# CENTRALISED DEMAND INFORMATION SHARING IN SUPPLY CHAINS

A Thesis submitted for the degree of Doctor of Philosophy

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# Abstract

This thesis explores Centralised Demand Information Sharing (CDIS) in supply chains. CDIS is an information sharing approach where supply chain members forecast based on the downstream member's demand.

The Bullwhip Effect is a demand variance amplification phenomenon: as the demand moves upstream in supply chains, its variability increases. Many papers in the literature show that, if supply chain members forecast using the less variable downstream member's demand, this amplification can be reduced leading to a reduction in inventory cost. These papers, using strict model assumptions, discuss three demand information sharing approaches: No Information Sharing (NIS), Downstream Demand Inference (DDI) and Demand Information Sharing (DIS). The mathematical analysis in this stream of research is restricted to the Minimum Mean Squared Error (MMSE) forecasting method.

A major motivation for this PhD research is to improve the above approaches, and assess those using less restrictive supply chain assumptions. In this research, apart from using the MMSE forecasting method, we also utilise two non-optimal forecasting methods, Simple Moving Averages (SMA) and Single Exponential Smoothing (SES). The reason for their inclusion is the empirical evidence of their high usage, familiarity and satisfaction in practice.

We first fill some gaps in the literature by extending results on upstream demand translation for ARMA (p, q) processes to SMA and SES. Then, by using less restrictive assumptions, we show that the DDI approach is not feasible, while the NIS and DIS approaches can be improved. The two new improved approaches are No Information Sharing – Estimation (NIS-Est) and Centralised Demand Information Sharing (CDIS). It is argued in this thesis that if the supply chain strategy is not to share demand information, NIS-Est results in less inventory cost than NIS for an Order Up To policy. On the other hand, if the strategy is to share demand information, the CDIS approach may be used, resulting in lower inventory cost than DIS.

These new approaches are then compared to the traditional approaches on theoretically generated data. NIS-Est improves on NIS, while CDIS improves on the DIS approach in terms of the bullwhip ratio, forecast error (as measured by Mean Squared Error), inventory holding and inventory cost. The results of simulation show that the performance of CDIS is the best among all four approaches in terms of these performance metrics.

Finally, the empirical validity of the new approaches is assessed on weekly sales data of a European superstore. Empirical findings and theoretical results are consistent regarding the performance of CDIS.

Thus, this research concludes that the inventory cost of an upstream member is reduced when their forecasts are based on a Centralised Demand Information Sharing (CDIS) approach.

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Dedicated to my mother

Shehzaadi Neelofer Ali

who passed away in Jan'07.

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# 1. Introduction

## 1.1. Business Context

Changes in the economic environment have led organisations to re-evaluate their business models and focus their attention towards better ways of providing products and services to their customers across complex networks of suppliers. Effective co-ordination of decisions across the supply chain has been recognised as a major source of competitive advantage. Cross-industry collaboration initiatives for formal coordination of decisions, such as Collaborative Planning, Forecasting and Replenishment (CPFR) and Vendor Managed Inventory (VMI), have been successful in terms of inventory reductions and service level improvements. Results from recent research (Kulp et al, 2004; Ernst and Young, 2007) have shown that supply chain collaboration activities may have a significantly greater effect on profit margins than other improvements in the supply chain.

The benefits of supply chain collaboration are leading many companies to re-model their supply chains. Examples include the collaboration programmes between Wal-Mart and Sara Lee, Schering-Plough Health Care with all their retail partners, and Marks and Spencer with Gunstones (Ireland and Crum, 2006). Seifert (2003) discusses more than 26 such initiatives in Europe alone. European retailers such as Carrefour in France, Metro in Germany and Tesco in the UK are working towards the improvement in efficiency that can result from supply chain collaboration. Findings from AMR research (Suleski, 2001) on the financial impacts of CPFR in the retail industry, based on 94 companies, reveal the benefits of supply chain collaborations. The results show that sales increased by up to 20%, with reduced inventory of up to 40% for retailers. In terms of benefits to the suppliers, inventory reductions of up to 40% and more frequent replenishment cycles were found in these companies.

Information sharing is an integral part and an enabler of collaborative partnerships. The development of web-enabled technologies provides a platform for exchange of real-time information with increased quantity and velocity and at less cost. Such cheaper information exchange technologies have made information sharing more achievable in recent years. Companies are leveraging information integration by forming collaborations, and visibility is proving to be a key ingredient in realising value chain excellence. In the last decade, some authors have argued that supply chain information sharing is one of the most rewarding applications of information technology (e.g. Edwards et al, 2001; Barut et al, 2002).

Sharing of consumer demand information has been extensively studied in the literature, specifically in terms of the reduction of the Bullwhip Effect. The Bullwhip Effect is a well-known phenomenon in supply chain management. It occurs when the demand variability amplifies as one moves up the supply chain. Empirical evidence and mathematical models, to be reviewed later in this thesis, show that the orders placed by a retailer on its supplier tend to be much more variable than the consumer demand seen by the retailer. This amplification in the variability of demand propagates upstream in the supply chain. Information sharing can counter this effect. How it does so is the subject of this research.

## 1.2. Theoretical Background and Research Motivations

Various demand information sharing approaches have been discussed extensively in the literature, mainly from a theoretical perspective. A substantial part of the demand information sharing literature has been devoted to discussions on the reduction of the Bullwhip Effect, which leads to reductions in inventory cost.

Research papers analysing the value of sharing demand information present two strategies that may be adopted by a supply chain. The first strategy is not to share the consumer demand information, in which case the forecasts will be based only on the orders received by the downstream members in the supply chain. On the other hand, a strategy of sharing consumer demand information can be adopted through some formal information sharing mechanism. In this case, the forecasts will be based on the consumer demand information. We argue in section 5.4 that the forecasting approaches used in the literature can be improved and present two new approaches, NIS-Estimation (NIS-Est) and Centralised Demand Information Sharing (CDIS). The NIS-Est approach is used when the consumer demand is not shared and the upstream member forecasts by using the orders received from the downstream member. The CDIS approach is used when the upstream member forecasts using the shared consumer demand information.

Based on a survey of various surveys of forecasting practices (see section 3.3), we find that practitioners' choice of forecasting methods is based not on optimality but rather on simplicity, ease of use and familiarity with methods. The literature on demand information sharing is dominated by papers that are restricted to the use of optimal forecasting methods. There is a gap in the literature on the analysis of the value of demand information sharing when non-optimal forecasting methods are utilised. Analysis of upstream demand translation plays a major role in investigating the value of information sharing and the literature is limited to upstream translation of an AR (1) demand process for non-optimal forecasting methods (Chen et al, 2000a; Chen et al, 2000b; Alwan et al, 2003; Zhang, 2004a). No other demand process has been examined. Thus, there is a need to extend the analysis of upstream demand translation for non-optimal methods to more general ARMA processes.

Some authors (e.g. Lee et al, 1997a; Chen et al, 2000a; Lee et al, 2000; Yu et al, 2002; Raghunathan, 2003; Cheng and Wu, 2005; Hosoda et al, 2008) have argued that demand information sharing is vital to reduce inventory costs. On the other hand, other authors (Graves, 1999; Raghunathan, 2001; Zhang, 2004b; Gaur et al, 2005; Gilbert, 2005) have argued that the orders from the downstream member to the upstream member already contain information about the market demand process. By using their order history, the upstream member can infer the demand at the downstream member. This is known as Downstream Demand Inference (DDI). According to the DDI approach, the savings in inventory costs from demand information sharing could be obtained without any formal information sharing with the downstream member. In this thesis, we analyse the supply chain models presented in previous papers, particularly with respect to their assumptions. We observe that the difference in conclusions of the above papers is due to the strict model assumptions made by authors advocating DDI. Specifically, we argue that in real life supply chains, the demand process and demand parameters are not known to the supply chain members. Thus, we analyse the value of sharing demand information by relaxing the assumption that these are known to all members in the mathematical model, and in the simulation and empirical analysis. More realistic assumptions in this thesis have led to a more realistic evaluation of the benefits of sharing demand information.

In this thesis, we compare demand information sharing approaches using four performance metrics, namely forecast error, bullwhip ratio, inventory holdings and inventory cost. The forecast error is measured using the Mean Squared Error and the Mean Absolute Percentage Error. In Chapter 3, we find that it is very complicated to derive mathematical expressions for the bullwhip ratio and forecast error. In the same chapter, we also show that the mathematical derivation for inventory holdings results in an approximate equation, yielding approximate values of inventory holdings and inventory costs. We use simulation to estimate the bullwhip ratio and forecast error and to assess the accuracy of the approximate values of inventory holdings and inventory costs. Research studies, to be reviewed in Chapter 3, have found the following factors to affect the value of sharing demand information: lead time, demand process parameters, demand variance, cost ratio and forecasting method parameters. Using simulation will also help to evaluate the sensitivity of the value of demand information sharing to these factors.

There is a lack of empirical research in the papers modelling the value of demand information sharing. Only two such papers (Wong et al, 2007; Hosoda et al, 2008) provide empirical evidence on the value of information sharing. Hosoda et al (2008) analyse the sales data of a cold drink supply chain and show that there is value in sharing demand information. However, they consider only three data series. Wong et al (2007) explore 46 series in a toy supply chain but restrict their analysis to calculation of the Bullwhip Effect. There is no examination of inventory costs, as in papers that theoretically quantify the value of demand information sharing, e.g. Lee et al (2000), Yu et al (2002). There is a need for a more comprehensive empirical analysis to evaluate demand information sharing models.

## 1.3. Research Aims and Objectives

The overall research aim of this thesis is to analyse the value of demand information sharing in supply chains, based on more realistic assumptions than in previous research.

There are two supply chain strategies for sharing demand information: either to share downstream demand or not to do so. If the supply chain members decide to share this demand information, there are different approaches to utilising this shared demand in their forecasts. A Centralised Demand Information Sharing (CDIS) approach is presented in this thesis. The value of this approach is quantified based on various performance metrics such as amplification of demand variance, forecast error, inventory holdings and inventory cost.

Based on the theoretical background and research motivations, six objectives have been formulated for this research:

1. To critically analyse and improve the current demand information sharing approaches discussed in the literature.

2. To extend the upstream translation of demand to a general ARMA (p, q) process for non-optimal forecasting methods.

3. To analyse the Downstream Demand Inference (DDI) approach and reflect on the implications for the value of sharing demand information.

4. To evaluate the performance of demand information sharing approaches with the help of simulation experiments, in the light of relaxed model assumptions.

5. To analyse the effect of lead time, demand variance, autoregressive parameters, moving average parameters, cost ratio and forecasting method parameters on the value of demand information sharing approaches.

6. To test the empirical validity and utility of the theoretical and simulation results on a large set of real world data.

## 1.4. Methodology

The research follows three research methods, namely mathematical analysis, simulation and testing on empirical data. The relationship between the three methods is illustrated in Figure 1-1:

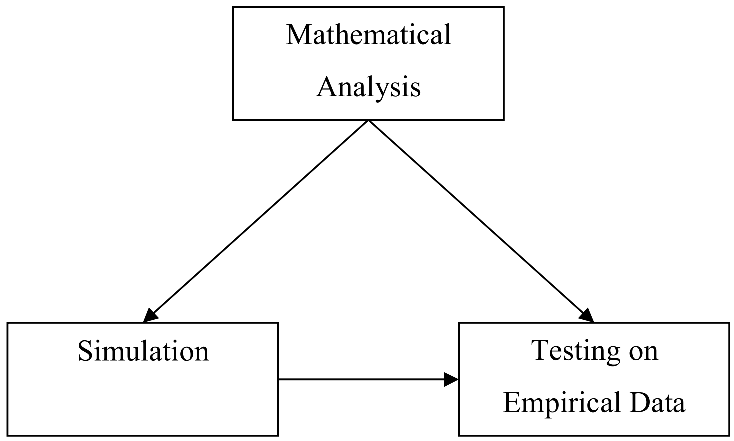


**Figure 1-1 Methodology of the Research**

We take a purely deductive approach in this thesis. The research will follow by developing a theoretical structure based upon well specified assumptions. These are then expressed in operational terms in the mathematical analysis stage. This mathematical model will be tested on empirical data as well as being simulated. Simulation is required as some approximate equations are used in the mathematical analysis. Simulation will also be used in order to gain a better understanding of the performance of CDIS and the factors that affect its value. The results attained from the simulation will also be tested on empirical data. Results of mathematical analysis will be tested on empirical data in order to ensure the applicability of the theory in real world situations.

## 1.5. Thesis Structure

In *Chapter* 2, an overview of the Bullwhip Effect is presented. Discussions are structured around the evidence, causes, control and mathematical analysis of the Bullwhip Effect.

In *Chapter 3*, the supply chain model is presented, concentrating on the demand process, forecasting methods, inventory policy and performance metrics used in this research.

A literature review on the upstream translation of demand is presented in *Chapter 4* and results are extended for multi-stage ARMA (p, q) processes for non-optimal forecasting methods.

In *Chapter 5*, we review and analyse the demand information sharing approaches in the literature and present two new approaches.

*Chapter 6* starts with a literature review of Downstream Demand Inference. We analyse this approach and show that it is not feasible for some forecasting methods.

In *Chapter 7*, the design of the simulation experiment is discussed and the results of the experiment are presented in *Chapter 8*.

*Chapter 9* assesses the empirical validity and utility of the analytical and simulation results on a set of data from a European superstore.

Finally, in *Chapter 10*, we summarise the findings from each chapter and discuss the conclusions of this thesis. Managerial implications and limitations of the research are discussed, along with opportunities for future research.

# 2. The Bullwhip Effect

## 2.1. Introduction

In supply chains, in addition to the physical flow of products downstream, there is a flow of information from downstream to upstream members, such as placement of orders.

The demand seen by upstream members is not the consumer demand of products, as each member in the supply chain adjusts their orders according to forecasting methods and inventory policies. It has been observed in many supply chains (Lee et al, 1997a) that orders placed in this fashion have a tendency to become more variable as they move upstream in the supply chain or further away from the consumer. As this demand variability amplifies as one moves up the supply chain, the orders seen by the upstream stages of a supply chain have more variability than the orders seen by the downstream stages. This phenomenon of increasing demand variability in supply chains is known as the Bullwhip Effect.

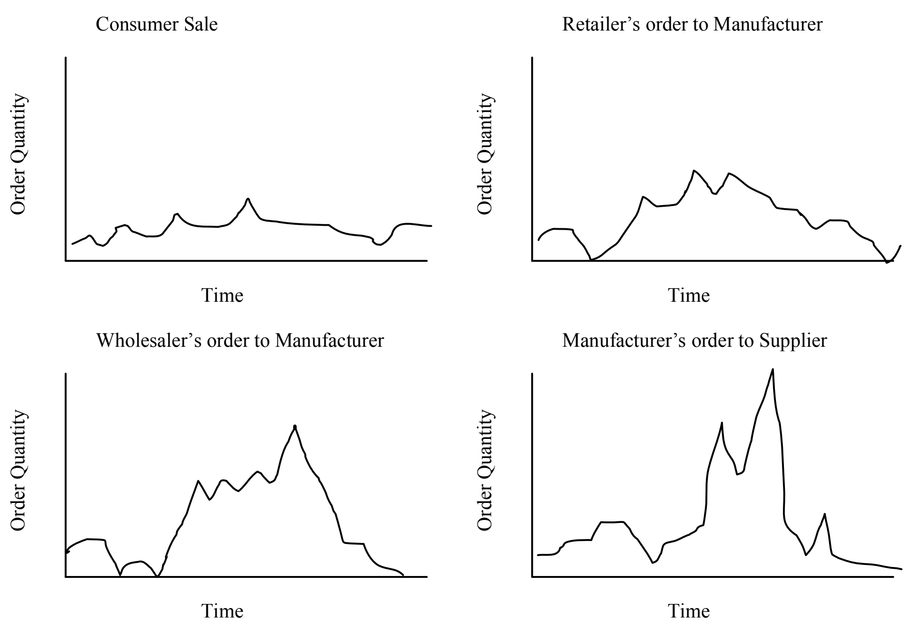


**Figure 2-1 Amplification of Demand Variability in Supply Chains (Lee et al, 1997a)**

The Bullwhip Effect results in huge operating costs for upstream suppliers in supply chains. Because of higher variability, these members either incur high inefficiencies or lack of customer responsiveness (Ouyang et al, 2006). Lee et al (1997a) estimated an increase of 12 – 25 percent operating cost due to the Bullwhip Effect. Other studies (e.g. Lee et al, 1997b; Cooke, 1999) have estimated that, by eliminating the Bullwhip Effect, the US grocery industry alone would save $30 billion each year. Ireland and Bruce (2000) studied the financial impact of the Bullwhip Effect in the retail industry in the USA and found that it lost between $7 and $12 billion in sales annually because of out-of-stock situations. Sterman (2006) remarked that the Bullwhip Effect was the most significant factor in the inventory write-off of $2.25 billion of obsolete inventory by Cisco Systems.

In this chapter, we present a literature overview of the Bullwhip Effect, before proceeding to a more detailed critique in subsequent chapters.

## 2.2. Early Research on the Bullwhip Effect

The Bullwhip Effect, introduced in section 2.1, is a term first used by Lee et al (1997a). The term is new, but the phenomenon is well-established. Forrester (1958, 1961) was the first to analyse amplification of demand variability. Forrester discussed its causes and remedies in the context of industrial dynamics by modelling the linkages between business activities in terms of flow of information, materials, money, manpower and capital equipment. In acknowledgement of this contribution, the phenomenon is also known as Forrester's Effect.

Burbidge (1991) reported the phenomenon of increase in demand variations in the context of controlling production and inventory. Various other studies regarding inventory volatility (Blinder, 1982; Blanchard, 1983; Blinder, 1986; Kahn, 1987) discussed effects similar to the Bullwhip Effect. The phenomenon was also experienced by players in the inventory management experimental beer game introduced by Sterman (1989), also known as the Beer Distribution Game. This is one of the most popular simulation games used to introduce students and managers to demand variance amplification in supply chains. The game involves independent inventory decision making by players. The players rely only on the orders from their neighbouring players. Sterman (1989) discusses the amplification in demand variability upstream and the systematic irrational behaviour of the players that causes this amplification.

## 2.3. Literature Overview of the Bullwhip Effect

Miragliotta (2006) divides the literature on the Bullwhip Effect into three streams: measurement and empirical assessment, causes, and remedies for the Bullwhip Effect. We use the same grouping except that we divide the first stream of Miragliotta (2006) into empirical evidence and mathematical analysis. As one of the objectives of this research is the quantification of the Bullwhip Effect, this further classification helps us clarify the contributions of papers providing empirical results and those offering theoretical insights into the Bullwhip Effect, based on mathematical models. As noted in section 1.2, there are very few papers that combine mathematical and empirical analyses.

The literature review in this section is thus divided into four streams: empirical evidence, causes, control and mathematical analysis. We start the review by looking at papers that provide empirical evidence of the bullwhip phenomenon in real life supply chains. After discussion of these empirical findings, we discuss the second stream in the literature, concerning the causes of the Bullwhip Effect. The third stream reviews the papers suggesting ways to control the Bullwhip Effect. Finally, we look at the papers that mathematically analyse the amplification of demand variability.

### 2.3.1. Empirical Evidence

We mentioned in sub-section 2.2 that Lee et al (1997a) first coined the term “Bullwhip Effect”. This term originated from an examination of the order patterns at Procter and Gamble for their product “Pampers”. Lee et al (1997a) report that, although the consumer demand for the product was steady, there was a high degree of variability in the orders to the distributors and even higher variability was observed at the raw material provider. Lee et al (1997a, 1997b) detail the occurrence of the Bullwhip Effect in other products such as noodles, soups and printers.

There is certainly no lack of evidence of the Bullwhip Effect from real world supply chains. Phenomena similar to those discussed in the above paragraph have been observed in empirical data in various other industries. Table 2-1 (page 14) lists papers providing empirical evidence of the Bullwhip Effect published in the last twenty years. Many earlier studies (e.g. Forrester, 1961) have provided examples of amplification of demand variability from real life and the literature is full of such examples. This review of the past twenty years is not necessarily exhaustive, but includes six papers that were not identified by Miragliotta (2006) who presented a similar literature review on empirical evidence of the Bullwhip Effect.

Many papers have analysed demand variance amplification in the grocery industry. Holmstrom (1997) reported a grocery supply chain where variability, as measured by the standard deviation of weekly demand relative to average weekly demand, increases from 9 to 29 for two different product groups going from consumer demand to plant supply. Gill and Abend (1997) presented the case study of Wal-Mart and how the demand variability amplifies when Wal-Mart places orders on their suppliers. Fransoo and Wouters (2000) observed ten weeks of daily demand data of two supply chains for ready-made pasteurised meals. Using the ratio of the coefficient of variation of production demand to consumer demand to calculate the Bullwhip Effect, they found an average amplification of 1.78 in both chains. Hammond (1994) reported a case study of the product, Barilla, and found amplification of demand variance in the supply chains for pasta. A similar effect has been observed in the dry grocery industry (Kurt Salmon Associates, 1993). Dejonkheere et al (2003) graphically display the order data at a retailer and its manufacturer for a product in the fast moving consumer goods sector. The graph clearly indicates that the order at the manufacturer is more variable than the order at the retailer. Disney (2007) analysed the sales pattern of Tesco, a major UK retailer, and found that Tesco had a bullwhip problem. The store replenishment system unnecessarily amplified the daily variability of workload by 185% in the distribution systems.

Evidence has also been presented in other retail sectors. Hameri (1996) has analysed the sales pattern of A4 size paper compared to the demand at the paper mill. He found that 75% of the orders from the paper wholesaler to the mill were never required by the final consumer. He suggested that the retailer should share the consumer demand information with the sales office, wholesaler and the paper mill. Wong et al (2007) measured the Bullwhip Effect of multiple toy products in a supply chain with high demand volatility, seasonality and high risk of inventory obsolescence. Utilising the ratio of the coefficient of variation, Wong et al (2007) showed that high demand variance amplification exists in nearly all 46 products considered. Lee et al (1997a) graphically displayed a retailer store's sales of a product and their orders to the suppliers. While the variation of sales was very low, the orders placed on the supplier for the same product had very high variability. Similar data were exhibited in Lee et al (1997b) for a soup manufacturer, whose leading brand had highly seasonal sales. When the order data in the supply chain were observed, the shipments from the manufacturer to the distributor varied highly compared to the retailer's sales.

Terwiesch et al (2005) explored demand variance amplification in the semiconductor and computer industry. They compared the ratio of demand variance at the retailer to the manufacturer, between the two industries, and concluded that the computer sector is less volatile than the semi-conductor sector. The amplification of demand variance in the semi-conductor industry has also been illustrated by Greek (2000). Lee et al (2004) observed that data from various computer and computer accessory companies such as Hewlett Packard, Xilinx, Canon, 3Com, Raychem and Intel, clearly indicated the existence of the Bullwhip Effect. Hejazi and Hilmola (2006) presented two case studies in the furniture and international electronics sectors and observed the Bullwhip Effect in both supply chains.

Sterman (2006) graphically presented US oil production data from 1950 to 2005. The data shows that the oil and gas drilling activities fluctuates about three times more than the production.

Edgehill and Olsmats (1988) presented a case study from the automotive industry and discussed the order variance amplification of a close-coupled production distribution system. Using examples ranging from the automotive industry to camera manufacturers, Blackburn (1991) argued that the time delay between supply chain links is a major source of the Bullwhip Effect. He showed that, by using time compression tactics, the mean squared error could be halved. Avery et al (1993) discussed the case of an automotive assembler which procures wire harness from a manufacturer. They illustrate the presence of the Bullwhip Effect in the automotive market as the order variability increases from the automobile assembler to the manufacturer of wire harness. The manufacturer procures 'steel tubes' to produce wire harness and the order variability of the tube supplier is higher than the order variability of the wire harness manufacturer. Fine (1998) discussed the effect of Gross Domestic Product on the machine tool industry. According to his research, from 1961 – 1991, the Gross Domestic Product of the USA had a variability of 2 to 3 percent. This affected the sales of automobiles in the USA, which had a variability of around 20%. The orders placed by automotive component suppliers on the machine tool industry resulted in variability of between 60 to 80 percent. However, the measure of variability was not specified by the author. Taylor (1999) analysed an automotive supply chain and found that the standard deviation of daily order sizes increases as the order moves upstream. The standard deviation of OEM demand is 0.88, then 1.63 at final assembly, 2.17 at pressing, 3.64 at blanking, 3.05 at the service centre and 13.76 at the steel mill for the order of raw materials. McCullen and Towill (2002) discussed bullwhip in a global supply chain for mechanical products. A study of the complex mechanical systems manufacturer, with three factories in the UK, showed that when the sales of a certain product ranged from 70 – 150, the production orders were ranging between 20 – 270.

In the following table (Table 2-1) the studies providing empirical evidence are listed along with the type of evidence provided. The type of evidence is divided into two categories: example and case study. When a paper only reports summary empirical evidence of demand variance amplification, we term such evidence as an 'example'. On the other hand, if a paper undertakes detailed analysis of a specific case of the Bullwhip Effect, such empirical evidence is called a 'case study'.

| **Paper** | **Industry** | **Evidence Type** |
|---|---|---|
| Edgehill and Olsmats (1988) | Automotive | Case Study |
| Blackburn (1991) | Various from Automotive to Cameras | Examples |
| Avery et al (1993) | Automotive | Examples |
| Kurt Salmon Ass. (1993) | Grocery | Case Study |
| Hammond (1994) | Grocery | Case Study |
| Hameri (1996) | Paper Making | Case Study |
| Gill and Abend (1997) | Retail | Case Study |
| Holmstrom (1997) | Grocery | Examples |
| Lee et al (1997a) | Home & Personal Care | Examples |
| Lee et al (1997b) | Soups, Printers | Case Study |
| Fine (1998) | Machine Tools | Examples |
| Taylor (1999) | Automotive | Case Study |
| Fransoo and Wouters (2000) | Perishable Food | Case Study |
| Greek (2000) | Semi Conductor | Examples |
| McCullen and Towill (2002) | Mechanical Parts | Case Study |
| Dejonkheere et al (2003) | FMCG | Examples |
| Lee et al (2004) | Computer & Computer Accessory | Examples |
| Terwiesch et al (2005) | Computer and Semi-conductor | Case Study |
| Hejazi and Hilmola (2006) | Electronics and Furniture | Case Studies |
| Sterman (2006) | Oil Industry | Examples |
| Disney (2007) | Retail Supermarket | Case Study |
| Wong et al (2007) | Toys | Case Study |

**Table 2-1 Empirical Evidence of the Bullwhip Effect (Adapted from Miragliotta (2006))**

In this sub-section, we provided an overview of empirical evidence of the Bullwhip Effect. We observe that the literature contains many examples of the demand variance amplification phenomenon. The empirical evidence is spread across many industries including groceries, automotive, electronics, computers and food. Some studies offer detailed analysis of a specific case; others are limited to short examples.

Although the quality of evidence is variable, it all points towards the existence of the Bullwhip Effect.

The existence of the phenomenon has led to research into the causes of demand variance amplification, which we discuss in the next sub-section.

### 2.3.2. Causes of the Bullwhip Effect

Another important stream of research focuses on evaluating the causes of the Bullwhip Effect. Lee et al (1997a) presented four causes of the Bullwhip Effect. The four causes are Demand Signal Processing, Rationing and Shortage Gaming, Batch Ordering and Price Fluctuations.

#### 2.3.2.1. Demand Signal Processing

Lee et al (1997a) mathematically identified that the Bullwhip Effect will naturally occur when forecasting is performed by multiple stages in a supply chain using an Order-up-to (OUT) policy. An OUT policy is where the inventory is reviewed at regular intervals and, at each of these intervals, an order is placed to bring the inventory to a pre-defined level. The upstream member will place the order based on the demand it receives, which is not the actual consumer demand of the products. The upstream member adjusts their orders according to the forecasting method, OUT inventory policy and lead time, and this results in an increase in the demand variance. Graves (1999) mathematically showed that the variability of an ARIMA (0, 1, 1) demand process at the retailer will amplify even when Single Exponential Smoothing (SES), which is the optimal forecasting method for such demand, is utilised. Chen et al (2000a, 2000b) showed that demand variance is amplified when the Simple Moving Averages (SMA) or SES method is employed, assuming an AR (1) demand process and an OUT inventory policy. Dejonkheere et al (2003) investigated the effect of inventory policies on demand variance amplification and confirmed that the Order-up-to inventory policy (OUT) is a contributor to the Bullwhip Effect. They mathematically showed that the OUT policy will always result in demand variance amplification, irrespective of the forecasting method employed. Other papers (e.g. Chen, 1998; Hanssens, 1998; Lee et al, 2000; Wong et al, 2007) have mathematically shown that demand signal processing is a major contributor to the Bullwhip Effect.

The literature on mathematical analysis of demand signal processing is reviewed more extensively in sub-section 2.3.4.

#### 2.3.2.2. Rationing and Shortage Gaming

Lee et al (1997a, 1997b) argued that rationing and shortage gaming is a major cause of the Bullwhip Effect and occurs in situations where the demand exceeds the production capacity. In these situations, the manufacturer may ration or allocate supplies to the retailers. On recognising the rationing criteria, the retailer may place orders exceeding the required quantity, to secure a greater share of the supplies from the manufacturer. This gives the manufacturer a false impression of the true demand and they in turn place large orders on their suppliers. This results in increased variability of the demand as it moves upwards in the supply chain. Cachon and Lariviere (1999) examined how the choice of allocation mechanism impacts retailer actions and supply chain performance and produces the Bullwhip Effect. Cheung and Zhang (1999) explored cases where, due to rationing, the retailer places a large order and then cancels the remaining balance when the required quantity has been received. They show that such order cancellations cause the Bullwhip Effect. Paik and Bagchi (2007) use simulation to show how rationing and shortage gaming results in the amplification of demand variability.

#### 2.3.2.3. Batch Ordering

A common practice in industry is not to place orders on the upstream link as soon as demand arises. Instead, the individual demands are batched or accumulated before placing the orders and thus, instead of frequent orders, weekly, biweekly or monthly orders are placed. This is done for various reasons including economies of scale, distribution efficiencies, and MRP or similar calculations.

Lee et al (1997a) identified that order batching is a major contributor to demand variance amplification. If the retailer is using batch ordering, the manufacturer would observe large orders in some periods and no orders in other periods. This results in amplifying the variability in demand and contributes to the Bullwhip Effect, as these activities destroy the connection between the actual demand patterns of the customers and the upstream links of the supply chain. Cachon (1999) showed that when a retailer orders in fixed periodic cycles and in multiples of fixed batch sizes, the Bullwhip Effect occurs naturally. Jung et al (1999) investigated the correlation of suppliers' demand and capacity utilisation when buyers' orders are impacted by batching and concluded that suppliers prefer infrequent large orders, which results in demand variance amplification. Moinzadeh and Nahmias (2000) argued that batch ordering results in variance amplification and suggested correlated ordering to reduce this amplification. Riddalls and Bennett (2001) examined the effect of batch production costs on the Bullwhip Effect. They found that the amplification of variability is related to the remainder of the ratio between the batch size and average demand. Holland and Sodhi (2003) quantified the Bullwhip Effect that occurs due to order batching. They assume orders to be an integer multiple of the batch size and they model demand noise as random identically and independently distributed (i.i.d.) errors or deviations from the optimal order size. Simulations were run for five different batch sizes and the results were analysed statistically. They concluded that the increase in order variance is directly proportional to the square of the batch size and to the variance of the order deviations.

Pujawan (2004) compared the mean and variance of two lot sizing rules: Silver Meal and Least Unit Cost. With the help of mathematical models, he examined the order quantity and interval produced by the two rules under low demand variability. The study reveals that addition of an appropriate amount to an order may significantly reduce order variability. The results provide insights on the choice of lot sizing rules to be applied by a channel of a supply chain in determining ordering policies.

Potter and Disney (2006) extended the above study by considering a full range of batch sizes, both greater and lesser than the average demand. They derive an expression for the bullwhip ratio when the consumer demand is deterministic. With the help of simulation, they looked at the impact of changing batch size on the Bullwhip Effect in a production control system. They show that the Bullwhip Effect from batching can be reduced if the batch size is a multiple of average demand.

In this section, we have found that batch ordering results in demand variance amplification. All the above papers show that when supply chain links resort to order batching, the Bullwhip Effect will take place.

#### 2.3.2.4. Price Fluctuations

It has been observed as a common practice of retailers that they offer discounts and clearance prices. For price-elastic products, when the price of an item changes, the customer demand will also change. Customers buy in bulk quantities when the price of the product is low. Then, customers stop buying when the price returns to normal, until they have exhausted their inventory. Thus, the actual customer sales do not match the true demand for the product when there are price variations. This results in the Bullwhip Effect, as the variance of the order quantities amplifies upstream because of the temporary price reductions. Reiner and Fichtinger (2006) mathematically, and with the help of simulation, show that price fluctuations lead to the Bullwhip Effect. Iyer and Ye (2000) and Gavirneni (2006) show that supply chain performance is affected if information on discounts is not passed on to the upstream link.

A summary of the papers discussing the causes of the Bullwhip Effect is presented in tabular form in Table 2-2.

| **Causes of the Bullwhip Effect** | **Papers** |
|---|---|
| Demand Signal Processing | Lee et al (1997a, 1997b); Chen (1998); Hanssens (1998); Graves (1999); Chen et al (2000a, 2000b); Lee et al (2000); Wong et al (2007) |
| Rationing and Shortage Gaming | Lee et al (1997a, 1997b), Cachon and Lariviere (1999); Cheung and Zhang (1999); Paik and Bagchi (2007) |
| Batch Ordering | Lee et al (1997a, 1997b); Cachon (1999); Jung et al (1999); Moinzadeh and Nahimas (2000); Riddalls and Bennett (2001); Holland and Sodhi (2003); Pujawan (2004); Potter and Disney (2006) |
| Price Fluctuations | Lee et al (1997a, 1997b); Iyer and Ye (2000); Gavirneni (2006); Reiner and Fichtinger (2006) |

**Table 2-2 Causes of the Bullwhip Effect**

It is noticeable that few of the papers shown in Table 2-2 are listed under more than one cause. The interaction between the four causes has yet to receive serious and sustained attention in the academic literature.

Some papers have identified factors such as time delays (Blackburn, 1991), demand uncertainty (Naish, 1994), lead time (Lee et al, 2000), machine breakdown (Paik and Bagchi, 2007), and behavioural factors (Croson and Donohue, 2006) that influence the above causes. In the following table (Table 2-3), we list some papers discussing various factors resulting in the four causes (as listed in Table 2-2) that lead to the Bullwhip Effect.

| Factors | Papers |
|---|---|
| Lead Times / Time Delay | Blackburn (1991); Chen et al (2000b); Lee et al (2000); Paik and Bagchi (2007); Lee et al (2000); Cachon and Fisher, 2000) |
| Behavioural Factors | Kahn (1987); Eichenbaum (1989); Naish (1994); Lee et al (1997a); Croson and Donohue (2006) |
| Demand Uncertainty | Naish (1994) |
| Machine Breakdown | Taylor (1999); Paik and Bagchi (2007) |
| Number of Echelons | Paik and Bagchi (2007) |

**Table 2-3 Factors Contributing to the Causes of the Bullwhip Effect**

The factors shown in Table 2-3 contribute to the causes of the Bullwhip Effect discussed earlier. For example, lead time/time delay, demand uncertainty and number of echelons affect demand signal processing, which in turns results in the Bullwhip Effect. Similarly, machine breakdowns, behavioural factors and demand uncertainty are some factors that can give rise to rationing and shortage gaming in supply chains. Identification of these causes aids the development of strategies to alleviate variance amplification.

### 2.3.3. Control of the Bullwhip Effect

Another important stream in the literature on the Bullwhip Effect identifies ways to control or reduce the Bullwhip Effect.

In sub-section 2.3.2, we considered the forces that lead to systematic distortion and amplification of demand variance or the Bullwhip Effect. In this sub-section, we briefly present the combination of activities proposed in the literature to control this phenomenon. Lee et al (1997b) group the approaches on the basis of system coordination, namely: Information Sharing, Channel Alignment and Operational Efficiency. Information Sharing is the transmission of various kinds of information from a downstream site in a timely fashion. 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 other activities that improve performance, such as reduced costs and lead time.

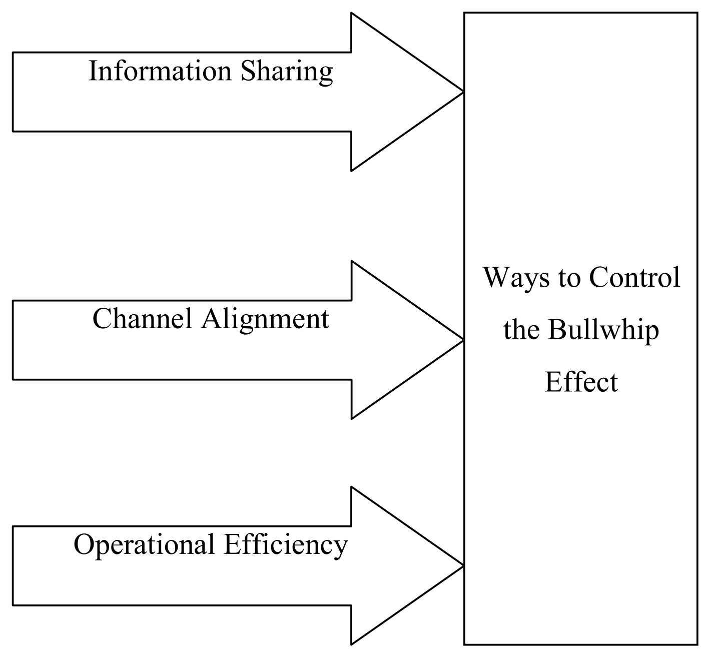


**Figure 2-2 Ways to Control the Bullwhip Effect (Lee et al, 1997b)**

In the following table (Table 2-4), we list various papers investigating the control of the Bullwhip Effect. These papers have been grouped according to the causes of the Bullwhip Effect discussed in sub-section 2.3.2 and the methods of controlling the Bullwhip Effect summarised in this sub-section.

| **Information Sharing** | **Channel Alignment** | **Operational Efficiency** |
|---|---|---|
| | Demand Signal Processing | |
| Sharing inventory and inventory rule data (Cachon and Fisher, 2000)<br>Demand Information Sharing (Bourland et al, 1996; Gavirneni et al , 1999; Lee et al, 2000)<br>Single Supply Chain Forecast (Chen et al, 2000a)<br>Sharing Explanatory variables (Aviv, 2002)<br>Future order information (Zhao et al, 2002) | Synchronisation in supply chain members (Cachon, 1999)<br>Vendor Managed Inventory (VMI) (Waller et al, 1999, Yu et al, 2002)<br>Same Ordering Policy (Hieber and Hartel, 2003) | Lead Time and Time Delay Reductions (Chen et al, 2000b; Cachon and Fisher, 2000; Lee et al, 2000; Boute et al, 2007)<br>Use of Optimal Time-Series Forecasting Models (Alwan et al, 2003)<br>Multi-echelon Inventory Control System (Warburton, 2004)<br>Use of proportional controllers (Disney et al, 2006) |
| | Rationing and Shortage Gaming | |
| Demand Information Sharing (Bourland et al, 1996; Gavirneni et al , 1999; Lee et al, 2000)<br>Sharing of Capacity and Inventory Data (Gavirneni et al, 1999, Gavirneni, 2002) | Inventory Balancing and Better Return Policies using Vendor Managed Inventory (VMI) (Waller et al, 1999) | |
| | Batch Ordering | |
| Demand Information Sharing (Bourland et al, 1996; Gavirneni et al , 1999; Lee et al, 2000)<br>Future order information (Zhao et al, 2002) | Vendor Managed Inventory (VMI) (Waller et al, 1999)<br>Correlated ordering (Moinzadeh and Nahmias, 2000) | Resort to different Batching Rules (Kelle and Milne, 1999; Riddalls and Bennett, 2001)<br>Batch size multiple of average demand (Potter and Disney, 2006) |
| | Price Fluctuations | |
| Sharing data on prices & price changes (Iyer and Ye, 2000) | Every Day Low Price (Kristofferson and Lal, 1996)<br>Link promotional allowances to demand data (Dreze and Bell, 2004) | Activity Based Costing (Lee et al, 1997b)<br>Incorporation of reference price in the Forecasting Model (Reiner and Fitchinger, 2006) |

**Table 2-4 Framework to Control the Bullwhip Effect.**
**(Adapted from Lee et al, 1997a; Miragliotta, 2006)**

There are numerous papers showing that the Bullwhip Effect can be controlled by sharing information among the supply chain members. Cachon and Fisher (2000) mathematically analyse a single manufacturer, multiple retailer supply chain with stationary stochastic consumer demand. Their simulation experiment shows that sharing information on the inventory rule and inventory data reduces the supply chain costs by between 2.2% and 12.1%, by reducing the distortion from Demand Signal Processing. Sharing demand data has been advocated by many authors to reduce the effect of demand signal processing and rationing and shortage gaming (e.g. Bourland et al, 1996; Gavirneni et al, 1999; Lee et al, 2000). These papers have shown that the Bullwhip Effect will be reduced if the demand data is shared with the upstream member. Zhao et al (2002) investigated sharing of future orders, while Aviv (2002) argued that using shared values of explanatory variables or any such advance information will reduce the effect of demand signal processing. Aviv (2002) and Chen et al (2000a) have shown that the Bullwhip Effect can be reduced if a single forecast is produced for the whole supply chain.

Gavirneni et al (1999) mathematically showed that sharing data on inventory will reduce the variability amplification due to the effects of rationing and shortage gaming. Gavirneni (2002) extended this study by exploring how capacity information will help in the reduction of the Bullwhip Effect. Iyer and Ye (2000) investigated the effect of price fluctuations on grocery supply chains. Their mathematical analysis concludes that the supplier may improve his performance by sharing information on price fluctuations with the retailer.

Various papers have discussed the issue of channel alignment to control the four causes of the Bullwhip Effect. Yu et al (2002) have investigated Vendor Managed Inventory (VMI) to reduce the amplification of demand variance. The study concludes that part echelon elimination, as in VMI, will help reduce the effects of demand signal processing. Hieber and Hartel (2003) argued that different inventory and ordering policies at different stages of supply chains are a source of the Bullwhip Effect. Their mathematical analysis concludes that amplification in variability can be dampened if all links in the supply chain use a single ordering policy. Cachon (1999) argued that not only the inventory policies but also the forecasting method should be synchronised between all members of the supply chain. They mathematically show that if all members of the supply chain use the same inventory policy and forecasting method, it will result in reduced bullwhip.

Waller et al (1999) investigates how a channel alignment programme such as Vendor Managed Inventory (VMI) can help reduce the effects of rationing and shortage gaming and batch ordering. They discussed the case of a retail supply chain where the manufacturer is involved in a VMI programme with many retailers. Firstly, they discuss that in the case of inventory shortages, it is easier to ration the supplies as the manufacturer can see the widespread disposition of inventory at the retailers. Secondly, if the manufacturer is not managing inventory of a major retailer and the retailer produces batch orders, this creates chaos in manufacturing. More inventory is required by the manufacturer to counter this uncertainty. They argue that the uncertainty can be reduced by bringing such major customers into a VMI programme. Moinzadeh and Nahmias (2000) recommended that the links should submit their orders with the same frequency to take into account the batching effect. Both supply chain links place orders with the same frequency in the same periods.

Kristofferson and Lal (1996) recommended instituting systems that create a more demand driven environment. They argue that it is beneficial for the whole supply chain to offer “Every Day Low Price” instead of frequent promotional activities that take the supply chain away from the actual consumer demand. “Every Day Low Price” has been used frequently in the grocery industry (Schiller, 1994). Dreze and Bell (2003) argue that manufacturers lose money on trade promotions as a result of forward buying by retailers. They discuss the concept of *scan-back* where the discount is given to the retailers on the units sold rather than the units bought. Using scan-backs will reduce the trade promotional offers, making the manufacturer more aware of the actual consumer demand.

Other papers have explored how increasing operational efficiency will result in reduction of the Bullwhip Effect. Alwan et al (2003), using an AR (1) demand process, mathematically compared the Minimum Mean Squared Error (MMSE) forecasting method (optimal) with Simple Moving Averages (SMA) and Single Exponential Smoothing (SES), which are non-optimal for the AR (1) demand process. They show that optimal forecasting methods result in less amplification of demand variance compared to non-optimal methods. Thus, they conclude that practitioners should resort to more operationally efficient forecasting methods to reduce the Bullwhip Effect. Warburton (2004) discussed centralising inventory to reduce demand variance amplification. He shows that a multi-echelon inventory control system will result in inducing lower variability in the demand upstream compared to individually controlled inventory systems. Disney et al (2006) analysed a supply chain using Proportional Controller methods. Proportional Controllers are based on a control engineering technique used to dampen the response of dynamic systems. The authors assume that the supply chain uses an OUT inventory policy. They discuss that the orders placed under such an inventory policy have two feedback loops: net stock and work in progress (WIP). They introduce the idea of using two proportional feedback controllers: one for regulating the net stock error feedback and the other for WIP error. They mathematically show that allowing such independent feedback loops will result in reduction of the Bullwhip Effect as the natural frequency and damping ratio of the OUT policy are decoupled from each other. Riddalls and Bennett (2001) examined the effect of batch production costs on the Bullwhip Effect. They find a relationship between the Bullwhip Effect and the remainder of the ratio between the batch size and average demand. For two links in the supply chain, Potter and Disney (2006), with the help of simulation, analyse the impact of changing batch sizes on the Bullwhip Effect in a production control system. They show that the Bullwhip Effect from batching can be reduced if the batch size is a multiple of average demand.

Several authors (Chen et al, 2000b; Cachon and Fisher, 2000; Lee et al, 2000; Boute et al, 2007) have shown that lead times and time delays are major contributors to amplification of demand variance. These authors recommend that the supply chain members should work towards reduction of lead times and time delays in order to reduce this effect.

Lee et al (1997b) have argued that conventional accounting systems do not enable companies to recognise the excessive cost incurred due to forward buying and promotions. They recommend that companies should use Activity-Based Costing which will reveal various hidden costs such as inventory, storage, special handling and premium transportation that offset the benefits of price promotions. Reiner and Fitchinger (2006) develop a model where reference prices of a product are used to optimise forecasts and inventory decisions. They conclude that incorporating pricing information in forecasting and inventory models will reduce the Bullwhip Effect and the average on-hand inventory.

In this sub-section, we have presented an overview of studies that have investigated controlling the Bullwhip Effect by three means: Information Sharing, Channel Alignment and Operational Efficiency. Although many of these studies mathematically analyse their models, in the next sub-section (sub-section 2.3.4) we will specifically discuss studies that quantify the Bullwhip Effect analytically.

### 2.3.4. Mathematical Analysis of the Bullwhip Effect

Many papers have mathematically investigated the existence of the Bullwhip Effect and quantified the increase in demand variability. As we use the bullwhip ratio as one of the performance metrics (see section 3.7), the papers mathematically quantifying demand variance amplification are highly relevant to this research. The literature review of these papers has thus become an important issue in this thesis. We present an overview of the papers in this sub-section and critically evaluate some important papers in this stream of research in Chapters 4 and 5.

On reviewing the literature, we observe that the supply chain models in these papers differ in four respects: demand process, inventory policy, forecasting method and bullwhip measure. Kim et al (2006) assume an i.i.d. consumer demand process, while Alwan et al (2003) assume AR (1) and Luong and Phien (2007) assume an AR (p) process. In terms of inventory policy, papers assume different rules, e.g. Caplin (1985) assumes a (s,S) policy, Metters (1997) assumes a cost minimisation model while Kahn (1987) assumes an OUT policy. The Bullwhip Effect has been quantified using different forecasting methods, e.g. Single Exponential Smoothing (Xu et al, 2001), Simple Moving Averages (Chen et al, 2000a), Minimum Mean Squared Error (Lee et al, 2000). Similarly, different measures have been adopted to quantify the Bullwhip Effect, e.g. variance ratio (Chen et al, 2000a), variance difference (Zhang, 2004a), standard deviation ratio (Wong et al, 2007), and coefficient of variation (Fransoo and Wouters, 2000). We list papers in this stream of research in the following table and summarise the demand process, inventory policy, forecasting method and bullwhip measure used in each paper (Table 2-5).

| Paper | Demand Process | Inventory Policy | Forecasting Method | Bullwhip Measure |
|---|---|---|---|---|
| Metters (1997) | Probability distribution | Cost minimisation model | Seasonality adjusted averages | Ratio of Variance / Mean |
| Graves (1999) | ARIMA (0, 1, 1) | Base Stock | SES | Variance ratio |
| Chen et al (2000a) | AR (1) | OUT | SMA | Variance ratio |
| Chen et al (2000b) | AR (1) | OUT | SMA, SES | Variance ratio |
| Xu et al (2001) | AR (1) | OUT | SES | Variance ratio |
| Alwan et al (2003) | AR (1) | OUT | MMSE, SMA, SES | Variance ratio |
| Dejonckheere et al (2003) | i.i.d. | OUT, smoothing replenish-ment | MMSE, SMA, SES | Coefficient of variation |
| Zhang (2004a) | AR (1) | OUT | SES, SMA, MMSE | Variance ratio, Variance difference |
| Chandra and Grabis (2005) | AR (p) | OUT, MRP | MMSE | Variance ratio |
| Li et al (2005) | ARIMA (p, d, q) | OUT | MMSE | Comparison of variance of sample points |
| Disney et al (2006) | i.i.d., ARMA | OUT | MMSE | Variance ratio |
| Gaalman and Disney (2006) | ARMA (1, 1) | OUT | MMSE | Variance ratio |
| Kim et al (2006) | i.i.d. | OUT | SMA | Variance ratio |
| Stamatopolous et al (2006) | AR (1) | OUT | SES | Variance ratio |
| Sucky (2006) | AR (1) | OUT | SMA | Variance ratio |
| Luong (2007) | AR (1) | OUT | MMSE | Variance ratio |
| Luong and Phien (2007) | AR(p) | OUT | MMSE | Variance ratio |

**Table 2-5 Assumptions in Papers Quantifying the Bullwhip Effect**

Dejonkheere et al (2003) and Kim et al (2006) investigated the Bullwhip Effect by assuming independently and identically distributed demand while Metters (1997) showed the existence of demand variance amplification by assuming that the consumer demand is stochastic and time dependent and has a known probability distribution. Graves (1999) and Lee et al (2000) argued that demand over consecutive time periods is rarely statistically independent and that the assumption of correlated demand is more appropriate to study the Bullwhip Effect. A common assumption in the mathematical analysis of the Bullwhip effect is of an AR(1) demand process (e.g. Chen et al, 2000a; Chen et al, 2000b; Alwan et al, 2003; Luong, 2007). Other papers analyse the Bullwhip Effect by considering more complex demand processes, by assuming ARIMA (0, 1, 1) (Graves, 1999) and by simulating ARIMA (p, d, q) processes (Li et al, 2005). As many other supply chain assumptions in these papers also vary, the results of these papers and thus the effect of demand process on the Bullwhip Effect cannot be directly compared. In this research, we assume nine different ARIMA processes (see sub-section 7.3.1). By keeping all other factors constant, we discuss the effect of demand processes on amplification of demand variability (see sub-section 8.4.1).

Table 2-5 also shows that an OUT inventory policy is commonly assumed. Disney (2007) has found that products accounting for 65% of the sale value at a major UK retailer, Tesco, follow forms of an OUT inventory policy. Dejonkheere et al (2003) have shown that an OUT policy will always result in demand variability amplification. They demonstrate the existence of the Bullwhip Effect for other replenishment rules but claim that smoothing replenishment rules may reduce demand variance amplification. Chandra and Grabis (2005) compared the OUT policy with a Material Replenishment Planning (MRP) scheme and show the existence of the Bullwhip Effect in both policies. Metters (1997) based their inventory policy on a cost minimisation model and show that demand variance amplification will occur in this model as well. In section 3.4, we discuss the adoption of the OUT policy in this research. This is consistent with the practice of organisations such as Tesco, and will facilitate critical comparison of this PhD research with earlier papers. However, in Chapter 10, we acknowledge that assuming one inventory policy (OUT) is one of the limitations of the supply chain model and further research in required to analyse the effect of inventory policy on demand variability amplification.

The third important assumption in mathematical analysis of the Bullwhip Effect is the forecasting method. Some authors assume non-optimal forecasting methods, e.g. Simple Moving Averages (SMA) (Chen et al, 2000a; Kim et al, 2006; Sucky, 2006) and Single Exponential Smoothing (SES) (Chen et al, 2000b; Xu et al, 2001; Stamatopolous et al, 2006). All these papers show that the Bullwhip Effect exists when non-optimal forecasting methods are employed by the supply chain members. Alwan et al (2003), Zhang (2004a) and Stamatopolous et al (2006) compare demand variance amplification of non-optimal methods with optimal methods. They show that the Bullwhip Effect is present, irrespective of the forecasting method employed. However, the mathematical analysis in these papers demonstrates that the amplification is more pronounced in the case of non-optimal methods (SMA and SES) compared to the optimal methods (Minimum Mean Squared Error (MMSE)). As is evident from the above table (Table 2-5), the analysis in the case of non-optimal methods is limited to i.i.d. and AR (1) demand processes. In this research, we assume three forecasting methods (SMA, SES and MMSE) (section 3.4) and calculate demand amplification for a more comprehensive range of nine ARIMA demand processes (see section 7.4).

Finally, the papers mathematically investigating the Bullwhip Effect use different measures to quantify the effect. Because the Bullwhip Effect is defined as the amplification in demand variability, it has been argued (Zhang, 2004a, Sucky, 2006) that the difference or ratio of variance at the stages under consideration are appropriate measures. Zhang (2004a) argued that the above two measures are equivalent measures and linked by $Difference = (Ratio - 1)Var(d_t)$. We use the variance or the bullwhip ratio in this research (section 3.7). The above table (Table 2-5) shows that this measure has been used by most of the papers. Thus, adopting the variance ratio will help in making comparisons with previous research.

