improvement, respectively. The last three scenarios where the worst improvement is obtained under the IID demand process listed as Scenario 10 with % 1.970 improvement, Scenario 8 with % 3.719 improvement, and Scenario 4 with % 3.965 improvement.

In addition to these, the biggest improvement in the bullwhip effect reduction under the AR(1) demand process is reached in Scenario 17 with a decrease in the BEM value from 3.328 to 2.472 and totally with a % 25.717 improvement. The second and the third best scenarios under the AR(1) demand process are Scenario 21 with % 24.949 improvement, and Scenario 25 with % 23.258 improvement. The last three scenarios where the worst improvement is

obtained under the AR(1) demand process listed as Scenario 20 with % 2.551 improvement, Scenario 24 with % 4.284 improvement, and Scenario 28 with % 4.292 improvement.

The total average improvement value for the manufacturer is 14.403. It can be stated that the passing from the decentralised case to the centralised case constitutes more advantages for the manufacturer than the retailer for the sample data set. Because, the average improvement for the retailer agent is % 3.857 for all of the 32 scenarios, which is smaller than the average improvement value encountered for the manufacturer agent.



6. CONCLUSIONS

Each agent in any supply chain tries to achieve maximum profits or minimum costs, and these aims cause many complex and complicated matters that should be solved as efficient as possible. For these reasons, the supply chain management is nowadays seen as one of the most important research areas for the industrial and systems engineering. One of the main problems in any supply chain is the bullwhip effect which has an undesired impact on costs and profits for each agent. Some causes of the bullwhip effect are defined as the ordering policy and the forecasting technique selections. On the other hand, some remedies are suggested to control and reduce the bullwhip effect, such as the demand information sharing in the supply chain management literature. Hence the present trend in management science seem to be management of the whole chain with cooperation and partnership.

This study presented a generic simulation model that is based on the systems dynamics modeling approach. This approach was chosen because it is well suited to treat the complex systems with interdependent variables that have nonlinear relationships between them. The model was used to gain a clearer insight into how changing of a series of the ordering policies and the forecasting techniques influence the order fluctuations under different demand processes. The exponential smoothing and the moving average methods were used as the forecasting alternatives. Moreover, the order up to S and the Reorder point (ROP) policies were used for the ordering policy selection alternatives. The cases with independently identically distributed or autoregressive end customer demands are also tested. In addition to these, the demand information sharing strategy is applied by the simulation study and the results for the decentralised and the centralised cases were compared. The improvement levels for the different scenarios were obtained and discussed.

For the decentralised case, 32 alternative scenarios were simulated by changing the forecasting techniques, and the ordering policies of the supply chain agents. It was observed that the bullwhip effect always existed for each scenario, but it was less in the IID demand process than the AR(1) demand process. All of the simulated 32 alternative scenarios of the decentralised case were also simulated in the centralised case. It was observed that the

bullwhip effect also existed between the retailer-customer and the manufacturer-customer branches for each scenario. Furthermore, in the centralised case, the analysis of the simulation model results revealed that the bullwhip effect was significantly reduced against the decentralised case for each of the 32 scenarios. Also it was observed that the bullwhip effect was fully prevented for the retailer-manufacturer branch in some scenarios. Similar to the decentralised case, order fluctuation was less in the IID demand process than AR(1) demand process in the centralised case.

In addition to this, it was found that the bullwhip effect reduction in both of the exponential smoothing forecasting method, and the moving average forecasting method depend on their specification of a single parameter selection. For moving averages the parameter is N , the number of periods in the moving average, and for exponential smoothing the parameter is α , the smoothing constant. Small values of N or large values of α result in forecast that put greater weight on current data, and large values of N and small values of α put greater weight on past data. Small N and large α are more responsive to changes in the demand process, but will result in forecast errors with higher variance. When $\alpha = 2 / (N+1)$, both methods have the same distribution of forecast error. This means that they should have roughly the same level of accuracy, but it does not mean that they will give the same forecast. By adjusting the values of N and α , it can be made that the two methods are more or less responsive to underlying pattern of the data. Analysis of the simulation results of the decentralised and the centralised cases reveal that the major cause of the bullwhip effect is the independent sequential demand forecasting performed at each agent of the supply chain, making use of previous stage's orders. Experiments with different α and N values also reveal that the bullwhip effect decreases, with a decrease in α and with an increase in N . The large values of N and small values of α means that demand forecast is less responsive to changes in the demand process.