The papers discussed in this section have used different patterns to model consumer demand and all papers have shown an increase in demand variability. Similarly, papers using different inventory policies have shown the presence of the Bullwhip

Effect, although the amplification may vary with different policies. The papers show similar effects for forecasting methods, where optimal forecasting methods may result in lower demand variance amplification compared to non-optimal forecasting methods. However, demand variance increases along the supply chain in all cases. Finally, the literature review in this section shows that although the Bullwhip Effect can be quantified by using different measures, all measures will show its presence. Thus, the literature review shows that the Bullwhip Effect is present in supply chains for a wide range of model assumptions regarding demand process, inventory policy, forecasting methods and bullwhip measures.

## 2.4. Anti-Bullwhip Effect

In the previous sub-sections, we discussed the phenomenon of the Bullwhip Effect and presented a brief literature review of its empirical evidence, mathematical analysis, causes and control. Some papers (Lee et al, 2000; Li et al, 2005; Hosoda and Disney, 2006; Luong and Phien, 2007) have identified that the Bullwhip Effect does not take place for certain values of the demand parameters. Lee et al (2000) show mathematically that for an AR (1) demand process, the variability of the demand does not amplify when the value of the autocorrelation coefficient ($\rho$) is negative. The same result is also given by Hosoda and Disney (2006) and Luong and Phien (2007), who show that for an AR (1) demand process, the Bullwhip Effect only occurs when $\rho$ is strictly positive.

Li et al (2005) also demonstrate the existence of the inverse of the Bullwhip Effect (BE), the Anti-Bullwhip Effect (ABE), whereby the variability in the order is less than the variability in the demand itself. They show via simulation that for any ARIMA (p, d, q) demand process, there exists a transition surface for parameter vectors $(\mathrm{P}, \Theta)$ where the vectors $(\mathrm{P}, \Theta)$ are defined as:

$P = (\rho_1, \rho_2, ..., \rho_p)$ and $\Theta = (\theta_1, \theta_2, ..., \theta_q)$.

When the transition surface is reached, there is information invariance and the variability in orders is equal to the variability in the demand. The Bullwhip Effect is observed on one side of this transition surface and the Anti-Bullwhip Effect on the other side.

They show the following transition points for the three cases when i) d, q = 0, ii) p, d = 0 and iii) d = 0 & p = q.

ARIMA (p, 0, 0): The transition point is $\rho_i = 0$. $(i \in [1, p])$

ARIMA (0, 0, q): The transition point is $\theta_i = 0$. $(i \in [1, q])$

ARIMA (r, 0, r): The transition point is $\rho_i = \theta_i$. $(i \in [1, r])$

The literature on the Anti-Bullwhip phenomenon is very limited. There are only a few papers that discuss its occurrence and only one paper (Li et al, 2005) uses the term ABE. Apart from the above transition points for certain stationary models, there is no mathematical derivation of the transition surface for demand parameter vectors $(\mathrm{P}, \Theta)$ that indicates when a decrease in demand variability will take place. Luong and Phien (2007) have shown that, in addition to the demand parameters, the definition of the Bullwhip Effect region also depends on the value of the lead time. With the help of simulation, they show values of the Bullwhip Effect for some parameter regions and lead time ranges for an AR (2) process (Luong and Phien, 2007).

As mentioned in section 1.3, this research focuses on reducing the amplification of demand variability. Thus, in the subsequent chapters, we restrict attention to the cases and parameter regions where the Bullwhip Effect takes place. As discussed in the literature review above, the parameter regions for the Bullwhip Effect have not been established for non-stationary processes (Li et al, 2005). In the simulation experiment, we generate five stationary and four non-stationary ARIMA processes (see sub-section 7.3.1). For the non-stationary processes used in the simulation, we simulate the stationary and invertible range, and then choose parameters exhibiting the Bullwhip Effect (see sub-section 7.3.9).

## 2.5. Conclusions

In this chapter, we have given an overview of the literature on the Bullwhip Effect. The overview has been presented by classifying the literature into four streams: empirical evidence, causes, control and mathematical analysis.

The first stream of papers provides empirical evidence of the presence of the Bullwhip Effect in various industries such as groceries, automotive, electronics, and toys. The evidence is of variable quality, but all the papers demonstrate the existence of the Bullwhip Effect.

The proof of the existence of the Bullwhip Effect has led various authors to look into the causes of the phenomenon. Four causes of the Bullwhip Effect have been discussed by Lee et al (1997a). These are Demand Signal Processing, Rationing and Shortage Gaming, Batch Ordering and Price Fluctuations. We present an overview of these causes and also discuss various factors that may lead to these four causes.

Identification of the causes of the Bullwhip Effect has helped the development of strategies to control the amplification in variability. A review of papers discussing how to control the effect has been presented. The papers in this stream of research have been classified on the basis of three control elements: Information Sharing, Channel Alignment and Operational Efficiency.

The fourth stream of research, mathematical analysis of the Bullwhip Effect, is particularly relevant to this Ph.D. research. The analyses in these papers are not directly comparable, owing to differences in model assumptions. The supply chain models in these papers differ according to four major assumptions: demand process, inventory policy, forecasting method and bullwhip measure. We first consider the assumption of demand process and observe that nearly all papers consider a single demand process. Thus, the effect of the demand process on the Bullwhip Effect has not been analysed in the literature. In order to fill this gap, we examine nine ARIMA demand processes and discuss the effect of demand processes on the amplification of demand variance. This effect is also discussed in the empirical analysis where 19 demand processes have been identified in the empirical data. We analyse 12 out of 19 ARIMA processes where there are a sufficient number of time series (see section

9.4 for details). Secondly, the OUT inventory policy has been employed in nearly all the papers. As inventory policy is not the focus of this Ph.D., we also assume an OUT policy so as to be able to compare this research with other papers. In terms of forecasting methods, we observe that three forecasting methods have been used in the literature, SMA, SES and MMSE. We use all three methods in this research. In previous research, the analysis of the Bullwhip Effect is limited to an AR (1) process for non-optimal forecasting methods. Using simulation, we calculate the Bullwhip Effect for two non-optimal forecasting methods, SMA and SES, for nine ARIMA processes.

Finally, we discuss the inverse of the bullwhip phenomenon called the Anti-Bullwhip Effect. The literature review shows that for some values of demand parameters and lead times, the variability of orders is less than the demand variability. In Chapter 1, we stated that one of the objectives of this research is to investigate the reduction of the amplification of variability. Thus, in simulation and empirical analysis, we restrict the focus to the parameter regions and values of lead times where the Bullwhip Effect takes place.

# 3. Supply Chain Model

## 3.1. Introduction

In the previous chapter, we presented a literature review on the Bullwhip Effect and the Anti-Bullwhip Effect. In this chapter, we will give a brief overview of the supply chain model used in this research.

We consider a two level supply chain having one upstream member, e.g. a manufacturer, and one downstream member, e.g. a retailer. The upstream and downstream members may be other than a manufacturer and a retailer, e.g. warehouse and distributor, but this does not affect the results. We consider the flow of a single product from the manufacturer to the retailer. The flow of orders and demand information is from the retailer to the manufacturer, as shown in Figure 3-1:

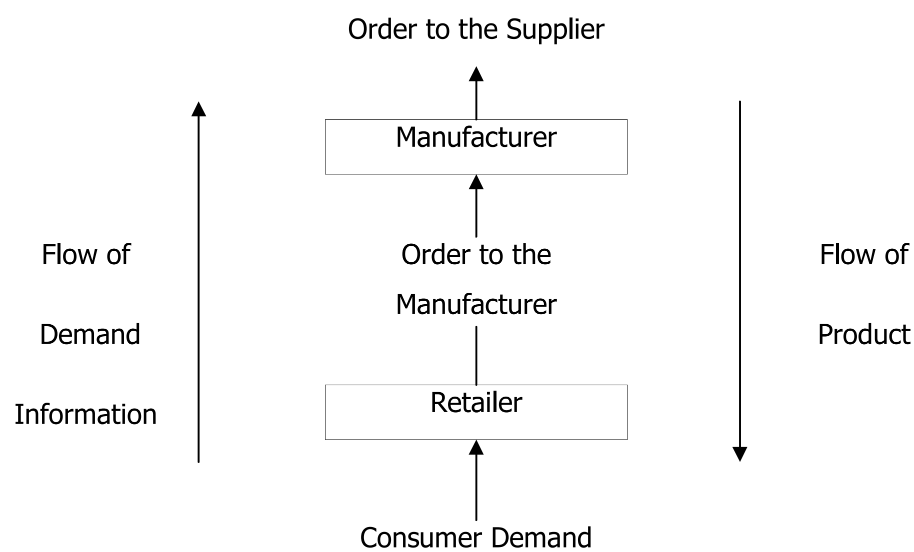


**Figure 3-1 Flows in the Supply Chain Model**

We assume that the replenishment lead times are fixed, known and strictly positive, denoted by $l$ from the manufacturer to the retailer and $L$ from the supplier to the manufacturer. Throughout this thesis, time is treated as a discrete variable. In the following sub-sections, we will discuss the demand process, forecasting methods, inventory policy and the ordering decisions made by the supply chain links in the model shown in Figure 3-1.

## 3.2. Demand Process

We assume that the demand process at the retailer can be represented by a univariate ARIMA (p, d, q) model (Box et al, 1994). There are three major reasons for using the ARIMA representation of demand in this research. Firstly, evidence from the M1 and M3 forecasting competitions has shown the ARIMA methodology to be competitive in terms of forecast accuracy (Makridakis et al, 1982; Makridakis and Hibon, 2000) and, hence, provides support for the assumption of ARIMA processes. Secondly, as outlined in the research aims and objectives (see section 1.3), this research quantifies the value of information sharing in supply chains. Many papers (e.g. Graves, 1999; Raghunathan, 2001; Zhang, 2004b; Gilbert, 2005) have adopted univariate ARIMA models and claimed that there is no value in sharing demand information in supply chains. Thus, in order to undertake critical analysis of these papers, an ARIMA demand process is assumed. Thirdly, other papers (Chen et al, 2000a; Chen et al, 2000b; Alwan et al, 2003; Zhang, 2004a) have analysed the value of sharing demand information using ARIMA models for non-optimal forecasting methods. But all these papers limit their analysis to an AR (1) demand process. Thus, on finding various gaps in the information sharing literature based on univariate ARIMA modelling, it is appropriate to resolve these issues before moving on to an alternative demand model, e.g. the state space representation.

Supply chain modelling, based on the upstream translation of demand (discussed in detail in Chapter 4), shows that ARIMA demand at the retailer is translated into ARIMA demand at the manufacturer (Gilbert, 2005) if the retailer uses an OUT policy. Thus, if ARIMA demand at the retailer is estimated using an MMSE forecasting method, the order placed on the manufacturer will also follow an ARIMA process. We consider a single retailer – single manufacturer supply chain. Various papers have used a similar supply chain model, but for a single manufacturer – multiple retailer scenario. Simchi-Levi and Zhao (2003) and Cheng and Wu (2005) have modelled the cross-correlation of multiple demand streams by assuming an identical correlation coefficient between any two distinct demand streams. Zhang and Zhao (2004) used a similar supply chain model for a single manufacturer and all retailers, assuming a Vector Autoregressive (VAR (1)) demand process at the retailers. Zhang (2006) has used a state space formulation to analyse multiple streams of demand in a similar supply chain model.

Hamilton (1994) has shown that the sum of uncorrelated ARMA processes remains an ARMA process. It can easily be shown to be true for ARIMA processes. Now consider a supply chain having multiple retailers and a single manufacturer and assume that the demands at the retailers are uncorrelated ARIMA processes. According to the results on the upstream translation of demand, the retailer's orders will also follow ARIMA processes. In this case, the sum of all the retailer's orders, or the final order on the manufacturer, will also follow an ARIMA process if the retailers' orders are uncorrelated. Thus, keeping the assumptions discussed above, the results of this doctoral research can be applied to a single manufacturer – multiple retailer supply chain model. However, further research is required to investigate correlated ARIMA processes.

We assume that the time series of demand ($d_t$), if stationary, can be represented by an ARMA (p, q) process given by:

$$d_t = \tau + \rho_1 d_{t-1} + \rho_2 d_{t-2} + \ldots + \rho_p d_{t-p} + \varepsilon_t - \theta_1^R \varepsilon_{t-1} - \theta_2^R \varepsilon_{t-2} - \ldots - \theta_q^R \varepsilon_{t-q} \qquad 3\text{-}1$$

where $d_t, d_{t-1}, \ldots, d_{t-p}$ are the observed demands at time periods *t, t-1,…, t-p* and all time periods are treated as distinct variables. $\tau$ is a constant and $\tau > 0$, $\rho_1, \rho_2, \ldots, \rho_p$ are the autoregressive parameters, and $\theta^R{}_1, \theta^R{}_2, \ldots, \theta^R{}_q$ are the moving average parameters at the retailer. $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ are the noise terms in the observed demands at time periods *t, t-1, t-2, …, t-q*. The noise terms are i.i.d. i.e. independent and identically distributed, with mean zero and constant variance $\sigma_\varepsilon^2$. Rewriting equation 3-1 using the backshift operator, *B*, and dropping the constant term ($\tau$):

$$\rho(B)(d_t) = \theta^R(B)\varepsilon_t \qquad 3\text{-}2$$

where:

$$\rho(B) = 1 - \rho_1 B - \rho_2 B^2 - \ldots - \rho_p B^p$$
$$\theta^R(B) = 1 - \theta^R{}_1 B - \theta^R{}_2 B^2 - \ldots - \theta^R{}_q B^q$$

We assume that the above demand is invertible, i.e. the roots of the following characteristic equation lie outside the unit circle.

$$1-\theta^{R}{}_{1}x-\theta^{R}{}_{2}x^{2}-\ldots-\theta^{R}{}_{q}x^{q}=0 \quad 3\text{-}3$$

The assumption of invertibility is important here, as Gilbert (2005) has modelled an invertible demand process, whereas Gaur et al (2005) assumed non-invertibility. We argue that for any non-invertible representation of an ARMA (p, q) process, there exists an invertible representation of the process and vice versa. Thus, if a retailer uses a non-invertible ARMA (p, q) representation, they may instead use the invertible representation of the demand. Hamilton (1994) comments that, in order to calculate the noise terms associated with any time series, the current and past values of demands are required if an invertible representation is used. On the other hand, in order to calculate the noise terms for a non-invertible representation, the future values of demands are required. Thus, it is not feasible to use the non-invertible representation.

We assume that the time series of demand ($d_t$), if non-stationary, can be represented by an ARIMA (p, d, q) process given by:

$$\rho(B)\nabla^{d}(d_t)=\theta^{R}(B)\varepsilon_t \quad 3\text{-}4$$

where $\nabla=1-B$ .

Standard conditions for the stationarity and invertibility of the dth differenced series are assumed to apply (Box et al, 1994).

## 3.3. Forecasting Methods

In order to examine the effect of the forecasting method, we assume that the supply chain members employ three different methods to forecast the lead time demand: Minimum Mean Squared Error (MMSE), Simple Moving Averages (SMA) and Single Exponential Smoothing (SES). The MMSE forecast is the MSE-optimal forecasting method for a specified ARIMA demand process.

The inclusion of non-optimal forecasting methods in this research reflects practice in industry. Forecasting is seen as an increasingly critical organisational capability (Sanders and Manrodt, 2003) but relatively few studies have assessed the usage, familiarity and satisfaction of forecasting methods among practitioners. Table 3-1 provides a summary of nine such surveys highlighting the methods that ranked first, according to these criteria. It shows that practitioners are more familiar, satisfied and more likely to use simpler forecasting methods compared to sophisticated quantitative methods. Thus, in the real world, a forecasting method is not always chosen on the basis of its optimality or accuracy but rather its simplicity and ease of use.

| | Year of Study | Researcher(s) | Familiarity (%) | Satisfaction (%) | Usage (%) |
|---|---|---|---|---|---|
| 1 | 2001 | Klassen and Flores | | | 27 (SMA) |
| 2 | 2000 | Mady | 67(SA) | | 40 (SA) |
| 3 | 1997 | Sanders | | | 32.9 (SMA) |
| 4 | 1995 | Mentzer and Kahn | 92 (SMA) | 72 (SES) | 92 (SES) |
| 5 | 1994 | Sanders and Manrodt | 96 (SMA) | 45.8 (RA) | 33.5 (SMA) |
| 6 | 1992 | Sanders | 96 (SLP) | | 37 (SMA) |
| 7 | 1987 | Dalrymple | | | 30.6 (Naïve) |
| 8 | 1984 | Mentzer and Cox | 85 (SMA) | 67 (RA) | 36 (RA) |
| 9 | 1984 | Sparkes and McHugh | | | 58 (SMA) |

**Table 3-1 Use of Forecasting Methods in Industry – Survey Results**

Legend:
SMA – Simple Moving Average
RA – Regression Analysis
SA – Simple Average of all data
SES – Single Exponential Smoothing
SLP – Single Line Projection

The practitioners' choice of two non-optimal forecasting methods, SMA and SES, is quite rational (NB: SES is optimal only for an ARIMA (0, 1, 1) process and is a non-optimal method for all other ARIMA demand processes). They are more intuitive, especially for those with a limited mathematical background (Boylan and Johnston, 2003). Difficult and sophisticated, but optimal, methods are seen as not worth the added effort (Sanders and Mandrot, 1994). Johnston et al (1999) compared the forecasting accuracy of combinations of SMA, a non-optimal forecasting method, with SES, the optimal forecasting method for an ARIMA (0, 1, 1) demand process. They showed that the variance of the forecast error for the non-optimal method was typically less than 3% higher than the optimal method.

The three forecasting methods are briefly discussed below:

### 3.3.1. Minimum Mean Squared Error (MMSE) Forecast

This is the expectation of the lead time demand, based on the known current demand and is given by:

$$\hat{D}_t^L = E(\sum_{i=1}^{L} D_{t+i} \mid D_t) \qquad 3\text{-}5$$

The MMSE forecast follows the Box-Jenkins Methodology where the model is identified, followed by demand parameter estimation. Once a model with required parameters is selected, the calculation of the above conditional expectation is quite straightforward. This will be further discussed in Chapter 7.

### 3.3.2. Simple Moving Averages (SMA)

The Simple Moving Average forecasting method is the arithmetic mean of the *n* most recent observations. Every forecasting period, the newest observation is included and the oldest is dropped out. Mathematically,

$$\hat{D}_t^L = L\hat{D}_{t+1} = L\left[\frac{1}{n}\sum_{i=0}^{n-1} d_{t-i}\right] \qquad 3\text{-}6$$

where,

$\hat{D}_{t+1}$= forecast value for next period

$n$ = number of terms in the Simple Moving Average.

Empirical results from the subset of 111 series from the M1 competition show that statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler methods like SMA (Makridakis and Hibon, 1979).

### 3.3.3. Single Exponential Smoothing (SES)

In the Simple Moving Average method discussed above, the past observations are weighted equally; SES assigns exponentially decreasing weights as the observations get older. Single Exponential Smoothing performed very well in the M1 and M3 competitions and its results in M1 were generally better than those of Simple Moving Averages (Makridakis et al, 1982).

There are two ways in which an SES forecast can be expressed. The first approach is to assume that an infinite data history ($d_t, d_{t-1}, d_{t-2}, \ldots$) is available. Then, the 'infinite representation' of SES is as follows:

$$\hat{D}_t^L = L\hat{D}_{t+1} = L[\alpha\sum_{j=0}^{\infty}(1-\alpha)^j d_{t-j}] \qquad 3\text{-}7$$

This can also be expressed recursively:

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

$$\hat{D}_t^L = L\hat{D}_{t+1} \qquad 3\text{-}8$$

where,

$\hat{D}_{t+1}$ is the forecast value for the next period, $d_t$ is the actual value of the observation in period t, $\alpha$ is the smoothing constant and $L$ is the lead time from the supplier to the manufacturer. (The same method applies for the retailer.)

The second approach is to assume a finite data history ($d_t, d_{t-1}, d_{t-2}, ..., d_0$). Then the 'finite representation' of SES is given by:

$$\hat{D}_{t+1}^L = L[\alpha d_t + \alpha(1-\alpha)d_{t-1} + \alpha(1-\alpha)^2 d_{t-2} + ... + \alpha(1-\alpha)^{t-1} d_1 + (1-\alpha)^t d_0] \qquad 3\text{-}9$$

Although the 'infinite representation' is more convenient for some mathematical derivations, the 'finite representation' is clearly more realistic.

In the following table (Table 3-2), we summarise the forecasting methods employed in this research.

| Forecasting Method | Mathematical Representation |
|---|---|
| Minimum Mean Squared Error (MMSE) | $\hat{D}_t^L = E(\sum_{i=1}^{L} D_{t+i} \mid D_t)$ |
| Simple Moving Averages (SMA) | $\hat{D}_t^L = L\hat{D}_{t+1} = L\left[\frac{1}{n}\sum_{i=0}^{n-1} d_{t-i}\right]$ |
| Single Exponential Smoothing (SES) (Finite Representation) | $\hat{D}_t^L = L[\alpha d_{t-1} + \alpha(1-\alpha)d_{t-2} + \alpha(1-\alpha)^2 d_{t-3} + ... + \alpha(1-\alpha)^{t-2} d_1 + (1-\alpha)^{t-1} d_0]$ |

**Table 3-2 Supply Chain Model Forecasting Methods**

The choice of the two non-optimal forecasting methods is not comprehensive but reflects their popularity, as shown in Table 3-1. There is scope to extend this research by examining the other non-optimal forecasting methods highlighted in this table.

## 3.4. Inventory Policy

We consider a periodic review inventory system where supply chain links review their inventory level every period. The links base their inventory replenishments on a simple order-up-to (OUT) policy. Each link replenishes the demand during the last period plus the change being made in the order-up-to levels.

We discussed in sub-section 2.3.4 that the assumption of an OUT policy is a common theme in nearly all the papers mathematically analysing the Bullwhip Effect. As the focus of this research is not to evaluate or compare inventory policies, we also assume an OUT inventory policy. This consistency with past papers will help facilitate critical analysis of the current literature. There is also some empirical evidence from Disney (2007) on the use of the OUT policy. As noted in sub-section 2.3.4, he analysed the inventory policy of Tesco, a major UK retailer, and found that forms of OUT policy were being used in products accounting to 65% of the sales value.

## 3.5. Ordering Decisions by the Retailer

Demand ($d_t$) is realised by the retailer, following an ARIMA (p, d, q) process given by equation 3-1 above. The retailer then forecasts its lead time demand and places an order $Y_t$ on the manufacturer. Now the order placed by the retailer on the manufacturer becomes the demand at the manufacturer:

*Yt* = order placed by retailer on the manufacturer = demand at the manufacturer

In an OUT inventory policy such an order would be calculated by:

$$Y_t = d_t + (S_t - S_{t-1}) \qquad 3\text{-}10$$

where $S_t$ and $S_{t\text{-}1}$ are the order up to levels for the periods t and t-1 respectively. These are calculated by:

$$S_t = E(\sum_{i=1}^{L+1} d_{t+i} \,|d_t) + k\sqrt{Var(\sum_{i=1}^{L+1} d_{t+i} \,|d_t)} \qquad 3\text{-}11$$

where $k = \Phi^{-1}\left(\frac{p}{p+h}\right)$ for the standard normal distribution function $\Phi$, $p$ is the retailer's shortage cost and $h$ is the retailer's holding cost. We assume the total lead time to be L+1, the replenishment lead time plus a review period, as recommended by Silver et al (1998).

## 3.6. Ordering Decisions by the Manufacturer

On realising its demand ($Y_t$), the manufacturer now makes its lead-time forecast. Using the same inventory policy as the retailer, the manufacturer will then place an order $Z_t$ on its supplier. The sequence of events of ordering, receipt and shipment for the manufacturer are the same as assumed by Lee et al (2000:630).

In this research, we will discuss various information sharing approaches that can be used by the manufacturer in making its lead-time forecast. These approaches are discussed in detail in Chapter 5.

## 3.7. Performance Metrics

In order to quantify the value of sharing demand information, we compare various performance metrics for the different approaches. In the following sub-sections, we briefly discuss these metrics.

### 3.7.1. The Bullwhip Ratio

One of the objectives of this thesis is to look at the amplification of variance upstream in supply chains, the Bullwhip Effect, and examine whether sharing demand information helps in reducing this variance. Thus, we quantify the Bullwhip Effect for each scenario in each stage.

In Chapter 2 (Table 2-5), we listed various bullwhip measures used in the literature. In this research, the variance ratio or the Bullwhip Ratio is used to quantify the Bullwhip Effect. Mathematically,

$$\text{Bullwhip Ratio} = \text{B} = \frac{Var(order)}{Var(demand)} \qquad 3\text{-}12$$

We will use the ratio B, as most of the papers discussed in the literature overview (Table 2-5) adopt this as a measure of the Bullwhip Effect. Deriving an equation to calculate the Bullwhip Ratio for an ARIMA (p, d, q) process is mathematically very complex; therefore we compare this performance metric via simulation (discussed further in Chapter 7).

### 3.7.2. Forecasting Accuracy

Mean Squared Error (MSE) is used in this research to measure forecast error and to compare the results for each approach. Whereas the Bullwhip Ratio utilises the variance of orders and demands, it is quite natural to use MSE, as it incorporates the variance of the forecast error. Mathematically,

$$\hat{f}_t^{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(D_t^{\,L} - \hat{D}_t^{\,L}\right)^2 \qquad 3\text{-}13$$

where $\hat{f}_t^{MSE}$ is the lead time mean squared error.

The MSE approach has the disadvantage of heavily weighting outliers, as the errors are squared. In the simulation experiment (see Chapter 7), the theoretical demand is generated in a controlled environment and outliers are not expected. However, this is not necessarily the case when empirical data are addressed (see Chapter 9), where MSE may not prove to be a reliable measure of forecast error. Another problem with MSE is its scale dependency which does not allow comparison of the forecast error across multiple time series with different levels which may occur in the empirical data.

Fildes (1992) and Armstrong and Fildes (1995) argue that no single forecast error measure will capture the necessary complexity of the error distribution (particularly for empirical data). Therefore, there is a need to examine more than one error measure. Further, they recommend using dimensionless error measures, i.e. those invariant to scalar transformations. In our empirical analysis, we also use the dimensionless Mean Absolute Percentage Error (MAPE) and compare the results of MSE with MAPE (see Chapter 9).

We use the following mathematical expression for MAPE.

$$\hat{f}_t^{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|D_t^{\,L} - \hat{D}_t^{\,L}\right|}{D_t^{\,L}} \times 100 \qquad \text{3-14}$$

where $\hat{f}_t^{MAPE}$ is the lead time mean absolute percentage error.

A disadvantage of MAPE is the problem of division by zero. This will not be a problem in the empirical analysis of this research as we cleaned the data and one of the criteria for selection of time series was no periods of zero demand.

Many other forecast error measures have been proposed in the literature such as Mean Error (ME), Symmetric Mean Absolute Percentage Error (sMAPE) and Mean Absolute Scaled Error (MASE). Mean Error (ME) will only be helpful when there is a systematic error or bias in the forecast, which is not the focus of this research. In terms of percentage errors, sMAPE resolves the issue of division by zero introducing the division of the error by the average of the actual observation and the forecast. However, although sMAPE is symmetric in the interchange of forecasts and actuals, it is asymmetric in its treatment of positive and negative errors (Goodwin and Lawton, 1999). Another percentage error, MASE, is based on the in-sample mean absolute error from a benchmark forecast method such as the naïve method. A disadvantage of MASE is that the in-sample MAE may make MASE vulnerable to outliers in the historical time series (Kolassa and Schütz, 2007). This discussion shows that there is a potential of using more complex percentage error measures than MAPE but they are not without their problems. To satisfy the requirements of this research, MAPE is chosen as it is the simplest scale-independent measure.

### 3.7.3. Inventory Holdings and Costs

Boylan and Syntetos (2006) argue that if we fix the inventory rule, the inventory holdings and the inventory costs become accuracy-implication performance metrics for the forecasting process. Therefore, we quantify the benefits of sharing demand information by comparing the average inventory holdings and average inventory costs for various approaches (see Chapter 5) and assuming the OUT inventory policy in all cases.

### 3.7.3.1. Average Inventory Holdings

The average inventory holdings can be approximated by the following equation (Lee et al, 2000, based on Silver and Peterson, 1985):

$$\tilde{I}_t = T_t - E(\sum_{i=1}^{L+1} Y_{t+i}) + \frac{E(Y_t)}{2} \quad \text{3-15}$$

where $\tilde{I}_t$ is the approximate average inventory and $T_t$ is the order up to level of the manufacturer.

As this is an approximate equation, we simulate average inventory holdings and compare the average inventory holdings for different scenarios.

Lee et al (2000) assumed an AR (1) demand process at the retailer and used equation 3-15 to derive the following equation (3-16) for the relative decrease in inventory due to sharing demand information (see detailed discussion on the paper in sub-section 5.3.1). They compare the inventory holdings for the No Information Sharing (NIS) approach, where supply chains do not share demand information, with Demand Information Sharing (DIS), where demand information is shared among the supply chain members. The relative decrease in the inventory holdings (ΔI = (I-I')/I) of DIS (average inventory I') and NIS (average inventory I) is mathematically shown to be:

$$\Delta I = \frac{1 - \sqrt{\frac{V'}{V}}}{\frac{\tau}{2k\sigma(1-\rho)\sqrt{V}} + 1} \quad \text{3-16}$$

where V' and V are the variances of the lead time forecast in the case of DIS and NIS approaches respectively. ρ is the autocorrelation coefficient and σ is the standard deviation of the noise term in the AR (1) process, while k is the safety factor.

Based on the above equation, the authors present the following results: i) ΔI is increasing in ρ, ii) ΔI is increasing in σ/τ and iii) ΔI is increasing in k. They also show that the percentage reduction in inventory is increasing in L, the lead time from the supplier to the manufacturer.

In this thesis we will also look at the impact of the four factors (demand parameters, noise in retailer's demand, safety factor and lead time) on the percentage reduction in inventory and thus on the value of sharing demand information.

#### 3.7.3.2. Average Inventory Costs

Lee et al (2000) derive an expression for the average inventory costs for the NIS and DIS approaches for an AR (1) demand process and show that:

Inventory Cost (NIS) > Inventory Cost (DIS)

Deriving an equation to calculate the average costs for an ARIMA (p, d, q) process is mathematically very complex; thus we compare this performance metric via simulation (discussed further in Chapter 7).

In the simulation and empirical analysis, we simulate the inventory holdings and, based on this, subsequently calculate the inventory cost for each period. The inventory cost is then averaged across all the periods. This is further discussed in Chapter 7.

## 3.8. Conclusions

In Chapter 2, we discussed four major assumptions in the papers mathematically investigating the Bullwhip Effect: demand process, forecasting methods, inventory policy and performance metrics (bullwhip measures). In this chapter, we presented an overview of the supply chain model adopted in this research and discussed these four assumptions.

The demand process in this research is modelled as an ARIMA (p, d, q) process. We argue that the existing literature of demand information sharing, assuming ARIMA models, has various problems and gaps. A stream of research papers, using restrictive assumptions, claims that there is no value in sharing demand information. Secondly, the mathematical analysis for non-optimal forecasting methods is limited to an AR (1) process. Finally, empirical evidence from the M1 and M3 competitions shows the competitive performance of the ARIMA methodology. Thus, it is appropriate to model the demand in terms of the ARIMA framework in this research.

Various papers assume only one demand process and thus the effect of the demand process on the value of demand information sharing has not been explored. In the simulation experiment conducted in this thesis, nine ARIMA (p, d, q) processes are assumed, enabling an investigation of the demand process dependent behaviour of the value of demand information sharing.

In terms of forecasting methods, we assume MMSE, SMA and SES. The inclusion of non-optimal forecasting methods (SMA and SES) is based on the familiarity, use and satisfaction of these methods.

The most restrictive assumption that is adopted in this thesis is the OUT inventory policy. An OUT inventory policy is a common theme in nearly all papers in this stream of research and thus consistency with them will facilitate critical analysis of the current literature. The aim and objectives, as given in Chapter 1, do not focus on the investigation of inventory policies. Therefore, looking at the effect of inventory policies on the value of demand information sharing has been left as a topic for further research.

Finally, we present four performance metrics, namely Bullwhip Ratio, forecast error, inventory holdings and inventory costs, to be used in the research to quantify the value of information sharing. Forecast error is measured by Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). We compare these performance metrics for the different supply chain approaches discussed in Chapter 5 and, based on the results, we assess the value of sharing demand information in supply chains.

# 4. Upstream Demand Translation

## 4.1. Introduction

Upstream demand translation is a term used to describe how a demand process at a supply chain member is mathematically translated to its upstream member. Studying the upstream translation of demand provides insights into the relationships between the order process and the original ARIMA demand process. The demand process at each stage contributes to the order process at the next stage of the chain, so upstream demand translation gives an entire depiction of the demand processes and their parameters.

Upstream translation of demand is important in terms of recognising and evaluating the forecasting challenges faced by upstream nodes. By deriving mathematical relationships, various papers (e.g. Graves, 1999; Chen et al, 2000a; Hosoda and Disney, 2006) have analysed the Bullwhip Effect and the value of information sharing in supply chains.

We first discuss upstream demand translation when supply chain links employ optimal forecasting methods. A method is said to be optimal if the forecasting method has minimum mean squared error (see section 3.3) and thus we also refer to an optimal forecast as an MMSE forecast in this thesis. In section 4.2, we present a literature review of papers discussing upstream demand translation using an ARIMA framework and an optimal forecasting method. Based on this framework, we discuss multi-stage demand translation.

Next, we consider some non-optimal forecasting methods (see section 3.3 for details on the rationale for using non-optimal methods). Alwan et al (2003) is the only paper that considers upstream translation in the case of non-optimal forecasting methods. One of the limitations of their paper is the assumption of an AR (1) demand process. Secondly, their analysis is limited to two-echelon supply chains. Finally, when they discuss the upstream characterisation for SES, they assume that the supply chain links have an infinite data history.

In this chapter, we generalise upstream demand translation for non-optimal forecasting methods to ARMA (p, q) processes for a multi-stage supply chain. We assume a finite data history when we consider demand translation for the SES method as this 'finite representation' is a more realistic assumption than the alternative representation, which assumes an infinite data history.

## 4.2. Optimal Forecasting Methods

For optimal forecasting methods, we divide the literature review into stationary and non-stationary demand processes.

### 4.2.1. Upstream Translation of Stationary Processes

Various papers have analysed the mathematical relationship between demand and orders of a supply chain link using an optimal forecasting method. Lee et al (2000) is one of the first studies to examine the upstream translation of demand when an MMSE forecasting method is used by the supply chain members (see detailed discussion on the paper in sub-section 5.2.1). They assume that the demand at the retailer (downstream member) follows an AR (1) process and that the supply chain links employ an Order up to (OUT) inventory policy.

The AR (1) demand process at the downstream member is:

$$d_t = \tau + \rho d_{t-1} + \varepsilon_t \qquad \text{4-1}$$

Lee et al (2000) show mathematically that this demand process will translate into the following demand process at the upstream member:

$$Y_t = \tau + \rho Y_{t-1} + \frac{1-\rho^{L+2}}{1-\rho}\varepsilon_t - \frac{\rho(1-\rho^{L+1})}{1-\rho}\varepsilon_{t-1} \qquad \text{4-2}$$

This is an ARMA (1, 1) process with *L* being the lead time from the upstream to the downstream member. The following figure illustrates the translation of demand processes, as shown by Lee el al (2000).

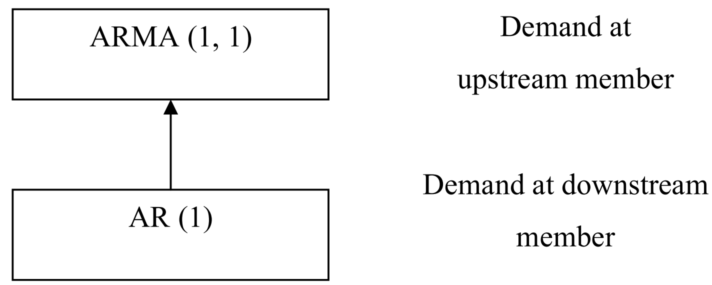


**Figure 4-1 Demand Translation as shown by Lee et al (2000)**

Alwan et al (2003) and Hosoda and Disney (2006) consider a three echelon supply chain and make the same assumptions about the demand process and inventory policy. Alwan et al (2003) take a mathematical approach, while Hosoda and Disney (2006) adopt discrete control theory and simulation methodologies. Both papers, using these different methodologies, confirm the result of Lee et al (2000) that an AR (1) process will translate into an ARMA (1, 1) process. Moreover, both papers show that the orders placed further upstream in the supply chain will also follow an ARMA (1, 1) process. Thus, if the demand process at any supply chain member follows an ARMA (1, 1) process, the order placed by them will also follow the same process, as shown in the following figure:

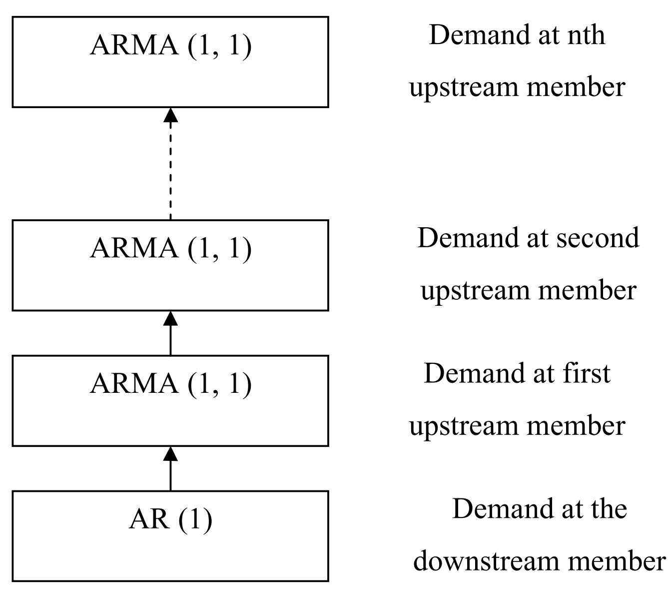


**Figure 4-2 Multi-Stage Translation**
**(Alwan et al, 2003; Hosoda and Disney, 2006)**

The papers then look at the upstream translation of the constant term, the autoregressive and the moving average terms of the demand process. They show that the constant term and autoregressive parameters keep their original values when translated upstream. On the other hand, the values of the moving average parameters change at every upstream echelon and are functions of the autoregressive parameters and the lead times. This is shown in the following figure (Figure 4-3) for ARMA (1, 1) processes at both supply chain links where $\theta^R$ and $\theta^M$ are the moving average parameters for the retailer and the manufacturer respectively, $L$ is the lead time from the supplier to the manufacturer and $\rho^L$ means $\rho$ to the power of $L$.

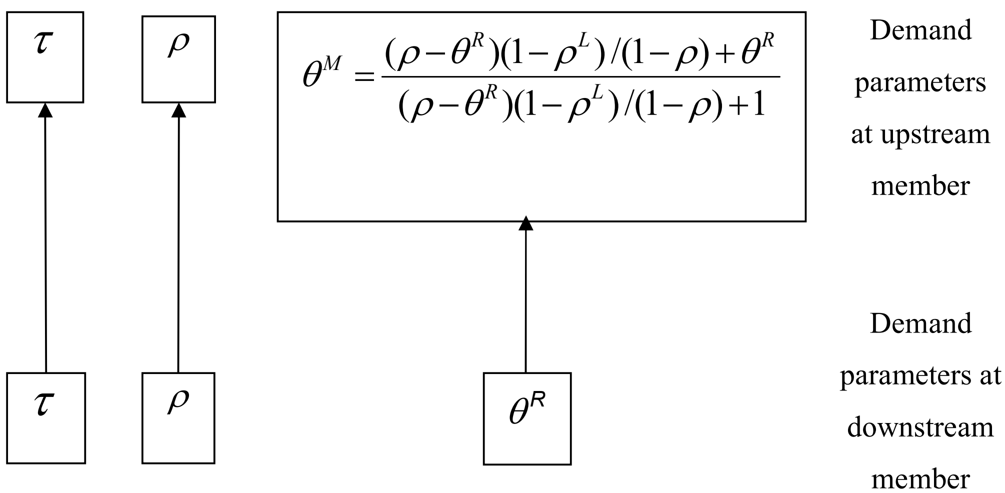


**Figure 4-3 Upstream Translation of Demand Parameters for ARMA (1,1) (Alwan et al, 2003; Hosoda and Disney, 2006)**

Zhang (2004b) obtained general results on the upstream translation of demand for an ARMA (p, q) demand process. He showed the existence of an ARMA-In-ARMA-Out (AIAO) property linking the demand processes between any two stages of the supply chain. According to the AIAO property, ARMA demands at any supply chain link generate ARMA orders for the subsequent upstream link, when the ordering decisions are based on an OUT inventory policy and an MMSE forecasting method.

Suppose the ARMA (p, $q^R$) demand process can be represented as:

$$\rho(B)(d_t) = \theta^R(B)\varepsilon_t \qquad 4\text{-}3$$

where $q^R$ denotes the number of moving average terms in the ARMA process at the retailer.

According to the AIAO property, the order generated from such a demand will follow an ARMA (p, $q^M$) process represented by:

$$\rho(B)(Y_t) = \theta^M(B)a_t \qquad 4\text{-}4$$

where $q^M$ = max (p, $q^R$-L) and $a_t$ is the noise term, at time *t*, in the manufacturer's demand and $a_t = \beta\varepsilon_t$. β is the factor by which all the noise parameters in the process increase and $\beta = \sum_{j=0}^{L}\psi_j$ where $\{\psi_1, \psi_2, \psi_3, ...\}$ are weights in the Infinite Moving Average Representation $d_t = \sum_{j=0}^{\infty}\psi_{t-j}\varepsilon_{t-j}$ and $\psi_k = \sum_{j=1}^{p}\rho_j\psi_{k-j} - \theta^R{}_k$.

The upstream translation of demand for an ARMA (p, q) process is shown in the following figure:

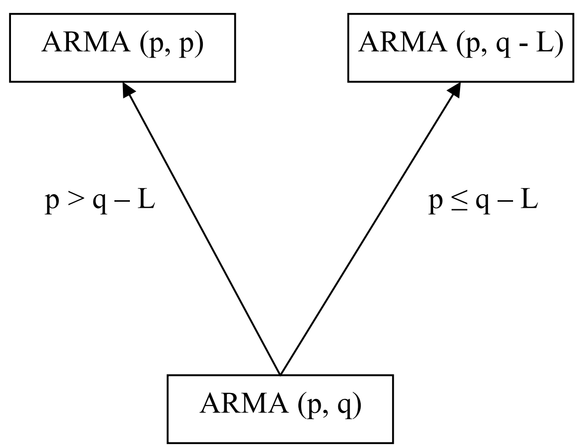


**Figure 4-4 Upstream Demand Translation for ARMA (p, q) (Zhang, 2004b)**

The mathematical analysis by Zhang (2004b) agrees with the findings of Alwan et al (2003) and Hosoda and Disney (2006) that the constant term and the autoregressive parameter remain the same in the upstream members. Further, Zhang (2004b) generalises the upstream translation of the vector moving average parameter ($\Theta$) as shown in the following figure (Figure 4-5) where $\delta_k$ is the factor by which the kth moving average parameter of the manufacturer increases and is given by

$$\delta_k = \frac{(\sum_{j=1}^{k-1} \rho_j \psi_{L+k-j} - \psi_{L+k})}{\beta}$$

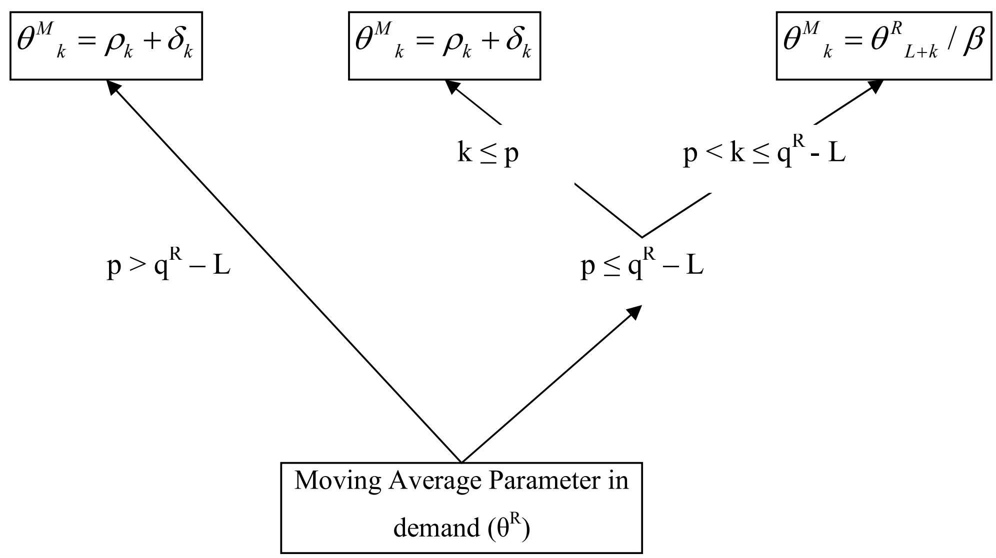


**Figure 4-5 Upstream Demand Translation of Moving Average Parameters (Zhang, 2004b)**

The AIAO property identified by Zhang (2004b) is based on the assumption that the demand process is invertible. Gaur et al (2005) extended this analysis by discussing the retailer's order translation when the retailer's demand follows a non-invertible ARMA (p, q) process. We argued in section 3.2 that it is not feasible to use the non-invertible representation of ARMA (p, q) and the invertible representation should instead be used. Hence, for upstream demand translation of ARMA (p, q), we consider only the result of Zhang (2004b).

### 4.2.2. Upstream Translation of Non-Stationary Processes

Graves (1999) looked at the upstream translation of an ARIMA (0, 1, 1) process. He also assumed an OUT inventory policy. The forecasting method employed in the supply chain model is the Exponentially Weighted Moving Averages (EWMA) method which is the optimal method for an ARIMA (0, 1, 1) process.

The ARIMA (0, 1, 1) demand process is of the form:

$$d_t - d_{t-1} = \tau + \varepsilon_t - \theta^R \varepsilon_{t-1} \qquad 4\text{-}5$$

Graves (1999) showed that the order generated from the above demand will also follow an ARIMA (0, 1, 1) demand process represented as:

$$Y_t - Y_{t-1} = \tau + a_t - \theta^M a_{t-1} \qquad 4\text{-}6$$

where $a_t = [1 + L(1-\theta^R)]\varepsilon_t$ and $\theta^M = \dfrac{1-\theta^R}{[1+L(1-\theta^R)]}$.

Thus, if the demand process at a downstream member is an ARIMA (0, 1, 1) process, and the supply chain links utilise the optimal forecasting method and an OUT policy, the demand process at all upstream members will also be ARIMA (0, 1, 1).

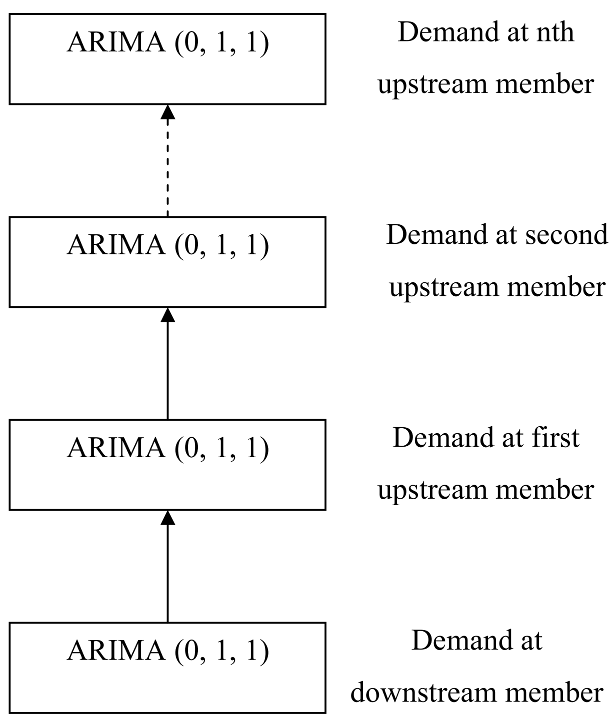


**Figure 4-6 Multi-Stage Demand Translation for ARIMA (0, 1, 1) (Graves, 1999)**

Gilbert (2005) obtained general results on demand translation in supply chains for an ARIMA (p, d, q) process. He showed that, if the demand process at the retailer follows an ARIMA (p, d, $q^R$) process, then the order process to the manufacturer will be ARIMA (p, d, $q^M$) where $q^M$ = max (p+d, $q^R$ -L) and L is the lead time from the manufacturer to the retailer.

An ARIMA (p, d, $q^R$) demand process can be represented as:

$$\rho(B)\nabla^d(d_t) = \theta^R(B)\varepsilon_t \quad \text{4-7}$$

or $\varphi(B)(d_t) = \theta^R(B)\varepsilon_t$

An alternative representation is:

$$d_t = \psi(B)(\varepsilon_t)$$

So: $\psi(B) = \dfrac{\theta^R(B)}{\varphi(B)}$

We derive the equations to calculate $\{\psi_1, \psi_2, ..., \psi_L\}$ later in this sub-section.

Gilbert (2005) showed that, on using the optimal forecasting method and an OUT policy, the demand process at the upstream link will be translated as:

$$\rho(B)\nabla^d(Y_t) = \theta^M(B)a_t \quad \text{4-8}$$

where $a_t = K_o\varepsilon_t$ and $K_o = 1 + \psi_1 + \psi_2 + ... + \psi_L$

The coefficients of the moving average parameters $\theta_1^M, \theta_2^M, ..., \theta_q^M$ can be expressed as:

$$\theta_1^M = \frac{-\psi_{L+1}}{K_o} + \varphi_1$$

$$\theta_2^M = \frac{-\psi_{L+2}}{K_o} + \frac{\varphi_1 \psi_{L+1}}{K_o} + \varphi_2$$

.

.

.

$$\theta_q^M = \frac{-\psi_{L+q}}{K_o} + \frac{\varphi_1 \psi_{L+q-1}}{K_o} + \frac{\varphi_2 \psi_{L+q-2}}{K_o} + \ldots + \frac{\varphi_{q-1} \psi_{L+1}}{K_o} + \varphi_q$$

We assume nine ARIMA (p, d, q) models in simulation (see sub-section 7.3.1). We now derive equations to calculate $\varphi_1, \varphi_2, \varphi_3$ and $\psi_1, \psi_2, ..., \psi_L$ from the above general equations given by Gilbert (2005). We restrict the derivations to $\varphi_1, \varphi_2$ and $\varphi_3$ as it is shown in sub-section 7.3.1 that, based on the selection of models for the simulation, $\theta_n, \varphi_n = 0$ for n > 3 .

$$\varphi(B) = \rho(B)\nabla^d$$

where $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots$

Based on the above, we can derive the following equations for $\varphi_1, \varphi_2$ and $\varphi_3$ :

$$\varphi_1 = \rho_1 + d \qquad \text{4-9}$$

$$\varphi_2 = \rho_2 - \rho_1 d - \frac{d(d-1)}{2} \qquad \text{4-10}$$

$$\varphi_3 = \rho_3 - \rho_2 d + \frac{\rho_1 d(d-1)}{2} + \frac{d(d-1)(d-2)}{6} \qquad \text{4-11}$$

Since $\psi(B) = \dfrac{\theta^R(B)}{\varphi(B)}$

$$\psi_1 = \varphi_1 - \theta^R{}_1 \quad \text{4-12}$$

$$\psi_2 = \varphi_2 + \psi_1\varphi_1 - \theta^R{}_2 \quad \text{4-13}$$

$$\psi_3 = \varphi_3 + \psi_1\varphi_2 + \psi_2\varphi_1 - \theta^R{}_3 \quad \text{4-14}$$

*and*

$$\psi_4 = \psi_1\varphi_3 + \psi_2\varphi_2 + \psi_3\varphi_1$$

$$\psi_5 = \psi_2\varphi_3 + \psi_3\varphi_2 + \psi_4\varphi_1$$

.

.

.

$$\psi_L = \psi_{L-3}\varphi_3 + \psi_{L-2}\varphi_2 + \psi_{L-1}\varphi_1 \quad \text{4-15}$$

See proof of Equations 4-9 – 4-15 in Appendix 4A.

We present the following figure (Figure 4-7) to show the links between the research papers on the upstream translation of demand in the case of an optimal forecasting method.

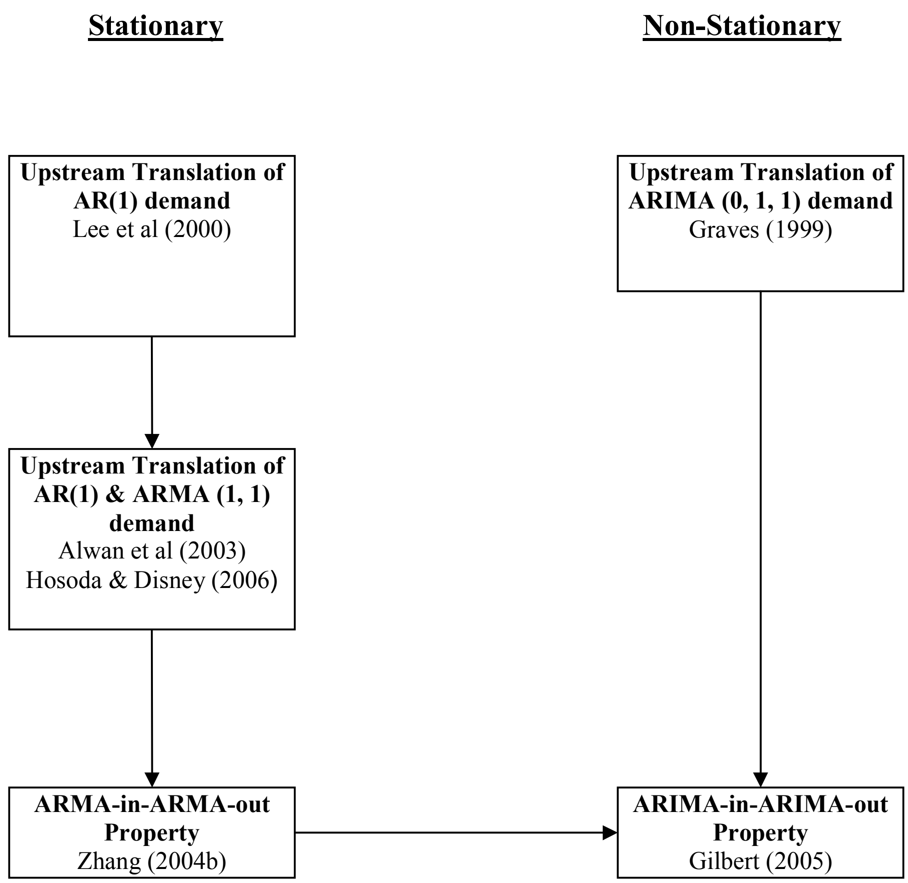


**Figure 4-7 Upstream Demand Translation (Optimal Forecasting Method)**

### 4.2.3. Multi-Stage Demand Translation

Based on the result of Gilbert (2005), we now present the following figure (Figure 4-8) to show the demand translation in a multi-stage supply chain for an ARIMA (p, d, q) process at the most downstream link.

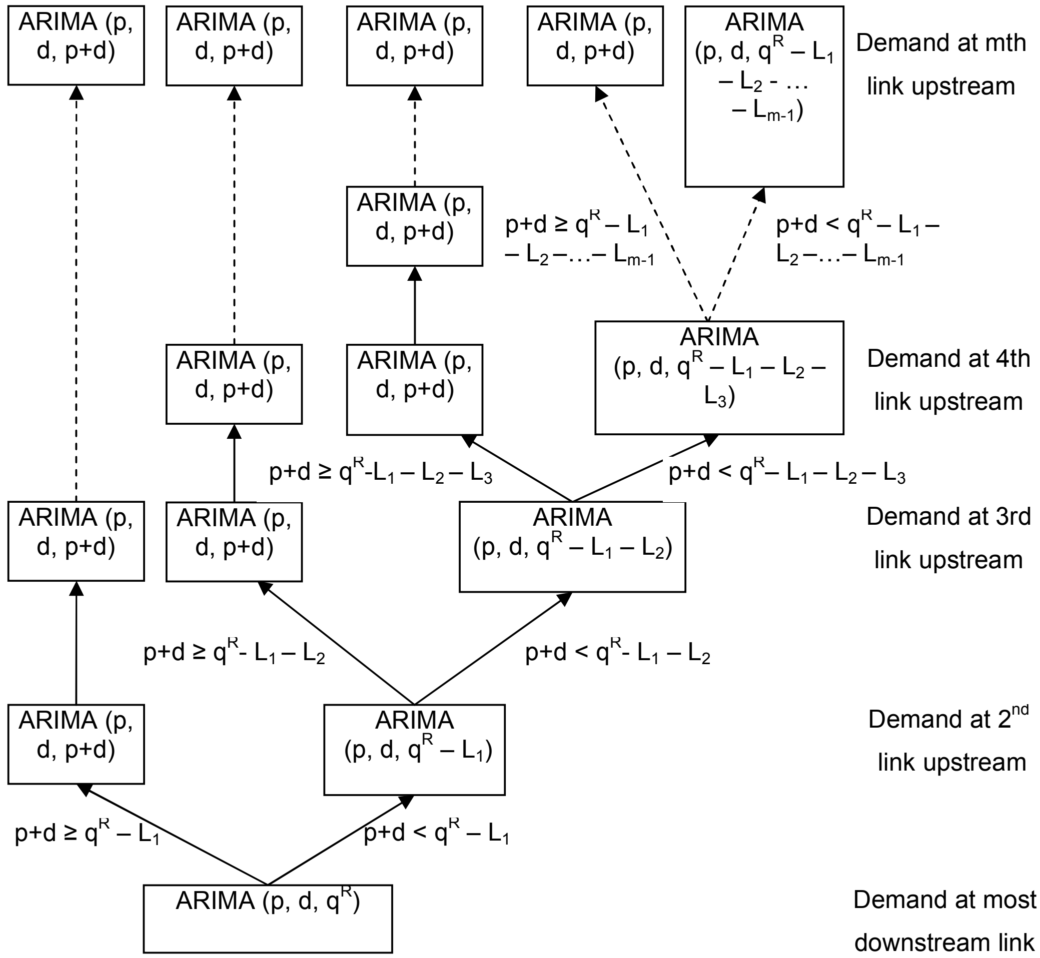


**Figure 4-8 Multi-Stage Demand Translation for ARIMA (p, d, q)**

The above figure clearly shows that the demand process at any upstream link of the supply chain depends not only on the consumer's demand process but also on the cumulative lead time from that link to the consumer. It also shows that if $p + d \geq q^R - \sum_{j=1}^{m-1} L_j$, then the propagation beyond the *mth* link upstream is ARIMA (p, d, p + d).

#### 4.2.3.1. Order Translation for MA (q) Processes

In this sub-section, we discuss upstream demand translation when the consumer's demand follows an MA (q) process. This is a special case of ARIMA demand translation because, when q ≤ L, the MA (q) process will translate into a random process. If $q \leq L$, then max $(p + d, q - L) = 0$. In this case the demand process ARIMA (0, 0, q) at the retailer will translate into an order process ARIMA (0, 0, 0) or a random process at the manufacturer. As we assume $q^R \leq L$ in the experiment (with one exception: $q^R=2$, $L=1$(see Chapter 7)), the MA (q) process in the simulation translates into a random process. The multi-stage translation for an MA (q) demand process is shown in the following figure (Figure 4-9):

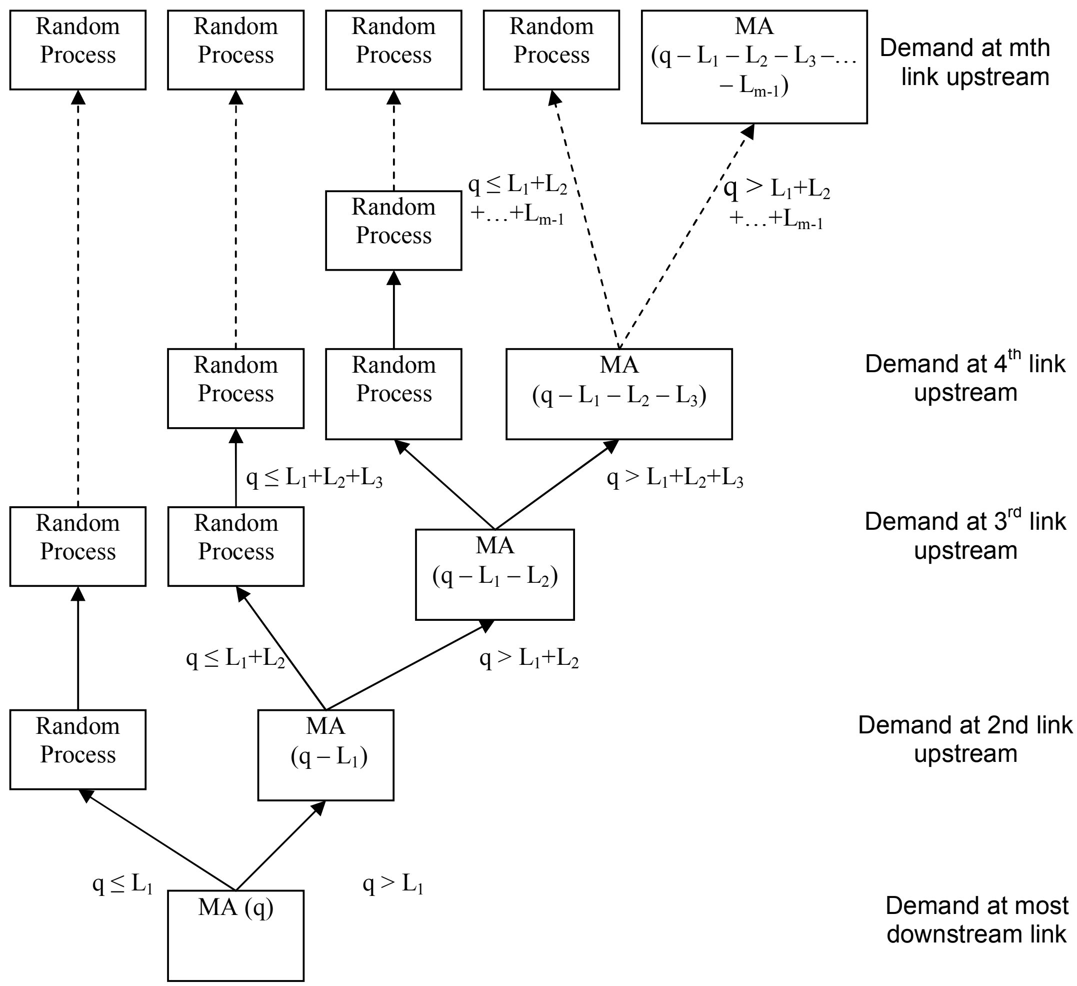


**Figure 4-9 Multi-Stage Demand Translation for MA (q)**

This is an important corollary of Gilbert (2005), as sharing demand information using the DIS approach (as advocated in the literature; see section 5.2) will not be valuable when $q \leq L$ for MA (q) demand processes.

## 4.3. Non-Optimal Forecasting Methods

Various papers (e.g. Chen et al, 2000a; Chen et al, 2000b; Zhang, 2004a; Stamatopoulos et al, 2006) have discussed the effect of non-optimal forecasting methods on upstream demand propagation. All these papers restrict their analysis to the effect of forecasting methods on order variability. Although they derive expressions for the demand process at the upstream member, they do not represent them in the form of an ARMA model.

Chen et al (2000a) examined the ratio of upstream to downstream demand variance, or the Bullwhip Ratio, when the demand pattern at a retailer follows an AR (1) process. They showed that when the retailer uses a Simple Moving Average method to forecast their lead time demand there is an increase in variability. This increase in variability is a function of three parameters: the number of historical terms (n) used in the Simple Moving Average, the lead time (L), and the autoregressive parameter ($\rho$).

Chen et al (2000b) performed a similar analysis on an AR (1) demand process based on Single Exponential Smoothing. They concluded that the increase in variability is an increasing function of α, the smoothing parameter, an increasing function of L, the lead time, and a decreasing function of $\rho$, the autoregressive parameter.

Zhang (2004a) compared the Bullwhip Effect for an AR (1) demand process for SMA, SES and an MMSE optimal forecasting method. He showed that the MMSE forecasting method results in lowest variability and lowest inventory.

Using an AR (1) demand process, Stamatopoulos et al (2006) argued that previous studies have only incorporated SES with a fixed smoothing constant. They compare the increase in variability when a best exponential smoothing method is chosen. A 'best' exponential smoothing method is one that minimises the mean square error. They show that this method results in lower variability than SES (fixed smoothing constant) and SMA, and thus can be used as an alternative to an MMSE forecasting method.

Alwan et al (2003), in addition to comparing the Bullwhip Effect for different forecasting methods, also examined demand propagation for an AR (1) demand process in the case of non-optimal forecasting methods. They employ two non-optimal forecasting methods, SMA and SES, and study the upstream translation of demand when these two methods are used by the supply chain links.

They assume an AR (1) process as shown in equation 4-1. First, they look at the upstream demand translation when the supply chain links use the SMA method as given by equation 3-6 (see section 3.3). They mathematically show that if the downstream member employs the SMA of the *n* most recent demands, an AR (1) process will translate into an ARMA (1, n) process at the upstream member given by:

$$Y_t = \tau + \rho Y_{t-1} + a_t - \theta^M a_{t-n} \qquad \text{4-16}$$

where $\theta^M = \dfrac{L}{L+n}$ and $a_t = \dfrac{L}{L+n}\varepsilon_t$

Alwan et al (2003) then look at upstream demand translation when the supply chain links use the SES forecasting method. They assume that an infinite data history $(d_t, d_{t-1}, d_{t-2}, \ldots)$ is available at the retailer. In this case, the retailer can use the 'infinite representation' of SES:

$$\hat{D}_{t+1} = \alpha \sum_{j=0}^{\infty} (1-\alpha)^j d_{t-j}$$

They show that an AR (1) process at the retailer (equation 4-1) will translate into an ARMA (1, $\infty$) process:

$$Y_t = \tau + \rho Y_{t-1} + a_t - \sum_{j=1}^{\infty} \theta^M{}_j a_{t-j} \qquad \text{4-17}$$

where $\theta^M{}_j = \dfrac{L\alpha^2(1-\alpha)^{j-1}}{L\alpha+1}$ and $a_t = (L\alpha+1)\varepsilon_t$

The upstream translation of demand in the case of non-optimal forecasting methods as discussed in Alwan et al (2003) is shown in the following figure (Figure 4-10).

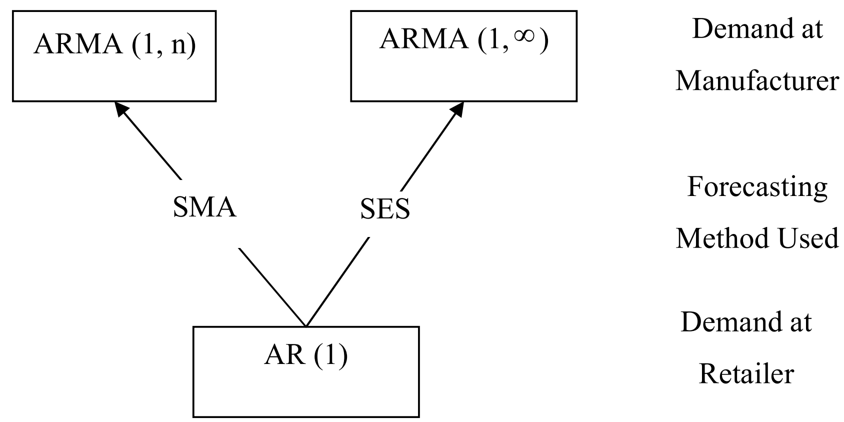


**Figure 4-10 Upstream Translation for Non-Optimal Methods (Alwan et al, 2003)**

Alwan et al (2003) is an important paper as it is the only one that discusses the upstream translation of demand when non-optimal forecasting methods are used. Secondly, this paper has also shown that upstream demand translation depends on the forecasting method used by the supply chain links. One of the limitations of the paper is that it only considers the upstream translation of an AR (1) demand process. Secondly, their analysis is limited to two echelon supply chains. Another limitation of Alwan et al (2003) is the assumption of the availability of an infinite data history at the retailer.

We generalise the results of Alwan et al (2003) for an ARMA (p, q) process. Thus, in the next section, we present a complete picture of upstream translation for an ARMA (p, q) process for multi-stage supply chains using two non-optimal forecasting methods. When we analyse upstream translation for SES, we consider the availability of a finite data history at the supply chain links.

## 4.4. Upstream Translation for an ARMA (p, q) Process

In sub-section 4.4.1, we analyse the upstream demand translation when the supply chain links utilise the SMA forecasting method. Then, in sub-section 4.4.2, we present the analysis for the case of SES.

### 4.4.1. Upstream Propagation for Simple Moving Averages

When a Simple Moving Average method is used to forecast the lead time demand for an ARMA (p, $q^R$) demand process (see equation 4-7) at the downstream member, the order to the upstream member follows an ARMA (p, n + $q^R$) process given by the following:

$$\rho(B)Y_t = \theta^M(B)a_t \quad \text{4-18}$$

where $\theta^M(B)$ is the moving average operator for the manufacturer, of the order $q^M = n + q^R$, and $a_t = \left(\frac{L}{n} + 1\right)\varepsilon_t$.

The proof is given in Appendix 4B.

The following figure illustrates the ARMA (p, q) upstream translation when the downstream link employs the SMA method.

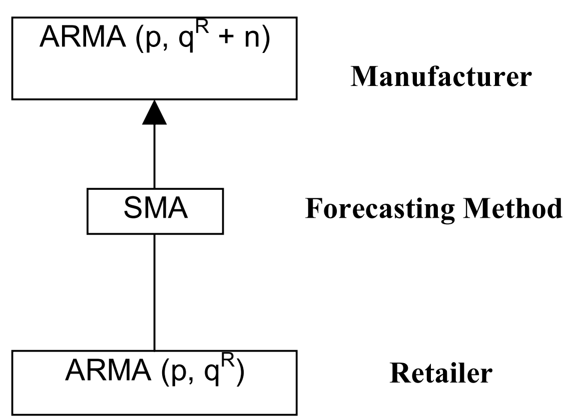


**Figure 4-11 Upstream Demand Translation for SMA**

### 4.4.2. Upstream Propagation for Single Exponential Smoothing

Alwan et al (2003) showed that when SES is employed on an AR (1) process, it propagates into an ARMA (1, ∞) process. This result was based on an infinite representation of SES. In real world applications, it is not possible to have a time series with an infinite data history. In this sub-section, using a finite representation of SES, as in equation 3-9, we generalise the results for an ARMA (p, q) demand process.

When the Single Exponential Smoothing forecasting method is used to forecast the lead time demand for an ARMA (p, $q^R$) demand process (equation 4-7) at the downstream member, the order on the upstream member approximately follows an ARMA (p, t – 1) process:

$$\rho(B)Y_t = \theta^M(B)a_t \qquad 4\text{-}19$$

where $\theta^M(B)$ is the moving average operator for the manufacturer and is of the order $q^M = t-1$, and $t$ is the current time period.

The approximation is due to the presence of an extra term on the right hand side. For an ARMA (p, q) process, this extra term is: $L[\alpha(1-\alpha)^{t-1}(d_1 - d_0) + \alpha d_0 \sum_{i=2}^{p}(1-\alpha)^{t-i}\rho_i]$. It is obvious from the expression that, for 0 < α < 2, this extra term will tend to zero as t tends to infinity.

The proof of the approximate equation 4-19 is given in Appendix 4C.

The following figure illustrates the upstream ARMA (p, q) demand translation when the downstream link employs SES.

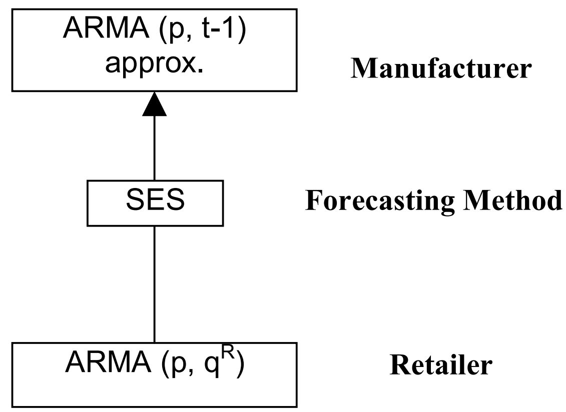


**Figure 4-12 Upstream Demand Translation for SES**

#### 4.4.2.1. Infinite Representation of SES

Alwan et al (2003) have used an infinite representation of SES for an AR (1) retailer model, assuming that an infinite data history is available. If we let *t* tend to infinity in expression 4-19 for an AR (1) demand process, it propagates into an ARMA $(1,\infty)$ process, with no extra term, which is the result of Alwan et al (2003). Thus, the result of Alwan et al (2003) is compatible and a special case of the result in sub-section 4.4.2 above.

### 4.4.3. Multi-Stage Propagation for Non-Optimal Methods

If there are m stages in a supply chain and all links use the n most recent historical demands to forecast using SMA and SES forecasting methods, the demand propagation is as shown in the following figures (Figures 4-13 and 4-14).

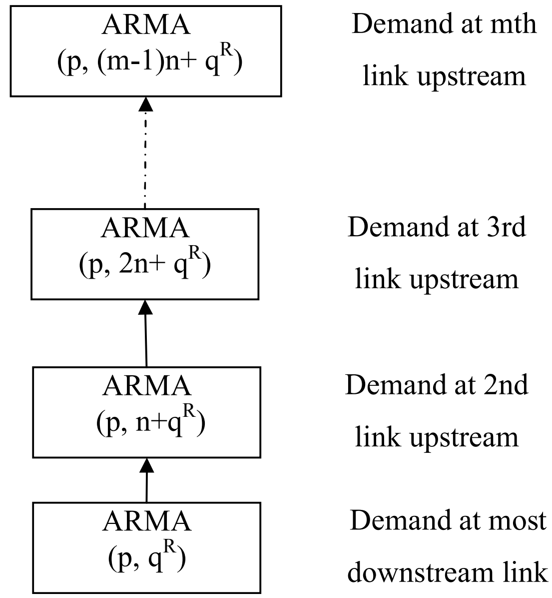


**Figure 4-13 Multi-Stage Upstream Demand Translation for SMA**

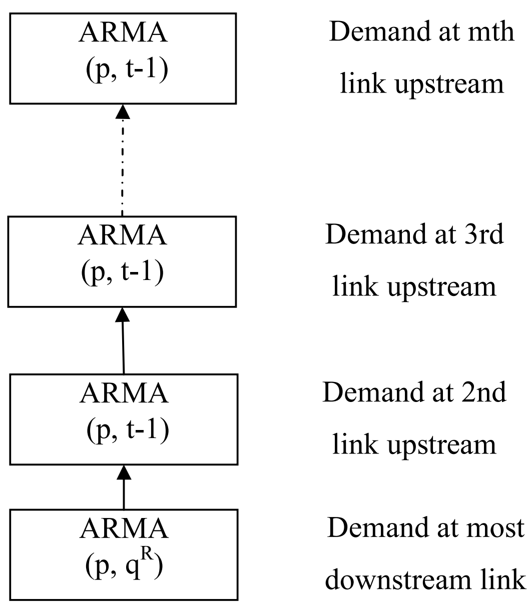


**Figure 4-14 Approximate Multi-Stage Upstream Demand Translation for SES**

We showed in sub-section 4.4.2 that when the supply chain links employ a SES forecasting method, the upstream translation into an ARMA process is an approximation. Therefore, the multi-stage upstream translation is also of an approximate nature. This approximation may become less accurate along the supply chain, because each link introduces another term.

## 4.5. Conclusions

In this chapter, we discussed the upstream demand translation of supply chains for optimal and non-optimal forecasting methods. Upstream demand translation shows the relationship between the demand and the order process at any supply chain link. The mathematical relationships established in the literature have provided insights into the progression of ARIMA processes through the supply chain. Many authors have quantified the Bullwhip Effect and the value of information sharing based on these relationships.

Much progress has been made in the literature on upstream demand translation for a two stage supply chain. Although the upstream translation for ARIMA (p, d, q) has been established for an optimal forecasting method, the case of non-optimal forecasting methods is limited to an AR (1) demand process.

In the case of an optimal forecasting method, Gilbert (2005) has presented the upstream demand translation for an ARIMA (p, d, q) process. We derive various equations (equations 4.9 – 4.15) from his mathematical results which we use in the simulation and empirical analysis. We specifically discuss demand translation for an MA (q) process where $q \leq L$ and L is the lead time; it translates into a random process and thus there will be no value of sharing demand information using DIS, a demand information sharing approach used in the literature to be discussed in Chapter 5.

For non-optimal forecasting methods, we analyse upstream demand translation for an ARMA (p, q) process. We show that an ARMA (p, $q^R$) will translate into ARMA (p, $q^R + n$) when SMA is employed and into ARMA (p, t-1) approximately when SES is employed, where n is the number of terms in SMA and t is the current time period.

Finally, we move the focus to the discussions of multi-stage upstream demand translation. None of the papers has explored multi-stage demand translation for non-optimal forecasting methods. In this chapter, we extended the analysis for upstream demand translation to ARMA (p, q) processes to non-optimal forecasting methods. Results have been established for multi-stage upstream translation for ARMA demands in the case of SMA and SES forecasting methods.

# 5. Demand Information Sharing Approaches

## 5.1. Introduction

The coordination of decisions among supply chain members is critical to the performance of supply chains. Coordination may be facilitated by some form of information sharing. Many papers can be found in the literature that explore the sharing of demand information in supply chains. As discussed in Chapter 3, we use an ARIMA methodology to represent demand in this research. Thus, in this chapter, we present a literature review of papers discussing sharing of demand information using the ARIMA framework. These papers can be divided into two streams: Sharing Demand Information and Downstream Demand Inference.

The stream of papers analysing sharing demand information presents two supply chain strategies. The first strategy is not to share the downstream demand information. In such a strategy, the upstream members base their forecasts on the orders received from downstream members and do not require a formal information sharing mechanism. This is termed a No Information Sharing (NIS) approach in the literature. On the other hand, if a supply chain adopts a strategy of sharing demand information with the help of a formal information sharing mechanism, their forecasts are based on the downstream demand information. Two approaches, Demand Information Sharing (DIS) and Vendor Managed Inventory (VMI), have been analysed in the literature for such a strategy.

Another stream of papers claims that, even in the absence of a formal information sharing mechanism, the upstream member can mathematically deduce the downstream demand information. This approach has been termed as Downstream Demand Inference (DDI), where the forecasts by the upstream members are based on the inferred downstream demand.

In this chapter, we present a critical review of these streams of research and analyse the approaches discussed in the literature. Based on this analysis, we present two new approaches, No Information Sharing –Estimation (NIS-Est) and Centralised Demand

Information Sharing (CDIS). We argue that these two new approaches should improve the existing approaches found in the literature.

## 5.2. Current Approaches of Sharing Downstream Demand

The papers discussed in this section argue that it is beneficial for the upstream member to know or deduce the demand at the downstream member and to use it in their forecasts. We discuss the two streams as introduced in section 5.1 in the following sub-sections.

### 5.2.1. Sharing Demand Information Approaches

Several papers (e.g. Chen et al, 2000a; Lee et al, 2000; Yu et al, 2002; Raghunathan, 2003; Cheng and Wu, 2005; Hosoda et al, 2008) quantify the value of sharing demand information by comparing various performance metrics (e.g. inventory holdings, inventory costs) resulting from the adoption of the two strategies discussed in section 5.1.

Lee et al (2000) showed the value of sharing demand information in a two-echelon supply chain, comprising a retailer and a manufacturer. An AR (1) demand process is assumed at the retailer:

$$d_t = \tau + \rho d_{t-1} + \varepsilon_t \qquad 5\text{-}1$$

where the notation is unchanged from previous chapters.

For simplicity of exposition in this chapter, the constant term ( $\tau$ ) will be dropped. This does not affect any of the arguments or conclusions presented.

The supply chain model consists of a periodic review system where each site reviews its inventory level and places orders on the upstream link, if required, every period. The inventory policy used is the order up to level (OUT) policy. The study by Lee et al (2000) assumes that the manufacturer is aware that the retailer's demand follows an AR(1) process and is also aware of the parameters $\tau$ and ρ. It is supposed that the manufacturer retrieves this information from the retailer through periodic discussions or alternatively through the historic demand data.

On observing the AR (1) demand process, the retailer uses a Minimum Mean Squared Error (MMSE) method to forecast their lead time demand. Based on this forecast, they place an order on the manufacturer; the order process can be expressed as:

$$Y_t = \rho Y_{t-1} + \frac{1-\rho^{l+2}}{1-\rho}\varepsilon_t - \frac{\rho(1-\rho^{l+1})}{1-\rho}\varepsilon_{t-1} \qquad 5\text{-}2$$

where the notation is defined in Chapter 3.

The order placed by the retailer is the demand of the manufacturer. Based on this demand, the manufacturer will make its forecast. The equation for the lead time forecast derived by the authors is:

$$\hat{Y}_t^{L+1} = \rho\frac{1-\rho^{L+1}}{1-\rho}\left[Y_t - \frac{(1-\rho^{l+1})}{1-\rho}\varepsilon_t\right] \qquad 5\text{-}3$$

They first assume that the supply chain adopts a strategy of not sharing the demand information. For such a strategy, the authors introduce a No Information Sharing (NIS) approach whereby the manufacturer remains unaware of the demand ($d_t$) at the retailer. The manufacturer makes its lead time forecast only on the basis of the order $Y_t$ received from the retailer. Thus, although $\varepsilon_t$ has been realised, it is unknown to the manufacturer and thus they assume its value to be zero. The manufacturer's forecast for the NIS approach will become:

$$\hat{Y}_t^{L+1} = \rho\frac{1-\rho^{L+1}}{1-\rho}\left[Y_t\right] \qquad 5\text{-}4$$

They calculate the inventory holdings and the inventory cost based on the above approach using equation 3-15.

Then the authors suppose that the supply chain members adopt the strategy of sharing the demand information. In this case, a Demand Information Sharing (DIS) approach has been presented where the retailer now shares its demand ($d_t$) with the manufacturer. The manufacturer, in this case, is now aware of the value of $\varepsilon_t$ and thus can utilise equation 5-3 to forecast their lead time demand. Inventory holdings and inventory costs are again calculated for this approach using the same methodology as for the NIS approach.

With the help of mathematical analysis and simulation, Lee et al (2000) compare the inventory holdings and inventory costs for the two approaches. Their simulation results show that, under certain conditions, the manufacturer can achieve a 42% reduction in inventory cost.

Although the supply chain model by Lee et al (2000) is quite simple: single retailer – single manufacturer, several papers show similar results for more complex models.

Raghunathan (2003) and Cheng and Wu (2005) extend the above supply chain model to a multi retailer-single manufacturer case and generalise the results of Lee et al (2000) to the extended model. Cheng and Wu (2005) assume that the demands among the retailers are uncorrelated, while Raghunathan (2003) assumes that the demands among the different retailers are correlated. Both assume that the demands at different retailers share the same autocorrelation. The studies mathematically show that the manufacturer benefits in terms of inventory holdings when they share and utilise the retailers' demand in their forecasts.

The above studies assume that there is no unit ordering cost involved. Yu et al (2002) extended the model of Lee et al (2000) by introducing a unit ordering cost. They used a different cost minimisation model to calculate the inventory safety factor ($k$), based on the unit ordering cost ($c$) and a discount factor ($\beta$):

$$k = \Phi^{-1}\left(\frac{p - c\,(1-\beta)/\beta^{L}}{p + h}\right) \qquad \text{5-5}$$

where the discount factor β embodies the manufacturer's time preference for money. As the unit cost is the same in both NIS and DIS, the introduction of the unit cost does not change the results of Lee et al (2000). Secondly, Yu et al (2002) also compare the two approaches of Lee et al (2000) with a Vendor Managed Inventory (VMI) approach. In this approach, the forecasts are the same but the retailer's inventory replenishment decisions are made by the manufacturer. However, they did not find any inventory costs savings when they compared DIS with a VMI approach. Thus, the value of sharing demand information does not depend on which member makes the replenishment decision. The reason that DIS yields lower inventory cost at the manufacturer than NIS is the use of less variable demand in their forecasts. As Yu et al (2002) assume sharing of demand information in both DIS and VMI, both give the same inventory cost. This agrees with Cheng and Wu (2005) who also include VMI in their analysis and find the same result. Thus, the above papers show that the main conclusion of Lee et al (2000), namely lower inventory cost by using the DIS approach, can also be applied to a multi retailer-single manufacturer supply chain and also to a supply chain when taking unit cost into account, and applying a discount factor.

In order to test whether the results can be extended to a multi-echelon supply chain, Wu and Cheng (2003) mathematically analysed the same model as Lee et al (2000) but for a three level supply chain: Retailer-Distributor-Manufacturer. The authors also suppose that the supply chain adopts two approaches, NIS and DIS. They conclude that the results of Lee et al (2000) can be extended to a three echelon supply chain.

The results in the above papers are based on mathematical and simulation analysis. Hosoda et al (2008) consider real data and investigate the benefit of sharing demand information in a soft drink supply chain. They consider three products and compare the standard deviation of the prediction errors (SDPE) for the two approaches, NIS and DIS. They conclude that sharing demand information results in better forecast accuracy for the manufacturer. Their numerical analysis, based on the data history of three products, shows that the manufacturer can reduce SDPE by 8 – 19% (a detailed critique of the paper is presented in Chapter 8).

#### 5.2.1.1. Discussion on NIS, DIS and VMI Approaches

The previous sub-section noted that various authors have extended the model of Lee et al (2000) by relaxing assumptions. All the papers show that their conclusions regarding the value of demand information sharing are also applicable to more complex supply chain models. The extensions of the Lee et al (2000) model are summarised in the following figure:

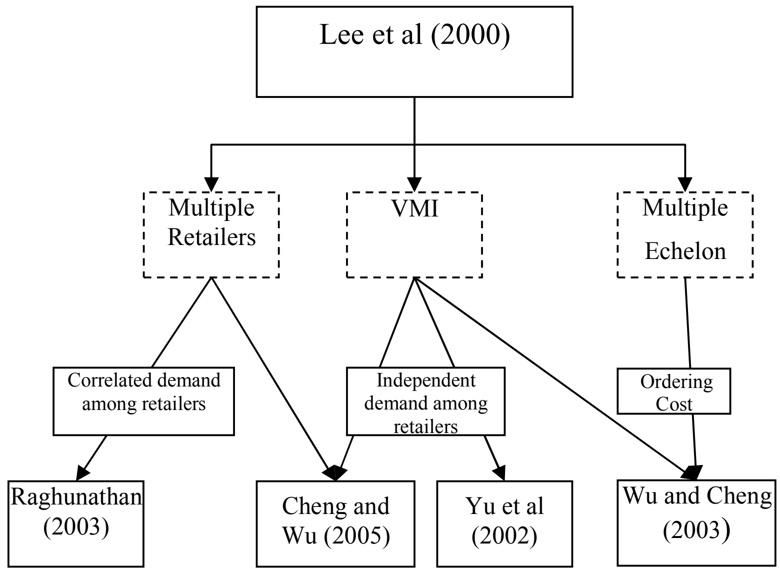


**Figure 5-1 Extensions of Lee et al (2000) Model**

The above figure shows that the supply chain model by Lee et al (2000), with somewhat restrictive assumptions, provided a basis for extended analysis by relaxation of assumptions. The papers in Figure 5-1 analysed the value of demand information sharing by considering three approaches: NIS, DIS and VMI. VMI and DIS share the same forecasting methodology and so there is no difference in the performance metrics of the two approaches in terms of inventory holdings and inventory costs. Thus, comparing inventory of either of them with NIS will quantify the value of demand information sharing. The replenishment policy in VMI is different from both NIS and DIS. As we do not focus on the effect of replenishment policies, we include only NIS and DIS in this research.

For a supply chain to adopt a strategy of not sharing demand information, we find that an NIS approach has been presented in the literature. In this approach, there is no sharing of demand information among the supply chain members. Instead, the supply chain members base their forecasts on the orders received from the downstream link. Although the demand is realised at the retailer, the upstream member is unaware of this demand and assumes the value of noise in the retailer's demand to be zero.

On the other hand, when the supply chain adopts a strategy of sharing demand, a DIS approach has been presented where the downstream member shares its demand information with the upstream member through some formal information sharing mechanism. The upstream member, in this case, is aware of the downstream member's demands. Thus, on making their lead time forecast, they utilise the shared value of the noise in the retailer's demand.

### 5.2.2. Downstream Demand Inference

We discussed in the previous sub-section that savings in inventory costs can be obtained if an upstream member utilises the downstream demand in their forecasts. In order to do so, the papers in the previous sub-section argue that the downstream member will have to share its demand information with the upstream member.

In Chapter 4, we discussed upstream demand translation, which shows that the demand and order processes of any supply chain member are linked by a mathematical relationship. Based on this upstream translation of demand, and using strict model assumptions, various authors (Graves, 1999; Raghunathan, 2001; Li et al, 2003; Zhang, 2004b, Gilbert, 2005; Hosoda and Disney, 2006) maintain that the inverse translation is also possible when an MMSE forecasting method is employed. The upstream member can infer the demand present at the downstream member, owing to the existence of mathematically tractable relationships. Thus, these papers present another approach which we term 'Downstream Demand Inference' (DDI).

In the DDI approach, the downstream member does not share its demand information with the upstream member. Instead, the upstream member tries to infer the retailer's demand by utilising mathematical equations. These mathematical equations have been presented in chapter 4 (see equations 4-8 – 4-15). The equations reveal that, under certain assumptions, the orders at the upstream member contain complete information on the downstream member's demands. Hence, under these assumptions, the manufacturer may exploit their orders to infer the actual consumer demand.

Various authors have shown that, in certain circumstances, the manufacturer can infer the actual consumer demand by the orders received. Raghunathan (2001), using an AR (1) demand process at the retailer, has shown that the retailer's order history to the manufacturer already contains information about the demand at the retailer. Therefore, the manufacturer can deduce the actual demand at the retailer by using the order history if they are aware of the retailer's demand process and its parameters. Thus, the author concludes that DIS is of no value to the manufacturer.

Graves (1999) modelled an ARIMA (0, 1, 1) demand process and concluded that there is no benefit from providing the upstream stage with the actual demand values, if the upstream member is aware of the demand process and parameters at the downstream member.

Hosoda and Disney (2006) have found the same results by using AR (1) and ARMA (1, 1) demand processes at the downstream member. Their study also concludes that, as the ordering process from the retailer to the manufacturer already contains complete market demand information, there is no benefit of DIS in terms of forecast accuracy.

Zhang (2004b) has generalised the above conclusions for an ARMA (p, q) process, while Li et al (2003) and Gilbert (2005) generalised further for an ARIMA (p, d, q) process. All three studies argue that the manufacturer can infer the demand at the retailer without requiring the demand information from the retailer.

#### 5.2.2.1. Discussion on the DDI Approach

In the previous sub-section, we reviewed the literature on another demand sharing approach: Downstream Demand Inference. This approach is based on the fact that under certain assumptions, the orders at any supply chain member contain complete information on the demands. The upstream supply chain member can thus exploit their orders to infer the downstream demand. We present the following figure (Figure 5-2) to summarise the links between papers discussing the DDI approach.

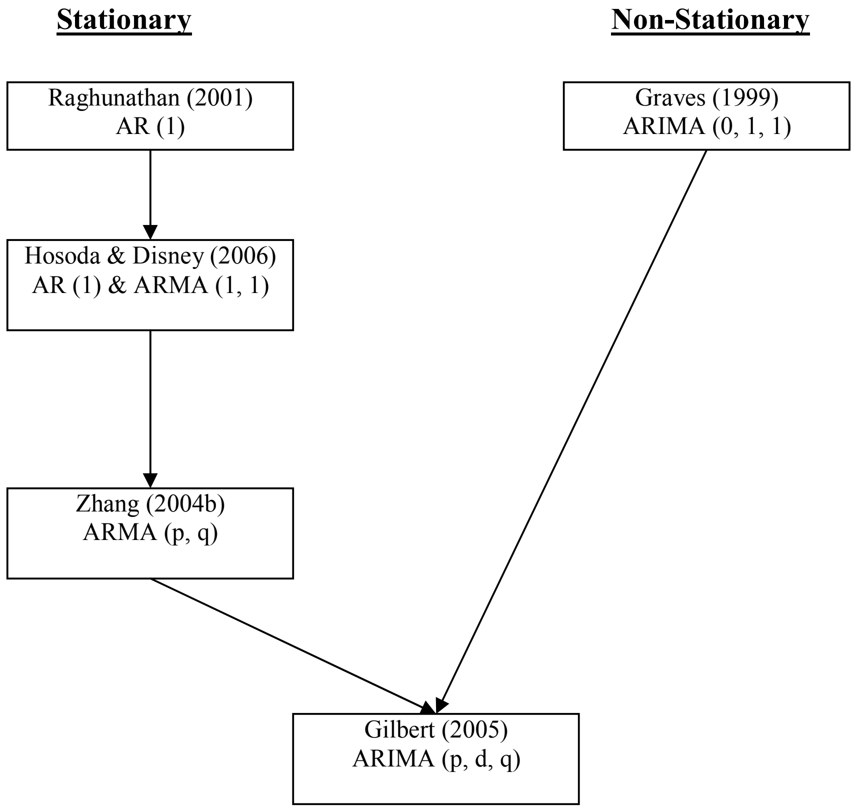


**Figure 5-2 Papers Discussing the DDI Approach**

We observe that inferring the demand at the downstream link, or Downstream Demand Inference (DDI), is sensitive to the model assumptions. This has also been acknowledged in other studies. For example, Raghunathan (2001) suggests that information sharing has no value only if both the supply chain members are aware of the demand process at the downstream link. Similarly, Graves (1999) acknowledged that DIS is valuable if the upstream stage is not aware of the demand parameters of the customer demand process.

Thus, the claim about no value in sharing demand information in the above papers (Graves, 1999; Raghunathan, 2001; Li et al, 2003; Zhang, 2004b; Gilbert, 2005; Hosoda and Disney, 2006) is dependent on the assumption that the manufacturer is aware of the process and the parameters of the retailer's demand.

We discussed in chapter 1 that, in this research, we relax many assumptions in the supply chain model to bring this work closer to reality. We show in Chapter 6, by relaxing some assumptions, that Downstream Demand Inference (DDI) is not feasible. Therefore, in the simulation and empirical analysis of this research, we do not consider the DDI approach.

## 5.3. New Approaches

In section 5.2, we discussed various approaches that have been adopted in previous research on the value of sharing demand information. Two of the approaches discussed above, NIS and DIS, will be adopted in this research (see sub-section 5.2.1.1 for reasons for selection of these approaches).

We observe that the value of demand information sharing has been quantified in the literature by comparing the performance metrics of the NIS and DIS approaches. In this research, we argue that these two approaches can be further improved. Thus, we present two new approaches of sharing demand information. One is based on improving NIS; the other is based on improving DIS. These new approaches are discussed in the following sub-sections.

### 5.3.1. No Information Sharing – Estimation (NIS-Est)

Before introducing the NIS-Est approach, the NIS approach will be explained with the help of two demand process as examples. In the NIS approach, as discussed in the literature, the manufacturer assumes the value of the retailer's noise to be zero, as it is not being shared.

For example, consider an AR (1) process at the retailer. Lee et al (2000) have shown that such a demand process at the retailer will be translated to the following demand process at the manufacturer (see section 5.2).

$$Y_t = \rho Y_{t-1} + \frac{1-\rho^{l+2}}{1-\rho}\varepsilon_t - \frac{\rho(1-\rho^{l+1})}{1-\rho}\varepsilon_{t-1} \qquad \text{5-6}$$

In section 5.2, we also discussed that the equation for the lead time forecast by the manufacturer for the above demand process will be:

$$\hat{Y}_t^{L+1} = \rho \frac{1-\rho^{L+1}}{1-\rho}\left[Y_t - \frac{(1-\rho^{l+1})}{1-\rho}\varepsilon_t\right] \quad 5\text{-}7$$

In the NIS approach, the value of the noise term ($\varepsilon_t$) is assumed as zero by the manufacturer. Thus, using a NIS approach, the manufacturer's forecast will become

$$\hat{Y}_t^{L+1} = \rho \frac{1-\rho^{L+1}}{1-\rho}\left[Y_t\right] \quad 5\text{-}8$$

The manufacturer's forecast in the NIS approach is based only on the previous order and autoregressive coefficient and not on the noise term as shown in equation 5-8. For any AR (p) process, the manufacturer's forecast using the NIS approach will be based on the last p orders and the autoregressive coefficients only, while the noise terms will be assumed to be zero.

Now we consider the following MA (3) process:

$$d_t = \tau + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \theta_3\varepsilon_{t-3} \quad 5\text{-}9$$

Using the upstream demand translation formula by Gilbert (2005), as discussed in sub-section 4.2.2, such a demand process at the retailer will be translated to the following demand process at the manufacturer for a lead time of unity:

$$Y_t = \tau + (1-\theta_1)\varepsilon_t - \theta_2\varepsilon_{t-1} - \theta_3\varepsilon_{t-2} \quad 5\text{-}10$$

In the literature the NIS approach has been presented only for an AR (1) process as discussed in section 5.2. If the NIS approach is applied to the above MA (3) process, the values of the noise terms will be assumed to be zero by the manufacturer. Thus, using a NIS approach, the manufacturer's forecast will simply be the mean of the process as shown in the following equation.

$$\hat{Y}_t^{L+1} = \tau \quad 5\text{-}11$$

For any MA (q) process, the manufacturer's forecast using the NIS approach will be the mean of the process only while the noise terms in the retailer will be assumed to be zero.

Now a new approach, the NIS-Est approach, will be presented. We argue that, for an AR (1) process, the demand at the manufacturer (equation 5-6) can be easily written in terms of the manufacturer's moving average terms shown as:

$$Y_t = \rho Y_{t-1} + a_t - \theta_1^M a_{t-1} \quad \text{5-12}$$

where $a_t, a_{t-1}$ are the noise terms in the manufacturer's demand process at time *t* and *t-1* respectively and $\theta_1^M$ is the moving average parameter.

The lead time forecast by the manufacturer in this case can be shown as:

$$\hat{Y}_t^{L+1} = \frac{1-\rho^{L+1}}{1-\rho}\left[\rho Y_t - \theta_1^M a_t\right] \quad \text{5-13}$$

In the NIS-Est approach, although there is no information sharing among the supply chain members, the manufacturer can still estimate the moving average terms in its demand and utilise the estimated values of these terms for its forecast.

Now we analyse the NIS-Est approach for the MA (3) process. The demand process at the manufacturer (equation 5-10) can be written in the following form:

$$Y_t = \tau + a_t - \theta_1^M a_{t-1} - \theta_2^M a_{t-2} \quad \text{5-14}$$

In the NIS-Est approach, the manufacturer can still estimate the moving average terms in its demand and forecast using these estimated terms. The forecast using the NIS-Est approach will include the mean of the process and the moving average terms compared with the forecast only being the mean of the process in the NIS approach (equation 5-11).

There are two methods by which the manufacturer can mathematically estimate the moving average terms, namely Recursive Estimation and Estimation by Forecast Error (Box et al, 1994; Chatfield, 2003). We adopt the recursive estimation method and discuss the reason for selection of this method in Chapter 7. All other replenishment and ordering policies remain the same as in the NIS approach.

We find that the value of sharing demand information has been discussed in the literature by comparing the demand information sharing approaches with the NIS approach. For an MMSE forecasting method, we argue that, even with a strategy of not sharing demand information, the manufacturer's forecasting approach can be improved by introducing estimation of the moving average terms at the manufacturer.

Stage I of the simulation results (see section 8.2) show the reduction in inventory costs when the NIS-Est approach is used, as compared to the NIS approach. In stages II and III of the simulation and in the empirical analysis, the value of demand information sharing is analysed by considering the NIS-Est approach as the base case.

Now, we move our discussion to the NIS approach for non-optimal forecasting methods. As for this approach, the manufacturer is not aware of the retailer's demand, it will base its lead time forecast on the orders received from the retailer. The equations 3-6 and 3-9 presented in chapter 3 for the retailer's forecasts are adopted here for the manufacturer to represent its SMA and SES forecasts using the NIS approach.

$$\hat{Y}_t^L = L\hat{Y}_{t+1} = L\left[\frac{1}{n}\sum_{i=0}^{n-1} Y_{t-i}\right] \qquad 5\text{-}15$$

$$\hat{Y}_t^L = L[\alpha Y_{t-1} + \alpha(1-\alpha)Y_{t-2} + \alpha(1-\alpha)^2 Y_{t-3} + ... + \alpha(1-\alpha)^{t-2} Y_1 + (1-\alpha)^{t-1} Y_0] \qquad 5\text{-}16$$

For non-optimal forecasting methods, there are no noise term estimation issues and the NIS-Est approach is not relevant. Therefore, the NIS-Est approach is limited to optimal forecasting methods. In simulation (see section 8.6) the value of demand information sharing for non-optimal forecasting methods is analysed by considering the NIS approach as the base case.

### 5.3.2. Centralised Demand Information Sharing

In the literature review presented in sub-section 5.2.1, we explored the DIS approach as discussed by various papers. These papers argue that if a supply chain follows a strategy of sharing demand information, they may use a DIS approach where the downstream member shares its demand information with the upstream member through some formal information sharing mechanism. In this case, the manufacturer is aware of both its order ($Y_t$) from the retailer and the actual demand ($d_t$) at the retailer. In the DIS approach, as the manufacturer is now aware of the demand at the retailer, they can utilise it to calculate the value of the noise terms in the retailer's demand. The manufacturer then uses the order ($Y_t$) received from the retailer and the calculated noise terms at the retailer to forecast its lead time demand.

For example, when the AR (1) demand process at the retailer (equation 5-1) is shared with the manufacturer, the manufacturer can calculate the value of the noise term from this shared demand. The manufacturer can then use equation 5-7 to forecast as now they are aware of the noise in the retailer's demand. A similar argument stands for the case of the MA (3) demand process at the retailer. When this demand process is shared with the manufacturer, the manufacturer can calculate the noise terms from the retailer's demand and use them in its lead time forecast.

The literature review shows that the DIS approach results in lower inventory holdings and inventory costs due to the fact that the manufacturer benefits by forecasting with a true value of $\varepsilon_t$. In the case of a no information sharing strategy, this value of $\varepsilon_t$ is either termed zero (NIS approach) or estimated (NIS-Est approach).

In the DIS approach, the manufacturer uses the order ($Y_t$) from the retailer in their lead time forecast (equation 5-7). The discussion on the Bullwhip Effect, in Chapter 2, summarised evidence that the retailer's order $Y_t$ is more variable than its demand $d_t$. As the manufacturer is aware of the demand $d_t$ at the retailer, the DIS approach can be improved if the manufacturer uses $d_t$ instead of $Y_t$ in making their lead time forecast. This new improved approach is called the Centralised Demand Information Sharing approach (CDIS). In the CDIS approach, the manufacturer utilises the retailer's demand $d_t$ and the noise in the retailer's demand $\varepsilon_t$ instead of $Y_t$ and $a_t$, the noise in the retailer' Thus, in this approach the manufacturer's forecast will be the same as the retailer's forecast as both the retailer and the manufacturer utilise $d_t$ and $\varepsilon_t$ to make their lead time forecast. The manufacturer's forecast using the CDIS approach will be the same as the retailer's NIS-Est forecast. This approach can be used with any ARIMA (p, d, q) process whereby both the retailer and the manufacturer will utilise $d_t$ instead of $Y_t$ and $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-q^R+1}$ instead of $a_t, a_{t-1}, ..., a_{t-q^M+1}$. In the CDIS approach, the manufacturer will be utilising the NIS-Est approach adopted by the retailer. The noise terms at the retailer will be estimated and then the noise terms and the demand at the retailer will be used to forecast the lead time demand.

We now move our discussion to the cases when non-optimal forecasting methods are used by the manufacturer to make their lead time forecast. As discussed in sub-section 5.3.1, there are no demand parameter estimation issues for non-optimal methods. Thus, the DIS approach is not relevant when non-optimal forecasting methods are employed.

When supply chain links share demand information, the CDIS approach can be utilised for non-optimal forecasting methods. As the manufacturer in this case is aware of the retailer's demand, it will utilise the retailer's demand in its lead time forecast. The forecast equations for SMA and SES in the case of the CDIS approach are:

$$\hat{Y}_t^L = L\hat{Y}_{t+1} = L\left[\frac{1}{n}\sum_{i=0}^{n-1} d_{t-i}\right] \qquad \text{5-17}$$

$$\hat{Y}_t^L = L[\alpha d_{t-1} + \alpha(1-\alpha)d_{t-2} + \alpha(1-\alpha)^2 d_{t-3} + ... + \alpha(1-\alpha)^{t-2} d_1 + (1-\alpha)^{t-1} d_0] \qquad \text{5-18}$$

In the simulation for non-optimal forecasting methods (section 8.6), we compare the two approaches of NIS and CDIS to evaluate the value of demand information sharing. While in the NIS approach, the manufacturer forecasts using the orders received from the retailer, in the CDIS approach the manufacturer's forecast is based on the shared retailer's demand.

## 5.4. Conclusions

Sharing demand information has been advocated by many authors, to coordinate decision making among supply chain members. We reviewed four approaches suggested in the literature for sharing demand information, namely No Information Sharing (NIS), Demand Information Sharing (DIS), Vendor Managed Inventory (VMI) and Downstream Demand Inference (DDI).

We argue that the incorporation of the downstream demand in the upstream member's forecast follows exactly the same rules in both VMI and DIS approaches. This is the reason why the papers analysing VMI conclude that there is no difference in the performance metrics of VMI and DIS in terms of inventory costs. VMI incorporates a different replenishment rule, but this is not the focus of this thesis and thus we do not consider VMI in this research. With regards to DDI, we show in Chapter 6 that this approach is not feasible when we consider more relaxed assumptions in the supply chain model.

We further argue that the NIS and DIS approaches can be improved. In this chapter, we introduce two new approaches: NIS-Estimation (NIS-Est) and Centralised Demand Information Sharing (CDIS).

We argue that when the supply chain members adopt the strategy of not sharing demand information, the NIS-Est approach will perform better than the NIS approach. The NIS-Est approach should work better than the NIS approach as it incorporates estimation of the noise term at the manufacturer.

On the other hand, when the supply chain adopts a strategy of sharing demand information, the CDIS approach will be more beneficial than DIS. In this case, because the upstream member has access to the downstream demand, they can use the demand at the retailer and the noise in the demand at the retailer to make their lead time forecast. This should result in the manufacturer's lead time forecast using CDIS being less variable than the DIS approach.

We test these approaches with the help of simulation and empirical analysis. The simulation and the empirical results (Chapters 8 and 9) show that the results for the performance metrics are better for NIS-Est compared to NIS and better for CDIS compared to DIS. The analyses also indicate that CDIS results in the least inventory holdings, inventory cost, Bullwhip Ratio and forecast error compared to the other three approaches.