However, using the order up to S inventory policy against to the ROP inventory policy gave less order fluctuations among the scenarios tested in the decentralised and the centralised cases. Orders are batched in ROP inventory policy (since they are not placed in each period) that caused an increase in the bullwhip effect. The decrease on the order fluctuation was less

for the retailer agent, compared to the manufacturer agent; this is because of the initial parameter selection of the simulation model.

The amount of improvements by passing from the decentralised case to the centralised case were evaluated for all of the 32 scenarios. It was found that passing from the decentralised case to the centralised case constituted more advantages for the manufacturer agent compared to the retailer agent. The average improvement values met by the retailer was % 3.857 for all of the 32 scenarios, which was smaller than the average improvement value encountered by the manufacturer, which was % 14.403. It should be noted that the benefits of information sharing strategy is a function of the data set used in the simulation studies. The corresponding benefits may be increased by selecting appropriate data set and initial values.

It was noted that the simulation model was based on the assumption that full demand information sharing was possible. In the real world, although the information technology is highly developed, instant access to demand data may be impossible for all of the agents in the supply chain. Based on the findings of the simulation model, it is clear that more powerful decisions can be made by each agent in the supply chain, if full demand data is shared instantly. Also, it should be accepted that the simulation models can not provide an optimal solution; they may help systems engineers to avoid making the wrong decisions by demonstrating the consequences of such decisions.

7. RECOMMENDATIONS

The simulation model developed in this study is a generic model which represents the general structure for any supply chain system. It is useful for studying the bullwhip effect in supply chains under different policies. It is recommended that the model be adapted to a special company's supply chain management system by making appropriate modifications. The Powersim software can harmonially work with other decision support tools such as SAP APO, or other database systems which can supply instant data to the simulation model by using the Electronic Data Interchange (EDI) or Point of Sales (POS) subsystems. Through these mechanism, the collaborative planning and the vendor managed inventory systems can be improved with more powerful and reliable managerial practices.

Some limitations exist for the System Dynamics modeling, such as the systems dynamics models concentrate on general system structure and behaviour rather than operational analysis. The discrete event models uses more microscopic approach, contrasted with the approach usually taken to the modeling and simulation of feedback systems. Such models may be used if a more detailed modeling and simulation study is desired.

There are two other major causes of bullwhip effect discussed in the literature: shortage (rationing) gaming and price variations. These two factors were beyond the scope of this study. The model can be extended for capturing these two causes of the bullwhip effect too. For a realistic study of shortage gaming, the model should have multiple suppliers and retailers at the same stage. For price variations, the model should include a price determination structure. All of these situations can be considered as further research areas.

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APPENDIX A

Software Support for System Dynamics Modeling

The main objective of system dynamics modeling is to capture mental models of the underlying behavior structure of organizational systems. The modeling software available on the market today contributes greatly toward achieving that objective by allowing model builders to concentrate on conceptualizing the system rather than on the technicalities of model building. There are four software programs that were designed to facilitate the building and use of System Dynamics models- Dynamo, iThink/Stella, PowerSim and Vensim. More information on these is given below.

DYNAMO

PA Consulting One Memorial Drive Cambridge MA 02142 Phone: 617 225 2700 Fax: 617 225 2631	DYNAMO was the first system dynamics simulation language, and for a long time the language and the field were considered synonymous. Originally developed by Jack Pugh at MIT the language was made commercially available from Pugh-Roberts in the early 1960s. DYNAMO today runs on PC compatibles under Dos/Windows. It provides an equation based development environment for system dynamics models.
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IThink/Stella

isee Systems 46 Centerra Parkway Suite 200 Lebanon NH 03766 Phone: 603 643 9636 Fax: 603 643 9502 http://www.iseesystems.com	Originally introduced on the Macintosh in 1984, the Stella software provided a graphically oriented front end for the development of system dynamics models. The stock and flow diagrams, used in the system dynamics literature are directly supported with a series of tools supporting model development. Equation writing is done through dialog boxes accessible from the stock and flow diagrams. IThink is available for Macintosh and Windows computers.
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Powersim

Powersim Software AS Sandbrugaten 5-7 P.O. Box 3961, Dreggen N-5835 Bergen, NORWAY Phone: 47 55 60 65 00 Fax: 47 55 60 65 01 Email: powersim@powersim.no URL: http://www.powersim.com	In the mid 1980s the Norwegian government sponsored research aimed at improving the quality of high school education using system dynamics models. This project resulted in the development of Mosaic, an object oriented system aimed primarily at the development of simulation based games for education. Powersim was later developed as a Windows based environment for the development of system dynamics models that also facilitates packaging as interactive games or learning environments.
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Vensim