The approaches used in this research for optimal forecasting methods are summarised in the following table.

| Approaches for Optimal Forecasting Methods | Operational Rules |
|---|---|
| No Information Sharing (NIS) | • Retailer does not share its demand information with the manufacturer.<br>• The manufacturer makes its forecast based on the orders from the retailer and assuming the noise term to be zero. |
| No Information Sharing - Estimation (NIS - Est) | • Retailer does not share its demand information with the manufacturer.<br>• The manufacturer makes its forecast based on the orders from the retailer and by estimating its noise terms. |
| Demand Information Sharing (DIS) | • Retailer shares its demand information with the manufacturer.<br>• The manufacturer makes its forecast based on the shared value of noise at the retailer. |
| Centralised Demand Information Sharing (CDIS) | • Retailer shares its demand information with the manufacturer.<br>• The manufacturer makes its forecast by utilising the demand and the noise in the demand of the retailer. |

**Table 5-1 Supply Chain Approaches for Optimal Forecasting Methods**

For non-optimal forecasting methods, there are no noise term estimation issues and thus the NIS-Est and DIS approaches are not relevant. In this case, we compare only NIS with the CDIS approach.

| Approaches for Non-Optimal Forecasting Methods | Operational Rules |
|---|---|
| No Information Sharing (NIS) | • Retailer does not share its demand information with the manufacturer.<br>• The manufacturer makes its forecast based on the orders from the retailer. |
| Centralised Demand Information Sharing (CDIS) | • Retailer shares its demand information with the manufacturer.<br>• The manufacturer makes its forecast by utilising the demand of the retailer. |

**Table 5-2 Supply Chain Approaches for Non-Optimal Forecasting Methods**

In the following table, we present the approaches used for the optimal and non-optimal forecasting methods in this research.

| Forecasting Methodology | Approaches used in the research |
|---|---|
| Optimal Forecasting Method | NIS, NIS – Est, DIS, CDIS |
| Non-Optimal Forecasting Methods | NIS, CDIS |

**Table 5-3 Approaches for Optimal and Non-Optimal Methods**

In the simulation (Chapters 7 and 8) of this research, we compare all four approaches for the optimal forecasting method and the two approaches, NIS and CDIS, for the non-optimal forecasting methods in terms of the four performance metrics discussed in section 3.7. In the empirical analysis (Chapter 9) we exclude the NIS approach for optimal forecasting methods from the investigation, the reasons for which are explained in section 9.5. Further, as discussed in sub-section 3.7.2, in addition to Mean Squared Error (MSE) we also use mean absolute percentage error (MAPE) to calculate the forecast error in the empirical analysis.

# 6. Downstream Demand Inference

## 6.1. Introduction

In Chapter 4, we discussed upstream demand translation for an Order up to (OUT) inventory policy, examining the mathematical relationships between the demand and order processes in a supply chain link. We further discussed in sub-section 5.5.2 that, based on this upstream translation of demand, and using strict model assumptions, various authors (e.g. Graves, 1999; Raghunathan, 2001; Zhang, 2004b; Gilbert, 2005) maintained that the inverse translation is also possible when the MMSE forecasting method is employed. They argued that the upstream member can infer the demand present at the downstream link, owing to the mathematical tractability of the relationships for the optimal forecasting method. We called this a Downstream Demand Inference (DDI) approach and presented a detailed discussion of it in sub-section 5.2.2.1. If the inverse translation (DDI) is possible, there will be no value of sharing demand information in supply chains.

In this chapter, we analyse the DDI approach using both optimal and non-optimal forecasting methods. We argue that the supply chain models presented in the above papers have very restrictive assumptions. These papers assume that the manufacturer is aware of the demand process and the demand parameters of the retailer even when they are unaware of the demand itself. The claim of no value in sharing demand information in these papers is sensitive to this assumption.

In a real world scenario, supply chain links need to have a formal information sharing mechanism if they decide to share demand information between downstream and upstream members. On the other hand, there is no need to invest in a formal information sharing mechanism if the strategy of the supply chain link is not to share demand information. Thus, it is very unlikely that the supply chain links will invest in a formal information sharing mechanism just to share the information on demand process and parameters and not on the actual value of demand itself.

For an optimal forecasting method (section 6.3), we argue that, under more realistic assumptions, the DDI approach is not feasible. The upstream member cannot infer the downstream demand when they are unaware of the demand process and its parameters at the downstream link.

Then we investigate the DDI approach when non-optimal forecasting methods (section 6.4) are employed. We show that for ARMA processes, in the case of SMA, the demand at the downstream link can be inferred. This is based on the assumption that the upstream member is aware of the number of historical terms (n) used in the SMA forecast. On the other hand, when supply chain links employ SES, DDI is not possible.

## 6.2. Requirements for DDI

We discussed in the previous section that papers advocating DDI have very restrictive supply chain model assumptions. We argue that, in real world supply chains, the upstream members are not aware of the demand process and the demand parameters at the downstream link, and thus relax these assumptions in this thesis (see Chapters 7 and 9).

For DDI, the upstream member needs to first identify the demand process at the downstream link and then estimate the required parameters to calculate the demand. It is shown in this chapter that the identification of the demand process and inference of demand depends on the relationship between the number of autoregressive and moving average parameters and the degree of differencing at the upstream link's demand process.

These two aspects of demand inference will now be addressed.

### 6.2.1. Identification of Demand Process

Results on the upstream translation of demand indicate that, in some cases, the translation is unique: only one demand process at the retailer would translate into a given demand process at the manufacturer. On the other hand, in some cases this translation is not unique: various demand processes at the retailer would translate into the same demand process at the manufacturer. In sub-section 4.2.2, we discussed that an ARIMA (p, d, $q^R$) demand process at the retailer will translate into an ARIMA (p, d, max {p + d, $q^R$ - L}) demand process at the manufacturer. Suppose the demand process is ARIMA (1, 1, 3) at the manufacturer. If the lead time between the manufacturer and the retailer is one and the supply chain links utilise MMSE forecasting methods, such a demand process could only translate from an ARIMA (1, 1, 4) process at the retailer. Thus, if a manufacturer identifies an ARIMA (1, 1, 3) process and its lead time is one, it can easily infer that the demand process at the retailer follows an ARIMA (1, 1, 4). On the other hand, suppose the demand process is ARIMA (1, 1, 2) at the manufacturer. Again, if we assume the lead time to be one, this demand process could propagate from various processes at the retailer, namely ARIMA (1, 1, 3), ARIMA (1, 1, 2), ARIMA (1, 1, 1) and ARIMA (1, 1, 0). In this case, the manufacturer will not be able to infer the demand process at the retailer.

Accurate identification of the demand process at the downstream link depends on whether the propagation is unique. If only one demand process is possible at the downstream link, then accurate identification is feasible. On the other hand, identification is not feasible if a range of demand processes is possible at the downstream link.

### 6.2.2. Calculation of the Demand

In Chapter 4, we examined the upstream translation of the demand process. We discussed that the constant term and the autoregressive terms remain the same, while it is only the moving average terms that are changed. Figure 4-5 shows the relationship that exists between the moving average terms in the downstream and upstream demand processes. Based on this mathematical relationship, the upstream member can calculate the corresponding moving average term at the downstream member, e.g. $\theta_1^R$ can be calculated from $\theta_1^M$ ; $\theta_2^R$ can be calculated from $\theta_2^M$ etc. Thus, calculation of the demand at the downstream member depends on the number of moving average terms at the link. If the upstream member has more than or equal to the number of moving average terms in the downstream link, then they can accurately calculate the demand at the downstream link. This is because the number of equations at the upstream link would be equal to or greater than the number of unknowns at the downstream link.

On the other hand, if the upstream member has fewer moving average terms, then it is not possible to calculate the demand at the downstream link. This is due to the presence of more unknowns than equations at the upstream link. Suppose the demand process at the retailer follows an ARIMA (1, 0, 5). If the lead time from the manufacturer to the retailer is 4, then according to the upstream translation of demand, the demand process at the manufacturer will be ARIMA (1, 0, 1). In this case the manufacturer has only one moving average term (i.e. one equation) as opposed to five moving average terms at the retailer (five unknowns) (see section 4.2). Therefore, it would not be possible to deduce the demand at the downstream link.

## 6.3. Optimal Forecasting Methods

We first analyse the DDI approach when the supply chain members employ an optimal forecasting method. In sub-section 5.2.2, we presented a literature review of the papers claiming that DDI is possible and thus there is no value in sharing demand information. We observe that inferring the demand at the downstream link, or Downstream Demand Inference (DDI), is sensitive to the model assumptions. This has also been acknowledged in other studies, as noted in Chapter 5. Raghunathan (2001) suggested that information sharing has no value only if both the supply chain members are aware of the demand process at the downstream link. Similarly, Graves (1999) has also acknowledged that DIS is valuable if the upstream stage is not aware of the demand parameters of the customer demand process. Based on similar assumptions of known demand process and demand parameters, various other papers (Zhang, 2004b; Gilbert, 2005; Hosoda and Disney, 2006) show that there is no value in sharing demand information.

We argued in sub-section 6.1 that the value of sharing demand information is sensitive to the assumption made in these papers. We show in this section, by relaxing the above two assumptions of known demand process and known demand parameters, that sharing demand information is valuable and Downstream Demand Inference (DDI) is not feasible. By presenting Uncertainty Principles, we state rules about when the manufacturer can accurately identify the demand process at the retailer but not the demand. The rules also show under what circumstances the manufacturer cannot even identify the demand process at the retailer.

### 6.3.1. Uncertainty Principles

PRINCIPLE I. *If the upstream member can identify the demand process at the downstream link, the demand at the downstream link cannot be exactly calculated.*

PRINCIPLE II. *If the upstream member cannot identify the demand process at the downstream link, then the demand at the downstream link can be exactly calculated, if a certain model is assumed from a restricted subset of the possible models.*

According to the Uncertainty Principles stated above, an upstream member in the supply chain cannot infer the demand at the retailer even if they can identify the model present at the downstream link. In some cases, they cannot even identify the demand process at the retailer from a range of feasible models. Calculation of demand in this case is only possible if the upstream member assumes a demand process at the downstream member. In order to prove the Uncertainty Principles, we first establish a rule for downstream demand calculation in the next sub-section, which is based on the requirements for DDI.

### 6.3.2. Rule for Downstream Demand Calculation

The discussion in section 6.2 reveals that, for demand inference, the upstream member needs to first identify the demand process and then calculate the demand at the downstream link. We discussed in sub-section 6.2.1 the circumstances under which the upstream member will be able to identify the demand process at the downstream member. In terms of the second requirement for DDI, which is the calculation of the demand, we present the following rule for the case of an optimal forecasting method.

RULE FOR DOWNSTREAM DEMAND CALCULATION: *An upstream member can accurately calculate the demand at the downstream member only if* $q^R \leq q^M$.

The proof is given in Appendix 6A.

## 6.3.3. Proof of Uncertainty Principles

As discussed in Chapter 4, Gilbert (2005) showed that for an OUT inventory policy and an MMSE forecasting method, an ARIMA (p, d, $q^R$) demand process at the downstream link will always be translated into an ARIMA (p, d, $q^M$) process at the upstream link where $q^M = \max\{p + d, q^R - L\}$. We show in the following sub-sections that Principle I applies when $q^M = q^R - L$ and Principle II applies when $q^M = p + d$.

### 6.3.3.1. Proof of Principle I

If $p + d < q^R - L$, then according to the upstream translation of demand, ARIMA (p, d, $q^R$) will translate into ARIMA (p, d, $q^M$) where $q^M = q^R - L$. Now we look at this translation from the perspective of the manufacturer. The manufacturer identifies its demand process as ARIMA (p, d, $q^M$) and observes that $p + d < q^M$. Based on the upstream translation of a demand we can present the following corollary, which follows immediately from the formula $q^M = \max\{p + d, q^R - L\}$.

COROLLARY 1. *If the demand at an upstream link is ARIMA (p, d, $q^M$) and $p + d < q^M$, then the demand process at the downstream link is ARIMA (p, d, $q^M + L$).*

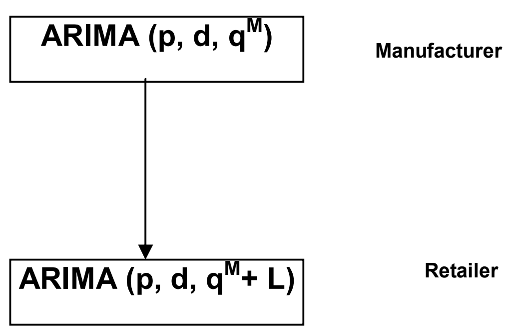


**Figure 6-1 DDI in case of $p + d < q^M$.**

The translation of demand in this case is unique (see sub-section 6.2.1); therefore the upstream member can identify the demand process at the downstream link. On the other hand, it is evident that the retailer has more moving average terms ($q^M + L$) than at the manufacturer ($q^M$) since lead-time (L) is strictly positive (see section 3.1).

Thus, the manufacturer is unable to accurately calculate the demand, as there are more unknowns than equations. Therefore, downstream demand inference in this case is not possible.

Since $p + d < q^M$, the upstream member can identify the demand process at the downstream member (Corollary 1). But they cannot calculate the demand at the downstream member (Rule for downstream demand calculation). This proves Principle I that if the demand process can be identified, then the demand values cannot be calculated.

### 6.3.3.2. Proof of Principle II

If $p + d \geq q^R - L$, then according to the upstream translation of demand, ARIMA ($p$, $d$, $q^R$) will translate into ARIMA ($p$, $d$, $q^M$) where $q^M = p + d$. Looking at this translation from the perspective of the manufacturer, it identifies its demand process as ARIMA ($p$, $d$, $q^M$) and observes that $p + d = q^M$. Based on the upstream translation of demand we can present the following corollary which, again, follows immediately from the formula $q^M = \max\{p + d, q^R - L\}$.

COROLLARY 2. *If the demand at an upstream link is ARIMA ($p$, $d$, $q^M$) and $p + d = q^M$, then the demand at the downstream link is ARIMA ($p$, $d$, $q^R$) where $q^R \in \{0, \ldots, q^M + L\}$.*

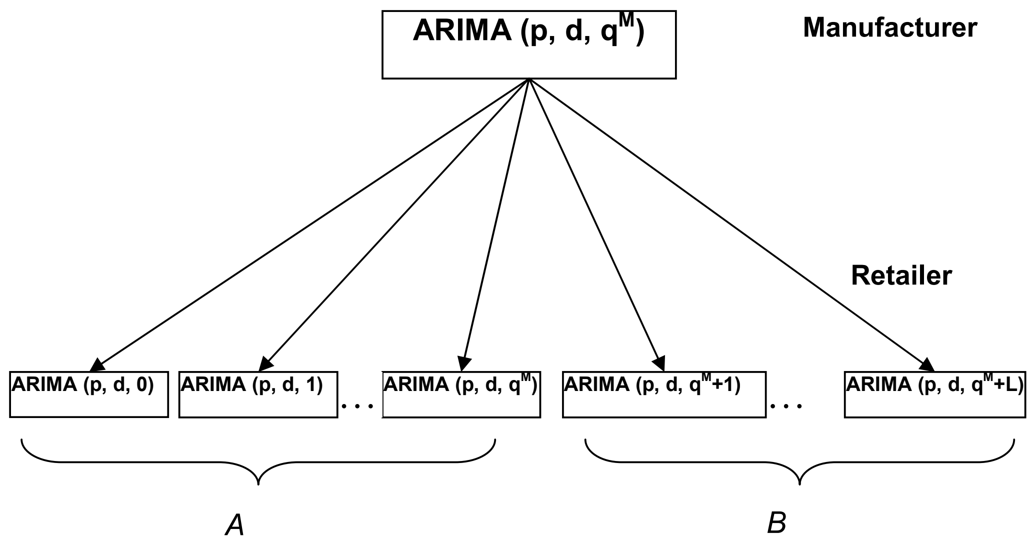


**Figure 6-2 DDI in the case of $p + d = q^M$**

In Figure 6-2:

A = {ARIMA (p, d, 0), ARIMA (p, d, 1) … ARIMA (p, d, $q^M$)}

B = {ARIMA (p, d, $q^M$+1) … ARIMA (p, d, $q^M + L$)}

The translation of demand in this case is not unique (as illustrated by Figure 6-2). There are $q^M$+L+1 possible demand processes at the retailer. Since $L \geq 1$, this means that there are at least two possible processes, and the upstream member will not be able to identify the demand process present at the downstream member.

If the upstream member assumes a demand process from the subset A, then they can exactly calculate the demand at the downstream link owing to the fact that, for demand processes in A, $q^R \leq q^M$. The downstream member has the same or fewer moving average terms than the moving average terms ($q^M$) at the upstream member. Thus, the number of equations at the upstream member will be more than or equal to the number of unknowns.

On the other hand, if the upstream member assumes a demand process from the subset B, then they cannot exactly calculate the demand at the downstream link owing to the fact that for demand processes in B, $q^R > q^M$ (Rule for downstream demand calculation). The downstream member has more moving average terms than the moving average terms ($q^M$) at the upstream member. Therefore, they will have more unknowns than available equations.

We mentioned in section 6.2 that Raghunathan (2001) has argued that DDI is possible for an AR (1) process at the retailer. We will look at the author's model in terms of the findings in this section. The demand process at the manufacturer, in his model, is ARMA (1, 1); therefore, it is case II of the study (i.e. $p + d = q^M$). In the model it is assumed that the manufacturer is aware of the demand process at the retailer, which is AR (1). The retailer demand model lies in the subset A of Figure 6-2 above because it has fewer moving average terms than the manufacturer. As mentioned earlier in this section, if the manufacturer assumes a demand process from subset A, they can accurately deduce the demand at the retailer. Thus, it is only due to the assumption of a known demand process (AR (1)) by the manufacturer that Raghunathan (2001) was able to conclude that DDI is possible. Similar arguments apply to the studies by Graves (1999) where an ARIMA (0, 1, 1) retailer demand process was assumed and Hosoda and Disney (2006) where AR (1) and ARMA (1, 1) retailer processes were assumed. Thus, we demonstrate here the sensitivity of the assumption of a known retailer demand model in these studies.

## 6.4. Non-Optimal Forecasting Methods

In this section, based on the upstream translation of demand, we analyse the possibility of Downstream Demand Inference (DDI) for non-optimal forecasting methods.

### 6.4.1. Downstream Demand Inference for Simple Moving Averages

In Chapter 4, we showed that if the retailer employs Simple Moving Averages to forecast its lead time demand, an ARMA (p, $q^R$) demand process would propagate into an ARMA (p, $q^M$) process at the manufacturer, where $q^M = q^R + n$.

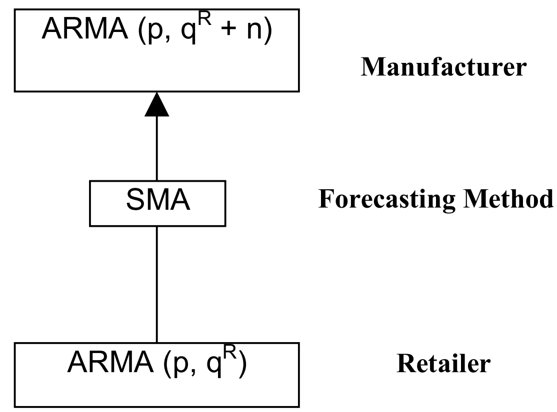


**Figure 6-3 Upstream Demand Translation for SMA**

### 6.4.1.1. Identification of Demand Process

The upstream propagation of demand is unique when the SMA method is used. A unique demand process at the downstream member would translate into a given demand process at the upstream member, as shown in Figure 6-3. Thus, the manufacturer would always be able to identify the demand process present at the retailer, assuming that they know the number of terms used in the Simple Moving Average by the retailer.

### 6.4.1.2. Calculation of the Demand

In the case of SMA, the upstream member would be able to accurately calculate the demand at the downstream member. This is because the downstream member has fewer moving average terms ($q^R$) than the moving average terms ($q^R$ +n) at the upstream member, as shown in Figure 6-3 above. Therefore, the upstream member will have more equations than unknowns.

Thus, DDI is feasible for ARMA processes when it is known that the SMA method is used and the manufacturer is aware of the number of terms (n) included in the average.

### 6.4.2. Downstream Demand Inference for Single Exponential Smoothing

In Chapter 4, we showed that if the SES method is used, then an ARMA (p, $q^R$) demand process would propagate into an ARMA (p, $q^M$) process at the manufacturer, plus another term, where $q^M$ = (t - 1) and t is the number of periods of data history available to the manufacturer.

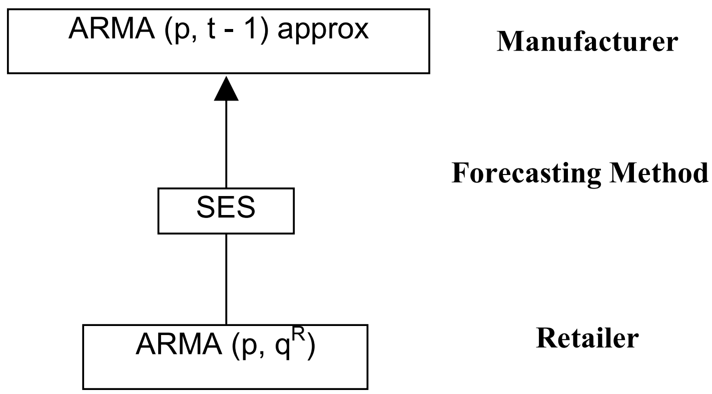


**Figure 6-4 Upstream Demand Translation for SES**

The above figure shows that the propagation of demand in the case of SES is not unique. There could be a range of demand processes present downstream, and the upstream member will not be able to identify the demand process at the downstream member.

In Corollary 2 above (sub-section 6.3.3.2), we discussed a similar demand translation for the case of an MMSE forecasting method where $q^R \in \{0,\dots, q^M + L\}$ and considered cases where the manufacturer makes assumptions about the demand. Although the principle of identification of demand processes for SES is the same, there are two issues that need consideration regarding the manufacturer making an assumption about the demand process. Firstly, a wider range of models could be present at the retailer in the case of SES as $q^R \in \{0,\dots, t - 1 + L\}$. Secondly, the translation for SES is of an approximate nature. Deducing demand at the retailer, based on demand process assumption at the manufacturer is therefore more challenging for SES than for SMA.

## 6.5. Conclusions

There is a stream of research claiming that the upstream member can infer the demand at the downstream member. If this were so, then there would be no value in sharing demand information in supply chains.

We argue that the papers concluding that there is no value of information sharing are based on the assumptions of a known demand process and parameters at the retailer. We argue that the value of information sharing is sensitive to these assumptions and that in a real world supply chain, an upstream member will not be aware of the demand process and parameters at the downstream member. The only way to be aware of demand process and parameters of the downstream link is through some formal information sharing mechanism. When members of a supply chain do share information though some formal information sharing mechanism it is unlikely that such a mechanism will be used to share information on demand process and parameters, but not on the actual value of demand itself.

In this chapter, we analyse the DDI approach using more realistic assumptions. When we examine the optimal forecasting methods, we present Uncertainty Principles to show that it is not possible for the upstream member to infer the demand at the downstream member.

We then move on to discuss the case when supply chain members employ non-optimal forecasting methods. We show that when the supply chain links use SMA for forecasting their lead time demand, the upstream member can accurately infer the demand present at the downstream member owing to the unique propagation of the demand process. When the supply chain links employ SES, the upstream member would not be able to accurately infer the demand at the downstream member. This is owing to the non-unique demand process propagation in this case.

When upstream members in a supply chain forecast using the actual consumer demand, this results in a reduction of the Bullwhip Effect. While various studies claim that this consumer demand can be inferred by the upstream members in the supply chain, we have shown that exact deduction of demand is not possible. For accurate demand, the downstream member will have to share its demand with the upstream member via some formal information sharing mechanism.

# 7. Simulation Design

## 7.1. Introduction

A simulation model represents a situation on a computer in order to study how it has arisen or how it could be improved. The behaviour of a system can be studied by changing the factors affecting it. Robinson (2004) has defined simulation as "*Experimentation with a simplified imitation (on a computer) of an operations system as it progresses through time, for the purpose of better understanding and/or improving the system*".

## 7.2. Rationale for using Simulation

The previous chapter discussed the effect of using different forecasting methods on Downstream Demand Inference and thus on the value of Demand Information Sharing in reducing the Bullwhip Effect. In this chapter, we use simulation to accomplish the following objectives:

- In Chapter 5, we discussed a number of approaches to sharing demand information. We now wish to establish the best approach in terms of various performance metrics (mean squared forecast error, Bullwhip Ratio, inventory holdings and inventory cost). It is very complicated to mathematically calculate the Bullwhip Ratio and forecast error (see section 3.7); thus we require simulation to calculate these values. In terms of inventory holdings, equation 3-15 in sub-section 3.7.3.1 gives only the approximate value of the inventory holdings. The inventory costs obtained, therefore, are also approximate. Simulation helps in assessing the accuracy of the values of inventory holdings and costs.
- We will also explore the sensitivity of the benefit of information sharing to various factors, namely lead time, autoregressive parameters, moving average parameters, demand variance, cost ratio and forecasting method parameters.
- The analytical model shows that, for MA (q) processes, there is no value of the traditional DIS approach. The simulation experiment not only helps us to validate this rule but also quantifies the value of CDIS.

We use simulation in this research not only to test and validate the approximations but also as a bridge linking the analytical model to the empirical analysis.

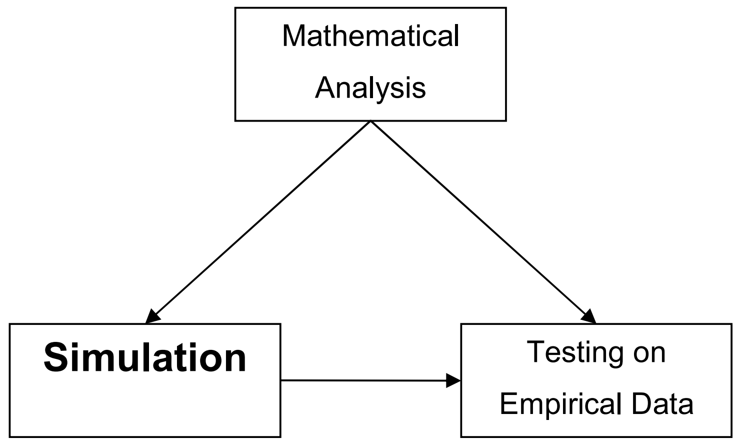


**Figure 7-1 Role of Simulation in the Research Methodology**

Simulation gives a good understanding of how various factors affect the dynamics of the system, by changing one variable at a time.

## 7.3. Simulation Design

In this section, we will discuss some design issues including the range of the factors (lead time, demand parameters, cost ratio, demand variance and forecasting parameters) analysed in the simulation experiment.

### 7.3.1. Demand Process

The literature review (see sub-section 5.2.1) shows that the supply chain models used in most papers are restricted to one or two demand processes. To cover a wider range of ARIMA (p, d, q) models, we generate nine demand processes in the supply chain model. This will help us test models that are addressed in the broader literature. We restrict the model selection to p, d, q $\leq$ 2, as in practice demand can usually be represented by limiting the ARIMA process within this range (Montgomery and Johnson, 1976; Box et al, 1994; Zhang, 2004a).

The following nine ARIMA (p, d, q) models are used in the simulation; ARIMA (1, 0, 0), ARIMA (2, 0, 0), ARIMA (0, 0, 1), ARIMA (0, 0, 2), ARIMA (1, 0, 1), ARIMA (0, 1, 1), ARIMA (0, 2, 2), ARIMA (1, 1, 1) and ARIMA (1, 1, 2).

The above nine models have been chosen, owing to their frequent occurrence in the real world (Roberts, 1982; Box et al, 1994). Another reason for the selection is that there is an optimal smoothing method for some of these models. Single Exponential Smoothing is an optimal forecasting method for ARIMA (0, 1, 1). Similarly, Holt's method is an optimal forecasting method for ARIMA (0, 2, 2) and Dampened Holt's method is an optimal forecasting method for ARIMA (1, 1, 2).

### 7.3.2. Information Sharing Approaches used in Simulation

In Chapter 5, we observed that supply chain links can adopt two strategies in terms of demand information sharing. Either they share the downstream demand information by a formal information sharing mechanism or they do not share the demand information at all. In this research, for the case of not having a formal information sharing mechanism, we discussed the use of two approaches: NIS and NIS-Est. On the other hand, we discussed the DIS and CDIS approaches in the case of a formal information sharing mechanism. NIS-Est and CDIS are new approaches introduced in this thesis which have not been examined via simulation previously.

| **Strategy** | **Demand Information Sharing Approaches** |
|---|---|
| No Formal Information Sharing mechanism | No Information Sharing (NIS) |
| | No Information Sharing – Estimation (NIS-Est) |
| Formal Information Sharing mechanism | Demand Information Sharing (DIS) |
| | Centralised Demand Information Sharing (CDIS) |

**Table 7-1 – Approaches in the Simulation Experiment**

### 7.3.3. Stages of the Model

The mathematical models found in the literature are restricted by various assumptions, which may not show the real value of information sharing. In this thesis, we argue that real world modelling requires less restrictive assumptions. In real world supply chains, the demand process and its parameters are not known and they need to be estimated (Cheng and Wu, 2005) and thus sharing demand information may be of value for the supply chain members (Gavirneni et al, 1999). Hence, the review of the literature reveals the need to incorporate more realistic assumptions into supply chain modelling. This may help in the analysis and quantification of a more pragmatic value of sharing demand information in supply chains.

Moving away from a model having a number of restrictive assumptions directly towards a less stringent model creates a very complex and confusing environment. We would not be able to analyse the relationship between the value of sharing demand information and each of these assumptions and appreciate the magnitude of these effects individually. Therefore, we have developed three stages in the supply chain model to allow staged relaxation of model assumptions. In stage I, we assume that the demand process and its parameters are known. Then, in stage II, we assume that only the demand process is known. Finally, in stage III, both the demand process and demand parameters are not known.

We have designed the simulation experiment in order to have a stage-wise comparison of the performance metrics of all the approaches to demand information sharing. We now present the structure of each of these three stages.

#### 7.3.3.1. Stage I

In this stage, we assume that the manufacturer is aware of their own demand process and the demand parameters. In addition, they are also aware of the demand process and the demand parameters at the retailer.

In this stage, the problem of deducing the demand at the retailer is analytically solvable and simulation is not required for the purpose of demand inference. One of the performance metrics we use in this stage to quantify the value of sharing demand information is average inventory holdings. In Chapter 3, we have used an approximate equation (see equation 3-15) to calculate inventory at the manufacturer. Furthermore, the other performance metrics (inventory cost, Bullwhip Ratio and forecast error) also need to be calculated via simulation.

Thus, simulation in this stage helps us to check the accuracy of the approximation for average inventory holdings and also to calculate the other performance metrics in order to quantify the value of sharing demand information.

#### 7.3.3.2. Stage II

One of the limitations in the supply chain models presented in the literature is the assumption of known demand parameters. In stage II of the simulation experiment, we relax this assumption and use estimation procedures to estimate the demand parameters at both the manufacturer and the retailer. These estimated demand parameters are then used to deduce the demand at the retailer. Details of the estimation procedures used in the simulation are further discussed in sub-section 7.3.5.

In this stage, the manufacturer is aware of its own demand process and that of the retailer. However, they are unaware of the exact values of their own demand parameters and those of the retailer.

#### 7.3.3.3. Stage III

Stage III has been designed to reflect more closely a real world scenario. In this stage, we relax the restriction of known demand processes. Thus, in this stage, the manufacturer is not aware of its demand process and demand parameters. They are also unaware of the demand process and demand parameters of the retailer. In Stage III, both supply chain links will identify their demand process as well as estimate their demand parameters.

### 7.3.4. Stages and Approaches for Non-Optimal Forecasting Methods

In the previous sub-sections, we presented the four approaches and three stages for relaxation of assumptions in the simulation experiment. These approaches and stages are based on ARIMA process identification and parameter estimation.

The staged relaxation has been designed in order to incorporate process identification and parameter estimation. In addition, both the NIS-Est and DIS approaches are based on estimation of parameters. However, non-optimal forecasting methods do not require demand parameter estimation or process identification. Therefore, the staged relaxation of assumptions is not required for non-optimal forecasting methods. In addition, the NIS-Est and DIS approaches are not relevant to non-optimal forecasting methods. Thus, we restrict the simulation of non-optimal methods to NIS and CDIS approaches for Stage I only.

In the following table we summarise the stages and the approaches for the optimal and non-optimal forecasting methods.

| **Forecasting Methodology** | **Stages** | **Approaches** |
|---|---|---|
| Optimal Method | I, II, III | NIS, NIS-Est, DIS, CDIS |
| Non-Optimal Methods | I | NIS, CDIS |

**Table 7-2 Stages and Approaches**

### 7.3.5. Estimation of Demand Parameters – Stage II

One of the limitations discussed in the literature review on supply chain models is that the demand parameters are assumed to be known. By contrast, we have assumed in Stage II that these parameters are not known but need to be estimated by the supply chain links. Thus in the simulation the supply chain links will estimate the parameter vectors $\mathrm{P}, \Theta$ and $\mathrm{E}_t$ where:

$P = (\rho_1, \rho_2, ..., \rho_p)$, $\Theta = (\theta_1, \theta_2, ..., \theta_q)$ and $\mathrm{E}_t = (\varepsilon_{t-1}, \varepsilon_{t-2}, ..., \varepsilon_{t-q})$.

In the time-series literature (e.g. Koreisha and Pukkila, 1990; Box et al, 1994; Chatfield, 2003; Kapetanios, 2003) two procedures have been discussed to estimate the model parameters for an ARIMA (p, d, q) process: Least Squares (LS) and Maximum Likelihood (ML).

For moderate and long data histories, the likelihood estimate gives a very close approximation to the least squares estimate (Box et al, 1994). There have been various studies (Hannan and Rissanen, 1982; Koreisha and Pukkila, 1990; Sabiti, 1996; McKenzie, 1997; Kapetanios, 2003) suggesting that the accuracy of Ordinary Least Squares (OLS) is comparable to ML estimates. As the data histories employed in this research are of moderate length (up to 104 observations) we employ OLS; it is simpler to compute than ML, and will give very similar results.

The *autoarima* function, of the C Library, has been used to perform estimation via the Ordinary Least Squares method in the simulation to estimate the parameters.

### 7.3.6. Identification of Demand Process – Stage III

In section 5.2, we saw that the papers discussing demand information sharing assume that the supply chain members are aware of their demand process. In addition, they assume that, even in the case where a No Information Sharing strategy is assumed, the upstream member knows the demand process at the downstream link. We argued in sub-section 7.3.3 that the demand process is not known in real world supply chains and needs to be identified. In stage III of the simulation experiment we relax the assumption of known demand processes. The supply chain links must identify the most appropriate ARIMA models to represent their demand processes.

The final selection of the model is based on the idea of balancing the risks of under-fitting and over-fitting and the model is chosen by minimising a penalty function. There are two criteria discussed frequently in the literature: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

$$\ln \hat{\sigma}^2 + \frac{2(p+q)}{n}$$ AIC (Akaike, 1974) 7-3

$$\ln \hat{\sigma}^2 + \frac{(p+q)\ln n}{n}$$ BIC (Rissanen, 1978; Schwarz, 1978) 7-4

where $\hat{\sigma}^2$ is the estimate of the variance of the noise term derived directly from the residuals of the ARIMA (p, d, q) fit and n is the effective number of observations given by n = N-d-p, where N is the total number of observations.

The first term in the above equations is simply a penalty for under-fitting. On the other hand, the second terms are directly proportional to the number of ARMA parameters and is a penalty for over-fitting. For $n \geq 8$, the penalty imposed for the number of estimated model parameters is greater in the BIC criterion than in AIC. Thus, the use of minimum BIC for model selection will result in a model whose number of parameters is no greater than that chosen by AIC. Harvey (1993) argues that there is evidence to suggest that AIC has a tendency to pick ARMA models that are over-parameterised compared to BIC and thus the BIC is a more satisfactory criterion than AIC. The BIC criterion is also used in well-known forecasting software packages, such as *Forecast Pro* (Goodrich, 2000). The *autoarima* function used in this research uses the BIC criterion to select the final ARIMA process for the given data series.

### 7.3.7. Series Splitting Rules

Process identification and parameter estimation require the specification of series splitting rules to be employed in the research. The time series is divided into two parts, namely the estimation and the performance measurement periods. As the discussion in this thesis relates specifically to the effect on the inventory of an upstream member (e.g. the manufacturer) we divide the first part into two sub-parts i.e. "retailer initial estimation period" and the "retailer and manufacturer estimation period". Now we discuss these parts in detail.

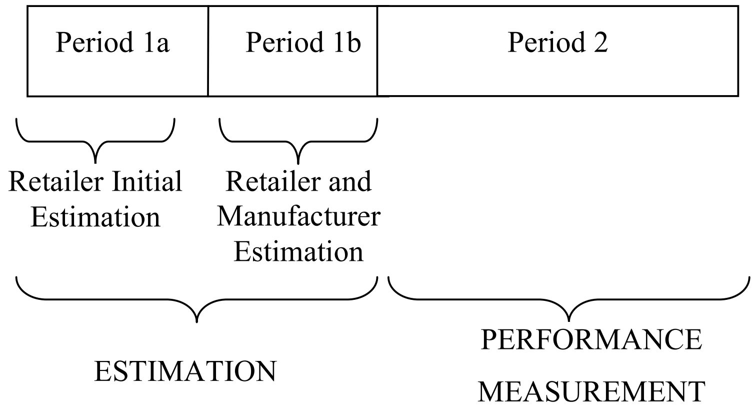


**Figure 7-2 – Series Splitting Rules**

### 7.3.7.1. Estimation Period

In this period, the demand process is identified and the demand parameters are estimated at both the retailer and the manufacturer. In period 1a, we generate the retailer's demand, from which the retailer estimates an initial set of parameters. In period 1b, we not only generate the retailer's demand, but also the manufacturer's demand with the help of the initial estimated parameters from 1a. Finally, the demand parameters for both the retailer and the manufacturer are estimated from 1b.

In No Information Sharing approaches, the manufacturer is not aware of the demand series at the retailer and the process identification and parameter estimation takes place from its own demand series. As the manufacturer's demand series is available only in period 1b, the identification and estimation takes place in period 1b in the No Information Sharing approaches. In order to make a fair comparison between the No Information and Information Sharing approaches, the retailer's parameter estimates from 1a are not used for initialisation of parameter estimation in 1b.

### 7.3.7.2. Performance Measurement Period

The final estimates from the first period are utilised in the Performance Measurement period and there is no further updating of parameters in this period. These estimates are then utilised to test the forecasting and inventory performance of all approaches. In section 3.7, we discussed the four performance measures that will be used in the simulation experiment: mean squared error, Bullwhip Ratio, inventory holdings and inventory cost.

The splitting rules are not relevant in the case of non-optimal forecasting methods and in Stage I for optimal forecasting methods as there is no estimation involved in these two cases. However, in Stages II and III for optimal forecasting methods, the total time series of 100 periods are split into two equal parts of 50 each for the estimation and performance measurement periods. Further, the estimation period has been split into two equal parts of 25 periods for 1a and 1b, as shown in Figure 7-2.

### 7.3.8. Demand and Order Generation

In this section, we will discuss how the demand is generated at the retailer and how it propagates to the upstream members.

#### 7.3.8.1. Demand Generation

In order to generate the demand at the most downstream link, i.e. the retailer, a standard normally-distributed random number is first generated by the Box-Muller method (Box and Muller, 1958). This is then multiplied by the standard deviation $\sigma$ of the noise term to calculate the noise term $\varepsilon_t$. Demand is generated according to the specified values of p, d and q for the ARIMA (p, d, q) demand process using different ranges of the autoregressive parameters ($\rho_1, \rho_2, ..., \rho_p$) and moving average parameters ($\theta_1, \theta_2, ..., \theta_q$) to be discussed further in sub-section 7.3.10.1.

#### 7.3.8.2. Order Generation

The simulation model assumes that the links in the supply chain use the order-up-to (OUT) policy to calculate the order-up-to level. This has already been discussed in detail in section 3.4.

According to the OUT policy, the order to the next upstream link is the current demand plus any change in the order up to level. Thus, we use this equation to generate the order to the next upstream link. This has already been discussed in detail in sections 3.5 and 3.6.

### 7.3.9. Anti-Bullwhip Effect

In section 2.4, we discussed the Anti-Bullwhip Effect (ABE) phenomenon. As the objective of this research is to minimise the amplification of demand variance (the Bullwhip Effect), ABE is out of the scope of the research. In the simulation experiment, for an optimal forecasting method, we simulate only the Bullwhip Effect (BE) region. In section 2.4, we presented a review of the papers discussing the bullwhip region for stationary ARIMA processes (Lee et al, 2000; Li et al, 2005; Hosoda and Disney, 2006; Luong and Phien, 2007). For non-stationary processes used in simulation, we simulate within the stationary and invertibility regions, and then choose parameters exhibiting the Bullwhip Effect.

The simulation results have shown that the ABE phenomenon does not occur for SMA and SES methods. The only exception is when SES is used for ARIMA (0, 1, 1) as then SES becomes an optimal method for the demand process. In order for the simulation experiment to be consistent for all forecasting methods, we use the same range for SMA and SES methods as used for the MMSE method.

### 7.3.10. Impact of Various Factors

Earlier, we discussed the need to simulate nine different demand processes. In this section, we look at the factors that may affect the value of sharing demand information in supply chains. The mathematical analysis for AR (1) (Lee et al, 2000) suggests that noise in the retailer's demand, the lead time from the supplier to the manufacturer, the demand parameters and the cost ratio (ratio of penalty to total cost) all affect the value of sharing demand information. Thus, we simulate the effect of these factors on all nine demand processes. When we use the SMA forecasting method, we also look at the effect of the number of terms used in the moving averages on the value of sharing demand information. In the case of SES, we look at the effect of the smoothing constant on the value of sharing demand information.

| Factors | Forecasting Methods |
|---|---|
| Demand Parameter Vectors ( $P, \Theta$ )<br>Std Dev (σ) in the Retailer's Demand<br>Lead Time (L) from the Supplier to the Manufacturer<br>Penalty Cost / Holding Cost Ratio | MMSE, SMA and SES |
| Number of Terms (n) used in Simple Moving Average | SMA |
| Smoothing Constant (α) | SES |

**Table 7-3 Factors affecting the Value of Demand Information Sharing**

In the following sub-sections we present the range of values for each of the above factors.

### 7.3.10.1. Demand Parameters

The regions of demand parameters selected in this research ensure that the demand processes are stationary and invertible. In addition, as discussed in the previous sub-section, the regions of demand parameters are restricted to those that lie within the Bullwhip Effect (BE) region. Although, for non-optimal forecasting methods, the Bullwhip Effect is observed in the whole stationary and invertible region, the same parameter ranges have been used as in optimal methods for consistency (see sub-section 7.3.9)

In the following table (Table 7-4) we present the demand ranges used in the simulation experiment.

| **Demand Process** | **Regions of values of $\mathrm{P}$ and $\Theta$ - based on the process being stationary, invertible and within the bullwhip region** |
|---|---|
| ARIMA (1, 0, 0) | $0 < \rho < 1$ |
| ARIMA (2, 0, 0) | $0 < \rho_1 < 2$<br>$0 < \rho_2 < 1$ |
| ARIMA (0, 0, 1) | $-1 < \theta < 0$ |
| ARIMA (0, 0, 2) | $-2 < \theta_1 < 0$<br>$-1 < \theta_2 < 0$ |
| ARIMA (1, 0, 1) | $-1 < \rho < 1$<br>$-1 < \theta < 1$<br>$\rho > \theta$ |
| ARIMA (0, 1, 1) | The bullwhip regions for non-stationary demand processes are unknown. Various parameter regions were simulated within stationary and invertibility regions and parameters were selected where amplification in demand variance was experienced. |
| ARIMA (1, 1, 1) | |
| ARIMA (0, 2, 2) | |
| ARIMA (1, 1, 2) | |

**Table 7-4 Range of Demand Parameters (Box et al, 1994, Li et al, 2005)**

None of the papers discussed in the literature review of the ABE (see section 2.4) analyse the parameter regions for the Bullwhip Effect for the non-stationary processes. In order to resolve this issue, we simulate various parameter regions for all the non-stationary processes and select the parameter values where we find an amplification of the demand variance.

### 7.3.10.2. Range of Values of Noise in the Retailer's Demand

We will assume that there is noise variance of 10, 50 and 100 in the demand generated. These values have also been used in Lee et al (2000) and Raghunathan (2001), while Li et al (2005) assumed the value to be 50. When we look at the effect of other factors on the value of information sharing, we assume the variance to be 50.

The rationale for the above choice of range of variance of noise is based on the comparison with previous papers (Lee et al, 2000; Raghunathan, 2001; Li et al, 2005). Real data may exhibit greater variability; the effects of such high variances are assessed in sub-section 9.7.4 of the empirical analysis.

#### 7.3.10.3. Range of Lead Times from the Supplier to the Manufacturer

We simulate Lead Times from the manufacturer to the retailer ($l$) and from the supplier to the Manufacturer ($L$) of 1, 6 and 12 periods. Lee et al (2000) and Raghunathan (2001) used simulation lead time values from 1 to 10 and kept 10 as constant when looking at the effect of other factors. When we look at the effect of other factors on the value of sharing demand information, we assume $L$ =12.

Lee et al (2000) has shown that $l$ has a slight effect on the manufacturer's inventory in the case of the DIS approach. Therefore, we only experiment by changing the value of ranging the value of L. In all replications, we assume that the retailer's and the manufacturer's lead times are equal i.e. $l = L$. One further scope for refinement of this research is to study the effect of $l$ on the value of information sharing.

#### 7.3.10.4. Range of Values of the Cost Ratio

As shown by Lee et al (2000), there is an effect of the Cost Ratio (as discussed in sub-section 3.7.3.1) on the value of sharing demand information for an AR (1) process. They assumed the value of the penalty cost to be 25 and that of the inventory holding cost to be 1. We use three values of the penalty cost, namely 2, 25 and 50, to evaluate the effect of the cost ratio on the value of information sharing. When we look at the effect of other factors, we assume the penalty cost to be 25.

#### 7.3.10.5. Forecasting Method Parameters

We have used three forecasting methods in the simulation program to forecast the lead time demand. These are the Minimum Mean Squared Error (MMSE) forecast, Single Exponential Smoothing (SES) and Simple Moving Averages (SMA). The MMSE forecast utilises the range of parameters which lie within the stationary, invertibility and bullwhip regions, as shown in Table 7-4.

For non-optimal methods, we choose parameter ranges for forecasting methods based on expert recommendation. For SES, the range recommended for the smoothing parameter (alpha) is between 0 and 1 (Gardner, 1985; Gardner, 2006). Thus, we use

0.1, 0.3 and 0.8 in the simulation. When we look at the effect of other factors, we assume the smoothing constant to be 0.3.

The range of number of terms in SMA is taken to be 3, 6 and 12 periods (Johnston et al, 1999; Boylan and Johnston, 2003). When we look at the effect of other factors, we assume the number of terms to be 6.

### 7.3.11. Performance Metrics

This has been discussed in detail in Chapter 3. The simulation program will result in calculating the values of the following performance metrics for the four approaches:

- Forecast Error (Mean Square Error)
- Bullwhip Ratio
- Average Inventory Holdings
- Average Inventory Costs

The measurements of the above performance metrics have been discussed in detail in Chapter 3. In the empirical analysis we also use Mean Absolute Percentage Error (MAPE) and compare the MSE with the MAPE results.

## 7.4. Technical Details

The simulation code is written in Visual Studio.net. The simulation is designed in such a way that the length of the data series and the number of replications can be varied. We simulate 2000 data series of 100 observations for each demand model. The process is repeated every time the simulation experiment is run. The simulation is run a number of times to ascertain the effect of factors by assuming different values of these factors, as discussed in this chapter. The results for all performance metrics are recorded for the 2000 series and then averaged.

In stages II and III, we use the *autoarima* function of the C Numerical Library (developed by Visual Numeric) for process identification and parameter estimation. The *autoarima* function automatically identifies the order of the ARIMA process and determines the parameters of the process. We use the Grid-Search method of the *autoarima* function for process identification and parameter estimation. The Grid-Search method in *autoarima* gives the option of specifying the range of the possible combinations of candidate values of p, d and q. The function then identifies the optimum values of p, d and q according to the BIC measure and returns these values in the form of an array. The function also estimates the constant term, the moving average parameters and the autoregressive parameters for the given time series based on an ordinary least squares method.

## 7.5. Verification

Davis (1992) defines verification as the process of ensuring that the model design has been transformed into a computer model with sufficient precision. Steps taken in order to verify the simulation model used in this research are summarised below:

- The Visual Basic code has been read through to ensure that the right data and logic have been entered.

- Visual checks have been carried out by stepping through the model at every event. This option is provided by default by the computer software Visual Basic.Net.

- A selection of the time series generated by the simulation has been exported to Microsoft Excel where the mean and standard deviation of the series have been verified by using the built-in Excel functions.

- The selection of demand parameters was made to ensure they lie within the Bullwhip Effect region. For each time series generated by the simulation experiment, the variances of the demand and order of the retailer were checked to verify that there is amplification in the demand variance.

- The same supply chain model was designed in Microsoft Excel and inventory costs were compared for selected series. The results of both models were found to be exactly the same.

- The simulation experiment in Lee et al (2000) was replicated by using the same values of lead time, standard deviation in the noise and the autoregressive parameter in the simulation of this research. The results were then compared and the performance metrics of both the research were found comparable (see section 8.4).

## 7.6. Conclusions

In Chapter 5, we presented four demand information sharing approaches. We use four performance metrics in this simulation experiment, namely forecast error (MSE), Bullwhip Ratio, inventory holdings and inventory cost. Simulation is used in this research to establish comparisons between the different approaches in terms of the four performance metrics. The first reason to use simulation is that the first two performance metrics, mean squared forecast error and Bullwhip Ratio, are very complex to analyse mathematically. Secondly, the mathematical analysis in this research incorporates an approximate inventory holdings equation. As the inventory cost calculation is based on inventory holdings, the values of inventory costs are also of an approximate nature.

The literature review shows that all papers restrict their simulation to one or two demand processes. In order to obtain more comprehensive results than previous authors, we simulate nine different demand processes. The mathematical analysis for AR (1) (Lee et al, 2000) suggests that noise in the retailer's demand, the lead time from the supplier to the manufacturer, the demand parameters and the cost ratio affect the value of DIS. Thus, we look at the effect of these factors on all nine demand processes. When we use the SMA forecasting method, we also look at the effect of the number of terms used in the moving average on the value of information sharing. In the case of SES, we look at the effect of the smoothing constant used on the value of information sharing. We calculate the four performance metrics for all four information sharing approaches for three stages in the case of optimal methods. For non-optimal methods, we compare two approaches for only the first stage of the analysis (see Table 7-2).

# 8. Simulation Results

## 8.1. Introduction

Following the discussion on the design of the simulation experiment in the previous chapter, we dedicate this chapter to the presentation and discussion of the results of the experiments. The results for the MMSE forecasting method are presented for each of the three stages. Then we move on to the discussion for the two non-optimal forecasting methods.

One of the main aims of this chapter is to provide insights into the performance of different approaches to demand information sharing. For the optimal forecasting methods, the performance of CDIS is compared with the two No Information Sharing approaches and the traditional Demand Information Sharing approach. In the case of non-optimal forecasting methods, the comparison is limited to CDIS and NIS, as NIS-Est and DIS are not relevant in this case (see sub-section 7.3.4).

We also wish to look at the effect of various factors (lead time, demand variance, autoregressive parameters, moving average parameters, cost ratio and forecasting method parameters) on the value of sharing demand information. Finally, the analytical model (see sub-section 4.2.3.1) shows that for MA (q) processes, there is no value of the DIS approach. We not only validate this analytical result via simulation, but also quantify the value of demand information sharing by comparing the other approaches with the CDIS approach.

We start the discussion of the results for the MMSE forecasting method by presenting a comparison between the three stages for each of the nine demand processes. We then proceed to a detailed discussion of the results of Stage I, where we show how the demand parameters, demand variability, lead time and cost ratio affect the value of CDIS by comparing it with the other three approaches, namely NIS, NIS-Est and DIS. The discussion on the results for Stages II and III is then presented and in this case we also look at the effect of the length of demand history, demand variability, process identification and parameter estimation method. We have discussed in Chapter 3 that the nature of MMSE forecasting in the ARIMA methodology requires a NIS-Est approach and therefore the supply chain links should not utilise a NIS approach. In the next section, while presenting the results of Stage I, we will also establish that NIS always results in higher inventory costs compared to the other three approaches. Thus, we show the value of CDIS in Stages II and III by comparing it only with NIS-Est and DIS.

The results for non-optimal forecasting methods are then presented. As discussed in Chapter 5, for non-optimal forecasting methods there are no noise term estimation issues and therefore the NIS-Est and DIS approaches are not relevant. The results for non-optimal forecasting methods are thus presented by comparing only NIS with the CDIS approach.

## 8.2. Performance of CDIS for Optimal Forecasting Methods

As mentioned above, when the supply chain links use the MMSE forecasting method (optimal forecasting method), there are different demand information sharing approaches. In order to discuss the performance of CDIS, we compare the reduction in inventory holdings, inventory costs and forecast error with the other approaches.

Before moving on to a detailed discussion of the results, we present three rules regarding the performance of demand information sharing approaches that are based on the simulation results. These rules apply to the Bullwhip Effect regions for all demand processes used in the simulation experiment.

### 8.2.1. Rules for Sharing of Demand Information

In this chapter, we establish the following three rules based on the results of the simulation experiment.

***Rule 1: Supply Chains with No Information Sharing Strategy***

**NIS-Est results in lower inventory cost than NIS for all demand processes investigated, except for pure moving average processes, in which case the inventory costs are the same.**

The simulation results show that the NIS-Est results in lower inventory cost, averaged over all replications, than the NIS approach, except for pure moving average processes. For these processes, the inventory cost remains the same due to their conversion into a random process as discussed in sub-section 4.2.3.1.

The NIS approach, as presented by various papers, involves the calculation of a forecast by assuming the noise term to be zero. On the other hand, we introduce the NIS-Est approach whereby the manufacturer estimates the noise term by its order history. In this case, by utilising an estimate of the noise term, the lead-time forecast results in reduced forecast error (as measured by MSE) and thus savings in inventory cost.

***Rule 2: Supply Chains with an Information Sharing Strategy***

**In all demand processes investigated, CDIS results in lower inventory costs compared to DIS**

The simulation results in this chapter show that, for all nine demand processes, in the case of an information sharing strategy, CDIS results in lower inventory cost, averaged over all replications, than the DIS approach.

In the DIS approach, the manufacturer makes its lead time forecast based on the value of the retailer's noise term. On the other hand, in the CDIS approach, the manufacturer not only shares the demand but also utilises the retailer's forecast in its lead-time forecast. In this way, the variability of the manufacturer's lead time forecast decreases.

***Rule 3: Supply Chains with or without an Information Sharing Strategy***

**In all demand processes investigated, CDIS results in lower inventory costs compared to NIS-Est**

The inventory cost in the case of CDIS is always less (averaged over all replications) than the inventory cost for an NIS-Est approach. Thus, the performance of CDIS in terms of inventory cost is the best among the four approaches discussed in the research.

These three rules are summarised in Figure 8-1 below. An approach is said to be a "winner" if, for all demand processes investigated, the average inventory cost is less than or equal to that of the alternative approach, averaged over all replications.

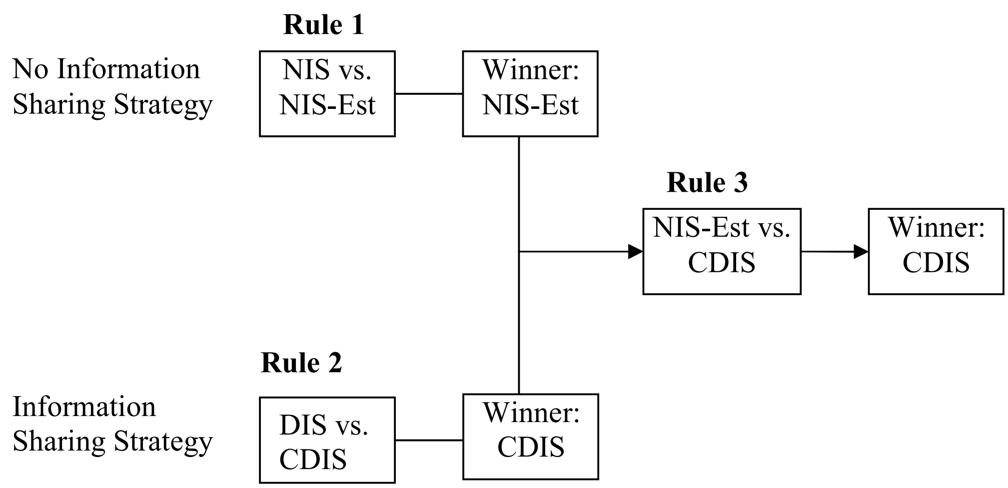


**Figure 8-1 Inventory Cost Comparison of Information Sharing Approaches**

### 8.2.2. Performance of CDIS

Now we move on to the presentation of results to show that, for optimal forecasting methods, on average, CDIS results in the lowest MSE, Bullwhip Ratio, inventory holdings and inventory cost among all the approaches in all stages. Overall, in all simulation runs, irrespective of the demand process and demand parameters, we observe that CDIS results in the least inventory cost.

Lee et al (2000) showed that, in the case of an AR (1) process at the retailer, there is value in information sharing. Lee et al (2000) compared the NIS and DIS approaches and concluded that DIS is valuable in terms of reduced inventory costs. The simulation results in section 8.4 show that the magnitude of savings, as found from this simulation, is comparable with the results of Lee et al (2000). The simulation design also permits comparisons among the two new approaches, NIS-Est and CDIS. Further, we also experiment allowing different model assumptions.

In stage I, we assume that the retailer and the manufacturer are aware of the demand processes and the demand parameters. As discussed in Chapter 5, the value of CDIS derives from the fact that the manufacturer forecasts with the less variable consumer demand. When we relax the assumption of known demand parameters in Stage II, we observe that the percentage reduction in inventory costs by using CDIS compared with the other three approaches is higher than in Stage I. This percentage reduction increases further when, in Stage III, we also relax the assumption of known demand processes. Thus, the value of CDIS is highest in stage III, less in stage II and is least in stage I. As discussed in sub-section 7.3.3, we perform staged relaxation in the study in order to look at the effect of different assumptions on the value of CDIS. Stage II is one step away from the strict mathematical model, while Stage III has been designed to more closely reflect a real situation, where the supply chain links need to first identify the demand process and estimate their parameters before making the forecast. One of the reasons for the high value of CDIS in stages II and III, as established in this chapter, is inherent in the identification and estimation in ARIMA modelling. It is quite possible for the supply chain links to identify the wrong demand process and/or estimate demand parameters inaccurately. Now, upstream translation of demand shows that the demand process always becomes more variable as it moves up the supply chain. Thus, in the case of DIS and CDIS, as the identification and parameter estimation is done through the retailer's demand, the probability of more accurate identification and estimation is higher. Thus, forecasting with more precise demand process and parameters results in lower inventory costs. Compared to DIS, as the forecasting in CDIS is done through a less variable demand process, CDIS results in the lowest inventory cost in all stages. In the following table (Table 8-1), we present an average of percentage savings in inventory costs for all simulation runs for an AR (1) process for the three stages. We first find that CDIS results in the least inventory cost among all approaches. We also find that as we relax assumptions, moving towards a more realistic supply chain, the value of Centralised Demand Information Sharing increases.

| Stages | Percentage savings in inventory cost by using CDIS compared with | | |
|---|---|---|---|
| | NIS | NIS-Est | DIS |
| Stage I | 32.1 | 10.8 | 7.6 |
| Stage II | - | 63.0 | 25.8 |
| Stage III | - | 72.0 | 33.8 |

**Table 8-1 Comparison of three Stages for an AR (1) Process**

As mentioned above, previous findings are limited to an AR (1) demand process at the retailer. In this research, we have simulated nine different demand processes (see sub-section 7.3.1 for details) to look at the effect of the demand process at the retailer on the value of CDIS. The percentage reductions in inventory cost are calculated by assuming the lead time to be 12 (see sub-section 7.3.10.3). The simulation results show that the value of CDIS is demand process dependent: the percentage inventory savings depends on the nature of the demand process. This is shown in Table 8-2 below.

| Demand Process | Percentage Reduction in Inventory Cost by using CDIS compared to | | | | | |
|---|---|---|---|---|---|---|
| | NIS-Est | DIS | NIS-Est | DIS | NIS-Est | DIS |
| | Stage I | | Stage II | | Stage III | |
| AR (1) | 10.8 | 7.6 | 63.0 | 25.8 | 72.0 | 33.8 |
| AR (2) | 41.0 | 11.7 | 71.4 | 38.2 | 74.4 | 41.0 |
| MA (1) | 2.3 | | 48.8 | 31.5 | 53.8 | 35.0 |
| MA (2) | 7.5 | | 59.6 | 21.5 | 63.0 | 28.8 |
| ARMA (1, 1) | 4.9 | 4.4 | 49.6 | 35.8 | 58.3 | 41.2 |
| ARIMA (0, 1, 1) | 39.9 | 17.8 | 46.5 | 22.3 | 63.3 | 45.4 |
| ARIMA (1, 1, 1) | 58.6 | 27.8 | 72.2 | 57.2 | 84.2 | 61.0 |
| ARIMA (1, 1, 2) | 57.7 | 21.4 | 74.4 | 34.6 | 86.7 | 52.5 |
| ARIMA (0, 2, 2) | 79.3 | 48.1 | 81.4 | 49.8 | 83.0 | 58.0 |

**Table 8-2 Demand Process Dependent value of CDIS in three stages**

Table 8-2 shows the demand process dependent behaviour of CDIS. In stationary processes, the pure autoregressive demand processes yield higher percentage savings, by using CDIS, compared to moving average or mixed processes. Pure moving average processes result in very low improvement. The results for percentage reduction in using CDIS compared to DIS and NIS-Est are the same for the pure moving average processes for stage I. The reason is the conversion of these processes into a random process as discussed in sub-section 4.2.3.1, yielding the same results for DIS and NIS-Est.

From Table 8-2, we also observe that the savings in inventory costs are greater when the demand process is non-stationary (compared to stationary processes). A higher value of the difference operator results in higher savings in inventory costs. In terms of stationary processes, more autoregressive parameters in the model result in higher savings in inventory cost. There is more cost savings in an AR (2) process compared to the AR (1) demand process. To summarise, the model dependency property of the value of CDIS shows that the percentage reduction in inventory cost in CDIS compared to other approaches is an increasing function of the number of autoregressive parameters, p, and the difference parameter, d, for the ARIMA models investigated.

We also observe from Table 8-2 that the percentage savings in Stages II and III are substantially greater than those in Stage I. Thus, when the demand process and demand parameters are known to the supply chain members, the value of CDIS is less. On the other hand, when we move towards more realistic models (Stages II and III), the value of CDIS becomes higher.

Detailed results for MSE, bullwhip ratio, inventory holdings and inventory costs, for each of the three stages are given in Appendices 8A, 8B and 8C. These results show that the CDIS approach performs better than the other three approaches in terms of all four performance metrics. The values of the performance metrics for non-stationary processes are higher than for stationary processes, owing to the choice of demand parameters that may lead to strong trends in the demand series.

## 8.3. MSE and the Bullwhip Ratio

We have discussed in the previous section that, on average, CDIS always results in the least inventory cost among the different information sharing approaches in all stages. In this section, we will look at two major factors linked with the inventory performance of CDIS, namely MSE and the Bullwhip Ratio. The percentage reduction in MSE, Bullwhip Ratio and inventory cost by utilising CDIS compared to DIS and NIS-Est for an MMSE method is given in Tables 8-3 and 8-4 below. Please note that in the two tables we abbreviate Bullwhip Ratio as BR and Inventory Cost as IC.

| Demand Process | Percentage Reduction in Performance Metrics by utilising CDIS instead of DIS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Simulation - Stage I | | | Simulation - Stage II | | | Simulation - Stage III | | |
| | MSE | BR | IC | MSE | BR | IC | MSE | BR | IC |
| AR(1) | 11.8 | 9.5 | 7.6 | 26.8 | 35.6 | 25.8 | 43.1 | 41.1 | 33.8 |
| AR(2) | 15.5 | 9.8 | 11.7 | 41.2 | 25.8 | 38.2 | 54.2 | 49.1 | 41.0 |
| MA(1) | 8.0 | 9.4 | 2.3 | 32.5 | 19.5 | 21.5 | 41.8 | 39.4 | 35.0 |
| MA(2) | 7.1 | 9.8 | 7.5 | 32.5 | 45.8 | 35.8 | 45.0 | 38.1 | 28.8 |
| ARMA (1,1) | 6.5 | 3.8 | 4.9 | 32.6 | 33.3 | 31.5 | 56.1 | 51.1 | 41.2 |
| ARIMA (0, 1, 1) | 22.5 | 21.6 | 17.8 | 25.0 | 25.9 | 22.3 | 60.1 | 58.8 | 45.4 |
| ARIMA (1, 1, 1) | 25.2 | 18.7 | 27.8 | 56.3 | 63.2 | 57.2 | 59.6 | 64.1 | 61.0 |
| ARIMA (1, 1, 2) | 22.2 | 18.0 | 21.4 | 36.9 | 29.8 | 34.6 | 49.1 | 60.4 | 85.2 |
| ARIMA (0, 2, 2) | 52.7 | 39.3 | 48.1 | 51.2 | 52.6 | 49.8 | 40.1 | 42.1 | 58.0 |

**Table 8-3 Performance of CDIS compared with DIS**

Lee et al (2000), using an AR (1) demand process and assuming the demand process and parameters to be known, have shown the existence of a relationship between the inventory costs and conditional variance of the lead time demand (conditioned on known demand, $d_t$). They compare the inventory costs and conditional variance of the lead time demand between the NIS approach and the DIS approach. This shows that by utilising an NIS approach, the manufacturer will have a higher conditional variance in the lead time demand, which results in higher values of inventory costs. When the manufacturer forecasts using the alternate DIS approach, the variability in the lead time demand forecast reduces, which results in a lower inventory cost.

In Table 8-3 above, we compare the percentage reductions in MSE, Bullwhip Ratio and inventory costs between the CDIS and the DIS approach for all nine demand processes. The results of the AR (1) process shows that high percentage reductions in MSE and Bullwhip Ratio are associated with high reduction in inventory costs, giving similar results as Lee et al (2000). Table 8-3 shows that for any individual demand process, apart from ARIMA (0, 2, 2), any increase in percentage reductions in MSE or BR results in increased percentage reductions in the inventory cost, although not with the same magnitude. Thus, our staged relaxation of assumptions methodology shows that when the forecast error or the variability in the demand decreases due to demand information sharing, the inventory cost will also decrease.

When the associations are compared across different demand processes, we observe that the magnitude with which the percentage reductions in MSE and BR are transferred to inventory cost also depends on the demand process. In sub-section 8.2.2 the demand process dependent behaviour of the value of CDIS was discussed. This behaviour is also observed in the Tables 8-3 and 8-4 where the magnitudes of transfer of reductions in forecast error and demand variability to inventory cost depends on the demand process.

| Demand Process | Percentage Reduction in Performance Metrics by utilising CDIS instead of NIS-Est | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Simulation - Stage I | | | Simulation - Stage II | | | Simulation - Stage III | | |
| | MSE | BR | IC | MSE | BR | IC | MSE | BR | IC |
| AR(1) | 9.8 | 11.5 | 10.8 | 52.5 | 65.3 | 63.0 | 83.6 | 90.0 | 72.0 |
| AR(2) | 18.0 | 7.8 | 41.0 | 29.8 | 36.5 | 71.4 | 96.7 | 85.6 | 74.4 |
| MA(1) | 7.1 | 9.4 | 2.3 | 52.8 | 42.5 | 48.8 | 61.9 | 51.2 | 53.8 |
| MA(2) | 7.1 | 9.8 | 7.5 | 63.7 | 62.5 | 59.6 | 81.9 | 71.9 | 63.0 |
| ARMA (1,1) | 8.0 | 3.8 | 4.4 | 39.4 | 52.8 | 49.6 | 75.8 | 62.9 | 58.3 |
| ARIMA (0, 1, 1) | 31.2 | 29.5 | 45.6 | 36.5 | 25.9 | 46.5 | 61.9 | 41.2 | 63.3 |
| ARIMA (1, 1, 1) | 31.4 | 44.2 | 56.9 | 66.0 | 39.6 | 72.2 | 75.8 | 65.0 | 84.2 |
| ARIMA (1, 1, 2) | 39.2 | 37.5 | 58.6 | 68.4 | 65.8 | 74.4 | 48.7 | 65.7 | 86.7 |
| ARIMA (0, 2, 2) | 61.0 | 48.5 | 57.7 | 72.6 | 75.8 | 81.4 | 45.2 | 58.0 | 83.0 |

**Table 8-4 Performance of CDIS compared with NIS-Est**

Next, we will discuss the simulation results for each of the three stages.

## 8.4. Simulation Results of Stage I

In this section, we present the simulation results for Stage I for the optimal forecasting methods. The results for non-optimal forecasting methods are presented in section 8.6.

In the table below (Table 8-5), we present the percentage reduction in the inventory cost by using CDIS, compared to the three other approaches (NIS, NIS-Est and DIS) for all the nine processes. The inventory cost for MA (1) and MA (2) is the same for the three approaches NIS, NIS-Est and DIS (see sub-section 4.2.3.1).

| Demand Process | Percentage reduction in inventory cost by CDIS compared with | | |
|---|---|---|---|
| | NIS | NIS-Est | DIS |
| AR (1) | 32.1 | 10.8 | 7.6 |
| AR (2) | 58.0 | 41.0 | 11.7 |
| MA (1) | 2.3 | | |
| MA (2) | 7.5 | | |
| ARMA (1, 1) | 32.0 | 4.9 | 4.4 |
| ARIMA (0, 1, 1) | 72.1 | 45.6 | 17.8 |
| ARIMA (0, 2, 2) | 83.6 | 79.3 | 48.1 |
| ARIMA (1, 1, 1) | 89.0 | 58.6 | 27.8 |
| ARIMA (1, 1, 2) | 87.4 | 57.7 | 21.4 |

**Table 8-5: Percentage Reduction in Inventory Cost by using CDIS**

The comparisons with the two No Information Sharing approaches show that sharing demand information can result in huge savings in inventory cost. The comparison with DIS shows that further significant savings in inventory costs can be achieved by using the CDIS approach. Similarly, the comparison between NIS and NIS-Est shows that NIS-Est results in lower inventory cost than the traditional No Information Sharing approach (NIS), with the exception of the pure MA processes.

Lee et al (2000) quantified the value of information sharing by comparing NIS with the DIS approach (see section 5.2). We replicated their simulation design by assuming the same values in the experiment (standard deviation ($\sigma$) = 50, Lead Time from the manufacturer to the retailer ($l$) = 5, Lead Time from the supplier to the manufacturer (L) = 10, autoregressive parameter (ρ) = 0.1 – 0.9) (see Lee et al (2000:636)). The following table (Table 8-6) shows a comparison of the results.

| $\rho$ | Percentage Reduction in Inventory Cost in DIS compared with NIS | |
|---|---|---|
| | Lee et al (2000) | Replication |
| 0.1 | 1% | 1% |
| 0.3 | 3% | 3% |
| 0.5 | 7% | 9% |
| 0.7 | 22% | 21% |
| 0.9 | 41% | 45% |

**Table 8-6: Replication of Lee et al (2000)**

Lee et al (2000) do not present the percentage inventory reductions in a tabular form and in Table 8-6 we have used approximate values from Figure 3 in their paper. The above table indicates that the results from the replication approximately agree with the results of Lee et al (2000).

### 8.4.1. Effect of Demand Parameters

The simulation results show that the performance of CDIS depends on the value of the demand parameters. As the objective of this research is to counter the amplification of demand variance, we experiment only with the demand parameters falling within the Bullwhip Effect region. We observe that when there is amplification of demand variance, CDIS always results in cost savings.

We discussed, in sub-section 7.3.8, that the values of parameters considered for non-stationary processes in this research are based on simulating different parameter regions. No research has yet established the parameter regions for the Bullwhip Effect for non-stationary ARIMA processes. Therefore, we restrict the analysis of the effect of demand parameters to the discussion of stationary processes. We discuss in Chapter 10 that one of the avenues of further research is to mathematically analyse the bullwhip regions for non-stationary ARIMA processes.

The following figure (Figure 8-2) shows the effect of the autoregressive parameter on percentage savings in inventory costs by using CDIS compared to the three other approaches for an AR (1) process. We observe that when there is very high autocorrelation in the demand ($\rho = 0.9$), the average percentage savings in inventory cost compared to NIS-Est is 35% and savings compared to DIS is 20%. Hence, when the value of the autocorrelation coefficient is very high, centralising demand information is very valuable for forecasting future demands and providing greater inventory cost savings. The results agree with the simulation findings reported earlier by Lee et al (2000), comparing DIS with NIS, that the percentage inventory reduction increases with increasing values of the autoregressive parameter (see Table 8-6).

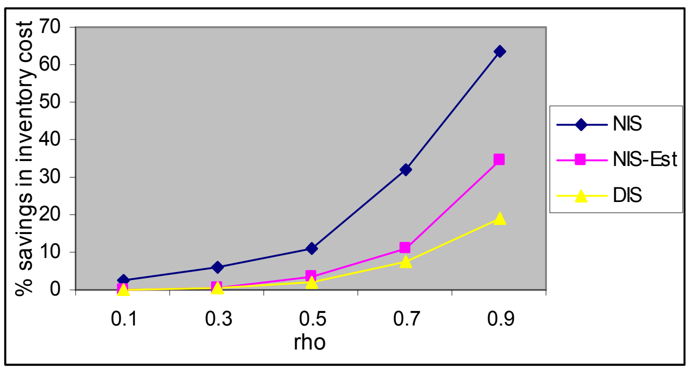


**Figure 8-2: Percentage Savings in Inventory Cost for an AR (1) Process by using CDIS**

A similar pattern was observed for an AR (2) process, showing that higher values of the autoregressive parameters ($\rho_1$ and $\rho_2$) result in greater inventory cost savings, as exhibited in Appendix 8F. The results in Appendix 8F for the MMSE forecasting method show that as the values of the autoregressive parameters increase, the value of CDIS also increases. Table 8-7 (page 132) shows a similar pattern for the ARMA (1, 1) process. We observe that as the value of $\rho$ increases, the value of CDIS also increases. Thus, we conclude from the above that the value of CDIS is an increasing function of the value of the autoregressive parameter, $\rho$.

In Figure 8-3 and Table 8-7, we look at the effect of the moving average demand parameter, $\theta$, on the performance of CDIS compared to the DIS approach. No previous research has investigated the effect of the moving average parameter on the value of demand information sharing. The new simulation results show that there is an inverse phenomenon for the moving average parameters in MA (q) as compared to the autoregressive parameter. In the case of a moving average parameter, we observe that the percentage reduction in inventory cost is a decreasing function of the moving average parameter. Thus, centralising demand information is more beneficial at lower values of the moving average parameter. This result is exhibited in the following figure, Figure 8-3, for an MA (1) process where we have experimented with $\theta < 0$ to confine ourselves to the Bullwhip Effect region (see sub-section 7.3.1 for details).

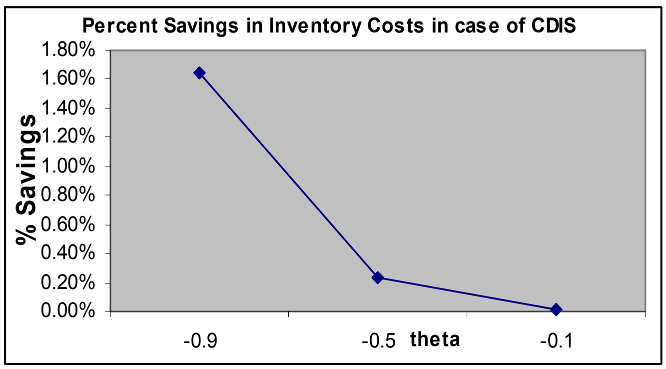


**Figure 8-3: Percentage Savings in Inventory Cost for an MA (1) Process by using CDIS instead of DIS**

A similar phenomenon has been observed for an MA (2) process, where the percentage savings in inventory cost reduces with the increasing value of both the moving average parameters $\theta_1$ and $\theta_2$, as shown in the MMSE results in the first table in Appendix 8G. The magnitude of this effect is more marked for an MA (2) process than an MA (1) process, where the effect of the moving average parameter is slight (see Figure 8-3).

With the mixed autoregressive moving average stationary process, ARMA (1, 1), similar results have been observed. The value of CDIS increases with the increasing value of the autoregressive parameter, $\rho$, and decreases with the increasing value of the moving average parameter, $\theta$. This is illustrated in the following table (Table 8-7):

| $\theta$ | $\rho$ | | | | | |
|---|---|---|---|---|---|---|
| | **-0.9** | **-0.5** | **-0.1** | **0.1** | **0.5** | **0.9** |
| **-0.9** | | 1.6 | 1.7 | 1.8 | 5.4 | 23.1 |
| **-0.5** | | | 1.0 | 1.1 | 4.4 | 20.1 |
| **-0.1** | | | | 1.0 | 3.9 | 19.4 |
| **0.1** | | | | | 2.5 | 18.1 |
| **0.5** | | | | | | 15.3 |

**Table 8-7: Percentage Savings in Inventory Cost for ARMA (1, 1) by using CDIS instead of DIS**

Table 8-7 shows the percentage decrease in inventory cost when CDIS is utilised instead of DIS for the parameter region following $\rho > \theta$. This region satisfies the conditions of stationarity and invertibility and exhibits the Bullwhip Effect. It is obvious from Table 8-7 that the value of CDIS is a function of the demand parameters and increases with increasing $\rho$ and decreasing $\theta$. However, the effect is not strong, except for high values of the autoregressive parameter.

## 8.4.2. Effect of Standard Deviation

In this sub-section, we discuss the effect of standard deviation of the noise in the retailer's demand on the performance of the CDIS approach. In the following table (Table 8-8), we compare the percentage reductions in the inventory cost of CDIS with the other three approaches. In calculating the inventory costs, we experiment with values of standard deviation in the retailer's demand noise in the range from 25 to 100.

| Demand Process | Standard Deviation of Noise | Percentage Savings in Inventory Cost using CDIS compared with | | |
|---|---|---|---|---|
| | | NIS | NIS-Est | DIS |
| AR (1) | 25 | 49.4 | 10.9 | 3.9 |
| | 50 | 62.2 | 10.8 | 7.6 |
| | 100 | 74.7 | 11.7 | 16.7 |
| AR (2) | 25 | 53.8 | 34.8 | 11.2 |
| | 50 | 58.0 | 41.0 | 11.7 |
| | 100 | 71.7 | 55.7 | 15.8 |
| MA (1) | 25 | 0.9 | | |
| | 50 | 2.3 | | |
| | 100 | 7.8 | | |
| MA (2) | 25 | 0.4 | | |
| | 50 | 7.5 | | |
| | 100 | 25.4 | | |
| ARMA (1, 1) | 25 | 23.2 | 3.6 | 4.2 |
| | 50 | 41.0 | 4.9 | 4.4 |
| | 100 | 46.9 | 11.3 | 9.4 |
| ARIMA (0, 1, 1) | 25 | 71.1 | 36.1 | 15.6 |
| | 50 | 75.4 | 39.9 | 17.8 |
| | 100 | 81.3 | 48.7 | 24.4 |
| ARIMA (0, 2, 2) | 25 | 76.0 | 40.8 | 40.4 |
| | 50 | 83.6 | 79.3 | 48.1 |
| | 100 | 88.9 | 92.6 | 91.0 |
| ARIMA (1, 1, 1) | 25 | 86.1 | 21.4 | 25.3 |
| | 50 | 89.0 | 58.6 | 27.8 |
| | 100 | 91.7 | 64.3 | 47.5 |
| ARIMA (1, 1, 2) | 25 | 85.3 | 56.6 | 20.7 |
| | 50 | 87.4 | 58.6 | 21.4 |
| | 100 | 90.8 | 67.0 | 36.7 |

**Table 8-8 Effect of Standard Deviation on the Performance of CDIS**

The above table shows that the cost savings can be substantial when the value of standard deviation is large. When the standard deviation of noise in the demand is high, it is quite logical that more safety stock will be required to counteract this variability. Lee et al (2000), using an AR (1) process at the retailer, showed analytically and via simulation that percentage savings in the case of DIS, compared to NIS, are an increasing function of standard deviation. We observe a similar phenomenon for the savings in the case of CDIS, compared to other approaches, for all nine demand processes in the study.

### 8.4.3. Effect of Lead Time

The effect of the lead time from the supplier to the manufacturer has also been discussed by Lee et al (2000) for an AR (1) process. The mathematical and simulation results in their study show that the value of information sharing increases with increasing lead time. Our simulation results confirm the findings of Lee et al (2000) and show that the same relationship holds for all the nine demand processes. The following figures 8-4 and 8-5 show the percentage savings in inventory cost for stationary and non-stationary demands for three different values of lead times.

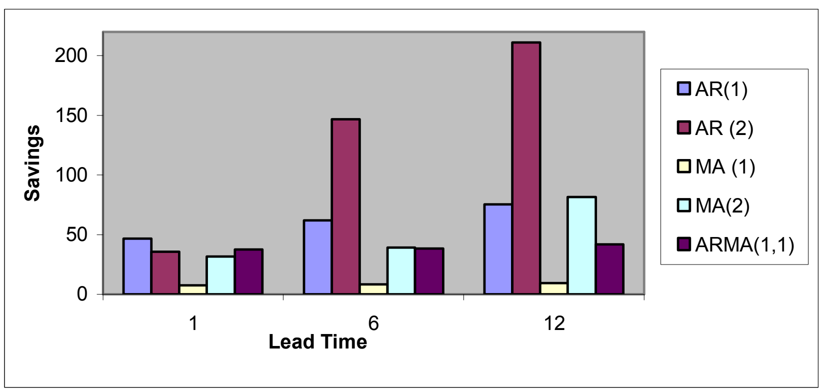


**Figure 8-4 Savings in Inventory Cost for Stationary Processes by using CDIS instead of DIS**

Figure 8-4 above shows that the savings in terms of inventory costs increase with lead time. In sub-section 8.4.1, we discussed that the savings for an AR (2) process are greater than for an AR (1) process. Figure 8-4 also shows that the effect on lead time for an AR (2) process is more pronounced for longer lead-times, compared to an AR (1) process. A similar result was observed in the previous sub-section when the effect of variability was discussed. In the same sub-section, we showed that the value of CDIS increases with the number of autoregressive parameters: it is more in AR (2) compared to AR (1). The above results show that the effect of lead time and variability is amplified when the demand process has more autoregressive components.

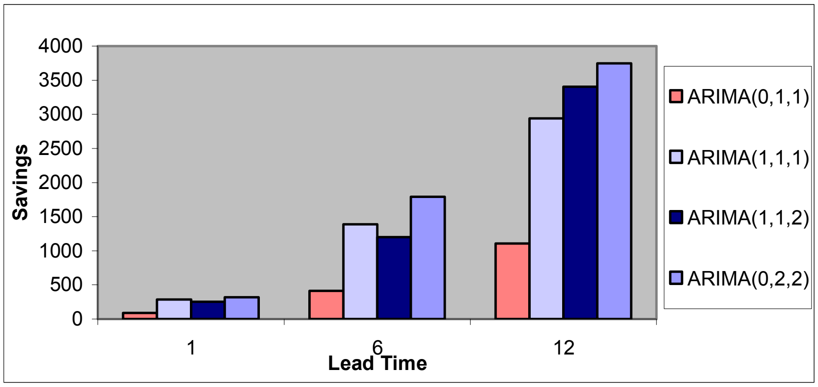


**Figure 8-5: Savings in Inventory Cost for Non-Stationary Processes by using CDIS instead of DIS**

Figure 8-5 also shows that the value of information sharing increases with the lead time. The effect of the number of autoregressive parameters is not the same as for stationary processes, and is worthy of further investigation (see sub-section 8.4.1).

Thus, centralised demand information sharing proves to be more beneficial when the lead time between the supplier and the manufacturer is large. This is logical, as the forecasts for smaller lead times would be less variable, compared to those for longer lead times, thus making centralised demand less critical (Lee et al, 2000; Chandra and Grabis, 2005).

### 8.4.4. Effect of Cost Ratio

In the simulation experiment, we vary the Cost Ratio in order to examine how the percentage reductions in inventory costs are affected by it.

It is worth mentioning here that none of the previous studies have looked at the effect of the Cost Ratio using simulation. Lee et al (2000) discussed this issue for an AR (1) process and showed mathematically that the percentage inventory reduction by using DIS instead of NIS is an increasing function of this ratio. The simulation results of this thesis are compatible with these findings. We also look at the effect of the Cost

Ratio for all nine demand processes and show that a similar pattern can be observed in all processes.

We look at the percentage savings in inventory cost by utilising CDIS compared with the traditional Demand Information Sharing (DIS) approach and observe that the percentage savings in inventory cost are an increasing function of this cost ratio. Thus, when the penalty cost is very high compared to the holding cost, Centralised Demand Information Sharing results in higher percentage reductions in the inventory costs. This is shown in the following table (Table 8-9):

| Demand Process | Cost Ratio( $\frac{p}{p+h}$ ) | Percentage Savings in Inventory Cost |
|---|---|---|
| AR (1) | 2/(2+1) | 2.1 |
| | 25/(25+1) | 5.9 |
| | 50/(50+1) | 6.1 |
| AR (2) | 2/(2+1) | 8.3 |
| | 25/(25+1) | 8.8 |
| | 50/(50+1) | 13.9 |
| MA (1) | 2/(2+1) | 0.6 |
| | 25/(25+1) | 1.2 |
| | 50/(50+1) | 1.6 |
| MA (2) | 2/(2+1) | 1.1 |
| | 25/(25+1) | 6.9 |
| | 50/(50+1) | 8.2 |
| ARMA (1, 1) | 2/(2+1) | 1.0 |
| | 25/(25+1) | 1.9 |
| | 50/(50+1) | 1.9 |
| ARIMA (0, 1, 1) | 2/(2+1) | 8.5 |
| | 25/(25+1) | 18.6 |
| | 50/(50+1) | 22.7 |
| ARIMA (0, 2, 2) | 2/(2+1) | 3.9 |
| | 25/(25+1) | 49.6 |
| | 50/(50+1) | 90.9 |
| ARIMA (1, 1, 1) | 2/(2+1) | 19.5 |
| | 25/(25+1) | 20.9 |
| | 50/(50+1) | 27.3 |
| ARIMA (1, 1, 2) | 2/(2+1) | 9.5 |
| | 25/(25+1) | 11.5 |
| | 50/(50+1) | 21.1 |

**Table 8-9 Effect of Cost Ratio on the Performance of CDIS compared to DIS**

The above table also indicates that the magnitude in savings for non-stationary processes is higher than for stationary processes.

## 8.5. Simulation Results for Stages II and III

Now we move on the presentation of results for Stages II and III. The purpose of the staged relaxation is to investigate the effect of different model assumptions (known demand process and known demand parameters) on the value of CDIS. Thus, while discussing Stages II and III, we do not experiment with different estimation and identification processes.

As discussed in Chapter 3, the nature of the MMSE forecast in an ARIMA framework requires the estimation of the noise in the demand. Hence, in order to remain consistent with the forecasting approach in the ARIMA methodology, the supply chain members do not use the NIS approach. Moreover, we have also shown via the simulation results of Stage I that NIS always results in a higher value of inventory costs compared to NIS-Est except for MA (1) and MA (2), where the results are the same. Thus, in discussing the results of states II and III, we will compare CDIS with DIS and NIS-Est only.

### 8.5.1. Value of CDIS in Higher Stages

In this sub-section, we discuss the reasons for higher values of savings by using CDIS in stages II and III. The rationale for the comparison of CDIS with NIS-Est is different than the comparison with DIS. We will look at these differences one by one.

#### 8.5.1.1. Comparison with NIS-Est

When we are analysing the value of CDIS compared to NIS-Est, we are interested in knowing what happens when the supply chain links identify and estimate the process and its parameters correctly and when they do so incorrectly. This is because the inventory cost in the case of NIS-Est depends on the accuracy with which the manufacturer performs the identification and the estimation processes. On the other hand, as the forecasting in CDIS is dependent on the retailer’s demand, the inventory cost in this case depends on how accurately the identification and estimation processes have been performed at the retailer.

When the manufacturer identifies and estimates its demand process and parameters correctly, we observe that there is less value of using the CDIS approach compared to when it does so incorrectly. This is because the former case then resembles a Stage I environment, where the manufacturer's forecasting incorporates the correct demand process and parameters.

Conversely, when the manufacturer is inaccurate in its identification and estimation process, the value of CDIS is greater (compared to the first case). The rationale is simply the incorporation of inaccurate demand parameters and process in its lead-time forecast when using NIS-Est.

To test this phenomenon, the simulation experiment was run for an AR (1) process and the results were divided into two groups depending on whether the manufacturer's identification and estimation was accurate or not. After observing the results (Table 8-10), a similar grouping was done for the retailer (Table 8-11).

The results for an AR (1) process (Stage III) are shown in the following table (Table 8-10) to show the effect of the manufacturer's identification process.

| **Identification by the Manufacturer** | **Comparison with NIS-Est** | |
|---|---|---|
| Accurate | 69% | Value of CDIS is lesser |
| Inaccurate | 77% | Value of CDIS is greater |

**Table 8-10 Percentage Savings in Inventory Cost of CDIS for Manufacturer's Process Identification Capability**

If we look at the identification process at the retailer (Table 8-11), we find that its accuracy will result in increased value of CDIS compared to inaccurate identification of process.

We summarise these findings in the following table (Table 8-11):

| Identification by the Retailer | Comparison with NIS-Est | |
|---|---|---|
| Accurate | 81% | Value of CDIS is greater |
| Inaccurate | 70% | Value of CDIS is lesser |

**Table 8-11 Percentage Savings in Inventory Cost of CDIS for Retailer's Process Identification Capability**

In summary, as the performance of NIS-Est depends on the identification by the manufacturer, the inventory costs decrease when the manufacturer performs better identification. Thus, on comparing CDIS with NIS-Est, we observe that better identification by the manufacturer will result in less value of CDIS.

On the other hand, we observe that the performance of CDIS depends on the identification of the retailer. Thus, better identification by the retailer will result in greater value of CDIS.

#### 8.5.1.2. Comparison with DIS

When we are analysing the value of CDIS compared to DIS, the identification process at the manufacturer does not matter. Thus, we only look at the two cases when the retailer's identification and estimation process is accurate, and when it is inaccurate. This is because, both in DIS and CDIS, the manufacturer does not estimate its parameters. Conversely, it calculates these estimates by the upstream characterisation of demand formulae.

Accurate identification and estimation will yield better performance of both DIS and CDIS. This has been confirmed by the simulation results as shown in Appendix 8H. It should be noted that the difference in performance is less marked than in Table 8-11. This would again resemble a Stage I environment, where the retailer forecasts, knowing the actual demand process. However, forecasting using less variable demand in CDIS results in its better performance as already shown in Stage I. On the other hand, we observe that when the retailer inaccurately identifies the process and its parameters, the inventory cost of both approaches would increase as shown in Appendix 8H. As already discussed, this is because the performance of CDIS and DIS depends on better identification of the demand process and its inaccurate parameters and incorrect identification leads to higher inventory. Again, we observe that there is still value in CDIS, owing to the utilisation of a less variable demand in its forecasting process.

### 8.5.2. Effect of Demand History

With ARIMA modelling, longer history facilitates better identification and parameter estimation of unchanging demand processes. Thus, when a longer history is available, the manufacturer can more accurately identify the process and estimate its demand processes. This leads to the manufacturer having less benefit from CDIS as the demand history increases. This phenomenon was tested in the simulation experiment by varying the length of history available to the manufacturer and the results are shown in the following table for an AR (1) demand process.

| Length of History | Percentage Reduction in Inventory Cost by utilising CDIS with NIS-Est | |
|---|---|---|
| | STAGE II | STAGE III |
| 24 | 64.1 | 73.1 |
| 48 | 63.0 | 72.0 |
| 72 | 57.6 | 60.9 |
| 144 | 51.2 | 57.2 |

**Table 8-12 Effect of Length of History for an AR (1) Process**

When comparing CDIS and NIS-Est, the benefit comes from the fact that in NIS-Est, the manufacturer has to identify the process and estimate its parameters. Longer history facilitates better identification and thus the value of CDIS decreases.

It was established in sub-section 8.5.1.2 that the accuracy of identification does not affect the comparison between CDIS and DIS, as longer history will facilitate both CDIS and DIS.

The above table also shows that although the value of CDIS becomes lower as the length of history increases, the effect of length of history is not very large. This is because the increased history length is available to both the retailer and the manufacturer (see section 7.3 for the details on the estimation procedure for both supply chain links).

### 8.5.3. Effect of Demand Variability

The effect of demand variability on the value of CDIS is analysed in this sub-section. The standard deviation of the demand is varied for an AR (1) process and the percentage reduction in inventory cost by using CDIS compared to NIS-Est and DIS is then calculated. The results are shown in Table 8-13 below.

| Standard Deviation | Percentage Reduction in Inventory Cost by utilising CDIS | | | |
|---|---|---|---|---|
| | STAGE II | | STAGE III | |
| | NIS-Est | DIS | NIS-Est | DIS |
| 25 | 55.5 | 22.2 | 70.0 | 33.1 |
| 50 | 63.0 | 25.8 | 72.0 | 33.8 |
| 100 | 68.9 | 37.7 | 76.7 | 34.6 |

**Table 8-13 Effect of Standard Deviation on Value of CDIS for an AR (1) Process**

In sub-section 8.4.2, the effect of standard deviation of noise on the value of CDIS was investigated and it was found that the percentage reduction in inventory cost increases with the increasing value of the standard deviation in the noise. The above table (Table 8-13) shows that the value of CDIS increases with the increasing value of standard deviation in the demand. This is because, the higher the variability, the more difficult it is to identify the demand process and estimate its parameters. Secondly, as we have discussed in sub-section 8.3.2, more safety stock needs to be kept to counter higher variability. Thus, we observe that the value of CDIS is an increasing function of the standard deviation in the retailer's demand.

### 8.5.4. Effect of Process Identification

In sub-section 8.5.1, we have shown that the value of CDIS is less when the manufacturer identifies the process accurately. Table 8-10 and Table 8-11 quantify how much on average the value of CDIS is reduced when accurate identification occurs. Thus, if the manufacturer utilises a better identification method than the one used in the simulation, the value of CDIS will be lesser. But as shown in Tables 8-10, 8-11, 8-12 and 8-13 even accurate process identification will result in having some value in CDIS.

## 8.6. Simulation Results for Non-Optimal Forecasting Methods

In the previous section, we presented the results of the simulation experiment for the three stages when supply chain links utilise an optimal forecasting method. In this section, we will present the results when non-optimal forecasting methods are employed by the supply chain links. As discussed in Chapter 3, in practice many forecasters choose to use non-optimal forecasting methods, such as SMA and SES, based on familiarity, simplicity and ease of use of these methods.

The simulation results show that, compared to the NIS approach, CDIS results in reduction of average inventory, inventory costs and forecast error. As discussed for optimal forecasting methods, we present the results by looking at the impact of various factors on the absolute values and percentage reduction of the performance metrics.

The objective of this simulation experiment is to evaluate the value of centralised demand information sharing. We emphasise the performance of CDIS and not the forecasting methods themselves. Stamatopoulos et al (2006), using an AR (1) demand process and the SES forecasting method, have shown that the Bullwhip Ratio decreases when the forecasting parameter (α) is optimised. As discussed in the previous chapter, we look at a range of forecasting parameters for both the methods, which may not be the optimised parameter for the given conditions. Thus, the reader should bear in mind that the following results provide a comparison between CDIS and NIS and not between the performances of the two forecasting methods, SMA and SES.

## 8.7. MSE and Bullwhip Ratio

In section 8.3, we showed that, for any individual process, MSE and the Bullwhip Ratio are two major factors linked with reduced inventory cost of CDIS in the case of optimal forecasting methods. We now consider the relationship between MSE, Bullwhip Ratio and inventory cost in the case of non-optimal forecasting methods. The results are given in the following table (Table 8-14).

| Demand Process | Percentage Reduction in the following variables by utilising CDIS against NIS | | | | | |
|---|---|---|---|---|---|---|
| | SMA | | | SES | | |
| | MSE | Bullwhip Ratio | Inventory Cost | MSE | Bullwhip Ratio | Inventory Cost |
| AR(1) | 65.7 | 55.2 | 46.4 | 71.5 | 70.6 | 65.6 |
| AR(2) | 65.3 | 54.2 | 44.9 | 73.7 | 62.1 | 60.3 |
| MA(1) | 62.2 | 65.3 | 58.0 | 66.6 | 72.1 | 68.8 |
| MA(2) | 70.8 | 63.6 | 57.5 | 70.8 | 64.5 | 63.9 |
| ARMA (1,1) | 53.5 | 39.5 | 29.3 | 62.0 | 76.2 | 71.0 |
| ARIMA (0, 1, 1) | 52.0 | 34.8 | 23.1 | 64.8 | 59.4 | 60.9 |
| ARIMA (1, 1, 1) | 61.1 | 53.6 | 47.7 | 72.0 | 78.0 | 70.9 |
| ARIMA (1, 1, 2) | 64.2 | 54.0 | 45.1 | 75.3 | 63.8 | 60.1 |
| ARIMA (0, 2, 2) | 57.1 | 42.1 | 31.7 | 76.6 | 62.2 | 61.2 |

**Table 8-14 Contribution towards the Performance of CDIS compared with NIS**

Table 8-14 shows that for any individual process, an increase in the percentage reduction in MSE or Bullwhip Ratio will result in the increase in the percentage reduction in the inventory cost. This is the same result as observed for the optimal forecasting methods. Although the results are process dependent, they are less sensitive to demand process than was the case for optimal forecasting methods.

### 8.7.1. Effect of Demand Parameters

In sub-section 8.3.1, we analysed the effect of demand parameters for the stationary processes when optimal forecasting methods are employed. We discussed, in the previous chapter, that the issue of parameter regions for the Bullwhip Effect is not relevant in the case of non-optimal forecasting methods. However, in order for the simulation design to be consistent for all forecasting methods, we restrict the analysis of non-optimal methods to stationary processes. For optimal forecasting methods, we observed that the percentage reduction in inventory costs by using CDIS is an increasing function of the autoregressive parameters for AR (1) and AR (2) demand processes. We observe that an inverse phenomenon exists in the case of non-optimal processes where, for an AR (1) process, the larger the value of $\rho$, the smaller is the percentage reduction in inventory costs.

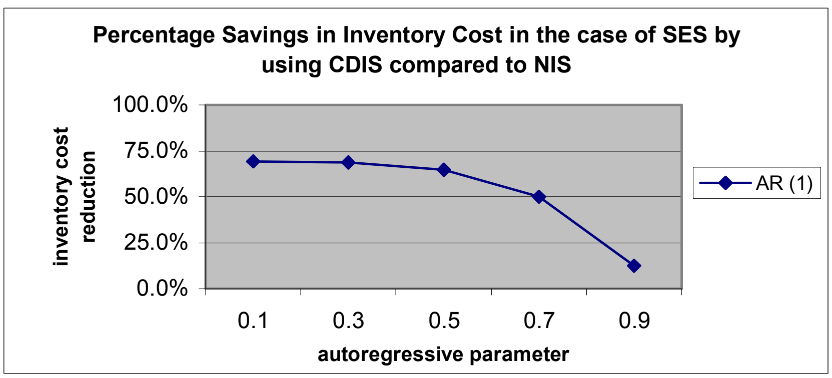


**Figure 8-6: Effect of Autoregressive Parameter in the case of SES**

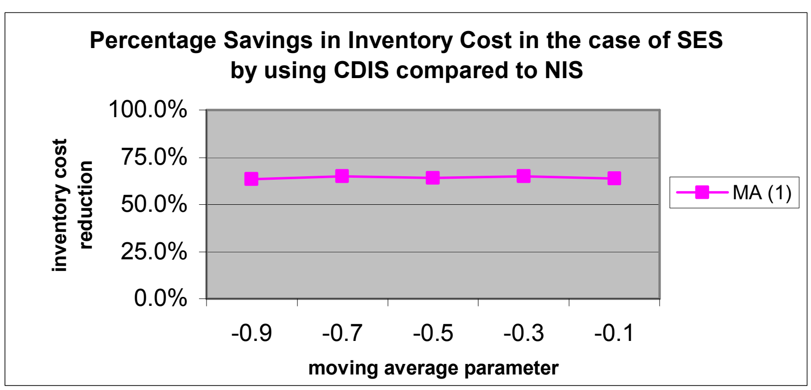


**Figure 8-7: Effect of Moving Average Parameter in the case of SES**

Chen et al (2000a) using SMA, and Chen et al (2000b) using SES methods, mathematically showed that, for an AR (1) demand process, the Bullwhip Ratio decreases with increasing values of the autocorrelation coefficient. We observe the same effect in the simulation results (see Figures 8-6 and 8-8). Thus, the simulation results are consistent with the mathematical findings of the above two papers. We also observe the same effect in an AR (2) process for both SMA and SES where the value of CDIS decreases with increasing values of $\rho_1$ and $\rho_2$ (Appendix 8F).

We now discuss the effect of the moving average parameters, $\theta_1$ and $\theta_2$, on the value of sharing demand information. We observe that the moving average parameter has no effect on the value of CDIS (see Figures 8-7 and 8-9) for an MA (1) process.

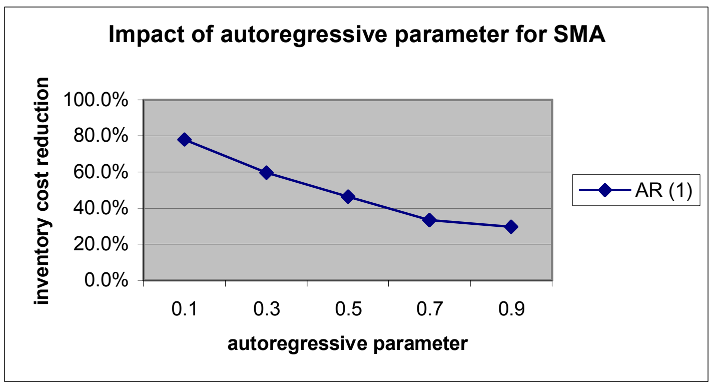


**Figure 8-8: Effect of Autoregressive Parameter in the case of SMA**

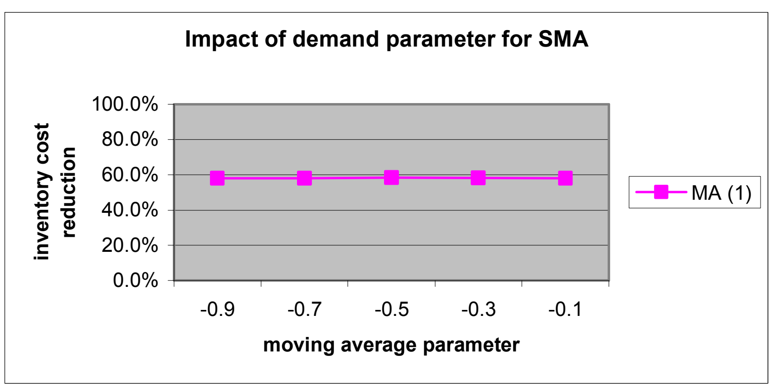


**Figure 8-9: Effect of Moving Average Parameter in the case of SMA**

The same results have been obtained for an MA (2) process where we observed that the percentage reduction in inventory costs by using CDIS compared to NIS remains the same irrespective of the value of the moving average parameters (see Appendix 8G).

In the literature, we find that none of the previous papers have looked at the effect of the moving average parameters on the value of CDIS. The same gap was also discussed for optimal forecasting methods. The simulation results (Figure 8-7, Figure 8-9 and Appendix 8G) show that the value of CDIS is not affected by the moving average parameters.

### 8.7.2. Effect of Standard Deviation

The simulation results show that the reduction in the manufacturer's inventory costs by using CDIS instead of NIS is an increasing function of the standard deviation of the noise term in the retailer's demand. This is the same result as already observed for optimal forecasting methods. Thus, the effect of standard deviation in the retailer's noise has the same effect on the performance of CDIS, irrespective of the forecasting method employed.

The average inventory cost reductions for SMA and SES are shown in the following two tables (Tables 8-15 and 8-16).

| Demand process | Standard deviation of noise | Reduction in inventory cost in using CDIS compared to NIS |
|---|---|---|
| AR(1) | 25 | 45.8% |
| | 50 | 46.4% |
| | 100 | 47.0% |
| AR(2) | 25 | 44.1% |
| | 50 | 44.9% |
| | 100 | 45.2% |
| ARMA (1, 1) | 25 | 29.1% |
| | 50 | 29.3% |
| | 100 | 29.5% |
| MA(1) | 25 | 56.8% |
| | 50 | 57.5% |
| | 100 | 57.3% |
| MA(2) | 25 | 41.6% |
| | 50 | 58.0% |
| | 100 | 60.1% |
| ARIMA (0, 1, 1) | 25 | 19.8% |
| | 50 | 23.1% |
| | 100 | 43.0% |
| ARIMA (1, 1, 1) | 25 | 20.8% |
| | 50 | 47.7% |
| | 100 | 74.1% |
| ARIMA (1, 1, 2) | 25 | 29.7% |
| | 50 | 45.1% |
| | 100 | 74.5% |
| ARIMA (0, 2, 2) | 25 | 33.0% |
| | 50 | 31.7% |
| | 100 | 59.8% |

**Table 8-15 Effect of Variability on the Percentage Reduction in Inventory Cost for SMA by using CDIS instead of NIS**

| Demand process | Standard deviation of noise | Reduction in inventory cost in using CDIS compared to NIS |
|---|---|---|
| AR(1) | 25 | 53.4% |
| | 50 | 65.6% |
| | 100 | 68.9% |
| AR(2) | 25 | 43.5% |
| | 50 | 60.3% |
| | 100 | 63.7% |
| ARMA (1, 1) | 25 | 60.7% |
| | 50 | 68.8% |
| | 100 | 71.4% |
| MA(1) | 25 | 49.9% |
| | 50 | 63.9% |
| | 100 | 70.9% |
| MA(2) | 25 | 65.1% |
| | 50 | 71.0% |
| | 100 | 70.0% |
| ARIMA (0, 1, 1) | 25 | 50.8% |
| | 50 | 60.9% |
| | 100 | 61.6% |
| ARIMA (1, 1, 1) | 25 | 43.7% |
| | 50 | 70.9% |
| | 100 | 75.5% |
| ARIMA (1, 1, 2) | 25 | 46.0% |
| | 50 | 60.1% |
| | 100 | 71.1% |
| ARIMA (0, 2, 2) | 25 | 38.8% |
| | 50 | 61.3% |
| | 100 | 74.7% |

**Table 8-16 Effect of Variability on the Percentage Reduction in Inventory Cost for SES by using CDIS instead of NIS**

Tables 8-15 and 8-16 report the percentage savings in inventory cost when σ varies from 25 to 100 for both SMA and SES. We observe that the percentage savings in inventory cost increases as σ increases. Thus, both tables suggest that CDIS enables the manufacturer to reduce the inventory cost and the percentage reduction is higher for larger values of standard deviation in the noise term of the demand process.

### 8.7.3. Effect of the Lead Time

In this section, we look at the effect of the lead time from the supplier to the manufacturer. The simulation results show that the manufacturer's average inventory, inventory costs and forecast errors (MSE) are all increasing functions of lead time. This is again similar to what has already been observed for an optimal forecasting method. Thus, there are more benefits of using Centralised Demand Information Sharing when lead times are large, irrespective of the forecasting method employed. Figure 8-10 and Figure 8-11 show the impact of lead time on the percentage reduction in inventory for SMA and SES forecasting methods respectively.