Ventana Systems, Inc. 60 Jacob Gates Road Harvard, MA 01451 Phone 508 651 0432 Fax: 508 650 5422 Email: vensim@vensim.com URL: http://www.vensim.com	Originally developed in the mid 1980s for use in consulting projects Vensim was made commercially available in 1992. It is an integrated environment for the development and analysis of system dynamics models. Vensim runs on Windows and Macintosh computers.
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APPENDIX B

Variable Definitions and Model Equations

The next two tables displays all of the variable names and their definitions in the supply chain simulation model for the decentralised, and the centralised cases, respectively. The “name” column gives all defined variables’ names with alphabetical order, and the “unit” column gives the measure used for each variable, where the “pd” indicates “products” and the “pd/da” indicates “products per day”. In addition to these, the “definition” columns give the definitions of all variables.

Table.B.1 The variable names and their definitions for the entire simulation model in the decentralised case

Name	Unit	Definition
AR 1 Process	pd	100<<pd>>
AR_1	pd	INTEGER(MAX(0<<pd>>;'AR 1 Process'))
Auxiliary_1	pd/da	DELAYPPL(Rate_1;1<<da>>;100<<pd/da>>)
backorders M	pd/da	('orders by R'/1<<da>>)-'M sales'
backorders R	pd/da	'customer order'-'R sales'
customer demand	pd/da	{(INTEGER(NORMAL(100;30))*1<<pd/da>>);(AR_1/1<<da>>)}[INDEX(secim)]
customer order	pd/da	'customer demand'
ex chang	pd/da	((('customer order'*1<<da>>)-'expected customer demand')/14<<da>>
exp dem by M	pd/da	{'movaverage_ M';'exp smoothing_ M'}[INDEX('secim 2')]
exp dem by R	pd/da	{'exp smoothing_ R';'moving average_ R'}[INDEX('secim 1')]
exp smoothing_ M	pd/da	'expected demand'/1<<da>>
exp smoothing_ R	pd/da	'expected customer demand'/1<<da>>
expectation change	pd/da	('orders by R'-'expected demand')/14<<da>>
expected customer demand	pd	'customer order'*1<<da>>
expected demand	pd	'orders by R'
IP M	pd	'Supply line M'+'M inventory'-'M backorder'
IP R	pd	'R inventory'+'Supply line R'-'R backorder'
M backorder	pd	0<<pd>>
M inventory	pd	3000<<pd>>
M sales	pd/da	MAX(0<<pd/da>>;(MIN('M inventory'/1<<da>>;(('orders by R'/1<<da>>)+('M backorder'/1<<da>>))))
movaverage_ M	pd/da	(SLIDINGAVERAGE('orders by R';28<<da>>))/1<<da>>
moving average_ R	pd/da	(SLIDINGAVERAGE('customer order'*1<<da>>;28<<da>>))/1<<da>>
order up to S_ M	pd	'rop M'+INTEGER(SQRT(3650<<pd*da>>*exp dem by M'))
order up to S_ R	pd	'rop R'+INTEGER(SQRT(3650<<pd*da>>*exp dem by R'))
orders by M	pd	{'orderupto Policy_ M';'ROP Policy_ M'}[INDEX(secim2_1)]
orders by R	pd	{'orderupto Policy_ R';'ROP Policy_ R'}[INDEX(secim1_1)]
orders received M	pd/da	MIN('Supply line M'/1<<da>>;(DELAYMTR('Supply line M'/1<<da>>;14<<da>>;1;0<<pd/da>>)))
orders received R	pd/da	MIN('Supply line R'/1<<da>>;(DELAYMTR('Supply line R'/1<<da>>;14<<da>>;1;0<<pd/da>>)))

Name	Unit	Definition
orderupto Policy_M	pd	INTEGER(MAX(('order up to S_M'-IP M');0<<pd>>))
orderupto Policy_R	pd	INTEGER(MAX(('order up to S_R'-IP R');0<<pd>>))
R backorder	pd	0<<pd>>
R inventory	pd	3000<<pd>>
R sales	pd/da	MAX(0<<pd/da>>;(MIN('R inventory'/1<<da>>;'shipment rate R')))
Rate_1	pd/da	((Rho*'AR 1 Process')+(100<<pd>>*(1-Rho)))+(INTEGER(NORMAL(0;30))*1<<pd>>))/1<<da>>
Rate_2	pd/da	Auxiliary_1
Rho		0,7
rop M	pd	('exp dem by M'*14<<da>>)+184<<pd>>
ROP Policy_M	pd	IF('IP M'<='rop M';('order up to S_M'-rop M');0<<pd>>)
ROP Policy_R	pd	IF('IP R'<='rop R';('order up to S_R'-rop R');0<<pd>>)
rop R	pd	('exp dem by R'*14<<da>>)+184<<pd>>
secim		1
secim 1		1
secim 2		1
secim1_1		1
secim2_1		1
shipment rate R	pd/da	'customer order'+('R backorder'/1<<da>>)
shipments from M	pd/da	'M sales'
shipments from supplier	pd/da	'orders by M'/1<<da>>
Supply line M	pd	0<<pd>>
Supply line R	pd	0<<pd>>