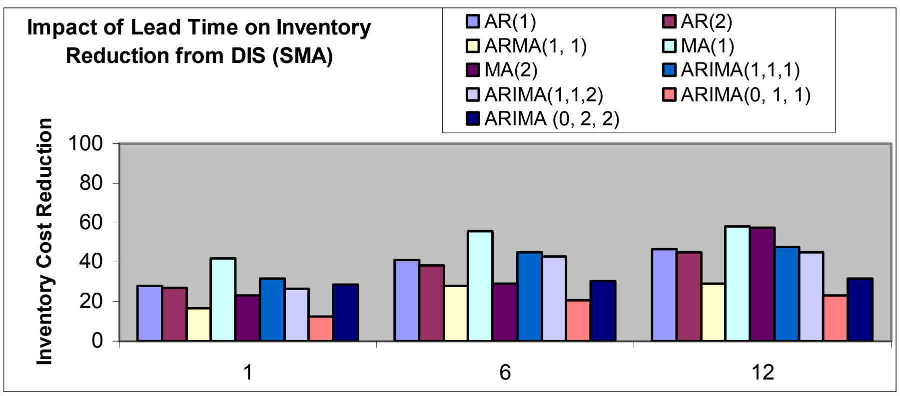


**Figure 8-10 Effect of Lead Time on Percentage Reduction in Inventory Cost for SMA by using CDIS instead of NIS**

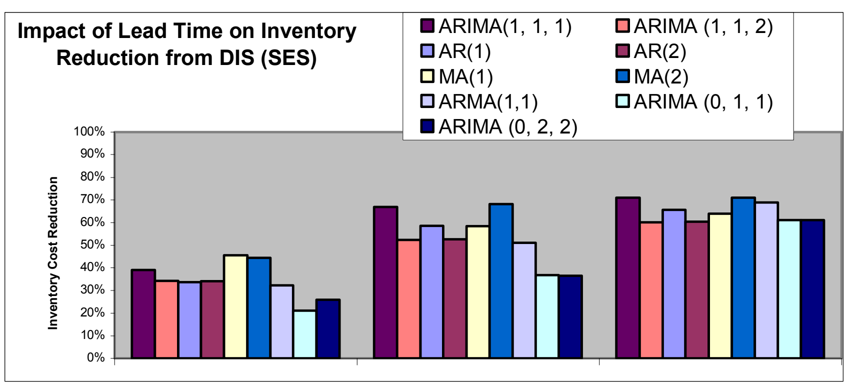


**Figure 8-11 Effect of Lead Time on Percentage Reduction in Inventory Cost for SES by using CDIS instead of NIS**

The above figures suggest that CDIS provides relatively small savings when the lead time is small but relatively large savings when it is large. The rationale for this effect is the same as that discussed for an optimal method. The forecast for a shorter lead times would be less variable compared to the one with longer lead time, thus making centralised demand less critical (see Lee et al (2000), Chandra and Grabis (2005) for details).

### 8.7.4. Effect of the Cost Ratio

In this section, we look at the impact of the cost ratio (penalty to the total cost ratio) on the percentage savings by using CDIS instead of NIS. The simulation results suggest that a higher cost ratio results in higher reduction in absolute values of average inventory and inventory costs. In terms of the impact of cost ratio on the percentage reduction, we observe an interesting phenomenon. For all stationary demand models, the percentage reduction in average inventory and inventory costs either increases slightly or remains constant. On the other hand, for non-stationary demand processes, the percentage reduction in the average inventory and inventory costs decreases with the increasing cost ratio. This is shown in Table 8-17 and Table 8-18.

| Demand Process | Forecasting Method | Cost Ratio ($\frac{p}{p+h}$) | Percentage Reduction in Inventory Cost |
|---|---|---|---|
| AR(1) | SMA | 2/(2+1) | 45.1% |
| | | 25/(25+1) | 46.4% |
| | | 50/(50+1) | 46.4% |
| | SES | 2/(2+1) | 63.6% |
| | | 25/(25+1) | 65.6% |
| | | 50/(50+1) | 65.6% |
| AR(2) | SMA | 2/(2+1) | 44.0% |
| | | 25/(25+1) | 44.9% |
| | | 50/(50+1) | 44.8% |
| | SES | 2/(2+1) | 58.3% |
| | | 25/(25+1) | 60.3% |
| | | 50/(50+1) | 60.3% |
| ARMA (1, 1) | SMA | 2/(2+1) | 57.2% |
| | | 25/(25+1) | 58.0% |
| | | 50/(50+1) | 58.1% |
| | SES | 2/(2+1) | 60.1% |
| | | 25/(25+1) | 68.8% |
| | | 50/(50+1) | 69.5% |
| MA(1) | SMA | 2/(2+1) | 56.1% |
| | | 25/(25+1) | 57.5% |
| | | 50/(50+1) | 57.7% |
| | SES | 2/(2+1) | 58.9% |
| | | 25/(25+1) | 63.9% |
| | | 50/(50+1) | 71.7% |
| MA(2) | SMA | 2/(2+1) | 27.9% |
| | | 25/(25+1) | 29.3% |
| | | 50/(50+1) | 29.5% |
| | SES | 2/(2+1) | 69.4% |
| | | 25/(25+1) | 71.0% |
| | | 50/(50+1) | 71.1% |

**Table 8-17 Effect of Cost Ratio on the Percentage Reduction in Inventory Cost for Stationary Demand Processes**

| Demand Process | Forecasting Method | Cost Ratio $(\frac{p}{p+h})$ | Percentage Reduction in Inventory Cost |
|---|---|---|---|
| ARIMA (0, 1, 1) | SMA | 2/(2+1) | 33.9% |
| | | 25/(25+1) | 23.1% |
| | | 50/(50+1) | 22.5% |
| | SES | 2/(2+1) | 84.2% |
| | | 25/(25+1) | 60.9% |
| | | 50/(50+1) | 48.0% |
| ARIMA (1, 1, 1) | SMA | 2/(2+1) | 75.7% |
| | | 25/(25+1) | 47.7% |
| | | 50/(50+1) | 45.3% |
| | SES | 2/(2+1) | 74.6% |
| | | 25/(25+1) | 70.9% |
| | | 50/(50+1) | 43.2% |
| ARIMA (1, 1, 2) | SMA | 2/(2+1) | 64.8% |
| | | 25/(25+1) | 45.1% |
| | | 50/(50+1) | 43.5% |
| | SES | 2/(2+1) | 70.5% |
| | | 25/(25+1) | 60.1% |
| | | 50/(50+1) | 44.4% |
| ARIMA (0, 2, 2) | SMA | 2/(2+1) | 52.4% |
| | | 25/(25+1) | 31.7% |
| | | 50/(50+1) | 28.9% |
| | SES | 2/(2+1) | 71.1% |
| | | 25/(25+1) | 61.2% |
| | | 50/(50+1) | 48.5% |

**Table 8-18 Effect of Cost Ratio on the Percentage Reduction in Inventory Cost for Non-Stationary Demand Processes**

Table 8-17 shows that in the case of stationary processes, the percentage reduction in inventory cost either increases or remains constant with increasing value of σ. This is in contrast with the non-stationary process (Table 8-18) where the percentage reduction in inventory cost decreases with increasing value of σ.

It is noticeable from Tables 8-17 and 8-18 that there is a marked difference between the results of SMA and SES. The choice of forecasting parameters for both SMA and SES, as discussed in sub-section 7.3.10.5, results in approximately the same average

age of the data used in the forecast (Johnston and Boylan, 2003). However, the distribution of the weights on historical data used in the methods is quite different, as shown in Table 3-2. This may be one factor leading to the greater value of CDIS in SES, but more detailed analysis is required to assess this.

In this research, we have not mathematically analysed the effect of cost ratio. In addition, in the literature review of non-optimal forecasting methods, we did not find any paper looking at the effect of cost ratio on the value of demand information sharing. Thus, we find this an interesting avenue for further research and this is further discussed in Chapter 10.

### 8.7.5. Effect of Smoothing Constant in SES

Here we discuss the effect of the smoothing constant, alpha, in SES on the percentage reduction of average inventory cost. Table 8-19 shows that the percentage reduction in inventory cost is an increasing function of the smoothing constant.

| Demand Process | Alpha | Percentage Reduction in Inventory Cost |
|---|---|---|
| AR(1) | 0.1 | 28.3% |
| | 0.3 | 65.6% |
| | 0.8 | 74.8% |
| AR(2) | 0.1 | 21.4% |
| | 0.3 | 60.3% |
| | 0.8 | 87.3% |
| MA(1) | 0.1 | 46.8% |
| | 0.3 | 63.9% |
| | 0.8 | 88.4% |
| MA(2) | 0.1 | 45.3% |
| | 0.3 | 71.0% |
| | 0.8 | 88.1% |
| ARMA(1, 1) | 0.1 | 14.3% |
| | 0.3 | 68.8% |
| | 0.8 | 84.2% |
| ARIMA(0, 1, 1) | 0.1 | 56.5% |
| | 0.3 | 60.9% |
| | 0.8 | 65.8% |
| ARIMA(1, 1, 1) | 0.1 | 59.7% |
| | 0.3 | 70.9% |
| | 0.8 | 87.0% |
| ARIMA(1, 1, 2) | 0.1 | 58.9% |
| | 0.3 | 60.1% |
| | 0.8 | 82.1% |
| ARIMA(0, 2, 2) | 0.1 | 54.7% |
| | 0.3 | 61.2% |
| | 0.8 | 72.1% |

**Table 8-19 Effect of the Value of the SES Smoothing Constant on the Percentage Reduction in Inventory Cost**

The upstream translation of demand (as discussed in chapter 4) shows that the manufacturer's history contains information about the retailer's demand. Higher values of the smoothing constant means there is a lower weighting on the history and thus more value of CDIS.

### 8.7.6. Effect of Number of Terms in SMA

The simulation results show that percentage reduction of average inventory, inventory costs and forecast errors are a decreasing function of the number of SMA terms. The rationale of the impact of number of SMA terms is similar to the impact of the smoothing constant in SES.

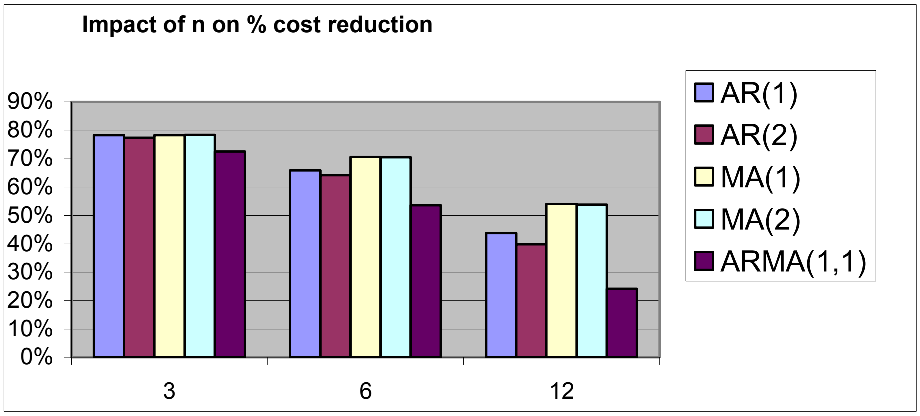


**Figure 8-12 Effect of the Number of Terms in SMA on CDIS for Stationary Demand Processes**

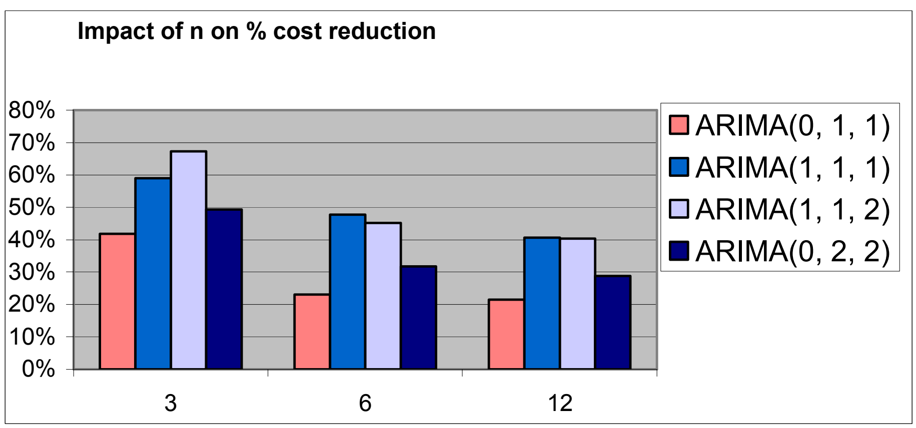


**Figure 8-13 Effect of the Number of Terms in SMA on CDIS for Non-Stationary Demand Processes**

Various papers (e.g. Lee et al, 2000; Raghunathan, 2001) have shown that the manufacturer's demand history contains information about the retailer's demand. Thus, when the manufacturer forecasts with more demand history, they are already utilising the information about the retailer's demand and there is less benefit from sharing the retailer's demand information.

Figure 8-13 also shows that the savings for ARIMA (0, 1, 1) are lower than for other models, since SES is the optimal method for an ARIMA (0, 1, 1) process.

## 8.8. Conclusions

In this chapter, we have presented the results of the simulation experiment. The simulation results show that, on average, Centralised Demand Information Sharing always results in the least inventory cost, irrespective of the forecasting method. We have also examined various factors: the demand parameters, demand variability, lead time and forecasting parameters and have shown that CDIS has some value irrespective of these factors.

Based on the results of the simulation experiment within the Bullwhip Effect regions, three rules have been established in terms of the performance of the demand information sharing approaches. The first rule refers to supply chains with a "No Information Sharing Strategy" and it is established that in all cases, the NIS-Est approach results in lower inventory cost than the NIS approach. For supply chains with an "Information Sharing Strategy", the second rule states that the CDIS approach results in lower inventory cost than the DIS approach. Finally, the third rule states that the CDIS approach results in lower inventory cost than NIS-Est. Thus, the CDIS approach, on average, has the lowest inventory cost over all replications.

In contrast to previous studies where only one demand process was utilised in simulation, we have experimented with nine different demand processes. The results were different for optimal and non-optimal forecasting methods.

For optimal forecasting methods, it was observed that the value of CDIS is model dependent. The value of CDIS was found to be higher for non-stationary demand processes compared to stationary processes. In terms of demand parameters, it was observed that the value of CDIS is an increasing function of the autoregressive parameters, $\rho_1$ and $\rho_2$, and a decreasing function of the moving average parameters $\theta_1$ and $\theta_2$.

For non-optimal forecasting methods, the value of CDIS is less sensitive to the choice of demand process. In terms of the demand parameters, it was found that the value of CDIS is a decreasing function of the autoregressive parameters $\rho_1$ and $\rho_2$. However, the moving average parameters $\theta_1$ and $\theta_2$ had no effect on the value of CDIS.

The staged relaxation approach has shown that the value of CDIS is dependent on the model assumptions. The value of CDIS was least in Stage I, higher in Stage II and highest in Stage III. Thus, the results show that on relaxing the assumptions (a move from a strict mathematical model towards a real life scenario) the value of CDIS increases.

The simulation results showed that, for any individual demand process, MSE and Bullwhip Ratio are associated with inventory cost savings. Higher percentage reductions in MSE or Bullwhip Ratio will result in higher reductions in the inventory cost, although not with the same magnitude. This was observed both for optimal and non-optimal forecasting methods.

We argued in Chapter 5 that utilising the demand and forecast of the downstream member in the CDIS approach will be beneficial to the upstream member in terms of the four performance metrics. The simulation results have shown that the CDIS approach results in the lowest forecast error, Bullwhip Ratio, inventory holdings and inventory cost among the four approaches discussed in this research.

# 9. Empirical Analysis

## 9.1. Introduction

In this chapter, we assess the empirical validity of the theoretical and simulation findings in this research. We developed the operational rules for the supply chain model in Chapters 3 and 7. These rules were then tested in the simulation experiment and results were presented in Chapter 8. Although some model assumptions were relaxed, other assumptions were retained (eg unchanging ARIMA processes with constant parameters over time). In this chapter, model assumptions are relaxed even further, by testing results on empirical data.

There are numerous papers giving empirical evidence of the Bullwhip Effect's existence (see sub-section 2.3.1). However, the literature review of papers modelling the value of demand information sharing (see section 5.2) shows that, with few exceptions, the papers are based on mathematical and simulation analysis. There has been very little empirical evidence to support these analyses. Hosoda et al (2008) quantify the value of sharing demand information in a cold drink supply chain but look at only three product series. Wong et al (2007) quantify the value of information sharing in a toy supply chain. Although they analyse 46 data series, the analysis is restricted to quantifying the value of information sharing in terms of reduced Bullwhip Effect. The empirical work presented in this chapter is therefore of some significance, as the analysis is based on 1773 fast moving products.

We analyse two year weekly sales data of a European grocery supermarket. For confidentiality reasons, the supermarket and their customers remain anonymous. A description of the dataset is provided in section 9.3.

## 9.2. Rationale for Empirical Analysis

Empirical analysis serves the following purposes in this research:

- Empirical analysis is performed to validate the theoretical and simulation findings in earlier chapters. The simulation findings show that the CDIS approach results in the least inventory cost among the supply chain members. We are interested in finding out whether the empirical analysis agrees with these earlier findings on the performance of CDIS.

- In the simulation experiment we also looked at the effect of various factors on the value of CDIS, namely lead time, demand parameters, demand variability, cost ratio and forecasting parameters. The empirical analysis will assess the effect of these factors in a real world scenario.

## 9.3. Data Series

The real demand data series acquired for this empirical research consist of two years of weekly sales data of a European grocery supermarket. The data provided was cleaned, leaving only fast moving products, and 3001 series were selected. The criterion for selection of fast moving products was an average demand of at least 100 units per month over two years with no periods of zero demand. Ignoring products having periods of zero demand cleaned the data for intermittence.

The forecasting and inventory rules presented in Chapters 3 and 7 have been established specifically for non-seasonal time series. The next step, therefore, was scanning monthly data for seasonality. Monthly data was used for this purpose, rather than weekly data, as it exhibited more stable seasonal patterns. For seasonal scanning, we used the Grid Search method of the *autoarima* function of the C Numerical Library (see details of the *autoarima* function in section 7.4) and set the seasonal parameters as 4, 6 and 12 in the grid search. This helped to identify any quarterly, biannual and annual seasonal patterns. Data series exhibiting seasonality were excluded from the detailed empirical analysis to follow, which left 1997 non-seasonal time series.

Further cleaning of data was performed for series with demand parameters lying within the Anti-Bullwhip Effect region (see Table 7-4 for details). This research focuses on reducing the amplification in demand variance in supply chains. Thus, data series where the demand parameters were within the Anti-Bullwhip regions (i.e. regions where the demand variance decreases) were ignored. There were 224 series identified within such regions. This ensures that our empirical analysis is consistent with the simulation experiment.

No information has been provided regarding the product description, product cost or any other details for the SKUs.

## 9.4. Identification of ARIMA Models

In total there are 1773 data series which match the definition of non-seasonal fast moving products lying within the bullwhip parameter region (see previous section for the detailed screening methodology). The grid method of the *autoarima* function (see section 7.4) was then used to identify the process on weekly data. This method requires specification of the range of values for p, d, q and s. The values of p, d and q refer to the coefficients in an ARIMA (p, d, q) process and s is the seasonality factor; its value depends on the seasonality pattern observed in the data history. We keep the value of s to be 1 in order to specify that the data series are non-seasonal.

| **Process Parameter** | **Range provided for Grid** |
|---|---|
| p | 0,1,2 |
| d | 0,1,2 |
| q | 0,1,2 |
| s | 1 |

**Table 9-1 Grid Range for Process Identification**

The ranges of p, d and q provided in the process identification, $p, d, q \leq 2$, have been chosen for consistency with the design of the simulation experiment.

The following tables give an overview of the properties of the empirical data.

| | |
|---|---|
| Stationary Series | 1007 |
| Non-Stationary Series | 766 |
| Total number of Series | 1773 |

**Table 9-2 – Number of Stationary and Non-stationary Series**

Table 9-2 shows that the empirical data contains a good mix of stationary and non-stationary data series with approximately 43% non-stationary and 57% stationary series. Further, we divide the empirical series into the demand processes as identified by the software (see sub-section 7.3.6 for details on the process identification process).

| Demand Process | No. of series |
|---|---|
| **Random Process** | |
| ARIMA(0,0,0) | 113 |
| ARIMA(0,1,0) | 76 |
| **Stationary Process** | |
| AR(1) | 295 |
| AR(2) | 246 |
| ARMA(1,1) | 76 |
| MA(1) | 76 |
| MA(2) | 71 |
| ARMA(2,1) | 40 |
| ARMA(2,2) | 29 |
| ARMA(1,2) | 61 |
| **Non-Stationary Process** | |
| ARIMA(0,1,1) | 17 |
| ARIMA(1,1,0) | 195 |
| ARIMA(1,1,1) | 5 |
| ARIMA(1,1,2) | 5 |
| ARIMA(1,2,0) | 3 |
| ARIMA(2,2,0) | 2 |
| ARIMA(2,1,2) | 4 |
| ARIMA(2,1,1) | 12 |
| ARIMA(2,1,0) | 447 |

**Table 9-3 Number of Series, by ARIMA Processes**

Table 9-3 above shows that, for some ARIMA processes, only a few series have been identified and thus in-depth analysis cannot be performed for those processes. However, these series are not excluded from aggregate analyses, as in Table 9-36 and Appendices 9D and 9E. We analyse twelve demand processes where at least 20 series have been identified. The above table (Table 9-3) shows that, using the criterion of at least 20 series, there are sufficient numbers of series for all random and stationary demand processes to permit in-depth analysis. In terms of non-stationary processes, apart from ARIMA (1, 1, 0) and ARIMA (2, 1, 0), very few series have been identified in the empirical data for the other processes, and these processes with few series will not be analysed in depth. A large number of series has been identified for ARIMA (2, 1, 0); as higher order processes of the form ARIMA (p, 1, 0) where $p \geq 3$ were not investigated, it is impossible to be certain that such series of higher orders were not present.

## 9.5. Design of Empirical Analysis

The design of the empirical analysis follows the simulation experiment design as discussed in detail in Chapter 7. Following the methodology in the simulation experiment, we utilise both optimal and non-optimal forecasting methods in the empirical analysis.

Based on the simulation results, we presented three rules regarding the performance of approaches to Demand Information Sharing in the Bullwhip Effect region (see sub-section 8.2.1). We showed, in Rule 1, that if a supply chain follows a strategy of not sharing demand information, NIS-Est results in lower inventory cost compared to the NIS approach. We have also discussed in detail in sub-section 7.3.4 that in order to maximise the benefits of the ARIMA methodology, a supply chain member should not utilise the NIS approach. Thus, similar to the approach in stages II and III in simulation, we compare only three approaches in the empirical analysis, namely NIS-Est, DIS and CDIS.

On the other hand, in the case of non-optimal forecasting methods, NIS-Est and DIS are not relevant. Thus, using the same approach as in simulation, we compare NIS and CDIS for non-optimal forecasting methods in the empirical analysis. For optimal forecasting methods, the same series splitting approach is employed as for the stages II and III of the simulation experiment. The series is broken into two equal parts of 52 periods each and the first part of the series is used for estimation and the second part for performance measurement. The estimation part is divided into two equal parts of 26 periods each (see sub-section 7.3.7).

Consistent with the simulation experiment, we use Mean Squared Error (MSE), Bullwhip Ratio, inventory holdings and inventory cost as the performance metrics. As discussed in section 3.7, we also calculate the Mean Absolute Percentage Error (MAPE) in the empirical analysis. As no information on product cost, lead time or inventory model has been provided, we will make similar assumptions for the inventory costs as made in the simulation experiment (see section 7.3 for details on the selection of these values). Using these performance metrics, we evaluate which of the approaches, as presented in Chapter 5, results in least inventory cost.

## 9.6. Results of Empirical Analysis for Optimal Forecasting Methods

Following the discussion in the previous section on the design of the empirical analysis, we move on to the presentation and discussion of the results of the analysis.

We start the discussions by looking at the performance of CDIS for different demand processes for the optimal forecasting methods. In doing so, we also compare the results of empirical analysis with those of the simulation. We then move on to the discussion of the effect of demand parameters, demand variability, cost ratio and manufacturer's lead time on the value of CDIS.

The results of the empirical analysis clearly show that the Centralised Demand Information Sharing (CDIS) approach always results in less inventory cost than DIS and NIS-Est. This finding is in accordance with the results of the simulation experiment. Thus, the rules established in Chapter 8 comparing CDIS with DIS and NIS-Est have been confirmed by the empirical analysis.

### 9.6.1. Demand Process Dependent Behaviour

The simulation findings have shown that the value of CDIS is demand process dependent: the values of the performance metrics depend on the demand process. These findings are confirmed by the empirical analysis.

In the following tables we not only present the findings from the empirical analysis but also compare them with the simulation results of the three stages. For comparison with simulation results, in Tables 9-4 and 9-5 we only present results for processes common to both simulation and empirical analysis. In Table 9-4, we show the percentage reduction in the inventory cost by using CDIS instead of NIS-Est, while the comparison with DIS is presented in Table 9-5. In Appendix 9A, we present the results of all performance metrics for all the demand processes with at least 20 series and we proceed to discuss the results of other performance metrics in sub-sections 9.6.2 and 9.6.3. In Appendix 9A, the twelve processes which have a sufficient number of data series for analysis (section 9.4) show a demand process dependent behaviour.

| Demand Process | Percentage Reduction in Inventory Cost by using CDIS instead of NIS-Est | | | |
|---|---|---|---|---|
| | Simulation Stage I | Simulation Stage II | Simulation Stage III | Empirical Analysis |
| AR (1) | 10.8 | 63.0 | 72.0 | 41.1 |
| AR (2) | 41.0 | 71.4 | 74.4 | 16.6 |
| MA (1) | 2.3 | 48.8 | 53.8 | 34.8 |
| MA (2) | 7.5 | 59.6 | 63.0 | 22.8 |
| ARMA (1, 1) | 4.9 | 49.6 | 58.3 | 48.6 |

**Table 9-4 Percentage Savings in Inventory Cost for Stationary Processes by using CDIS instead of NIS-Est**

| Demand Process | Percent Reduction in Inventory Cost by using CDIS instead of DIS | | | |
|---|---|---|---|---|
| | Simulation Stage I | Simulation Stage II | Simulation Stage III | Empirical Analysis |
| AR (1) | 7.6 | 25.8 | 33.8 | 6.2 |
| AR (2) | 11.7 | 38.2 | 41.0 | 7.2 |
| MA (1) | 2.3 | 31.5 | 35.8 | 15.5 |
| MA (2) | 7.5 | 21.5 | 28.8 | 8.1 |
| ARMA (1, 1) | 8.2 | 35.8 | 41.2 | 14.9 |

**Table 9-5 Percentage Savings in Inventory Cost for Stationary Processes by using CDIS instead of DIS**

The above tables clearly show the demand process dependent value of CDIS which was also revealed in the simulation analysis in Chapter 8. We have discussed in detail the rationale for the increasing value of CDIS as the stages proceed in sub-section 8.1.2. The objective of presenting the above tables is to give some insights into the comparison of the theoretical and empirical research.

Firstly, consistent with the simulation findings, the results of empirical analysis also show that there is value in CDIS.

The staged relaxation approach in the simulation experiment showed that the percentage reduction in inventory cost is highest in stage III, less in stage II and is least in stage I. This indicates that as we move away from a model with strict assumptions towards a one with more relaxed assumptions, the value of CDIS increases. For further comparison between the theoretical and empirical findings, we compare the results of the empirical analysis with those of Stage III of the simulation. In the simulation study, Stage III has been designed to most closely reflect a real life scenario (see details on this in Chapter 7). Thus the value of CDIS for the empirical data was expected to be closer to stage III. However, it is evident from Tables 9-4 and 9-5 that the value of CDIS is always higher in Stage III of the simulation experiment than in the empirical analysis.

In the simulation study, we generated different demand processes in a controlled environment. This is in contrast to the empirical data which is more complex in terms of changes to parameters or to the model itself. One possible reason for the value of

CDIS being smaller in the empirical data could be the changing demand model or parameters. Further research is required to investigate the value of CDIS in the empirical data by updating the demand parameters and model in every period.

### 9.6.2. Forecast Error Measures

In Chapter 3, we discussed that one of the performance metrics of this research is forecast error. We also mentioned that where the distribution may not be well behaved (particularly for empirical data) a single forecast error measure may not capture the necessary complexity of the error distribution and that dimensionless error measures should be used (Fildes, 1992; Armstrong and Fildes, 1995). Thus, in the empirical analysis, we have also used Mean Absolute Percentage Error (MAPE) and compare the results of MSE with MAPE.

In the following tables (Table 9-6 and Table 9-7), we present two comparisons in terms of the percentage reduction of forecast error by utilising CDIS instead of DIS and NIS-Est. In both tables, the first comparison is of the forecast error measure, MSE, between the simulation and empirical analysis. The second comparison is between the two error measures, MSE and MAPE, used in the empirical analysis.

| Demand Process | Percentage Reduction in MSE (Simulation Stage III) | Percentage Reduction in MSE (Empirical) | Empirical Analysis MAPE | | |
|---|---|---|---|---|---|
| | | | DIS | CDIS | % reduction |
| AR(1) | 43.1 | 7.1 | 42.6 | 39.2 | 7.9 |
| AR(2) | 54.2 | 19.1 | 41.9 | 37.5 | 10.4 |
| MA(1) | 41.8 | 7.8 | 41.7 | 36.2 | 13.1 |
| MA(2) | 45.0 | 12.8 | 38.2 | 32.5 | 14.9 |
| ARMA (1,1) | 56.1 | 48.0 | 64.7 | 55.0 | 15.0 |

**Table 9-6 Comparison between MMSE Forecast Error Measures (DIS v CDIS)**

| Demand Process | Percentage Reduction in MSE (Simulation Stage III) | Percentage Reduction in MSE (Empirical) | Empirical Analysis MAPE | | |
|---|---|---|---|---|---|
| | | | NIS-Est | CDIS | % reduction |
| AR(1) | 83.6 | 46.2 | 49.2 | 39.2 | 20.3 |
| AR(2) | 96.7 | 32.4 | 47.5 | 37.5 | 21.3 |
| MA(1) | 61.9 | 28.1 | 44.1 | 36.2 | 17.9 |
| MA(2) | 81.9 | 29.7 | 43.2 | 32.5 | 24.8 |
| ARMA (1,1) | 75.8 | 54.4 | 76.1 | 55.0 | 27.7 |

**Table 9-7 Comparison between MMSE Forecast Error Measures (NIS-Est v CDIS)**

The comparison between percentage reduction in MSE of simulation and empirical analysis shows that the MSE reduction is less in empirical analysis than in simulation. We observed the same phenomenon when we compared inventory cost between simulation and empirical analysis. We discuss this further in the next section (section 9.7).

Next, we compare the two forecast errors, MSE and MAPE, which we have used in our empirical analysis. We observe that the percentage reduction in MSE is high compared to the percentage reduction in MAPE. This difference is inherent in the nature of these forecast measures as MSE is a squared measure while MAPE is not. Most importantly, we observe that the results of MAPE show improvements by using CDIS, consistent with the results of all other performance metrics (Appendix 9A).

### 9.6.3. Performance of CDIS

We have discussed in the previous section that, on average, CDIS always results in the least inventory cost among the different information sharing approaches. In this section, we will look at two factors linked with the inventory cost performance of CDIS, namely Forecast Error (in terms of MSE and MAPE) and the Bullwhip Ratio. We present results of the empirical analysis in terms of the Forecast Error (MSE and MAPE) and the Bullwhip Ratio in the following tables.

| Demand Process | Percentage Reduction in the following variables by utilising CDIS instead of DIS | | | | | | |
|---|---|---|---|---|---|---|---|
| | Simulation Results – Stage III | | | Empirical Analysis | | | |
| | MSE | Bullwhip Ratio | Inventory Cost | MAPE | MSE | Bullwhip Ratio | Inventory Cost |
| AR(1) | 43.1 | 41.1 | 33.8 | 7.9 | 7.1 | 23.3 | 6.2 |
| AR(2) | 54.2 | 49.1 | 41.0 | 10.4 | 19.1 | 27.6 | 7.2 |
| MA(1) | 41.8 | 39.4 | 35.0 | 13.1 | 7.8 | 32.2 | 15.5 |
| MA(2) | 45.0 | 38.1 | 28.8 | 14.9 | 12.8 | 19.8 | 8.1 |
| ARMA (1,1) | 56.1 | 51.1 | 41.2 | 27.7 | 48.0 | 42.9 | 14.9 |

**Table 9-8 Performance of CDIS compared to DIS (Stage III Simulation and Empirical Analysis)**

| Demand Process | Percentage Reduction in the following variables by utilising CDIS instead of NIS-Est | | | | | | |
|---|---|---|---|---|---|---|---|
| | Simulation Results – Stage III | | | Empirical Analysis | | | |
| | MSE | Bullwhip Ratio | Inventory Cost | MAPE | MSE | Bullwhip Ratio | Inventory Cost |
| AR(1) | 83.6 | 90.0 | 72.0 | 20.3 | 46.2 | 44.8 | 41.1 |
| AR(2) | 96.7 | 85.6 | 74.4 | 21.3 | 32.4 | 25.8 | 16.6 |
| MA(1) | 61.9 | 51.2 | 53.8 | 17.9 | 28.1 | 28.9 | 34.8 |
| MA(2) | 81.9 | 71.9 | 63.0 | 24.8 | 29.7 | 41.8 | 22.8 |
| ARMA (1,1) | 75.8 | 62.9 | 58.3 | 15.1 | 54.4 | 25.4 | 48.6 |

**Table 9-9 Performance of CDIS compared to NIS-Est (Stage III Simulation and Empirical Analysis)**

The simulation results (section 8.3) show that Forecast Error (in terms of MSE) and the Bullwhip Ratio are associated with inventory cost. It was found that for any individual demand process, the percentage reductions in MSE and Bullwhip Ratio by using CDIS are transferred to percentage reductions in inventory cost, although not with the same magnitude.

The empirical results (Tables 9-8 and 9-9) show the same phenomenon as observed in the simulation experiment. Thus for any individual demand process, as a consequence of changed assumptions in modelling, we observe when the forecast error or the demand variability decreases due to demand information sharing, the inventory cost will also decrease. This is now established in both simulation and empirical analysis for optimal forecasting methods.

### 9.6.4. Effect of Demand Variability

In order to consider the effect of demand variability in the empirical analysis, we have looked at the effect of standard deviation in the demand on the value of CDIS. In the simulation experiment, demand variability was analysed by looking at the effect of standard deviation in the noise of the demand on the value of CDIS. Of course, the standard deviation in the demand increases with the standard deviation in the noise of the demand. It was also observed in the simulation that the inventory cost results recorded by varying the standard deviation in the noise of the demand were consistent with those observed by examining demand variability. As it is very time consuming to calculate the standard deviation in the noise of the demand for each of the 1773 series, we looked at the standard deviation of the demand.

For some demand processes, due to smaller number of series, the effect of standard deviation could not be analysed. In section 9.4, we discussed that for in-depth analysis we will only consider the processes having at least 20 series. All processes with 20 series cannot be analysed here as analysis of demand variability requires breaking down the total number of series in three groups. Thus, we will only analyse those processes for the effect of demand variability where at least 60 series have been identified. The selection of processes with at least 60 series for in-depth analysis by breaking them down into three groups is consistent with our earlier rule of a minimum of 20 series for in-depth empirical analysis.

| Demand process | Std dev of Demand | Number of Series | Reduction in inventory cost in using CDIS compared with | |
|---|---|---|---|---|
| | | | DIS | NIS-Est |
| AR(1) | 0 – 25 | *169* | 1.0 | 30.6 |
| | 25 – 50 | *98* | 5.1 | 37.3 |
| | 50 - above | *28* | 9.4 | 48.2 |
| AR(2) | 0 – 25 | *139* | 2.9 | 9.5 |
| | 25 – 50 | *63* | 2.0 | 30.3 |
| | 50 - above | *41* | 7.8 | 18.0 |
| ARMA (1, 1) | 0 – 25 | *49* | 14.4 | 22.1 |
| | 25 – 50 | *26* | 20.4 | 60.4 |
| | 50 - above | *12* | -0.3 | 33.3 |
| MA(1) | 0 – 25 | *43* | 3.2 | 28.1 |
| | 25 – 50 | *12* | 9.8 | 30.1 |
| | 50 - above | *8* | 30.7 | 41.7 |
| MA(2) | 0 – 25 | *43* | 18.7 | 19.6 |
| | 25 – 50 | *16* | 5.5 | 12.5 |
| | 50 - above | *11* | -1.4 | 39.9 |
| ARMA (1, 2) | 0 – 25 | *45* | 5.2 | 33.4 |
| | 25 – 50 | *8* | 12.8 | 68.2 |
| | 50 - above | *8* | 6.7 | 25.9 |
| ARIMA (1, 1, 0) | 0 - 25 | *69* | 11.8 | 59.1 |
| | 25 - 50 | *86* | 10.4 | 11.7 |
| | 50 - above | *39* | 28.9 | 33.1 |
| ARIMA (2, 1, 0) | 0 - 25 | *206* | 22.0 | 22.4 |
| | 25 - 50 | *141* | 29.7 | 23.1 |
| | 50 - above | *66* | 35.1 | 33.2 |
| ARIMA (0, 0, 0) | 0 - 25 | *83* | 0 | 72.1 |
| | 25 - 50 | *33* | 0 | 47.0 |
| | 50 - above | *13* | 0 | 26.6 |
| ARIMA (0, 1, 0) | 0 - 25 | *40* | 16.3 | 60.3 |
| | 25 - 50 | *13* | 14.2 | 69.8 |
| | 50 - above | *23* | 15.0 | 60.0 |

**Table 9-10 Effect of Demand Variability on the Value of CDIS**

The simulation results showed that percentage reduction in inventory cost, by utilising CDIS, is an increasing function of standard deviation in the noise of demand. We observe in the above table (Table 9-10) that the results are process dependent. The results of AR (1), MA (1) and ARIMA (2, 1, 0) show that the value of CDIS increases with the increasing value of standard deviation in the demand. The empirical analysis for these three processes reinforces the earlier simulation results. On the other hand, this pattern is not observed for the other seven processes.

The effect of demand variability in the simulation experiment was analysed by keeping the demand parameters constant. This is not the case for the empirical analysis and thus a possible reason for the inconsistency is the interaction between the demand parameters and the demand variability. This is further discussed in the next sub-section 9.6.5.

### 9.6.5. Effect of Demand Parameters

Now, we consider the effect of demand parameters on the value of CDIS. The simulation results in sub-section 8.3.1 showed that the performance of CDIS depends on the value of the demand parameters. In the empirical analysis, we look at each process individually and compare the simulation and empirical results. Using the same rationale as discussed in sub-section 9.6.4, we restrict discussion to the processes where at least 60 series were identified in the empirical analysis. As we are looking at the effect of autoregressive and moving average parameters in this sub-section, ARIMA (0, 0, 0) and ARIMA (0, 1, 0) processes are not discussed.

We discuss the remaining processes in two sub-sections. AR (1) and MA (1), having only demand parameter to estimate, are discussed in sub-section 9.6.5.1. Then, in sub-section 9.6.5.2, we discuss AR (2), MA (2) and ARMA (1, 1) as two demand parameters must be estimated for these processes.

#### 9.6.5.1. Single Parameter Processes

We first look at the effect of demand parameters for processes where only one parameter is required to be estimated, i.e. AR (1) and MA (1). There were 294 series identified as AR (1) and 76 series as MA (1) in the empirical data.

We divide the 294 data series identified as AR (1) into three groups based on the value of the autoregressive parameter $\rho_1$. The parameter range is selected so as to have an appropriate number of series in each group. The results are shown in Table 9-11 below.

| Demand process | $\rho_1$ | Number of Series | Reduction in inventory cost in using CDIS compared | |
|---|---|---|---|---|
| | | | DIS | NIS-Est |
| AR(1) | < 0.2 | *75* | 5.0 | 38.7 |
| | 0.2 - 0.4 | *137* | 6.3 | 39.4 |
| | > 0.4 | *82* | 8.1 | 44.1 |

**Table 9-11 Effect of $\rho_1$ on the Value of CDIS for AR (1) Process**

The simulation results showed that the value of CDIS is an increasing function of the autoregressive parameter. This result is confirmed in the empirical analysis for comparison of inventory cost with both DIS and NIS-Est approaches.

Lee et al (2000), by simulating an AR (1) process, quantified the value of demand information sharing. They showed that this value is an increasing function of the autoregressive parameter, $\rho_1$. The simulation and empirical results in this research agree with the findings of Lee et al (2000).

We now move the discussion to looking at the effect of the moving average parameters on the value of CDIS. We first look at an MA (1) process.

| Demand process | $\theta_1$ | Number of Series | Reduction in inventory cost in using CDIS compared | |
|---|---|---|---|---|
| | | | DIS | NIS-Est |
| MA(1) | < -0.4 | *7* | 26.0 | 40.7 |
| | -0.4 - -0.2 | *32* | 11.5 | 33.1 |
| | > -0.2 | *34* | 0.5 | 29.7 |

**Table 9-12 Effect of $\theta_1$ on the Value of CDIS for MA (1) Process**

The above results are similar to the earlier findings in the simulation experiment. The simulation results showed that the value of CDIS decreases with the increasing value of the moving average parameter $\theta$. This result is also exhibited in the empirical findings as shown in Table 9-12 above. Indeed, the effect of the moving average parameter is more pronounced in empirical analysis than in simulation.

In this sub-section, the effect of demand parameters on the value of CDIS for AR (1) and MA (1) processes have been discussed. We observe that the empirical findings are consistent with the earlier simulation results on the effect of autoregressive and moving average parameters on the value of CDIS. The value of CDIS is an increasing function of the autoregressive parameter, $\rho_1$, and a decreasing function of the moving average parameter $\theta_1$.

### 9.6.5.2. Double Parameter Processes

The three processes AR (2), MA (2) and ARMA (1, 1) will be discussed separately in this sub-section as there are two demand parameters to be estimated for these processes.

We first analyse the effect of the autoregressive parameters for an AR (2) process. The numbers in each box are the percentage reductions in inventory cost obtained by using CDIS, while the numbers in brackets are the number of series for each of the groups. The rationale for the division of groups is the same as discussed for the AR (1) process in the previous sub-section (9.6.5.1).

| $\rho_1$ | $\rho_2$ | |
|---|---|---|
| | **< 0.2** | **≥ 0.2** |
| **< 0.2** | 2.6 (*35*) | 5.8 (*66*) |
| **≥ 0.2** | 3.3 (*91*) | 16.6 (*52*) |

**Table 9-13 Percentage Reduction in Inventory Cost by using CDIS compared to DIS for AR (2) Process**

The simulation results for AR (2) show that, as the value of the autoregressive parameters $\rho_1$ and $\rho_2$ increases, the value of CDIS also increases. We observe that when the value of CDIS is calculated in comparison with DIS, the empirical results confirm the earlier simulation experiment findings. The value of CDIS in the above table (Table 9-13) is increasing both in $\rho_1$ and $\rho_2$.

| $\rho_1$ | $\rho_2$ | |
|---|---|---|
| | **< 0.2** | **≥ 0.2** |
| **< 0.2** | 38.5 (*35*) | 18.3 (*66*) |
| **≥ 0.2** | 17.7 (*91*) | 1.9 (*52*) |

**Table 9-14 Percentage Reduction in Inventory Cost by using CDIS compared to NIS-Est for AR (2) Process**

In Table 9-14, the value of CDIS is calculated by comparing the inventory cost for CDIS with the inventory cost for NIS-Est. We observe that the value of CDIS is decreasing with the increasing value of both $\rho_1$ and $\rho_2$. This is an opposite phenomenon as to what was revealed from our simulation experiment.

We now analyse the MA (2) process to look at the effect of the moving average parameters on the value of CDIS.

| $\theta_1$ | $\theta_2$ | |
|---|---|---|
| | **< -0.2** | **≥ -0.2** |
| **< -0.2** | 5.6 (*15*) | 9.1 (*24*) |
| **≥ -0.2** | 21.6 (*12*) | 1.6 (*18*) |

**Table 9-15 Percentage Reduction in Inventory Cost by using CDIS compared to DIS for MA (2) Process**

| $\theta_1$ | $\theta_2$ | |
|---|---|---|
| | **< -0.2** | **≥ -0.2** |
| **< -0.2** | 3.1 (*15*) | 7.4 (*24*) |
| **≥ -0.2** | 43.8 (*12*) | 30.0 (*18*) |

**Table 9-16 Percentage Reduction in Inventory Cost by using CDIS compared to NIS-Est for MA (2) Process**

The results of the simulation experiment for MA (2) process showed that the value of CDIS is a decreasing function of the value of both $\theta_1$ and $\theta_2$. The above tables (Table 9-15 and 9-16) show that this pattern does not hold for the empirical analysis, when we look at the effect of the moving average parameters on the value of CDIS for comparisons with DIS and NIS-Est. The effect of autoregressive and moving average parameters are now analysed for the mixed ARMA (1, 1) process. The reduction in inventory cost by using CDIS compared with DIS is given in Table 9-17, while the results when compared with NIS-Est are given in Table 9-18.

| $\theta_1$ | $\rho_1$ | |
|---|---|---|
| | **-0.9 — 0.5** | **0.5 — 0.9** |
| **-0.9 — -0.3** | 1.1 *(11)* | |
| **-0.3 — 0.5** | 5.0 *(11)* | 15.3 *(24)* |
| **0.5 — 0.9** | | 56.6 *(41)* |

**Table 9-17 Percentage Reduction in inventory Cost by using CDIS compared to DIS for ARMA (1, 1) Process**

Simulation results showed that when the autoregressive parameter $\rho_1$ increases, the value of CDIS will increase and this is also observed in empirical analysis. However, the simulation also showed that when $\theta_1$ increases, the value of CDIS will decrease. This pattern is not observed in Table 9-17.

| $\theta_1$ | $\rho_1$ | |
|---|---|---|
| | **-0.9 — 0.5** | **0.5 — 0.9** |
| **-0.9 — -0.3** | 9.1 *(11)* | |
| **-0.3 — 0.5** | 54.7 *(11)* | 47.0 *(24)* |
| **0.5 — 0.9** | | 6.2 *(41)* |

**Table 9-18 Percentage Reduction in Inventory Cost by using CDIS compared to NIS-Est for ARMA (1, 1) Process**

The comparison with NIS-Est (Table 9-18) also shows that the pattern expected from the simulation results is not observed in the empirical analysis. However, the analysis presented in Tables 9-17 and 9-18 are limited to only two intervals for $\rho_1$ and three intervals for $\theta_1$ due to small number of series observed for ARMA (1, 1).

It is clear that, for double parameter processes, the empirical results do not all agree with the simulation findings. The empirical analysis often does not confirm the relationship observed in the simulation experiment. One reason for the difference in results in the empirical analysis could be that in the simulation experiment, the effect of demand parameters was considered by keeping the standard deviation of the noise constant. This is not the case with the empirical analysis where both the demand parameters and the standard deviation in the noise vary in these groups. The dual effect of both demand parameters and standard deviation of the noise is a possible reason for the difference in results for some processes. In order to resolve this, investigation is required to assess the dual effect of the demand parameters and standard deviation of noise. Such an analysis should be based on larger data sets, which would enable interaction between variables to be analysed in depth, and non-linear effects (such as those shown in Table 8-7) to be identified.

### 9.6.6. Effect of Cost Ratio

In the simulation experiment, the cost ratio was varied to investigate how the percentage reductions in the inventory costs are affected by the cost ratio. In Table 9-19, we present the results of empirical analysis for the effect of cost ratio on the value of CDIS.

| Cost Ratio | Percentage Savings in Inventory Cost by using CDIS compared to | |
|---|---|---|
| | **DIS** | **NIS-Est** |
| **2/(2+1)** | 14.5 | 22.5 |
| **25/(25+1)** | 29.5 | 53.0 |
| **50/(50+1)** | 32.9 | 68.9 |

**Table 9-19 Effect of Cost Ratio on Percentage Reduction in Inventory Cost**

In the simulation experiment, it was found that the value of CDIS is an increasing function of the cost ratio. This result has now been validated by the empirical analysis. The results of simulation and empirical analysis have shown that the value of CDIS is high when the penalty cost is high compared to the inventory cost.

## 9.7. Results of Empirical Analysis for Non-Optimal Forecasting Methods

The results of the empirical analysis for the non-optimal forecasting methods are discussed in this section. The results clearly show that the Centralised Demand Information Sharing (CDIS) approach always results in less inventory cost than NIS. This finding is consistent with the results from the simulation experiment. Thus, the rules established in Chapter 8 with respect to non-optimal forecasting methods have been confirmed by the empirical analysis.

### 9.7.1. Results for Demand Processes

We start this discussion by first looking at the value of CDIS for individual demand processes. The values presented in the following table compare the percentage reduction in inventory cost by using CDIS instead of NIS when the Simple Moving Average forecasting method is employed. As the purpose of the following table is to present a comparison between simulation and empirical analysis, only the results of ARIMA processes common to both in-depth simulation and empirical analysis are presented.

| Demand Process | Percentage Reduction in Inventory Cost by using CDIS compared with NIS | |
|---|---|---|
| | Simulation Experiment | Empirical Analysis |
| AR (1) | 46.4 | 42.3 |
| AR (2) | 44.9 | 39.7 |
| MA (1) | 58.0 | 58.0 |
| MA (2) | 57.5 | 54.4 |
| ARMA (1, 1) | 29.3 | 32.9 |

**Table 9-20 Results of Empirical Analysis compared with Simulation for SMA**

The above table shows that the results of empirical analysis are consistent with the results of the simulation experiment. Similar results can be observed when the Single Exponential Smoothing forecasting method is employed. The results are summarised in the following table.

| Demand Process | Percentage Reduction in Inventory Cost by using CDIS compared with NIS | |
|---|---|---|
| | Simulation Experiment | Empirical Analysis |
| AR (1) | 65.6 | 71.7 |
| AR (2) | 60.3 | 72.5 |
| MA (1) | 68.8 | 74.3 |
| MA (2) | 63.9 | 72.8 |
| ARMA (1, 1) | 71.0 | 73.2 |

**Table 9-21 Results of Empirical Analysis compared with Simulation for SES**

Detailed results of all the performance metrics for both forecasting methods are presented in Appendices 9B and 9C. The patterns of the results of all the other processes not included in the above two tables (Tables 9-20 and 9-21) are consistent with the results of the above five processes.

### 9.7.2. Forecast Error Measures

One of the performance measures used in this research is Forecast Error (see sub-section 3.7.2). The use of a dimensionless accuracy measure in empirical analysis was also discussed in the same sub-section and in sub-section 9.6.2. Thus, in the empirical analysis, we use Mean Absolute Percentage Error (MAPE) and compare the results of MSE with MAPE.

In the following tables (Table 9-22 and Table 9-23), similar to optimal forecasting methods, we present two comparisons in terms of the percentage reduction of MSE by utilising CDIS instead of NIS. MSE of simulation is first compared with MSE of empirical analysis followed by comparison of MSE and MAPE in empirical analysis.

| Demand Process | Percentage Reduction in MSE (Simulation) | Percentage Reduction in MSE (Empirical) | Empirical Analysis MAPE | | |
|---|---|---|---|---|---|
| | | | NIS | CDIS | % reduction |
| AR(1) | 41.7 | 39.0 | 64.9 | 47.0 | 20.6 |
| AR(2) | 41.0 | 38.9 | 59.1 | 48.0 | 18.7 |
| MA(1) | 52.9 | 42.7 | 62.1 | 42.1 | 32.2 |
| MA(2) | 52.6 | 45.3 | 66.8 | 47.5 | 28.8 |
| ARMA (1,1) | 27.6 | 35.4 | 49.2 | 37.8 | 23.0 |

**Table 9-22 Comparison between SMA Forecast Error Measures (NIS vs. CDIS)**

| Demand Process | Percentage Reduction in MSE (Simulation) | Percentage Reduction in MSE (Empirical) | Empirical Analysis MAPE | | |
|---|---|---|---|---|---|
| | | | NIS | CDIS | % reduction |
| AR(1) | 71.5 | 70.0 | 55.2 | 37.1 | 32.7 |
| AR(2) | 73.7 | 70.8 | 59.1 | 48.0 | 34.6 |
| MA(1) | 66.6 | 81.3 | 53.4 | 28.9 | 45.8 |
| MA(2) | 70.8 | 64.2 | 56.6 | 39.3 | 29.4 |
| ARMA (1,1) | 62.0 | 73.4 | 48.7 | 30.9 | 36.6 |

**Table 9-23 Comparison between SES Forecast Error Measures (NIS vs. CDIS)**

In terms of the first comparison, between MSE of simulation and empirical analysis, we find that the empirical results are broadly consistent with simulation results. This is true for both forecasting methods: SMA and SES. Similar results were observed for the processes in terms of inventory costs (see sub-section 9.7.1).

The second comparison is between the percentage reductions of MSE and MAPE in the empirical analysis. The percentage reduction in MSE is found to be higher compared to MAPE. This is similar to what was observed for the optimal forecasting methods (sub-section 9.6.2). The reason for this, as already mentioned for the optimal forecasting method, is that MSE is a squared measure while MAPE is not. Most importantly, consistent with the results of optimal methods, we observe that the results of MAPE show improvements by using CDIS, consistent with the results of all other performance metrics (Appendices 9B and 9C).

### 9.7.3. Performance of CDIS

In section 8.7, we analysed two factors linked with the performance of CDIS for non-optimal methods. The simulation results showed that, for any demand process, percentage reductions in inventory costs on using CDIS approach were associated with percentage reductions in Forecast Error and Bullwhip Ratio.