Table B.2 The variable names and their definitions for the entire simulation model in the centralised case

Name	Unit	Definition
AR 1 Process	pd	100<<pd>>
AR_1	pd	INTEGER(MAX(0<<pd>>;'AR 1 Process'))
Auxiliary_1	pd/da	DELAYPPL(Rate_1;1<<da>>;100<<pd/da>>)
backorders M	pd/da	('orders by R'/1<<da>>)-'M sales'
backorders R	pd/da	'customer order'-'R sales'
customer demand	pd/da	{(INTEGER(NORMAL(100;30))*1<<pd/da>>);(AR_1/1<<da>>)}[INDEX(secim)]
customer order	pd/da	'customer demand'
ex chang	pd/da	((('customer order'*1<<da>>)-'expected customer demand')/14<<da>>
exp dem by M	pd/da	{'movaverage_ M';'exp smoothing_ M'}[INDEX('secim 2')]
exp dem by R	pd/da	{'exp smoothing_ R';'moving average_ R'}[INDEX('secim 1')]
exp smoothing_ M	pd/da	'expected demand'/1<<da>>
exp smoothing_ R	pd/da	'expected customer demand'/1<<da>>
expectation change	pd/da	((('customer order'*1<<da>>)-'expected demand')/14<<da>>
expected customer demand	pd	'customer order'*1<<da>>
expected demand	pd	'customer order'*1<<da>>
IP M	pd	'Supply line M'+ 'M inventory'- 'M backorder'
IP R	pd	'R inventory'+ 'Supply line R'- 'R backorder'
M backorder	pd	0<<pd>>

Name	Unit	Definition
M inventory	pd	3000<<pd>>
M sales	pd/da	MAX(0<<pd/da>>;(MIN('M inventory'/1<<da>>;(('orders by R'/1<<da>>)+('M backorder'/1<<da>>))))))
movaverage_M	pd/da	(SLIDINGAVERAGE(('customer order'*1<<da>>;28<<da>>))/1<<da>>
moving average_R	pd/da	(SLIDINGAVERAGE('customer order'*1<<da>>;28<<da>>))/1<<da>>
order up to S_M	pd	'rop M'+INTEGER(SQRT(3650<<pd*da>>*exp dem by M'))
order up to S_R	pd	'rop R'+INTEGER(SQRT(3650<<pd*da>>*exp dem by R'))
orders by M	pd	{'orderupto Policy_M';'ROP Policy_M'}[INDEX(secim2_1)]
orders by R	pd	{'orderupto Policy_R';'ROP Policy_R'}[INDEX(secim1_1)]
orders received M	pd/da	MIN('Supply line M'/1<<da>>;(DELAYMTR('Supply line M'/1<<da>>;14<<da>>;1;0<<pd/da>>)))
orders received R	pd/da	MIN('Supply line R'/1<<da>>;(DELAYMTR('Supply line R'/1<<da>>;14<<da>>;1;0<<pd/da>>)))
orderupto Policy_M	pd	INTEGER(MAX(('order up to S_M'-IP M');0<<pd>>))
orderupto Policy_R	pd	INTEGER(MAX(('order up to S_R'-IP R');0<<pd>>))
R backorder	pd	0<<pd>>
R inventory	pd	3000<<pd>>
R sales	pd/da	MAX(0<<pd/da>>;(MIN('R inventory'/1<<da>>;'shipment rate R')))
Rate_1	pd/da	((Rho*'AR 1 Process')+(100<<pd>>*(1-Rho)))+(INTEGER(NORMAL(0,30))*1<<pd>>))/1<<da>>
Rate_2	pd/da	Auxiliary_1
Rho		0,7
rop M	pd	('exp dem by M'*14<<da>>)+184<<pd>>
ROP Policy_M	pd	IF('IP M'<='rop M';('order up to S_M'-rop M');0<<pd>>)
ROP Policy_R	pd	IF('IP R'<='rop R';('order up to S_R'-rop R');0<<pd>>)
rop R	pd	('exp dem by R'*14<<da>>)+184<<pd>>
secim		1
secim 1		1
secim 2		1
secim1_1		1
secim2_1		1
shipment rate R	pd/da	'customer order'+('R backorder'/1<<da>>)
shipments from M	pd/da	'M sales'
shipments from supplier	pd/da	'orders by M'/1<<da>>
Supply line M	pd	0<<pd>>
Supply line R	pd	0<<pd>>

APPENDIX C

The Extreme Condition Test Results for Model Validation

1. The results for the assumed initial position where “End Customer Order” = 100 pd / day

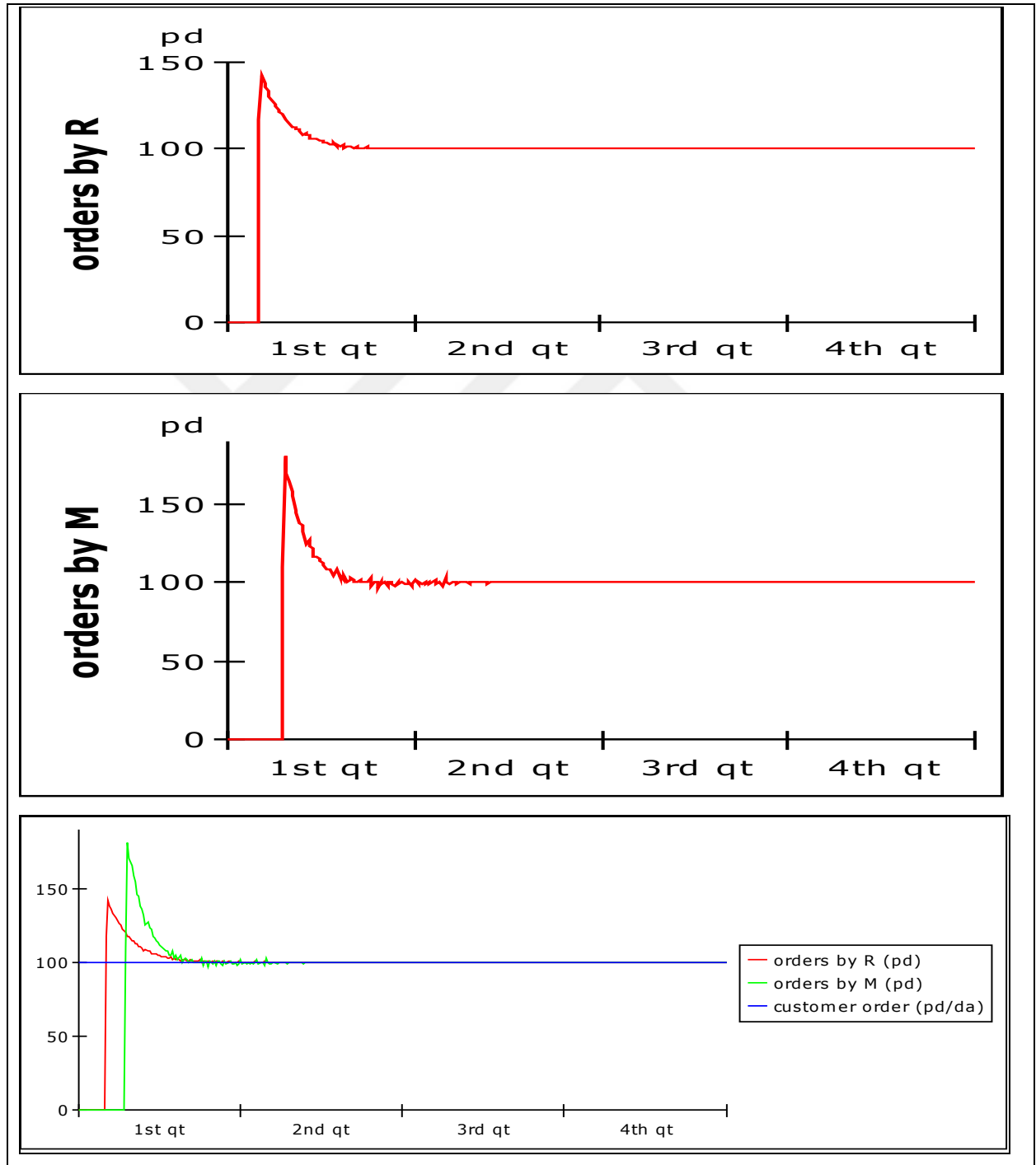


Figure C.1 Results for the assumed initial position for the model

2. The results for the “PULSE” increase in the end customer demand where the “End Customer Order” = 100 pd / day.

For Pulse input: “End Customer Order” = (100 <<pd/da>>) + (PULSE (30 <<pd>> ; STARTTIME + 30 <<da>> ; 30 <<da>>))