In the following tables (Table 9-24 and Table 9-25), we present the percentage reductions of the Forecast Error (MSE and MAPE), Bullwhip Ratio and inventory cost by using CDIS approach compared to NIS for SMA and SES methods.

| Demand Process | Percentage Reduction in the following variables by utilising CDIS instead of NIS | | | | | | |
|---|---|---|---|---|---|---|---|
| | Simulation Results | | | Empirical Analysis | | | |
| | MSE | Bullwhip Ratio | Inventory Cost | MAPE | MSE | Bullwhip Ratio | Inventory Cost |
| AR(1) | 65.7 | 55.2 | 46.4 | 20.6 | 39.0 | 54.8 | 42.3 |
| AR(2) | 65.3 | 54.2 | 44.9 | 18.7 | 38.9 | 50.0 | 39.7 |
| MA(1) | 72.2 | 65.3 | 58.0 | 32.2 | 42.7 | 62.8 | 58.0 |
| MA(2) | 70.8 | 63.6 | 57.5 | 28.8 | 45.3 | 62.8 | 54.4 |
| ARMA (1,1) | 53.5 | 39.5 | 29.3 | 23.0 | 35.4 | 35.5 | 27.9 |

**Table 9-24 Performance of CDIS for SMA**

| Demand Process | Percentage Reduction in the following variables by utilising CDIS instead of NIS | | | | | | |
|---|---|---|---|---|---|---|---|
| | Simulation Results | | | Empirical Analysis | | | |
| | MSE | Bullwhip Ratio | Inventory Cost | MAPE | MSE | Bullwhip Ratio | Inventory Cost |
| AR(1) | 71.5 | 70.6 | 65.6 | 32.7 | 70.0 | 81.3 | 71.7 |
| AR(2) | 73.7 | 62.1 | 60.3 | 34.6 | 70.8 | 79.7 | 72.5 |
| MA(1) | 66.6 | 64.5 | 63.9 | 45.8 | 81.3 | 72.1 | 68.8 |
| MA(2) | 70.8 | 76.2 | 71.0 | 29.4 | 64.2 | 64.5 | 63.9 |
| ARMA (1,1) | 62.0 | 72.1 | 68.8 | 36.6 | 73.4 | 76.2 | 71.0 |

**Table 9-25 Performance of CDIS for SES**

Tables 9-24 and 9-25 show that for any demand process, as a consequence of changed model assumptions, an increase in the percentage reduction in MSE and Bullwhip Ratio (by using CDIS compared to NIS) results in an increase in the percentage reduction in the inventory cost, although not with the same magnitude. This phenomenon has now been observed for optimal and non-optimal forecasting methods in both simulation and empirical analysis.

In addition, consistent with the simulation results, Tables 9-24 and 9-25 also show that non-optimal forecasting methods are less sensitive to demand process as compared to optimal methods.

### 9.7.4. Effect of Demand Variability

In the simulation experiment, we looked at the effect of demand variability by considering the standard deviation in the noise of the demand. We discussed in sub-section 9.6.4 that the effect of demand variability in the empirical analysis has been measured by calculating the standard deviation of the demand. It is obvious that the standard deviation in the demand increases with the standard deviation in the noise of the demand. It was also observed in the simulation that the simulation results on inventory cost reductions obtained by varying the standard deviation in the noise of the demand were consistent with those obtained for demand variability.

We present the effect of demand variability on the percentage reduction in inventory cost for the two non-optimal forecasting methods, SMA and SES in the following table (Table 9-26).

| Demand process | Std dev of Demand | Number of Series | Reduction in inventory cost in using CDIS compared with NIS | |
|---|---|---|---|---|
| | | | SMA | SES |
| AR(1) | 0 – 25 | *169* | 40.2 | 51.8 |
| | 25 – 50 | *98* | 44.6 | 61.7 |
| | 50 – above | *28* | 46.6 | 75.0 |
| AR(2) | 0 – 25 | *139* | 38.1 | 80.5 |
| | 25 – 50 | *63* | 37.3 | 69.2 |
| | 50 – above | *41* | 48.5 | 71.5 |
| ARMA (1, 1) | 0 – 25 | *49* | 37.2 | 71.0 |
| | 25 – 50 | *26* | 39.5 | 75.2 |
| | 50 – above | *12* | 28.4 | 71.8 |
| MA(1) | 0 – 25 | *43* | 55.3 | 74.0 |
| | 25 – 50 | *12* | 57.2 | 74.1 |
| | 50 – above | *8* | 59.2 | 74.8 |
| MA(2) | 0 – 25 | *43* | 52.1 | 73.6 |
| | 25 – 50 | *16* | 58.4 | 71.0 |
| | 50 – above | *11* | 49.5 | 74.2 |
| ARMA (1, 2) | 0 – 25 | *45* | 35.6 | 60.4 |
| | 25 – 50 | *8* | 48.0 | 88.2 |
| | 50 - above | *8* | 32.2 | 58.4 |
| ARIMA (1, 1, 0) | 0 – 25 | *69* | 66.8 | 69.5 |
| | 25 – 50 | *86* | 66.8 | 77.1 |
| | 50 – above | *39* | 70.5 | 68.3 |
| ARIMA (2, 1, 0) | 0 – 25 | *206* | 59.8 | 71.9 |
| | 25 – 50 | *141* | 66.6 | 72.1 |
| | 50 – above | *66* | 72.5 | 77.2 |
| ARIMA (0, 0, 0) | 0 – 25 | *83* | 69.5 | 73.6 |
| | 25 – 50 | *33* | 66.2 | 69.9 |
| | 50 – above | *13* | 66.2 | 70.0 |
| ARIMA (0, 1, 0) | 0 – 25 | *40* | 70.2 | 66.6 |
| | 25 – 50 | *13* | 59.9 | 65.2 |
| | 50 – above | *23* | 69.2 | 76.2 |

**Table 9-26 Effect of Demand Variability on the Value of CDIS compared with NIS**

The simulation results revealed that percentage reduction in inventory cost on utilising CDIS, is an increasing function of standard deviation in the noise of demand or standard deviation in the demand (see sub-section 8.5.3). We observe in the above table (Table 9-26) that the results are process dependent. The results of AR (1), MA (1) and ARIMA (2, 1, 0) show that the value of CDIS increases with the increasing value of standard deviation in the demand. The empirical analysis for these three processes reinforces the earlier simulation results. On the other hand, this pattern is not observed for the other processes i.e. AR (2), ARMA (1, 1), ARMA (1, 2), MA (2), ARIMA (1, 1, 0), ARIMA (0, 0, 0) and ARIMA (0, 1, 0). The same phenomenon was observed for the optimal forecasting method (sub-section 9.6.4) and the suggested reasons are the same as mentioned earlier.

### 9.7.5. Effect of Demand Parameters

In this sub-section, we analyse the effect of demand parameters on the value of CDIS for non-optimal forecasting methods. In the simulation experiment, we analysed the effect of demand parameters for the five stationary processes used in the research. For the empirical analysis, in this sub-section, the same processes are analysed. The results are discussed in the following sub-sections.

#### 9.7.5.1. Single Demand Parameter

AR (1) and MA (1) demand processes are discussed in this sub-section as both processes have only one demand parameter to estimate. The total number of series for both processes has been divided into three groups so that we have appropriate numbers of series in each group. The grouping is similar to that for optimal forecasting methods.

| Demand process | $\rho_1$ | Number of Series | Reduction in inventory cost in using CDIS compared | |
|---|---|---|---|---|
| | | | SMA | SES |
| AR(1) | < 0.2 | *75* | 44.4 | 71.9 |
| | 0.2 – 0.4 | *137* | 43.9 | 71.6 |
| | > 0.4 | *82* | 39.6 | 71.0 |

**Table 9-27 Effect of $\rho_1$ on the Value of CDIS for AR (1) Process**

For non-optimal forecasting methods, the simulation results showed an opposite trend compared to optimal forecasting methods. For both SMA and SES, it was observed that the value of CDIS decreases with the increasing value of the autoregressive parameter, $\rho_1$. This result is confirmed in the empirical analysis for comparison of inventory cost for both SMA and SES methods.

Chen et al (2000a; 2000b), by simulating an AR (1) process, quantified the value of demand information sharing. They showed that the value of sharing demand information decreases with the increasing value of the autoregressive parameter, $\rho_1$ for both SMA and SES. The simulation and empirical results in this research confirm the findings of Chen et al (2000a; 2000b).

We now move the discussion to looking at the effect of the moving average parameters on the value of CDIS and first look at an MA (1) process in this sub-section.

| Demand process | $\theta_1$ | Number of Series | Reduction in inventory cost in using CDIS compared | |
|---|---|---|---|---|
| | | | SMA | SES |
| MA(1) | < -0.4 | *7* | 44.2 | 70.8 |
| | -0.4 - -0.2 | *32* | 66.1 | 77.3 |
| | > -0.2 | *34* | 39.8 | 71.8 |

**Table 9-28 Effect of $\theta_1$ on the Value of CDIS for MA (1) Process**

It was discussed in sub-section 8.4.1 that none of the earlier papers have looked at the effect of the moving average parameter on the value of CDIS. In the simulation experiment, we found that the moving average parameter has no effect on the value of CDIS. This result is not contradicted in the empirical findings as shown in Table 9-28 above, where for both SMA and SES, there is no consistent upward or downward trend, as $\theta_1$ is varied. A limitation of the above table is the small number of series when $\theta_1 < 0.4$.

In this sub-section, the effect of demand parameters on the value of CDIS for AR (1) and MA (1) processes has been discussed. It is observed that the empirical findings are consistent with the earlier simulation results on the effect of autoregressive and moving average parameters on the value of CDIS. The value of CDIS is an increasing function of the autoregressive parameter, $\rho_1$, while the value of CDIS for non-optimal forecasting methods is neither an increasing nor decreasing function of the moving average parameter, $\theta_1$.

#### 9.7.5.2. Double Demand Parameters

The three processes AR (2), MA (2) and ARMA (1, 1) will be discussed in this sub-section as there are two demand parameters to be estimated for each of these processes.

The AR (2) process is considered first and the results are shown in Table 9-29 and Table 9-30. The numbers in each box are the percentage reduction in inventory cost by using CDIS compared to NIS, while the numbers in brackets are the number of series for each of these groups. The rationale for the division of group is the same as discussed for the AR (1) process in the previous sub-section (9.6.5.1).

| $\rho_1$ | $\rho_2$ | |
|---|---|---|
| | **< 0.2** | **≥ 0.2** |
| **< 0.2** | 40.8 (*35*) | 22.1 (*66*) |
| **≥ 0.2** | 30.2 (*91*) | 55.0 (*52*) |

**Table 9-29 Percentage Reduction in Inventory Cost for AR (2) Process using SMA Method**

| $\rho_1$ | $\rho_2$ | |
|---|---|---|
| | **< 0.2** | **≥ 0.2** |
| **< 0.2** | 68.6 (*35*) | 80.0 (*66*) |
| **≥ 0.2** | 68.9 (*91*) | 79.9 (*52*) |

**Table 9-30 Percentage Reduction in Inventory Cost for AR (2) Process using SES Method**

The simulation results for AR (2) showed that the as the value of the autoregressive parameters $\rho_1$ and $\rho_2$ increases, the value of CDIS decreases. We do not find this effect in the empirical analysis.

We now analyse the MA (2) process to further look at the effect of $\theta_1$ and $\theta_2$ on the value of CDIS.

| $\theta_1$ | $\theta_2$ | |
|---|---|---|
| | **< -0.2** | **≥- 0.2** |
| **< -0.2** | 55.6 (*15*) | 49.1 (*24*) |
| **≥ -0.2** | 41.6 (*12*) | 71.6 (*18*) |

**Table 9-31 Percentage Reduction in Inventory Cost for MA (2) Process using SMA Method**

| $\theta_1$ | $\theta_2$ | |
|---|---|---|
| | **< -0.2** | **≥- 0.2** |
| **< -0.2** | 81.3 *(15)* | 67.9 *(24)* |
| **≥ -0.2** | 81.3 *(12)* | 68.8 *(18)* |

**Table 9-32 Percentage Reduction in Inventory Cost for MA (2) Process using SES Method**

The results of the simulation experiment for MA (2) process showed that the value of CDIS does not depend on the values of $\theta_1$ and $\theta_2$.

The above tables (Table 9-31 and 9-32) do not contradict the simulation findings, as there is no consistent effect of the moving average parameters on the value of CDIS for both SMA and SES forecasting methods.

The effect of autoregressive and moving average parameters are now analysed for the mixed ARMA (1, 1) process. The reduction in inventory cost by using CDIS compared with NIS is given in Table 9-33 for SMA and in Table 9-34 for SES.

| $\theta_1$ | $\rho_1$ | |
|---|---|---|
| | **-0.9 — 0.5** | **0.5 — 0.9** |
| **-0.9 — -0.3** | 39.0 (*11*) | |
| **-0.3 — 0.5** | 22.1 *(11)* | 20.4 *(24)* |
| **0.5 — 0.9** | | 36.0 *(41)* |

**Table 9-33 Percentage Reduction in Inventory Cost for ARMA (1, 1) Process using SMA**

Simulation results showed that when the autoregressive parameter $\rho_1$ increases, the value of CDIS will decrease. The simulation showed that there is no effect of $\theta_1$ on the value of CDIS.

| $\theta_1$ | $\rho_1$ | |
|---|---|---|
| | **-0.9 — 0.5** | **0.5 — 0.9** |
| **-0.9 — -0.3** | 73.0 *(11)* | |
| **-0.3 — 0.5** | 73.5 *(11)* | 69.2 *(24)* |
| **0.5 — 0.9** | | 75.9 *(41)* |

**Table 9-34 Percentage Reduction in Inventory Cost for ARMA (1, 1) Process using SES**

The empirical analysis (Table 9-33 and Table 9-34) does not show any pattern in terms of the effect of $\rho_1$ and $\theta_1$ on the value of CDIS. For the moving average parameter, the result is consistent with the simulation findings. In terms of the autoregressive parameter, the simulation experiment showed that the value of CDIS decreases when the value of autoregressive parameter increases. The results of the empirical analysis do not agree with these findings. However, the analysis presented for AR (2) and MA (2) is limited to only two intervals for the demand parameters due to small number of series. Similarly, for ARMA (1, 1) the intervals are limited to only two intervals for $\rho_1$ and three intervals for $\theta_1$.

It has been argued in sub-section 9.6.5 that the standard deviation of noise was kept constant in the simulation experiment when the effect of demand parameters was analysed, which is not the case in the empirical analysis. Thus, there is a need in the empirical analysis to investigate the interaction between the demand parameters and standard deviation of noise. However, as already discussed in sub-section 9.6.5, such an investigation, taking into account $\rho_1$, $\rho_2$ and standard deviation in the noise should be based on larger data sets.

### 9.7.6. Effect of Cost Ratio

In the simulation experiment, the effect of the cost ratio on the value of CDIS was analysed. For non-optimal forecasting methods, the simulation results showed an interesting phenomenon. It was observed that the percentage savings in inventory cost using CDIS compared to NIS increased with the increasing value of the cost ratio for stationary processes but decreased with the increasing value of cost ratio for the non-stationary processes. In order to validate this, a similar analysis was performed on stationary and non-stationary processes on the empirical data. The results are given below in Table 9-35.

| Demand Process | Cost Ratio | Percentage Savings in Inventory Cost by using CDIS compared to NIS | |
|---|---|---|---|
| | | SMA | SES |
| Stationary Processes | 2/(2+1) | 46.8 | 70.4 |
| | 25/(25+1) | 52.9 | 75.5 |
| | 50/(50+1) | 54.6 | 77.1 |
| Non-Stationary Processes | 2/(2+1) | 55.8 | 73.6 |
| | 25/(25+1) | 55.6 | 71.5 |
| | 50/(50+1) | 54.9 | 70.9 |

**Table 9-35 Effect of Cost Ratio for Non-Optimal Methods**

Table 9-35 shows that the empirical results agree with the simulation findings about the effect of cost ratio on the value of CDIS. For stationary processes, the value of CDIS is an increasing function of the cost ratio. The phenomenon is totally opposite when the demand process is non-stationary. For such demand processes, the value of CDIS decreases with increasing value of the cost ratio, although the effect is not strongly marked (see Table 9-35).

### 9.7.7. Effect of Forecasting Parameters

Here we discuss the effect of the forecasting parameters on the value of CDIS for the two non-optimal forecasting methods. For SMA, we look at the effect of the length of the moving average and, for SES, we look at the effect of the smoothing constant.

#### 9.7.7.1. Effect of the Smoothing Constant in SES

The following figure (Figure 9-1) shows the percentage reduction in the inventory cost by employing the CDIS approach instead of NIS, when we consider the effect of the smoothing constant in SES for an AR (1) process.

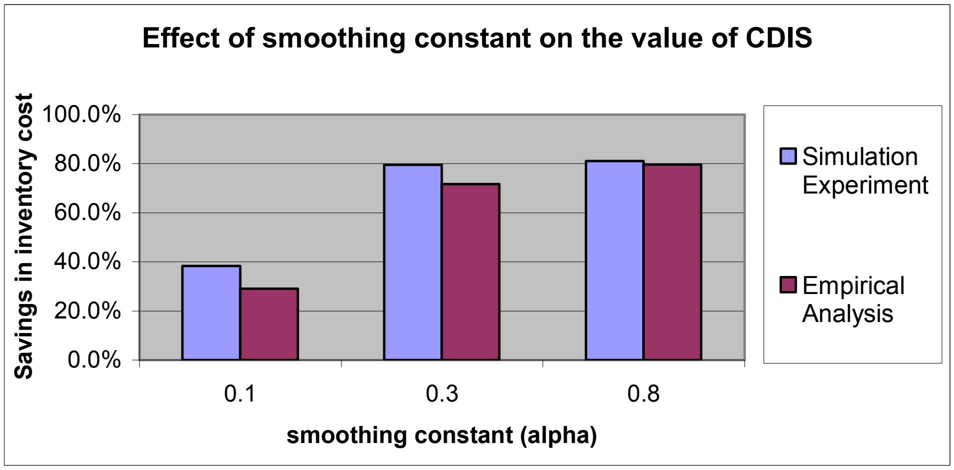


**Figure 9-1 Effect of Smoothing Constant on CDIS for an AR (1) Process**

The above figure clearly indicates that the value of CDIS is an increasing function of the smoothing constant in SES in the empirical analysis, which is in close agreement with the simulation experiment.

The upstream translation of demand, as discussed in detail in Chapter 4, shows that the manufacturer's demand history contains information about the retailer's demand. Thus, when a higher value of the smoothing constant is used, it shows less weighting has been put on the demand history. This results in more value of CDIS.

The same effect of the smoothing constant has been observed when all demand processes were analysed by changing the value of alpha. The results are presented in Appendix 9D.

### 9.7.7.2. Effect of Number of Terms in SMA

The following figure (Figure 9-2) shows the effect of number of terms (n) in SMA for an AR (1) process on the percentage reduction in the inventory cost by employing the CDIS approach instead of NIS.

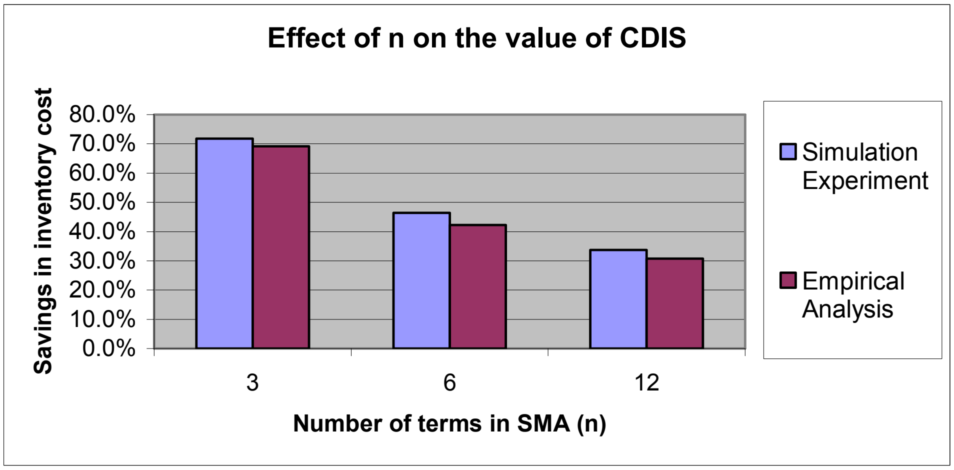


**Figure 9-2 Effect of Number of Terms in SMA on CDIS for an AR (1) Process**

It is evident from the above figure that the value of CDIS decreases as the value of the number of terms (n) in SMA increases. These results are consistent with the findings in the simulation experiment.

The rationale for this effect is similar to that for the SES method. A higher value of n means that more demand history has been taken into account by the manufacturer in its forecasting. As the manufacturer's history contains information about the retailer's demand, more history means less value in CDIS.

The same effect of the smoothing constant has been observed when all demand processes were analysed by changing the value of alpha. The results are presented in Appendix 9E.

### 9.7.8. Effect of Lead Time

The empirical results show that the percentage reduction in inventory cost is an increasing function of the lead time from the supplier to the manufacturer. This has already been established by Lee et al (2000) for optimal forecasting methods and is consistent with the simulation results.

Table 9-36 shows the percentage reduction in inventory cost by using CDIS compared to NIS-Est (for an MMSE forecasting method) and compared to NIS (for the two non-optimal forecasting methods, SMA and SES).

| Lead Time | Average Percentage Savings over all Demand Processes in Inventory Cost by using CDIS for | | |
|---|---|---|---|
| | MMSE | SMA | SES |
| **1** | 8.6 | 5.7 | 6.4 |
| **6** | 21.9 | 26.4 | 48.1 |
| **12** | 25.6 | 42.6 | 72.6 |

**Table 9-36 Effect of Lead Time on the Percentage Savings in Inventory Cost**

The above table clearly indicates that there is more value in centralising the demand information when the lead time between the supplier and the manufacturer is large. This is true irrespective of the forecasting method employed in the supply chain.

There are more benefits of centralising the demand information when lead times are longer. This is quite logical, as the forecast for shorter lead times would be less variable compared to the one with longer lead time, thus making centralised demand less critical (see details in sub-section 8.4.3).

## 9.8. Conclusions

In this chapter we have presented the results of the empirical analysis. The purpose of the empirical analysis was to assess the empirical validity and utility of the findings suggested by the theoretical and simulation exercises.

In the preceding sections, three forecasting methods, MMSE, SMA and SES, were employed and the performance metrics were calculated. The assumptions and supply chain model used in the empirical analysis have been chosen to be consistent with the simulation experiment, as discussed in Chapter 7.

CDIS outperformed all other approaches irrespective of the forecasting method used. This empirical evidence validates the findings from the simulation experiment as detailed in Chapter 8. The design of the empirical analysis also confirms that the operational rules for the two approaches, NIS-Est and CDIS, can be applied to a real world scenario.

Similar to the simulation findings, we observed that the value of CDIS is quite consistent when non-optimal forecasting methods are employed. In the case of the

MMSE method, the value exhibits a demand process dependent behaviour and this behaviour is consistent with the findings in the simulation experiment.

In the empirical analysis, we found that for some processes, the effect of demand variability and the effect of demand parameters were not consistent with the simulation experiment. We discussed in sub-section 9.6.4 that one of the reasons may be the interaction between the demand parameters and demand variability. In the simulation experiment, we analysed one factor while keeping the others constant, which was not the case with the empirical analysis. An investigation of the interaction between demand parameters and demand variability should be based on a larger data set. Other factors that would require analysis include changes in demand model and demand parameters over the performance measurement period. This investigation remains an area for further research.

The effect of forecasting parameters and the manufacturer's lead time was also investigated in the empirical analysis. The results showed that the value of CDIS decreases when more history is utilised in the forecasting method. Further, it was also shown that the value of CDIS increases with increasing values of the lead time from the manufacturer to the retailer. In terms of cost ratio, for optimal forecasting methods, the value of CDIS is an increasing function of the cost ratio. The same relationship has been observed for non-optimal forecasting methods but only when the demand is stationary. When the demand is non-stationary and non-optimal methods are used, the value of CDIS decreases with increasing cost ratio. These results are consistent with the simulation findings.

Given the above empirical analysis, we conclude that the Centralised Demand Information Sharing (CDIS) approach, as advocated in Chapter 3 (theory) and Chapter 8 (simulation), is robust and clearly reduces the inventory cost against the other two approaches NIS-Est and DIS.

# 10. Conclusions, Implications and Further Research

## 10.1. Introduction

In this chapter, the main threads of the research presented in the thesis are drawn together and the principal conclusions are summarised in a concise form. The main limitations of the work are assessed and, where appropriate, avenues of further research are suggested.

In order to achieve the above task, we divide this chapter into three sections. We first present the main contributions from this Ph.D. thesis and then summarise and conclude our findings arising from each of our methodological approaches: theory, simulation and empirical analysis. The next section is devoted to a discussion on the managerial implications of the conclusions arising from this research. Finally, we discuss the limitations of the research and some areas of further research.

The overall research aim of this thesis is to analyse the value of demand information sharing in supply chains, based on more realistic assumptions than in previous research.

The objectives of this research, as already stated in Chapter 1 of this thesis, are as follows:

1. To critically analyse and improve the current demand information sharing approaches discussed in the literature.

2. To extend the upstream translation of demand to a general ARMA (p, q) process for non-optimal forecasting methods.

3. To analyse the Downstream Demand Inference (DDI) approach and reflect on the implications for the value of sharing demand information.

4. To evaluate the performance of demand information sharing approaches with the help of simulation experiments, in the light of relaxed model assumptions.

5. To analyse the effect of lead time, demand variance, autoregressive parameters, moving average parameters, cost ratio and forecasting method parameters on the value of demand information sharing approaches.

6. To test the empirical validity and utility of the theoretical and simulation results on a large set of real world data..

All the above objectives have been achieved and the contributions of the thesis are summarised in the next section.

## 10.2. Summary and Conclusions

### 10.2.1. Contributions of the Thesis

The contributions of the thesis are as follows:

- Two new demand information sharing approaches, NIS-Est and CDIS, have been developed in this research (Objective 1).
    - When supply chain links adopt a strategy of not sharing demand information, we show with the help of simulation that NIS-Est will always result in lower inventory cost than the traditional NIS approach, except for pure moving average processes, in which case the inventory costs are the same. Thus, we introduce a new benchmark for quantifying the value of demand information sharing.
    - On the other hand, when supply chain links adopt a strategy of sharing demand information, we show, with the help of simulation and empirical analysis that CDIS will result in lower inventory cost than the traditional DIS approach presented in the literature.
- The multi-stage mathematical translation for the upstream translation of demand for non-optimal forecasting methods has been generalised to ARMA (p, q) processes (Objective 2). This extension helps us in proving the value of the Downstream Demand Inference (DDI) approach for demand information sharing (Objective 3).

- Based on more realistic assumptions, we have shown that Downstream Demand Inference (DDI) is not feasible for MMSE and SES forecasting methods. We have also shown that DDI is possible for ARMA demand processes when the SMA forecasting method is employed and the upstream link is aware of the number of historical terms used in SMA and the demand parameters at the downstream link (Objective 3).

- We show that there are benefits when an upstream member in a supply chain forecasts uses the demand information of the downstream member. The benefits arise from reduction in forecasting errors, resulting in reduction of the Bullwhip Effect and lower inventory holdings and inventory costs (Objectives 4 and 6).

- The traditional DIS approach showed that there is no value of sharing demand information when the demand follows an MA (q) process. With the help of simulation and empirical analysis, we have proved that there is value of sharing demand information when the CDIS approach is used (Objectives 4 and 6).

- We quantify the value of demand information sharing for the two non-optimal forecasting methods, SMA and SES. It was shown that, for the nine ARIMA processes used in simulation and twelve ARIMA processes in empirical analysis, there is value of sharing demand information when non-optimal forecasting methods are utilised. The results from empirical analysis support the simulation results (Objectives 4 and 6).

- With the help of simulation and empirical analysis, we have analysed the effect of various factors such as lead time, demand variance, demand parameters, cost ratio and forecasting method parameters on the value of sharing demand information. The simulation results have shown that the value of CDIS increases with increasing lead time, demand variance, autoregressive parameters and the smoothing constant used in SES. On the other hand, the value of CDIS decreases with increasing value of the moving average parameter and the historical terms used in SMA. The effect of cost ratio on the value of CDIS depends on the forecasting method used. In the case of optimal methods, the value of CDIS is an increasing function of the cost ratio. On the other hand, for non-optimal forecasting methods, the value increases with increasing cost ratio for stationary demand processes but shows an opposite trend for non-stationary demand processes. The empirical findings agree with all the above simulation results for lead time, forecasting parameters and cost ratio; however, the empirical findings did not agree with the simulation results for demand variance and demand parameters for most ARIMA processes (Objective 5 and 6).

### 10.2.2. Conclusions from the Theoretical Part of the Thesis

#### 10.2.2.1. Upstream Demand Translation

In the literature, we observe that the analysis of the Bullwhip Effect and the evaluation of sharing demand information have been achieved by deriving mathematical relationships between demand processes at downstream and upstream links in the supply chain. These mathematical relationships on upstream demand translation have been derived for an ARIMA (p, d, q) process in the case of MMSE forecasting methods. The demand translation for a MA (q) process for $q \leq L$, where L is the lead time, was specifically discussed as it translates into a random process. For such a process, the traditional DIS approach to demand information sharing will not yield any benefits. By utilising the CDIS approach, supply chain links will benefit from demand information sharing even when the demand process is MA (q) ($q \leq L$).

In terms of non-optimal forecasting methods, the literature on upstream demand translation is limited to an AR (1) demand process. As one of the objectives of this research is to quantify the value of demand information sharing for non-optimal forecasting methods, generalisations to an ARMA (p, q) process became imperative. We analysed the upstream demand translation for an ARMA (p, q) process for non-optimal methods and showed that an ARMA (p, $q^R$) will translate into ARMA (p, $q^R$+n) when the SMA forecasting method is employed, where n is the number of terms in SMA. On the other hand, our analysis for the SES method showed that an ARMA (p, $q^R$) method will approximately translate into an ARMA (p, t-1) process, where t is the current time period.

### 10.2.2.2. New Demand Information Sharing Approaches

To forecast the future demand, an upstream member in the supply chain can utilise two strategies in terms of sharing demand information. The first strategy is not to share any downstream member's demand information. In the literature, we find that two demand information sharing approaches have been discussed, namely No Information Sharing (NIS) and Downstream Demand Inference (DDI). On the other hand, Vendor Managed Inventory (VMI) and Demand Information Sharing (DIS) approaches have been proposed in the literature when the supply chain links adopt the strategy of sharing demand information.

#### 10.2.2.2.1. The No Information Sharing Strategy

Lee et al (2000) discussed the NIS approach, where the downstream member does not share demand information with the upstream member. Although the demand at the downstream member has been realised, the upstream member is unaware of it and they forecast on the basis of the order they have received, assuming the noise term to be zero.

We argue that, for an optimal forecasting method, the upstream member can estimate the noise term in its own demand, even when the downstream demand is not being shared. Based on this argument, we introduce a new approach, No Information Sharing –Estimation (NIS-Est). In this new approach, the forecast of the upstream member is still based on the orders from the downstream member, but the noise term is estimated and not equated to zero. The estimation can be performed by two methods, namely Recursive Estimation and Estimation by Forecast Error (Box et al, 1994, Chatfield, 2003). All other replenishment and ordering policies of the NIS-Est approach remain the same as in the NIS approach.

The introduction of the NIS-Est approach provides a new base case for quantification of the value of demand information sharing. Various papers (e.g. Lee et al, 2000; Raghunathan, 2001; Yu et al, 2002) have quantified the value of information sharing by comparing the demand information sharing approaches with NIS. In this research, a new approach has been presented for the no information sharing strategy which is also used as a base case to quantify the value of demand information sharing.

Stage I of the simulation experiment showed that using the NIS-Est approach, compared to NIS, results in lower Mean Squared Forecast Error and Bullwhip Ratio and ultimately in lower inventory holdings and inventory cost. The reason for better performance of NIS-Est is the additional estimation process incorporated in this approach. In stages II and III of simulation and in the empirical analysis, the value of demand information is quantified based on comparison with NIS-Est.

For non-optimal forecasting methods, there are no noise term estimation issues. Therefore, the NIS-Est approach is limited to optimal forecasting methods.

#### 10.2.2.2.2. The Information Sharing Strategy

Supply chain links can utilise two approaches, VMI and DIS, in the case of a strategy of sharing demand information. The VMI and DIS approaches utilise the same forecasting process and the difference is only in the replenishment policy. This is the reason there is no difference in the forecast variance of the two approaches and the reason for their comparison in the literature is to discuss another means of replenishment policy (Yu et al, 2002). As the focus of this research is not on replenishment policies, we restrict the discussions to the DIS approach.

The DIS approach for optimal forecasting methods, as presented in the literature, incorporates sharing the downstream demand information with the upstream member. The forecasting methodology in the DIS approach incorporates the use of the orders from the downstream member instead of their demand. As discussed in Chapter 5, the downstream member's orders are more variable than their demand. Thus, the DIS approach can be improved by using an approach based on the incorporation of demand instead of the orders. This new approach is called the Centralised Demand Information Sharing (CDIS) approach.

For non-optimal forecasting methods, there are no noise term estimation issues and therefore the DIS approach is limited to optimal forecasting methods. When the supply chain links adopt a Demand Information Sharing Strategy, they can utilise the CDIS approach. The manufacturer in such a case will be aware of the retailer's demand and will use these in its forecast rather than the orders from the retailer.

The results of simulation and empirical analysis in this research show that CDIS results in lower forecast error (MSE and MAPE), Bullwhip Ratio, inventory holdings and inventory cost than the DIS approach. The reason for the better performance of CDIS is the use of the downstream demand, which are less variable.

#### 10.2.2.3. Downstream Demand Inference

The literature on value of demand information sharing in supply chains can be broadly divided into two streams. While one stream of papers argues that the supply chain links benefit by sharing demand information, the second stream maintains the opposite. Papers in the second stream of research argue that the upstream member can infer the demand at the downstream member and claim that there is no value in sharing demand information. Thus, they maintain that supply chain links do not need a formal information sharing mechanism.

In this research, we perform a detailed analysis of these research streams and argue that papers claiming no value of demand information sharing are based on strict supply chain model assumptions. These papers assume that supply chain links are aware of the demand process and parameters at the downstream links. In this research, it is argued that the supply chain links will need a formal information sharing mechanism to share the information about the process and parameters with the downstream member. It is difficult to reason why, in the presence of such a formal mechanism, the supply chain links will choose to share information on ARIMA processes and parameters but not on the demand itself. Thus, the assumptions of known process and parameters are quite unrealistic.

We assume in this research that the supply chain links are unaware of the demand parameters and processes. Using this assumption, we analyse Downstream Demand Inference (DDI) for the three forecasting methods used in this research: MMSE, SMA and SES. We show that when supply chain links employ MMSE and SES methods, DDI is not possible. On the other hand, when the supply chain links employ SMA method, the demand at the downstream member can be inferred.

We show in this research, with the help of simulation and empirical analysis, that forecasting using the downstream member's demand results in reduced demand variance, forecast error, and ultimately lower inventory holdings and inventory cost. A stream of research papers argue that the downstream member's demand can be inferred with the help of mathematical relationships that exist between demand and orders. We have shown in this research, using more realistic assumptions, that inference of the downstream member's demand, or DDI, is not possible for some forecasting methods. For accurate demand, the downstream member will have to share its demand with the upstream member via some formal information sharing mechanism.

### 10.2.3. Conclusions from the Simulation Part of the Thesis

Simulation methodology is adopted in this research to establish comparisons between different demand information sharing approaches. Four performance metrics are used for such comparisons, namely mean squared forecast error, Bullwhip Ratio, inventory holdings and inventory cost.

In the following sub-sections, we summarise the most important findings from the simulation experiment.

#### 10.2.3.1. Establishment of Rules

The following three rules were established based on the results of the simulation. These rules apply to the Bullwhip Effect region for all demand processes used in the simulation experiment.

Rule 1: NIS-Est results in lower inventory cost than NIS for all demand processes investigated, except for pure moving average processes, in which case the inventory costs are the same.

Rule 2: In all demand processes investigated, CDIS results in lower inventory costs compared to DIS

Rule 3: In all demand processes investigated, CDIS results in lower inventory costs compared to NIS-Est

Establishment of the above rules shows that when the supply chain adopts a strategy of not sharing demand information, the NIS-Est approach performs better than the NIS approach. On the other hand, in the case of the strategy of sharing demand information, CDIS performs better than DIS. The overall results show that the CDIS approach performs better than all the other three approaches, averaged over all simulation replications. We discussed in sub-section 10.2.2.2 that one of the reasons of better performance of CDIS is the use of less variable demand in the forecast.

In terms of non-optimal forecasting methods, we have only two demand information sharing approaches, NIS and CDIS. The simulation results show that CDIS always results in lower forecast error, Bullwhip Ratio, inventory holdings and inventory cost.

Thus, the simulation results show that the CDIS approach performs the best in terms of the four performance metrics, irrespective of the forecasting method employed.

#### 10.2.3.2. Dependence of Value of CDIS on Model Assumptions

The simulation experiment was designed as a staged relaxation of assumptions. In Stage I, we assumed that the supply chain members are aware of their demand process and parameters. In Stage II, we relaxed the assumption of known demand parameters and assumed that the supply chain members have to estimate the demand parameters. Finally, Stage III was developed closer to a real life situation by assuming that the supply chain members have to identify the demand process and estimate the parameters.

The simulation results show that the value of CDIS increases as the model assumptions are relaxed. The value of CDIS is highest in Stage III, not so high in Stage II and is least in Stage I. One of the reasons for higher values of CDIS in more relaxed models is inherent in the identification and estimation issues in ARIMA modelling. For unknown demand parameters in Stage II, and then unknown processes in Stage III, it is quite possible for supply chain links to inaccurately identify and estimate the process and the parameters. The simulation results show that the value of CDIS increases when the supply chain links perform inaccurate identification and estimation. Thus, one of the reasons for higher values of demand information sharing at higher stages is because of inaccurate identification and estimation with more relaxed supply chain model assumptions.

#### 10.2.3.3. Demand Process Dependent Value of CDIS

In previous studies (see Chapter 5), only one ARIMA demand process was considered to calculate the value of demand information sharing. In the simulation experiment of this research, we explored the value of demand information sharing for nine demand processes. The simulation results showed that the value of demand information sharing depends on the nature of the process. Overall, it was found that the value of demand information sharing is higher for non-stationary demand processes than for stationary processes. In stationary processes, the results showed that the value is higher for pure autoregressive process compared to moving averages or mixed processes.

It was found from the simulation experiment results that the value of CDIS is an increasing function of the number of autoregressive parameters and the degree of differencing for the ARIMA models investigated.

#### 10.2.3.4. Effect of Demand Parameters

The effect of demand parameters on the value of CDIS was explored for the stationary processes. The reason for not exploring the effect for non-stationary processes is due to the absence of the discussion of the bullwhip region for the non-stationary processes in the literature. Mathematical exploration of bullwhip regions for non-stationary demand processes is thus an interesting area for further research.

The simulation results showed that the value of CDIS is an increasing function of the autoregressive parameters. This result was shown earlier in Lee et al (2000) but only for an AR (1) demand process. None of the papers in the literature have explored the effect of the moving average parameters on the value of demand information sharing. The simulation results in this experiment show that the value of CDIS decreases with the increasing value of the moving average parameters. This was found in all the three stationary processes, MA (1), MA (2) and ARMA (1, 1), examined in this research. This is an interesting finding and needs to be further explored for other demand processes.

For non-optimal forecasting methods, we observed a different phenomenon. The value of CDIS decreases with the increasing value of the autoregressive parameter. Chen et al (2000b) found similar results when they mathematically explored the value of demand information sharing using an AR (1) demand process and the SES forecasting method. In terms of the moving average parameters, the simulation results show that there is no effect of the moving average parameter on the value of CDIS.

#### 10.2.3.5. Effect of Standard Deviation

The effect of standard deviation in the noise of the demand on the value of demand information sharing was explored in the simulation experiment. The simulation results show that the value of CDIS increases with increasing standard deviation in the noise term of the demand. Thus, it was found from the simulation results that demands with more variability will result in higher savings from CDIS irrespective of the forecasting method or demand process. These results are consistent with findings of previous papers (e.g. Lee et al, 2000; Yu et al, 2002) showing that the value of CDIS is an increasing function of the value of standard deviation in the noise term of the demand.

#### 10.2.3.6. Effect of Lead Time

Another factor that is explored in the simulation experiment is the lead time from the supplier to the manufacturer. The simulation results show that demand information sharing becomes more beneficial when the manufacturer's lead time is large. This is quite logical, as the forecast for larger lead times will be more variable compared to the forecast for smaller lead times. This effect was observed in both optimal and non-optimal forecasting methods.

#### 10.2.3.7. Effect of Cost Ratio

Cost Ratio is the ratio between the penalty cost and the total cost (holding cost + penalty cost). Lee et al (2000), using an AR (1) demand process and an MMSE forecasting method, have shown mathematically that the percentage reduction in inventory holdings is an increasing function of this ratio. It was found that none of the papers in the literature have explored this effect with the help of simulation. Three different values of the ratio were assumed in the simulation experiment and the results show a similar effect as identified by Lee et al (2000), but for all the nine processes. The simulation results, thus, show that the higher the cost ratio, the higher will be the value of demand information sharing.

The effect of cost ratio is then explored for non-stationary forecasting methods. The simulation results show quite an interesting pattern. For stationary ARIMA processes, the value of demand information sharing either remains constant or increases with the increasing value of the cost ratio. In contrast, for non-stationary demand processes, the value decreases with increasing cost ratio.

#### 10.2.3.8. Effect of Demand History

Longer demand history in ARIMA methodology facilitates better identification and estimation of demand process and parameters (Box et al, 1994). A longer demand history leads to the upstream member having lesser benefits from demand information sharing. The simulation results also show similar effects. When we move from a history of 24 periods to 144 periods, the value of CDIS tends to decrease.

In sub-section 10.2.3.2, we discussed that there is more value in CDIS when the manufacturer identifies and estimates parameters inaccurately. The simulation results on the effect of demand history reinforce the earlier results as higher values of CDIS are observed when the demand history is shorter.

#### 10.2.3.9. Effect of Forecasting Parameters for Non-Optimal Methods

The effect of the smoothing constant, $\alpha$ , for the Single Exponential Smoothing (SES) method and the effect of the number of terms used in the Simple Moving Averages method, n, is analysed in this research.

Some papers (Lee et al, 2000; Raghunathan, 2001) show that the upstream member's demand already contains information about the downstream member's demand. Thus, when the upstream member forecasts using more demand history, they are actually utilising more downstream member's demand. This results in lower benefits from sharing demand information.

The simulation results agree with this earlier finding and show that, when there is more weighting on the historical terms, the value of CDIS decreases. It was found that lower values of $\alpha$ in SES and higher values of n in SMA both result in lower benefits from demand information sharing. This is because both lower $\alpha$ and higher 'n' put more weighting on the demand history.

### 10.2.4. Conclusions from the Empirical Part of the Thesis

The theoretical and simulation analyses in this research have established comparisons among the four information sharing approaches. Empirical analysis is performed to validate the earlier theoretical and simulation findings. Two year weekly sales data of a European Grocery Retailer was cleaned to remove all series except non-seasonal fast moving products exhibiting the Bullwhip Effect. In total, 1773 data series were found to fit this definition and these were analysed. The design of the empirical analysis follows the simulation design and both optimal and non-optimal forecasting methods were used. The information sharing approaches were compared using the same four performance metrics as in simulation: mean squared forecast error, Bullwhip Ratio, inventory holdings and inventory cost. In the empirical analysis, we also used the mean absolute percentage error (MAPE) in addition to MSE to measure the forecast error.

#### 10.2.4.1. Performance of CDIS Compared with the Other Approaches

The results of the empirical analysis validated the earlier findings that the CDIS approach results in the least inventory cost compared to the NIS-Est and DIS approaches. MSE and Bullwhip Ratio are two major factors that were identified in the simulation experiment to be associated with the better performance of the CDIS approach. This association was found to be strong in Stage I where the demand process and parameters are assumed to be known. This agrees with the mathematical results of Lee et al (2000) and Graves (1999) who, assuming known demand process and parameters, showed that an increase in percentage reduction of demand variability will lead to increase in percentage reduction of inventory cost. However, the staged relaxation of assumptions showed that the association was weaker for stages II and III. Thus, in stages II and III, an increase in percentage reduction in MSE or Bullwhip Ratio may not be transferred to the percentage reduction in inventory cost by the same magnitude. The empirical results were compared with the simulation results of Stage III which they broadly agreed with.

The percentage savings in inventory cost reduction in the empirical analysis were not as high as those identified in the simulation experiment. The simulation results showed that we get a lower value of CDIS when the retailer inaccurately identifies and estimates the process and its parameters. The demand process in the simulation is generated in a controlled environment; real data may exhibit more complexities for example in terms of changes to parameters or to the model itself.

#### 10.2.4.2. Demand Process Dependent Value of CDIS

The simulation results showed that, for the optimal forecasting methods, the value of CDIS depends on the nature of the process. These results were validated in the empirical analysis not only for the 6 demand processes used in simulation but for all 12 demand processes analysed in the empirical analysis.

#### 10.2.4.3. Effect of Demand Parameters and Standard Deviation

The simulation results showed that, for optimal forecasting methods, the value of CDIS increases with the increasing value of the autoregressive parameter. The relationship is exactly the opposite when non-optimal forecasting methods are considered. In terms of the moving average parameter, simulation findings showed that the value of CDIS is a decreasing function of the moving average parameter for optimal forecasting methods. However, there is no effect of the moving average parameter on the value of CDIS for non-optimal forecasting methods. For the effect of standard deviation, it was found that the value of CDIS is an increasing function of the standard deviation in the demand.

In the empirical analysis, it was found that, for processes where only one parameter needs estimation (AR (1) and MA (1)), the empirical results agree with the simulation findings. However, the empirical results do not agree with the simulation findings for the processes where two parameters need estimation (AR (2), MA (2) and ARMA (1, 1)).

The effect of parameter estimation in the simulation experiment was analysed by keeping the standard deviation of the noise constant. One reason for difference in findings from the empirical analysis could be the dual effect of the demand parameters and the standard deviation. An analysis to investigate the dual effect and any non-linear effects should be based on larger data sets.

#### 10.2.4.4. Effect of Lead Time

The empirical findings validated the simulation results that the value of CDIS is an increasing function of the lead time. Thus, there are more benefits of centralising the demand information when lead times are longer. This is quite logical, as the forecast for shorter lead times would be less variable than longer lead times, thus making information sharing less critical.

#### 10.2.4.5. Effect of Cost Ratio

The results from the empirical analysis showed that the value of CDIS is an increasing function of the cost ratio for stationary processes. However, for non-stationary processes, the value of CDIS decreases with the increasing value of the cost ratio. Similar results were found in the simulation experiment and thus the empirical findings agree with the simulation results in terms of the effect of cost ratio on the value of CDIS.

#### 10.2.4.6. Effect of Forecasting Parameters for Non-Optimal Methods

For SMA and SES, the empirical results show that when the manufacturer utilises more history in the forecasting method, the value of CDIS goes down. This is because the order from the retailer already contains some information about the retailer's demand. When the manufacturer is utilising more history in its forecast, it is already using more demand information, resulting in a lower value of CDIS. Thus, in SMA, high values of the moving average term 'n' and in SES, lower values of the smoothing constant, $\alpha$, will yield lower values of CDIS, as in both cases more history is being used in the forecast. These results are consistent with the findings from the simulation experiment.

### 10.2.5. Summary of Conclusions of the thesis

This thesis critically analyses the demand information sharing approaches and supply chain models presented in the literature. A stream of research papers propose the Downstream Demand Information (DDI) approach and claim that using the DDI approach will result in no value of demand information sharing. We argue in this thesis that the model assumptions made in these papers are clearly unrealistic. All models must make assumptions, but it is desirable that they are robust to deviation from these assumptions. It has been shown in this thesis that a slight change to the assumptions in the supply chain model of these papers leads to the opposite conclusion: DDI is not feasible. The remaining assumptions may also be criticised for their lack of fidelity to real world assumptions. Further relaxation would not change the conclusion that DDI is not feasible.

This thesis has progressed on the basis of simulation, using both theoretically generated and empirical data. The challenge remains to establish more general theory, with less restrictive assumptions. This is further discussed in section 10.4.

## 10.3. Managerial Implications

Many companies are embarking on strategies to share consumer sales data among supply chain members. This is a move away from being 'customer centric' towards being 'consumer centric'. Previous case studies of such supply chains show how this increases forecasting accuracy, thus resulting in lower inventory costs and increased revenues. Reduction of inventory levels up to 50% (Disney and Towill, 2002) and reduction in inventory costs up to 40% (Ireland and Crum, 2006) have been reported. The high savings in cost justifies the implementation of systems and structures to support sharing of information. Mentzer (2001) argues that, although a great deal of discussion takes place on supply chain collaborations, the discussion on specifics on how it should be done is missing. This research analyses how supply chain collaborations should be conducted through demand information sharing.

Four demand information sharing approaches have been compared in this research: NIS and NIS-Est approaches when the supply chain strategy is not to share demand information, and DIS and CDIS for a demand information sharing strategy. The theoretical and empirical analyses in this research show that sharing demand information results in lower forecast error, Bullwhip Ratio, inventory holdings and inventory cost for the upstream member. On comparing the two approaches for demand information sharing strategy, DIS and CDIS, the analysis shows that the CDIS approach performs best in terms of the four performance metrics.

The above results imply that, in order to achieve reduced supply chain costs, organisations should share the consumer demand with their upstream members and should consider the CDIS approach as an alternative to the DIS approach. It is especially beneficial to share information, using CDIS, in supply chains with long lead-times to the upstream member, and which have high stock-out penalty costs. Since the magnitude of savings in real applications does not necessarily reflect those found from simulations on theoretically generated data, if organisations wish to quantify the benefit of CDIS, they should simulate its effect using their own supply chain demand data. The need for simulation is particularly acute for supply chains with three or more levels, or those with multiple entities at one level, as these were not investigated in the thesis. If simulations on real demand data confirm the benefit of CDIS, and the approach is to be implemented, further detailed simulations on real data are needed for seasonal items or those for which the Anti-Bullwhip Effect may prevail, as these were not analysed in the simulation and empirical parts of the thesis

The foundation of supply chain collaboration is information sharing (Lee et al, 2000); decisions on collaborations are strongly based on what information should be shared. In the CDIS approach, the manufacturer produces their forecast by not only utilising the demand but also the forecast of the retailer. Thus, when organisations have in place a formal information sharing mechanism with their downstream members, they can share both the demand and the forecast and utilise both in their forecasting process. CDIS is operationally a better method as the forecasting process takes place once only, either at the retailer or the manufacturer. In fact, the forecast can be produced collaboratively by both the manufacturer and the retailer. Both members can bring in their expertise in the process and produce a better forecast using the actual consumer demand. Empirical research into 54 manufacturers in the Food and Consumer Package Goods (F&CPG) industry have shown that the highest profit margin companies are not simply exchanging information but using this as a vehicle for supply chain collaborations (Kulp et al, 2004). Finally, CDIS encourages companies to pay more attention to consumer demand, which may contribute to a more consumer-centric approach.

This research focuses on the benefits of demand information sharing for the manufacturer or an upstream member in a supply chain. Previous studies have shown that when two supply chain links share information on the demand of the downstream member, it is the upstream member who gets the direct benefits from this information sharing (Simchi-Levi and Zhao, 2003; Kulp et al, 2004). These manufacturer benefits have been quantified in this research. However, various authors have suggested that, in return, the retailer can negotiate indirect benefits from the manufacturer in terms of cost and lead time reduction (Lee et al, 2000), VMI programs (Yu et al, 2002) or by getting subsidies for sharing information (Raghunathan, 2003). This issue has not been investigated in this thesis. Nevertheless, if the issue is resolved, both parties will benefit from this demand information sharing strategy.

Recently, a steady stream of research papers has argued that upstream members can extract the sales data from the history of orders they receives from retailers. It this is possible, no formal information sharing mechanism would be required to share sales data. In this research, adopting more realistic assumptions, we show that an upstream link in the supply chain cannot infer the consumer's sales from its order history if the supply chain links utilise SES or MMSE forecasting methods. In the case of SMA and ARMA demand, the demand information can be extracted by the upstream member if the number of historical terms used in the SMA forecast is known to the upstream member. The business forecasting approach most organisations take is based on forecasting various demand forecasting units which may be stock keeping units (SKUs) or an aggregate of various SKUs (Holmstrom, 1998). The historical data for each of these demand forecasting units is analysed to determine the average, trend and seasonal demand components (e.g. SAP, 2004) and then the appropriate forecasting method is selected for each of these demand forecasting units based on the historical data. Thus, when a retailer places an order on the manufacturer of various products, the order generation process may involve different forecasting methods for different products e.g. SMA for some products and SES or MMSE for others. In order to know the retailer's demand, the manufacturer, in the case of MMSE and SES, will have to make use of some formal information sharing mechanism. On the other hand, if the retailer has employed SMA for some products, the demand can be mathematically calculated. But if the manufacturer already has in place a formal information sharing mechanism (e.g. an integrated ERP solution) for information sharing, there is no need for them to use another mechanism (mathematical calculation) for products forecasted with the SMA method. They can simply use the information system to find the demand of such products at the retailer. Hence, we conclude that companies have to resort to formal information sharing systems to extract the consumer's sales data and reduce the Bullwhip Effect.

## 10.4. Limitations and Further Research

In this section, suggestions for future research are discussed from theoretical, simulation and empirical perspectives.

In Chapter 2, we discussed a stream of research that focuses on evaluating the causes of the Bullwhip Effect. The literature review reflects four major causes, which are Demand Signal Processing, Rationing and Shortage Gaming, Batch Ordering and Price Fluctuations. This research analyses Demand Signal Processing in isolation. An avenue for further research would be to examine the interaction between these four causes of the Bullwhip Effect.

One major limitation of the supply chain model in this thesis is the assumption of an Order up to (OUT) inventory policy. Although we have provided empirical evidence of usage of the OUT policy, it is obvious that companies resort to various different inventory policies. A major area of further research is to investigate the effect of inventory policies on the value of demand information sharing.

The comparison of demand information sharing in this research is based on the assumption of a two stage supply chain with one entity at each stage. An interesting area of research would be to check whether the results are valid in more complex supply chain systems such as a multi-stage supply chain with more than one entity at each stage.

Another limitation of this research is the assumption of non-seasonal demand. In practice, demand for certain products show seasonal variations. The time series of demand for such products exhibit a seasonal periodic component which repeats after every *s* observation (Chatfield, 2003). In order to generalise ARIMA demand models to deal with seasonality, Box et al (1994) have derived seasonal ARIMA or SARIMA models. Another interesting avenue for further research would be to analyse upstream demand translation for SARIMA models, and to assess the CDIS approach for such models.

One of the limitations of the research is that we have limited the investigation of the effect of demand parameters on the value of CDIS to stationary ARIMA processes. The reason for this limitation is that the mathematical analysis of the Bullwhip region in the literature is limited to stationary ARIMA processes. Thus, one important avenue for further research is to generalise the mathematical analysis of the Bullwhip region to all ARIMA (p, d, q) processes.