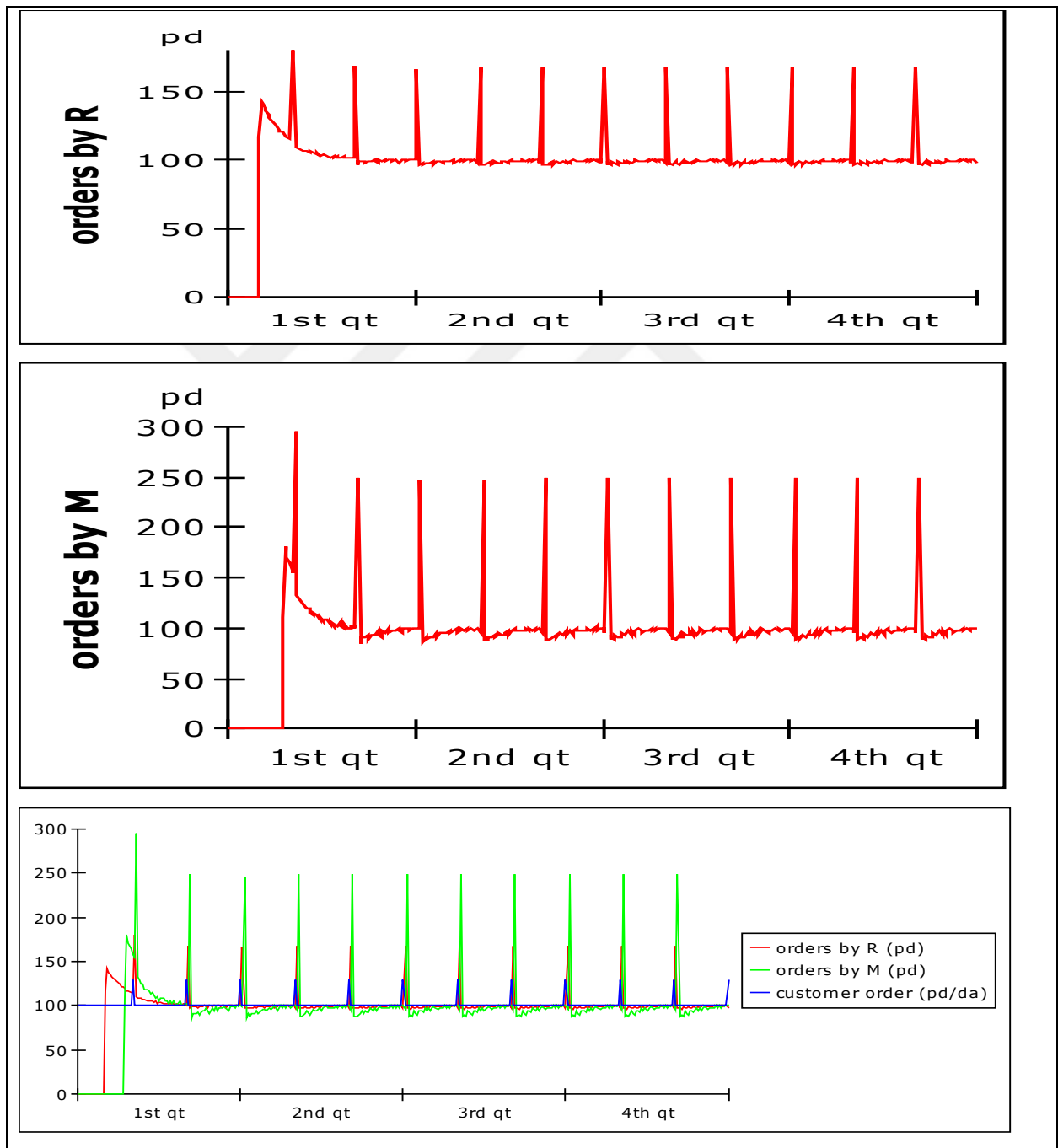


Figure C.2 . Results for the “PULSE” input for end customer demand

3. The results for the “STEP” increase in the end customer demand where the “End Customer Order” = 100 pd / day .

For STEP input: “End Customer Order” = (100 << pd/da >>) + (STEP (30 << pd/da >>; STARTTIME + 30 << da >>))

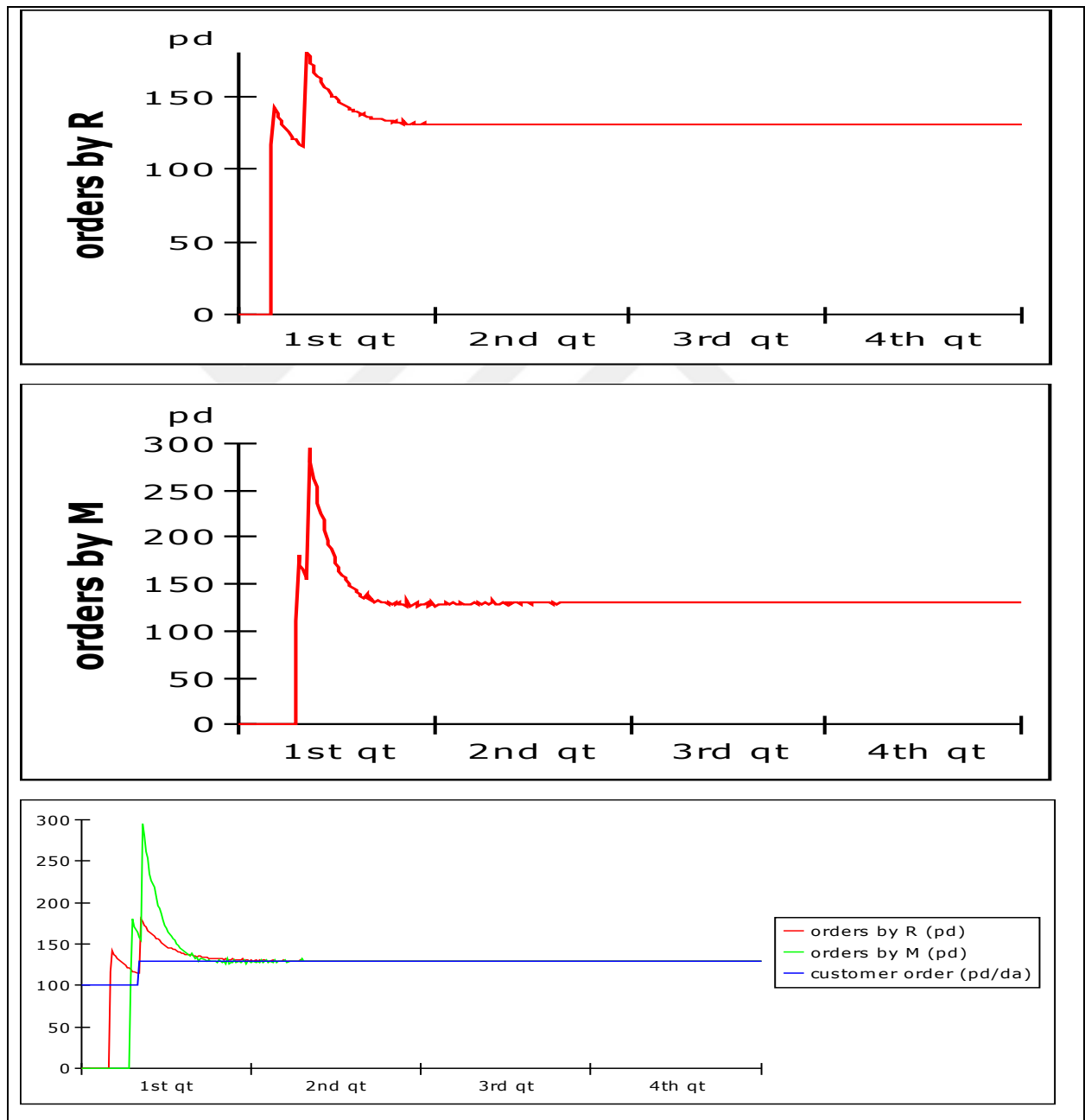


Figure C.3 . Results for the “STEP” input for end customer demand

4. The results for the “RAMP” increase in the end customer demand where the “End Customer Order” = 100 pd / day.

For RAMP input “End Customer Order” = $(100 \ll \text{pd/da} \gg) + ((\text{RAMP}(30 \ll \text{pd/da} \gg; \text{STARTTIME} + 30 \ll \text{da} \gg)) / 1 \ll \text{da} \gg)$

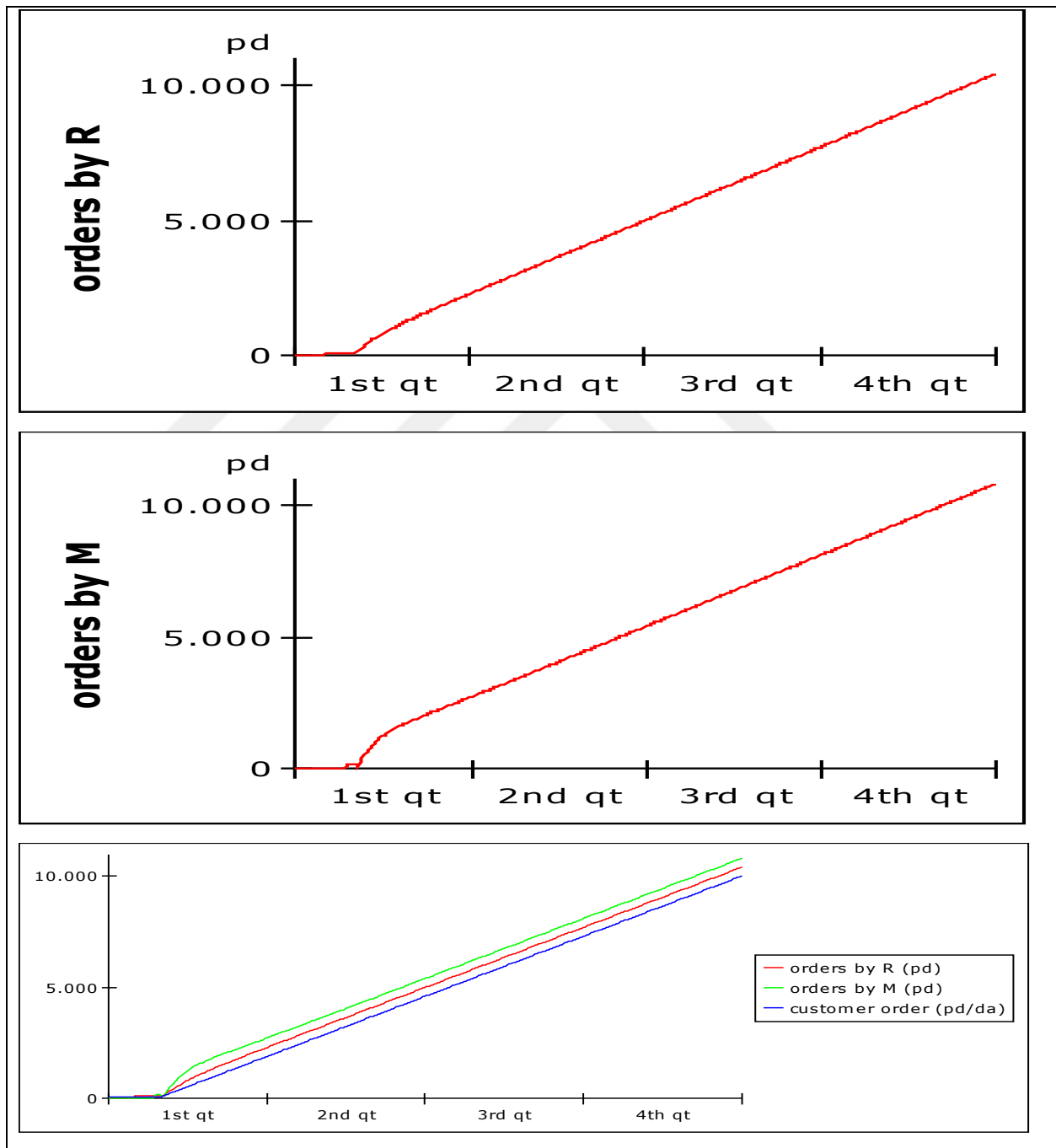


Figure C.4 Results for the “RAMP” input for end customer demand

APPENDIX D

CD-Rom Content

All of the simulated scenario models and results for the decentralised and the centralised cases are given in the attached CD-Rom. There are two folders in the CD-Rom which are named as the “Decentralised Case”, and the “Centralised Case”, respectively. The “Decentralised Case” folder includes the results for the decentralised information sharing strategy, and the “Centralised Case” folder contains the results for the centralised information sharing strategy. Both of the folders include 32 files of Powersim models with 32 files of Excel spreadsheets. The Powersim model files have “.sip” extensions which can be opened by only Powersim Studio 7th Edition where its set up program is also included inside the “Centralised Case” folder.

The Excel files show the results of simulation model with 10 replications for each scenario. The amounts of placed orders by each agent with their graphical representations for all of the simulated scenarios is given in there. In addition to these, possible runs for the forecasting methods with different parameter selections ($\alpha = 1/30$ that indicates $N \approx 60$) is also given with 2 different Excel files for the centralised, and the decentralised cases, respectively. Moreover, Minitab files of the “paired t-test”, and the “two sample t-test” is given for both of the decentralised and the centralised cases.