As this research focuses on reduction in the demand variance amplification, the choice of parameters in the simulation experiment is limited to regions where the Bullwhip Effect takes place. Similarly, in the empirical analysis, all series that resulted in decrease in demand variability were ignored. However, in real life supply chains, a decrease in demand variability or Anti-Bullwhip Effect may occur (Li et al, 2005). Thus, another avenue for further research would be to investigate the effect of demand information sharing when Anti-Bullwhip Effect occurs in supply chains.

In chapters 3 and 7, we discussed the complexities of mathematically comparing the four demand information sharing approaches. Thus the performance of the demand information sharing approaches has been compared only in simulation and empirical analysis. Another future direction is to analyse the four approaches and compare the performance metrics mathematically. For example in Chapter 8, we observed that the effect of cost ratio is different for stationary and non-stationary processes. Thus, an interesting avenue would be to model the effect of cost ratio on the value of CDIS mathematically. This will also help in better understanding the reasons for better performance of the CDIS approach.

The survey of forecast practice showed that most practitioners use non-optimal forecasting methods. Based on this survey, we examined two non-optimal forecasting methods, SMA and SES. As the survey revealed high usage of some other non-optimal forecasting methods as well, the value of CDIS can further be quantified by examining other non-optimal forecasting methods. The upstream translation of demand in the case of non-optimal forecasting methods have been generalised to an ARMA (p, q) demand process. Further research is required to generalise the upstream demand translation to ARIMA (p, d, q) demand processes.

In sub-section 7.3.7, the series splitting rules were presented and it was discussed that the process identification and parameter estimation is performed on a one-time basis from the data on the first half of the series while the second half is used for performance measurement. We have also discussed in Chapter 9 that some series in the empirical data may be subject to parameter and model changes. An avenue for further research could be to update the parameter and model at every time period during the performance measurement part.

The existing supply chain models in the literature are based on various strict assumptions. Some severe limitations such as known demand process and known demand parameters have been broken in this research. The Centralised Demand Information Sharing (CDIS) approach, as presented in this thesis, results in reduced inventory costs when the demand is non-seasonal for a two stage supply chain utilising an OUT inventory policy. We now need to assess whether the CDIS approach results in cost savings for supply chain models with more relaxed assumptions.

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# Appendix 4A: Proof of Equations 4-9 – 4-15

In this Appendix, for reasons of simplicity, we replace $\theta^R$ with $\theta$.

$$As\ \varphi(B) = \rho(B)\nabla^d$$
$$\varphi(B) = \rho(B)(1-B)^d$$
$$(1-\varphi_1 B - \varphi_2 B^2 - ... - \varphi_{p+d} B^{p+d}) =$$
$$(1-\rho_1 B - \rho_2 B^2 - ... - \rho_p B^p)(1 - dB + \frac{d(d-1)}{2}B^2 - \frac{d(d-1)(d-2)}{6}B^3 + ... + (-1)^d B^d)$$

In order to find $\varphi_1$ we equate all B terms to get

$$\varphi_1 = \rho_1 + d$$

Similarly, we equate all $B^2$ and $B^3$ terms to get $\varphi_2$ and $\varphi_3$

$$\varphi_2 = \rho_2 - \rho_1 d - \frac{d(d-1)}{2}$$

$$\varphi_3 = \rho_3 - \rho_2 d + \frac{\rho_1 d(d-1)}{2} + \frac{d(d-1)(d-2)}{6}$$

$$As\ \psi(B) = \frac{\theta(B)}{\varphi(B)}$$
$$\theta(B) = \psi(B)\varphi(B)$$
$$(1-\theta_1 B - \theta_2 B^2 - ... - \theta_q B^q) =$$
$$(1+\psi_1 B + \psi_2 B^2 + ...)(1-\varphi_1 B - \varphi_2 B^2 - ... - \varphi_{p+d} B^{p+d})$$

In order to find $\psi_1$ we equate all B terms to get

$$\theta_1 = \varphi_1 - \psi_1$$
*or*
$$\psi_1 = \varphi_1 - \theta_1$$

Similarly, we equate all $B^2$ and $B^3$ terms to get $\psi_2$ and $\psi_3$

$$\psi_2 = \varphi_2 + \psi_1\varphi_1 - \theta_2$$
$$\psi_3 = \varphi_3 + \psi_1\varphi_2 + \psi_2\varphi_1 - \theta_3$$

Now as in our simulation $\theta_n, \varphi_n = 0$ for n > 3, the equations for $\psi_4$ onwards are reduced to

$$\psi_4 = \psi_1\varphi_3 + \psi_2\varphi_2 + \psi_3\varphi_1$$
$$\psi_5 = \psi_2\varphi_3 + \psi_3\varphi_2 + \psi_4\varphi_1$$

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$$\psi_L = \psi_{L-3}\varphi_3 + \psi_{L-2}\varphi_2 + \psi_{L-1}\varphi_1$$

# Appendix 4B: Upstream Propagation for SMA

Suppose the demand ($d_t$) at the retailer follows an ARMA (p, q) process:

$$d_t = \tau + \rho_1 d_{t-1} + \rho_2 d_{t-2} + ..... + \rho_p d_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - ..... - \theta_q \varepsilon_{t-q} \tag{4B-1}$$

and the forecasting method used by the retailer is the Simple Moving Average (SMA) of the n most recent demands given by:

$$\hat{D}_{t+1} = \sum_{i=0}^{n-1} \frac{d_{t-i}}{n}$$

The lead time demand forecast, $\hat{D}_t^L$, is given by:

$$\hat{D}_t^L = L \sum_{i=0}^{n-1} \frac{d_{t-i}}{n}$$

Now, the order-up-to level is calculated by:

$$S_t = \hat{D}_t^L + z\sigma_\varepsilon^2$$

where z is the safety factor and $\sigma_\varepsilon^2$ is the variance of the noise in the lead time demand.

The order from the retailer to the manufacturer can be calculated by summing the demand at the retailer plus any change in the order-up-to level in the current period.

$$Y_t = S_t - S_{t-1} + d_t$$

$$Y_t = \hat{D}_t^L + z\sigma_\varepsilon^2 - \hat{D}_{t-1}^L - z\sigma_\varepsilon^2 + d_t$$

$$Y_t = (\frac{L}{n} + 1) d_t - \frac{L}{n} d_{t-n} \tag{4B-2}$$

Substituting the expression for $d_t$ from equation 4B-1 into equation 4B-2,

$$Y_t = \left(\frac{L}{n}+1\right)\left(\tau + \rho_1 d_{t-1} + \rho_2 d_{t-2} + \ldots + \rho_p d_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}\right)$$
$$-\left(\frac{L}{n}\right)\left(\tau + \rho_1 d_{t-n-1} + \rho_2 d_{t-n-2} + \ldots + \rho_p d_{t-n-p} + \varepsilon_{t-n} - \theta_1 \varepsilon_{t-n-1} - \theta_2 \varepsilon_{t-n-2} - \ldots - \theta_q \varepsilon_{t-n-q}\right)$$

$$Y_t = \tau + \left[\left(\frac{L}{n}+1\right)\rho_1 d_{t-1} - \left(\frac{L}{n}\right)\rho_1 d_{t-n-1}\right] + \ldots$$
$$+\left[\left(\frac{L}{n}+1\right)\rho_p d_{t-p} - \left(\frac{L}{n}\right)\rho_p d_{t-n-p}\right] +$$
$$\left(\frac{L}{n}+1\right)\left(\varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}\right)$$
$$-\left(\frac{L}{n}\right)\left(\varepsilon_{t-n} - \theta_1 \varepsilon_{t-n-1} - \theta_2 \varepsilon_{t-n-2} - \ldots - \theta_q \varepsilon_{t-q-n}\right)$$

Recalling equation (4B-2) and letting $\left(\frac{L}{n}+1\right)\varepsilon_t = a_t$ the equation for the order to the manufacturer becomes:

$$Y_t = \tau + \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \ldots + \rho_p Y_{t-p}$$
$$+a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q} \qquad \text{(4B-3)}$$
$$-\left(\frac{L}{L+n}\right)\left(a_{t-n} - \theta_1 a_{t-n-1} - \theta_2 a_{t-n-2} - \ldots - \theta_q a_{t-n-q}\right)$$

which is an ARMA (p, n+q) process.

Therefore, if the demand at the retailer follows an ARMA (p, q) process, and the retailer uses the Simple Moving Average of the n most recent observations as the forecast, the order generated for the manufacturer will follow an ARMA (p, n+q) process.

# Appendix 4C: Upstream Propagation for SES

Suppose the demand at the retailer follows an ARMA (p, q) process given by:

$$d_t = \tau + \rho_1 d_{t-1} + \rho_2 d_{t-2} + ..... + \rho_p d_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - ..... - \theta_q \varepsilon_{t-q}$$

and the forecasting method used by the retailer is Single Exponential Smoothing (SES) given by:

$$\hat{F}_{t+1} = \alpha d_t + (1-\alpha)\hat{F}_t .$$

Assuming $F_1$=$d_0$ and solving the above equation recursively we get:

$$\hat{F}_{t+1} = \alpha d_t + \alpha(1-\alpha) d_{t-1} + \alpha(1-\alpha)^2 d_{t-2} + ... +$$
$$\alpha(1-\alpha)^{t-1} d_1 + (1-\alpha)^t d_0$$

Calculating the lead time forecast $\hat{F}_{t+1}{}^L$ for SES:

$$\hat{F}_{t+1}{}^L = L\begin{bmatrix} \alpha d_t + \alpha(1-\alpha) d_{t-1} + \alpha(1-\alpha)^2 d_{t-2} + ... + \\ \alpha(1-\alpha)^{t-1} d_1 + (1-\alpha)^t d_0 \end{bmatrix} \tag{4C-1}$$

Now, the order-up-to level is calculated by:

$$S_t = \hat{F}_{t+1}{}^L + z\sigma_\varepsilon{}^2$$

where z is the safety factor and $\sigma_\varepsilon{}^2$ is the variance of the noise in the lead-time demand.

The order from the retailer to the manufacturer can be calculated by summing the demand at the retailer plus any change in the order-up-to level in the current period.

$$Y_t = S_t - S_{t-1} + d_t$$

$$Y_t = \hat{F}_{t+1}{}^L + z\sigma_\varepsilon{}^2 - \hat{F}_t{}^L - z\sigma_\varepsilon{}^2 + d_t$$

$$Y_t = \hat{F}_{t+1}{}^L - \hat{F}_t{}^L + d_t$$

The order from the retailer to the manufacturer is:

$$Y_t = L[\alpha d_t + \alpha(1-\alpha)d_{t-1} + \alpha(1-\alpha)^2 d_{t-2} + ... + \alpha(1-\alpha)^{t-1} d_1 + (1-\alpha)^t d_0]$$
$$-L[\alpha d_{t-1} + \alpha(1-\alpha)d_{t-2} + \alpha(1-\alpha)^2 d_{t-3} + ... + \alpha(1-\alpha)^{t-2} d_1 + (1-\alpha)^{t-1} d_0] + d_t$$

Re-arranging the terms, we get:

$$Y_t = L[\alpha(d_t - d_{t-1}) + \alpha(1-\alpha)(d_{t-1} - d_{t-2}) + \alpha(1-\alpha)^2 (d_{t-2} - d_{t-3}) + ... +$$
$$\alpha(1-\alpha)^{t-2}(d_2 - d_1) + \alpha(1-\alpha)^{t-1}(d_1 - d_0)] + d_t \qquad (4C\text{-}2)$$

$$\rho_j Y_{t-j} = L[\alpha(\rho_j d_{t-j} - \rho_j d_{t-j-1}) + \alpha(1-\alpha)(\rho_j d_{t-j-1} - \rho_j d_{t-j-2}) + ... +$$
$$\alpha(1-\alpha)^{t-j-2}(\rho_j d_2 - \rho_j d_1) + \alpha(1-\alpha)^{t-j-1}(\rho_j d_1 - \rho_j d_0) + \rho_j d_{t-j}]$$

We note that using a similar argument to Alwan et al (2003), and substituting ARMA (p, q) expressions for $d_t$, $d_{t-1}$,…, $d_1$ in the above, and summarising terms that equate to $\rho_1 Y_{t-1}, \rho_2 Y_{t-2}, ..., \rho_p Y_{t-p}$ we get:

$$Y_t = \tau + \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + ... + \rho_p Y_{t-p} + (1 + L\alpha)\varepsilon_t$$
$$-[(1+L\alpha)\theta_1 + L\alpha^2]\varepsilon_{t-1} - [(1+L\alpha)\theta_2 - L\alpha^2\theta_1 + L\alpha^2(1-\alpha)]\varepsilon_{t-2}$$
$$-... - L[\alpha(1-\alpha)^{t-2}(\theta_1 + 1) + \alpha(1-\alpha)^{t-3}(\theta_2 - \theta_1) + \alpha(1-\alpha)^{t-4}(\theta_3 - \theta_2) + ...]\varepsilon_1 \qquad (4C\text{-}3)$$
$$+L[\alpha(1-\alpha)^{t-1}(d_1 - d_0) + \alpha d_0 \sum_{i=2}^{p} (1-\alpha)^{t-i} \rho_i]$$

which is an ARMA (p, t-1), plus another term, namely: $L[\alpha(1-\alpha)^{t-1}(d_1 - d_0) + \alpha d_0 \sum_{i=2}^{p} (1-\alpha)^{t-i} \rho_i]$

Therefore, if the demand at the retailer follows an ARMA (p, q) process, and the retailer uses SES to forecast, the order generated for the manufacturer would follow ARMA (p, t-1) + other term.

# Appendix 6A: Proof of Rule for Downstream Demand Calculation

Suppose a manufacturer realises the following order from the retailer identified as an ARIMA (p, d, $q^M$) demand process.

$$\rho(B)\nabla^d(Y_t) = \theta^M(B)a_t$$

where

$$\rho(B) = 1 - \rho_1 B - \rho_2 B^2 - \ldots - \rho_p B^p$$
$$\theta^M(B) = 1 - \theta^M{}_1 B - \theta^M{}_2 B^2 - \ldots - \theta^M{}_{q^M} B^{q^M}$$

$\rho_1, \rho_2, \ldots, \rho_p$ are the autoregressive parameters chosen to ensure stationarity.

$a_t, a_{t-1}, \ldots, a_{t-q^M}$ are the noise terms in the manufacturer's demand and $\theta^M{}_1, \theta^M{}_2, \ldots, \theta^M{}_{q^M}$ are the moving average parameters in the manufacturer's demand chosen to ensure invertibility.

If $q^R > q^M$, the order at the retailer would be a unique ARIMA (p, d, $q^M$ + L) model:

$$\rho(B)\nabla^d(d_t) = \theta^R(B)\varepsilon_t$$

where

$$\rho(B) = 1 - \rho_1 B - \rho_2 B^2 - \ldots - \rho_p B^p$$
$$\theta^R(B) = 1 - \theta_1^R B - \theta_2^R B^2 - \ldots - \theta^R{}_{q^M+L} B^{q^M+L}$$

where $d_t, d_{t-1}, \ldots, d_{t-p}$ are the observed demands at time period t, t-1,…, t-p, $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-(q^M+L)}$ are the noise terms. The noise terms are independent and identically distributed with mean zero and variance $\sigma_\varepsilon{}^2$.

In order to calculate the demand at the retailer, the manufacturer would need to calculate the following moving average terms $\theta^R{}_1, \theta^R{}_2, ..., \theta^R{}_{q^M+L}$ and the following noise terms $\varepsilon_t, \varepsilon_{t-1}, ..., \varepsilon_{t-(q^M+L)}$.

Zhang (2004b) has shown that for any ARMA (p, q) demand process, when $q^R > q^M$, the moving average terms at the retailer ($\theta^R$) can be calculated by using the following relationship.

$$\theta^R{}_{L+s} = K_0 \theta^M{}_s \qquad \text{6A-1}$$

where s = 1, 2, 3, … , $q^M$ + L, L is the lead time from the supplier to the manufacturer and $K_0$ is the amount with which the moving average term is amplified as defined in Chapter 4.

The above relationship can easily be shown to exist for an ARIMA (p, d, q) using the moving average parameter equations in Gilbert (2005: 307). Looking at these equations it is obvious that the manufacturer has $q^M$ equations. However, the manufacturer has $q^M$ + L unknown moving average terms. As the manufacturer has to calculate $q^M$ + L unknowns but only has $q^M$ equations, they are unable to accurately calculate all the moving average parameter terms. Using the same argument, we can show that the manufacturer would be unable to accurately calculate all the noise terms at the retailer. Thus, in this case the manufacturer is unable to calculate the demand at the retailer.

# Appendix 8A: Results for Optimal Method: Stage I

| Demand Process | Mean Squared Error | | | | Percentage Reduction by using CDIS compared to | | |
|---|---|---|---|---|---|---|---|
| | NIS | DIS | NIS-Est | CDIS | NIS | DIS | NIS-Est |
| AR(1) | 971 | 500 | 488 | 441 | 54.6% | 11.8% | 9.8% |
| AR(2) | 451 | 297 | 306 | 251 | 44.4% | 15.5% | 18.0% |
| ARMA(1,1) | 433 | 443 | 451 | 414 | 4.3% | 6.5% | 8.0% |
| MA(1) | 109 | 109 | 109 | 100 | 8.0% | 8.0% | 7.1% |
| MA(2) | 234 | 234 | 234 | 217 | 7.1% | 7.1% | 7.1% |
| ARIMA(0,1,1) | 2144 | 1730 | 1949 | 1341 | 37.5% | 22.5% | 31.2% |
| ARIMA(1,1,1) | 7651 | 4238 | 4621 | 3170 | 58.6% | 25.2% | 31.4% |
| ARIMA(1,1,2) | 3469 | 1834 | 2347 | 1427 | 58.9% | 22.2% | 39.2% |
| ARIMA(0,2,2) | 10177 | 7503 | 9133 | 3562 | 65.0% | 52.7% | 61.0% |

| Demand Process | Bullwhip Ratio | | | | Percentage Reduction by using CDIS compared to | | |
|---|---|---|---|---|---|---|---|
| | NIS | DIS | NIS-Est | CDIS | NIS | DIS | NIS-Est |
| AR(1) | 3.1 | 2.8 | 2.8 | 2.5 | 18.7% | 9.5% | 11.5% |
| AR(2) | 2.3 | 2.0 | 2.0 | 1.8 | 21.5% | 9.8% | 7.8% |
| ARMA(1,1) | 2.1 | 2.1 | 2.1 | 2.0 | 3.8% | 3.8% | 3.8% |
| MA(1) | 1.2 | 1.2 | 1.2 | 1.1 | 9.4% | 9.4% | 9.4% |
| MA(2) | 2.8 | 2.8 | 2.8 | 2.5 | 9.8% | 9.8% | 9.8% |
| ARIMA(0,1,1) | 4.9 | 3.6 | 4.1 | 2.9 | 42.0% | 21.6% | 29.5% |
| ARIMA(1,1,1) | 5.4 | 2.3 | 3.4 | 1.9 | 65.0% | 18.7% | 44.2% |
| ARIMA(1,1,2) | 5.7 | 3.2 | 4.2 | 2.6 | 54.0% | 18.0% | 37.5% |
| ARIMA(0,2,2) | 5.9 | 2.1 | 2.5 | 1.3 | 78.0% | 39.3% | 48.5% |

| Demand Process | Inventory Holdings | | | | Percentage Reduction by using CDIS compared to | | |
|---|---|---|---|---|---|---|---|
| | NIS | DIS | NIS-Est | CDIS | NIS | DIS | NIS-Est |
| AR(1) | 1072 | 724 | 736 | 665 | 38.0% | 8.2% | 9.6% |
| AR(2) | 3296 | 1428 | 2281 | 1095 | 66.8% | 23.3% | 52.0% |
| ARMA(1,1) | 996 | 1813 | 1680 | 524 | 47.4% | 71.1% | 68.8% |
| MA(1) | 478 | 478 | 478 | 466 | 2.6% | 2.6% | 2.6% |
| MA(2) | 422 | 422 | 422 | 386 | 8.4% | 8.4% | 8.4% |
| ARIMA(0,1,1) | 24169 | 3521 | 2921 | 1542 | 93.6% | 56.2% | 47.2% |
| ARIMA(1,1,1) | 218840 | 27264 | 40900 | 16413 | 92.5% | 39.8% | 59.9% |
| ARIMA(1,1,2) | 100814 | 17641 | 32983 | 11765 | 88.3% | 33.3% | 64.3% |
| ARIMA(0,2,2) | 116069 | 27480 | 29906 | 16598 | 85.7% | 39.6% | 44.5% |

| Demand Process | Inventory Cost | | | | Percentage Reduction by using CDIS compared to | | |
|---|---|---|---|---|---|---|---|
| | NIS | DIS | NIS-Est | CDIS | NIS | DIS | NIS-Est |
| AR(1) | 1087 | 798 | 827 | 738 | 32.1% | 7.6% | 10.8% |
| AR(2) | 3138 | 1493 | 2234 | 1318 | 58.0% | 11.7% | 41.0% |
| ARMA(1,1) | 853 | 610 | 606 | 580 | 32.0% | 4.9% | 4.4% |
| MA(1) | 537 | 537 | 537 | 525 | 2.3% | 2.3% | 2.3% |
| MA(2) | 488 | 488 | 488 | 451 | 7.5% | 7.5% | 7.5% |
| ARIMA(0,1,1) | 6853 | 2326 | 3515 | 1912 | 72.1% | 17.8% | 45.6% |
| ARIMA(1,1,1) | 112299 | 25508 | 88971 | 18417 | 83.6% | 27.8% | 59.9% |
| ARIMA(1,1,2) | 115527 | 16168 | 30696 | 12708 | 89.0% | 21.4% | 58.6% |
| ARIMA(0,2,2) | 141698 | 34401 | 42208 | 17854 | 87.4% | 48.1% | 57.7% |

# Appendix 8B: Results for Optimal Method: Stage II

| Demand Process | Mean Squared Error | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 964 | 1486 | 706 | 26.8% | 52.5% |
| AR(2) | 621 | 520 | 365.3 | 41.2% | 29.8% |
| ARMA(1,1) | 598 | 854 | 403.2 | 32.6% | 52.8% |
| MA(1) | 226 | 420 | 152.5 | 32.5% | 63.7% |
| MA(2) | 380 | 423 | 256.3 | 32.5% | 39.4% |
| ARIMA(0,1,1) | 1852 | 2187 | 1389 | 25.0% | 36.5% |
| ARIMA(1,1,1) | 6911 | 8882 | 3020 | 56.3% | 66.0% |
| ARIMA(1,1,2) | 4593 | 9171 | 2898 | 36.9% | 68.4% |
| ARIMA(0,2,2) | 7098 | 12642 | 3464 | 51.2% | 72.6% |

| Demand Process | Bullwhip Ratio | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 3.9 | 7.2 | 2.5 | 35.6% | 65.3% |
| AR(2) | 2.6 | 3.0 | 1.9 | 25.8% | 36.5% |
| ARMA(1,1) | 3.3 | 3.8 | 2.2 | 33.3% | 42.5% |
| MA(1) | 2.0 | 4.3 | 1.6 | 19.5% | 62.5% |
| MA(2) | 2.8 | 3.2 | 1.5 | 45.8% | 52.8% |
| ARIMA(0,1,1) | 3.9 | 3.9 | 2.9 | 25.9% | 25.9% |
| ARIMA(1,1,1) | 4.9 | 3.0 | 1.8 | 63.2% | 39.6% |
| ARIMA(1,1,2) | 5.1 | 10.5 | 3.6 | 29.8% | 65.8% |
| ARIMA(0,2,2) | 6.1 | 12.0 | 2.9 | 52.6% | 75.8% |

| Demand Process | Inventory Holdings | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 1338 | 2157 | 906 | 32.3% | 58.0% |
| AR(2) | 2559 | 4891 | 1213 | 52.6% | 75.2% |
| ARMA(1,1) | 970 | 1373 | 652 | 32.8% | 52.5% |
| MA(1) | 719 | 1544 | 582 | 19.1% | 62.3% |
| MA(2) | 1564 | 1945 | 807 | 48.4% | 58.5% |
| ARIMA(0,1,1) | 4948 | 7841 | 3152 | 36.3% | 59.8% |
| ARIMA(1,1,1) | 63191 | 57094 | 19526 | 69.1% | 65.8% |
| ARIMA(1,1,2) | 22519 | 86364 | 15200 | 32.5% | 82.4% |
| ARIMA(0,2,2) | 41700 | 121282 | 17222 | 58.7% | 85.8% |

| Demand Process | Inventory Cost | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 1327 | 2662 | 985 | 25.8% | 63.0% |
| AR(2) | 2502 | 5406 | 1546 | 38.2% | 71.4% |
| ARMA(1,1) | 952 | 1273 | 652 | 31.5% | 48.8% |
| MA(1) | 878 | 1705 | 689 | 21.5% | 59.6% |
| MA(2) | 1382 | 1760 | 887 | 35.8% | 49.6% |
| ARIMA(0,1,1) | 4190 | 6086 | 3256 | 22.3% | 46.5% |
| ARIMA(1,1,1) | 48105 | 74061 | 20589 | 57.2% | 72.2% |
| ARIMA(1,1,2) | 23310 | 59551 | 15245 | 34.6% | 74.4% |
| ARIMA(0,2,2) | 39016 | 105301 | 19586 | 49.8% | 81.4% |

# Appendix 8C: Results for Optimal Method: Stage III

| Demand Process | Mean Squared Error | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 1293 | 4488 | 736 | 43.1% | 83.6% |
| AR(2) | 929 | 12888 | 425.3 | 54.2% | 96.7% |
| ARMA(1,1) | 1081 | 1961 | 474.5 | 56.1% | 75.8% |
| MA(1) | 559 | 855 | 325.6 | 41.8% | 61.9% |
| MA(2) | 473 | 1436 | 260 | 45.0% | 81.9% |
| ARIMA(0,1,1) | 3930 | 4115 | 1568 | 60.1% | 61.9% |
| ARIMA(1,1,1) | 8059 | 13455 | 3256 | 59.6% | 75.8% |
| ARIMA(1,1,2) | 6607 | 6556 | 3363 | 49.1% | 48.7% |
| ARIMA(0,2,2) | 9673 | 10573 | 5794 | 40.1% | 45.2% |

| Demand Process | Bullwhip Ratio | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 5.9 | 11.7 | 3.5 | 41.1% | 70.0% |
| AR(2) | 5.7 | 8.4 | 2.9 | 49.1% | 65.6% |
| ARMA(1,1) | 6.3 | 8.4 | 3.1 | 51.1% | 62.9% |
| MA(1) | 3.3 | 4.1 | 2.0 | 39.4% | 51.2% |
| MA(2) | 2.4 | 5.3 | 1.5 | 38.1% | 71.9% |
| ARIMA(0,1,1) | 8.7 | 6.1 | 3.6 | 58.8% | 41.2% |
| ARIMA(1,1,1) | 11.3 | 12.6 | 4.2 | 64.1% | 65.0% |
| ARIMA(1,1,2) | 11.4 | 13.1 | 4.5 | 60.4% | 65.7% |
| ARIMA(0,2,2) | 7.8 | 10.7 | 4.5 | 42.1% | 58.0% |

| Demand Process | Inventory Holdings | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 1987 | 3784 | 1192 | 40.0% | 68.5% |
| AR(2) | 5388 | 10927 | 3125 | 42.0% | 71.4% |
| ARMA(1,1) | 1714 | 2033 | 974 | 43.2% | 52.1% |
| MA(1) | 791 | 1336 | 465 | 41.2% | 65.2% |
| MA(2) | 1359 | 2514 | 875 | 35.6% | 65.2% |
| ARIMA(0,1,1) | 5487 | 8949 | 3177 | 42.1% | 64.5% |
| ARIMA(1,1,1) | 61520 | 105034 | 21532 | 65.0% | 79.5% |
| ARIMA(1,1,2) | 31246 | 76225 | 15245 | 51.2% | 80.0% |
| ARIMA(0,2,2) | 76199 | 132876 | 32156 | 57.8% | 75.8% |

| Demand Process | Inventory Cost | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|
| | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| AR(1) | 2089 | 4939 | 1383 | 33.8% | 72.0% |
| AR(2) | 5519 | 12719 | 3256 | 41.0% | 74.4% |
| ARMA(1,1) | 1856 | 2617 | 1091 | 41.2% | 58.3% |
| MA(1) | 1008 | 1418 | 655 | 35.0% | 53.8% |
| MA(2) | 1270 | 2443 | 904 | 28.8% | 63.0% |
| ARIMA(0,1,1) | 6870 | 10221 | 3751 | 45.4% | 63.3% |
| ARIMA(1,1,1) | 57567 | 142095 | 22451 | 61.0% | 84.2% |
| ARIMA(1,1,2) | 37568 | 134173 | 17845 | 52.5% | 86.7% |
| ARIMA(0,2,2) | 103521 | 255759 | 43479 | 58.0% | 83.0% |

# Appendix 8D: Results for SMA

| Demand Process | Mean Squared Error | | Percentage Reduction by using CDIS compared to NIS |
|---|---|---|---|
| | NIS | CDIS | |
| AR(1) | 1759 | 603 | 65.7% |
| AR(2) | 1566 | 543 | 65.3% |
| ARMA(1,1) | 2239 | 1041 | 53.5% |
| MA(1) | 995 | 377 | 62.2% |
| MA(2) | 989 | 289 | 70.8% |
| ARIMA(0,1,1) | 1042 | 500 | 52.0% |
| ARIMA(1,1,1) | 1138 | 443 | 61.1% |
| ARIMA(1,1,2) | 1650 | 591 | 64.2% |
| ARIMA(0,2,2) | 2895 | 1242 | 57.1% |

| Demand Process | Bullwhip Ratio | | Percentage Reduction by using CDIS compared to NIS |
|---|---|---|---|
| | NIS | CDIS | |
| AR(1) | 8.7 | 3.9 | 55.2% |
| AR(2) | 8.4 | 3.8 | 54.2% |
| ARMA(1,1) | 8.3 | 5.0 | 39.5% |
| MA(1) | 8.7 | 3.0 | 65.3% |
| MA(2) | 8.8 | 3.2 | 63.6% |
| ARIMA(0,1,1) | 8.1 | 5.3 | 34.8% |
| ARIMA(1,1,1) | 8.6 | 4.0 | 53.6% |
| ARIMA(1,1,2) | 8.5 | 3.9 | 54.0% |
| ARIMA(0,2,2) | 8.8 | 5.1 | 42.1% |

| Demand Process | Inventory Holdings | | Percentage Reduction by using CDIS compared to NIS |
|---|---|---|---|
| | NIS | CDIS | |
| AR(1) | 6587 | 1935 | 70.6% |
| AR(2) | 5779 | 1830 | 68.3% |
| ARMA(1,1) | 6785 | 2877 | 57.6% |
| MA(1) | 4875 | 1261 | 74.1% |
| MA(2) | 4797 | 1254 | 73.9% |
| ARIMA(0,1,1) | 7525 | 3612 | 52.0% |
| ARIMA(1,1,1) | 5035 | 1959 | 61.1% |
| ARIMA(1,1,2) | 6031 | 2159 | 64.2% |
| ARIMA(0,2,2) | 9235 | 3962 | 57.1% |

| Demand Process | Inventory Cost | | Percentage Reduction by using CDIS compared to NIS |
|---|---|---|---|
| | NIS | CDIS | |
| AR(1) | 6588 | 3531 | 46.4% |
| AR(2) | 5780 | 3185 | 44.9% |
| ARMA(1,1) | 6790 | 4801 | 29.3% |
| MA(1) | 4875 | 2048 | 58.0% |
| MA(2) | 4797 | 2039 | 57.5% |
| ARIMA(0,1,1) | 8956 | 6887 | 23.1% |
| ARIMA(1,1,1) | 5035 | 2633 | 47.7% |
| ARIMA(1,1,2) | 6033 | 3312 | 45.1% |
| ARIMA(0,2,2) | 9584 | 6546 | 31.7% |

# Appendix 8E: Results for SES

| Demand Process | Mean Squared Error | | Percentage Reduction by using CDIS compared to NIS |
|---|---|---|---|
| | NIS | CDIS | |
| AR(1) | 1548 | 441 | 71.5% |
| AR(2) | 1444 | 380 | 73.7% |
| ARMA(1,1) | 1960 | 745 | 62.0% |
| MA(1) | 1033 | 345 | 66.6% |
| MA(2) | 953 | 278 | 70.8% |
| ARIMA(0,1,1) | 854 | 301 | 64.8% |
| ARIMA(1,1,1) | 1091 | 306 | 72.0% |
| ARIMA(1,1,2) | 903 | 223 | 75.3% |
| ARIMA(0,2,2) | 2895 | 1242 | 76.6% |

| Demand Process | Bullwhip Ratio | | Percentage Reduction by using CDIS compared to NIS |
|---|---|---|---|
| | NIS | CDIS | |
| AR(1) | 9.7 | 2.9 | 70.6% |
| AR(2) | 9.6 | 3.6 | 62.1% |
| ARMA(1,1) | 9.1 | 2.5 | 72.1% |
| MA(1) | 12.4 | 4.4 | 64.5% |
| MA(2) | 12.6 | 3.0 | 76.2% |
| ARIMA(0,1,1) | 11.8 | 4.8 | 59.4% |
| ARIMA(1,1,1) | 9.2 | 2.0 | 78.0% |
| ARIMA(1,1,2) | 12.8 | 4.6 | 63.8% |
| ARIMA(0,2,2) | 10.5 | 4.0 | 62.2% |

| **Demand Process** | **Inventory Holdings** | | **Percentage Reduction by using CDIS compared to NIS** |
|---|---|---|---|
| | **NIS** | **CDIS** | |
| AR(1) | 7110 | 2169 | 69.5% |
| AR(2) | 7986 | 3280 | 58.9% |
| ARMA(1,1) | 7954 | 3261 | 59.0% |
| MA(1) | 7865 | 1840 | 76.6% |
| MA(2) | 6819 | 1282 | 81.2% |
| ARIMA(0,1,1) | 10425 | 3617 | 65.3% |
| ARIMA(1,1,1) | 15422 | 4657 | 69.8% |
| ARIMA(1,1,2) | 18720 | 5597 | 70.1% |
| ARIMA(0,2,2) | 10279 | 2734 | 73.4% |

| **Demand Process** | **Inventory Cost** | | **Percentage Reduction by using CDIS compared to NIS** |
|---|---|---|---|
| | **NIS** | **CDIS** | |
| AR(1) | 8325 | 2864 | 65.6% |
| AR(2) | 8265 | 3281 | 60.3% |
| ARMA(1,1) | 8954 | 2794 | 68.8% |
| MA(1) | 8008 | 2891 | 63.9% |
| MA(2) | 7433 | 2156 | 71.0% |
| ARIMA(0,1,1) | 11452 | 4478 | 60.9% |
| ARIMA(1,1,1) | 17660 | 5139 | 70.9% |
| ARIMA(1,1,2) | 21240 | 8475 | 60.1% |
| ARIMA(0,2,2) | 12458 | 4834 | 61.2% |

# Appendix 8F: Effect of Autoregressive Parameters on the value of CDIS for AR (2) process

| **Percentage Reduction in CDIS compared to DIS for MMSE (Stage I)** | | | |
|---|---|---|---|
| $\rho_1$ | $\rho_2$ | | |
| | **0.2** | **0.4** | **0.6** |
| **0.2** | 0.6 | 9.5 | 15.8 |
| **0.4** | 3.9 | 11.7 | |
| **0.6** | 6.1 | | |

| **Percentage Reduction in CDIS compared to DIS for SMA** | | | |
|---|---|---|---|
| $\rho_1$ | $\rho_2$ | | |
| | **0.2** | **0.4** | **0.6** |
| **0.2** | 67.8 | 66.0 | 58.3 |
| **0.4** | 66.5 | 64.1 | |
| **0.6** | 52.0 | | |

| **Percentage Reduction in CDIS compared to DIS for SES** | | | |
|---|---|---|---|
| $\rho_1$ | $\rho_2$ | | |
| | **0.2** | **0.4** | **0.6** |
| **0.2** | 70.1 | 64.4 | 32.2 |
| **0.4** | 43.2 | 33.7 | |
| **0.6** | 51.8 | | |

# Appendix 8G: Effect of Moving Average Parameters on the value of CDIS for MA (2) process

| **Percentage Reduction in CDIS compared to DIS for MMSE (Stage I)** | | | |
|---|---|---|---|
| $\theta_1$ | $\theta_2$ | | |
| | **-0.6** | **-0.4** | **-0.2** |
| **-0.6** | 15.0 | 12.4 | 3.8 |
| **-0.4** | 9.8 | 7.5 | 1.6 |
| **-0.2** | 6.9 | 2.5 | 0.6 |

| **Percentage Reduction in CDIS compared to DIS for SMA** | | | |
|---|---|---|---|
| $\theta_1$ | $\theta_2$ | | |
| | **-0.6** | **-0.4** | **-0.2** |
| **-0.6** | 68.9 | 69.8 | 70.0 |
| **-0.4** | 70.8 | 71.2 | 70.9 |
| **-0.2** | 70.4 | 70.5 | 70.5 |

| **Percentage Reduction in CDIS compared to DIS for SES** | | | |
|---|---|---|---|
| $\theta_1$ | $\theta_2$ | | |
| | **-0.6** | **-0.4** | **-0.2** |
| **-0.6** | 69.9 | 70.8 | 70.5 |
| **-0.4** | 69.8 | 70.8 | 70.9 |
| **-0.2** | 70.8 | 71.2 | 70.5 |

# Appendix 8H: Percentage Reduction in Inventory Cost by using CDIS compared to DIS in Stages II and III

| **Identification & Estimation by the Retailer** | **Percentage Reduction in inventory in using CDIS compared to DIS** | |
|---|---|---|
| Accurate | 45.8% | Value of CDIS is greater |
| Inaccurate | 45.1% | Value of CDIS is lesser |

# Appendix 9A: Results for Optimal Method

| Demand Process | No. of series | Mean Squared Error | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|---|
| | | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| ARIMA(0,0,0) | *113* | 127 | 249 | 127 | 0.0% | 49.0% |
| ARIMA(0,1,0) | *76* | 996 | 1681 | 884 | 11.2% | 47.4% |
| AR(1) | *295* | 196 | 338 | 182 | 7.1% | 46.2% |
| AR(2) | *246* | 191 | 229 | 155 | 19.1% | 32.4% |
| ARMA(1,1) | *76* | 202 | 231 | 105 | 48.0% | 54.4% |
| MA(1) | *76* | 142 | 182 | 131 | 7.8% | 28.1% |
| MA(2) | *71* | 101 | 125 | 88 | 12.8% | 29.7% |
| ARMA(2,1) | *40* | 157 | 232 | 128 | 18.5% | 44.8% |
| ARMA(2,2) | *29* | 454 | 587 | 421 | 7.3% | 28.3% |
| ARMA(1,2) | *61* | 670 | 1188 | 608 | 9.3% | 48.8% |
| ARIMA(1,1,0) | *195* | 841 | 2087 | 421 | 49.9% | 79.8% |
| ARIMA(2,1,0) | *447* | 644 | 837 | 295 | 54.1% | 64.7% |

| Demand Process | No. of series | Mean Absolute Percentage | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|---|
| | | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| ARIMA(0,0,0) | *113* | 36.1 | 47.2 | 36.1 | 0.0% | 23.5% |
| ARIMA(0,1,0) | *76* | 31.7 | 39.7 | 28.9 | 9.1% | 27.2% |
| AR(1) | *295* | 42.6 | 49.0 | 39.2 | 7.9% | 20.3% |
| AR(2) | *246* | 41.9 | 47.5 | 37.5 | 10.5% | 21.1% |
| ARMA(1,1) | *76* | 64.7 | 76.1 | 55.0 | 15.0% | 27.7% |
| MA(1) | *76* | 41.7 | 44.1 | 36.2 | 13.2% | 17.9% |
| MA(2) | *71* | 38.2 | 43.2 | 32.5 | 14.9% | 24.8% |
| ARMA(2,1) | *40* | 41.9 | 43.7 | 35.4 | 15.6% | 19.1% |
| ARMA(2,2) | *29* | 34.3 | 46.5 | 32.1 | 6.5% | 31.0% |
| ARMA(1,2) | *61* | 43.3 | 52.7 | 42.5 | 2.0% | 19.4% |
| ARIMA(1,1,0) | *195* | 39.5 | 51.4 | 33.2 | 16.0% | 35.4% |
| ARIMA(2,1,0) | *447* | 85.1 | 96.3 | 52.2 | 38.7% | 45.8% |

| Demand Process | No. of series | Bullwhip Ratio | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|---|
| | | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| ARIMA(0,0,0) | *113* | 2.4 | 4.0 | 2.4 | 0.0% | 40.0% |
| ARIMA(0,1,0) | *76* | 2.0 | 2.8 | 1.6 | 19.5% | 42.8% |
| AR(1) | *295* | 2.3 | 3.3 | 1.8 | 23.3% | 44.8% |
| AR(2) | *246* | 2.3 | 2.3 | 1.7 | 27.6% | 25.8% |
| ARMA(1,1) | *76* | 3.3 | 2.5 | 1.9 | 42.9% | 25.4% |
| MA(1) | *76* | 1.9 | 1.8 | 1.3 | 32.2% | 28.9% |
| MA(2) | *71* | 2.4 | 3.3 | 1.9 | 19.8% | 41.8% |
| ARMA(2,1) | *40* | 3.4 | 4.9 | 2.9 | 13.8% | 40.5% |
| ARMA(2,2) | *29* | 2.1 | 2.0 | 1.5 | 29.8% | 26.2% |
| ARMA(1,2) | *61* | 3.8 | 4.9 | 2.8 | 26.3% | 42.5% |
| ARIMA(1,1,0) | *195* | 2.2 | 3.3 | 1.9 | 12.7% | 42.3% |
| ARIMA(2,1,0) | *447* | 4.8 | 4.9 | 2.9 | 39.2% | 40.4% |

| Demand Process | No. of series | Inventory Holdings | | | Percentage Reduction by using CDIS compared to | |
|---|---|---|---|---|---|---|
| | | DIS | NIS-Est | CDIS | DIS | NIS-Est |
| ARIMA(0,0,0) | *113* | 267 | 442 | 267 | 0.0% | 39.6% |
| ARIMA(0,1,0) | *76* | 12524 | 26325 | 11967 | 4.4% | 54.5% |
| AR(1) | *295* | 389 | 748 | 375 | 3.6% | 49.9% |
| AR(2) | *246* | 398 | 450 | 366 | 8.0% | 18.7% |
| ARMA(1,1) | *76* | 863 | 1412 | 686 | 20.5% | 51.4% |
| MA(1) | *76* | 262 | 410 | 245 | 6.5% | 40.2% |
| MA(2) | *71* | 342 | 477 | 353 | -3.1% | 26.0% |
| ARMA(2,1) | *40* | 1046 | 1496 | 745 | 28.8% | 50.2% |
| ARMA(2,2) | *29* | 1063 | 1252 | 952 | 10.5% | 24.0% |
| ARMA(1,2) | *61* | 865 | 1389 | 696 | 19.5% | 49.9% |
| ARIMA(1,1,0) | *195* | 2147 | 3976 | 2097 | 2.3% | 47.2% |
| ARIMA(2,1,0) | *447* | 1782 | 1997 | 1139 | 36.1% | 43.0% |

| **Demand Process** | **No. of series** | **Inventory Cost** | | | **Percentage Reduction by using CDIS compared to** | |
|---|---|---|---|---|---|---|
| | | **DIS** | **NIS-Est** | **CDIS** | **DIS** | **NIS-Est** |
| ARIMA(0,0,0) | *113* | 308 | 461 | 308 | 0.0% | 33.2% |
| ARIMA(0,1,0) | *76* | 14258 | 32694 | 12221 | 14.3% | 62.6% |
| AR(1) | *295* | 454 | 723 | 426 | 6.2% | 41.1% |
| AR(2) | *246* | 472 | 525 | 438 | 7.2% | 16.6% |
| ARMA(1,1) | *76* | 991 | 1639 | 843 | 14.9% | 48.6% |
| MA(1) | *76* | 453 | 587 | 383 | 15.5% | 34.8% |
| MA(2) | *71* | 442 | 526 | 406 | 8.1% | 22.8% |
| ARMA(2,1) | *40* | 1148 | 1636 | 830 | 27.7% | 49.3% |
| ARMA(2,2) | *29* | 1165 | 1328 | 1041 | 10.6% | 21.6% |
| ARMA(1,2) | *61* | 921 | 1541 | 763 | 17.2% | 50.5% |
| ARIMA(1,1,0) | *195* | 3662 | 5556 | 2819 | 23.0% | 49.3% |
| ARIMA(2,1,0) | *447* | 2090 | 2139 | 1528 | 26.9% | 28.5% |

# Appendix 9B: Results for Single Exponential Smoothing

All results in Appendix 9B show the percentage reduction in inventory cost by using CDIS instead of NIS.

| Demand Process | No. of series | Mean Squared Error | | Percentage Reduction |
|---|---|---|---|---|
| | | NIS | CDIS | |
| ARIMA(0,0,0) | *113* | 306.5 | 100.1 | 67.3% |
| ARIMA(0,1,0) | *76* | 473.2 | 156.6 | 66.9% |
| AR(1) | *295* | 352.1 | 105.6 | 70.0% |
| AR(2) | *246* | 297.8 | 87.0 | 70.8% |
| ARMA(1,1) | *76* | 298.5 | 79.4 | 73.4% |
| MA(1) | *76* | 283.2 | 53.0 | 81.3% |
| MA(2) | *71* | 309.3 | 110.7 | 64.2% |
| ARMA(2,1) | *40* | 304.2 | 99.5 | 67.3% |
| ARMA(2,2) | *29* | 238.4 | 83.4 | 65.0% |
| ARMA(1,2) | *61* | 229.3 | 76.3 | 66.7% |
| ARIMA(1,1,0) | *195* | 387.2 | 124.5 | 67.8% |
| ARIMA(2,1,0) | *447* | 350.0 | 111.9 | 68.0% |

| Demand Process | No. of series | Mean Absolute Percentage Error | | Percentage Reduction |
|---|---|---|---|---|
| | | NIS | CDIS | |
| ARIMA(0,0,0) | *113* | 73.2 | 56.2 | 23.2% |
| ARIMA(0,1,0) | *76* | 69.2 | 37.9 | 45.2% |
| AR(1) | *295* | 55.2 | 37.1 | 32.7% |
| AR(2) | *246* | 52.3 | 39.4 | 34.6% |
| ARMA(1,1) | *76* | 48.7 | 30.9 | 36.6% |
| MA(1) | *76* | 53.4 | 28.9 | 45.8% |
| MA(2) | *71* | 56.6 | 40.0 | 29.4% |
| ARMA(2,1) | *40* | 52.1 | 31.8 | 39.0% |
| ARMA(2,2) | *29* | 59.8 | 47.1 | 21.2% |
| ARMA(1,2) | *61* | 61.2 | 45.5 | 25.6% |
| ARIMA(1,1,0) | *195* | 48.7 | 32.9 | 32.4% |
| ARIMA(2,1,0) | *447* | 59.6 | 26.8 | 55.0% |

| **Demand Process** | **No. of series** | **Bullwhip Ratio** | | **Percentage Reduction** |
|---|---|---|---|---|
| | | **NIS** | **CDIS** | |
| ARIMA(0,0,0) | *113* | 14.6 | 3.1 | 79.0% |
| ARIMA(0,1,0) | *76* | 14.0 | 2.6 | 81.4% |
| AR(1) | *295* | 14.8 | 2.8 | 81.3% |
| AR(2) | *246* | 15.1 | 3.1 | 79.7% |
| ARMA(1,1) | *76* | 14.9 | 2.6 | 82.4% |
| MA(1) | *76* | 14.8 | 2.6 | 82.1% |
| MA(2) | *71* | 14.6 | 2.8 | 81.1% |
| ARMA(2,1) | *40* | 14.6 | 2.6 | 82.5% |
| ARMA(2,2) | *29* | 14.2 | 1.9 | 86.6% |
| ARMA(1,2) | *61* | 14.6 | 3.1 | 78.9% |
| ARIMA(1,1,0) | *195* | 14.9 | 3.0 | 80.2% |
| ARIMA(2,1,0) | *447* | 14.1 | 2.1 | 85.2% |

| **Demand Process** | **No. of series** | **Inventory Holdings** | | **Percentage Reduction** |
|---|---|---|---|---|
| | | **NIS** | **CDIS** | |
| ARIMA(0,0,0) | *113* | 8025 | 2149 | 73.2% |
| ARIMA(0,1,0) | *76* | 13477 | 3803 | 71.8% |
| AR(1) | *295* | 8895 | 2458 | 72.4% |
| AR(2) | *246* | 7818 | 2123 | 72.8% |
| ARMA(1,1) | *76* | 7897 | 2072 | 73.8% |
| MA(1) | *76* | 7488 | 1904 | 74.6% |
| MA(2) | *71* | 7965 | 2124 | 73.3% |
| ARMA(2,1) | *40* | 6781 | 1847 | 72.8% |
| ARMA(2,2) | *29* | 6138 | 1575 | 74.3% |
| ARMA(1,2) | *61* | 7202 | 1815 | 74.8% |
| ARIMA(1,1,0) | *195* | 9398 | 2661 | 71.7% |
| ARIMA(2,1,0) | *447* | 9170 | 2381 | 74.0% |

| Demand Process | No. of series | Inventory Costs | | Percentage Reduction |
|---|---|---|---|---|
| | | NIS | CDIS | |
| ARIMA(0,0,0) | *113* | 8025 | 2181 | 72.8% |
| ARIMA(0,1,0) | *76* | 13477 | 3942 | 70.7% |
| AR(1) | *295* | 8900 | 2518 | 71.7% |
| AR(2) | *246* | 7818 | 2153 | 72.5% |
| ARMA(1,1) | *76* | 7897 | 2115 | 73.2% |
| MA(1) | *76* | 7488 | 1921 | 74.3% |
| MA(2) | *71* | 7965 | 2163 | 72.8% |
| ARMA(2,1) | *40* | 6781 | 1904 | 71.9% |
| ARMA(2,2) | *29* | 6138 | 1583 | 74.2% |
| ARMA(1,2) | *61* | 7202 | 1853 | 74.3% |
| ARIMA(1,1,0) | *195* | 9409 | 2804 | 70.2% |
| ARIMA(2,1,0) | *447* | 9172 | 2437 | 73.4% |

# Appendix 9C: Results for Simple Moving Averages

All results in Appendix 9C show the percentage reduction in inventory cost by using CDIS instead of NIS.

| Demand Process | No. of series | Mean Squared Error | | Percentage Reduction |
|---|---|---|---|---|
| | | NIS | CDIS | |
| ARIMA(0,0,0) | *113* | 425.7 | 187.3 | 56.0% |
| ARIMA(0,1,0) | *76* | 545.3 | 223.6 | 59.0% |
| AR(1) | *295* | 158.3 | 96.6 | 39.0% |
| AR(2) | *246* | 415.0 | 253.6 | 38.9% |
| ARMA(1,1) | *76* | 376.8 | 243.4 | 35.4% |
| MA(1) | *76* | 280.3 | 153.3 | 45.3% |
| MA(2) | *71* | 414.8 | 237.7 | 42.7% |
| ARMA(2,1) | *40* | 366.3 | 168.5 | 54.0% |
| ARMA(2,2) | *29* | 451.6 | 185.2 | 59.0% |
| ARMA(1,2) | *61* | 290.3 | 116.1 | 60.0% |
| ARIMA(1,1,0) | *195* | 514.9 | 216.3 | 58.0% |
| ARIMA(2,1,0) | *447* | 391.1 | 144.7 | 63.0% |

| Demand Process | No. of series | Mean Absolute Percentage Error | | Percentage Reduction |
|---|---|---|---|---|
| | | NIS | CDIS | |
| ARIMA(0,0,0) | *113* | 66.6 | 32.0 | 52.0% |
| ARIMA(0,1,0) | *76* | 66.0 | 41.0 | 37.9% |
| AR(1) | *295* | 64.9 | 47.0 | 20.6% |
| AR(2) | *246* | 59.1 | 48.0 | 18.7% |
| ARMA(1,1) | *76* | 49.2 | 37.9 | 23.0% |
| MA(1) | *76* | 62.1 | 42.1 | 32.2% |
| MA(2) | *71* | 66.8 | 47.6 | 28.8% |
| ARMA(2,1) | *40* | 57.2 | 40.0 | 30.0% |
| ARMA(2,2) | *29* | 55.3 | 27.7 | 50.0% |
| ARMA(1,2) | *61* | 58.6 | 40.1 | 31.5% |
| ARIMA(1,1,0) | *195* | 79.6 | 46.1 | 42.1% |
| ARIMA(2,1,0) | *447* | 64.5 | 27.5 | 57.4% |

| **Demand Process** | **No. of series** | **Bullwhip Ratio** | | **Percentage Reduction** |
|---|---|---|---|---|
| | | **NIS** | **CDIS** | |
| ARIMA(0,0,0) | *113* | 8.9 | 2.8 | 69.0% |
| ARIMA(0,1,0) | *76* | 8.2 | 2.5 | 70.0% |
| AR(1) | *295* | 7.9 | 3.5 | 54.8% |
| AR(2) | *246* | 7.2 | 3.6 | 50.0% |
| ARMA(1,1) | *76* | 8.6 | 5.5 | 35.5% |
| MA(1) | *76* | 7.5 | 2.8 | 62.8% |
| MA(2) | *71* | 8.6 | 3.2 | 62.8% |
| ARMA(2,1) | *40* | 8.9 | 3.1 | 65.0% |
| ARMA(2,2) | *29* | 8.2 | 3.4 | 58.0% |
| ARMA(1,2) | *61* | 7.8 | 4.9 | 37.0% |
| ARIMA(1,1,0) | *195* | 8.6 | 3.3 | 61.0% |
| ARIMA(2,1,0) | *447* | 8.3 | 2.2 | 74.0% |

| **Demand Process** | **No. of series** | **Inventory Holdings** | | **Percentage Reduction** |
|---|---|---|---|---|
| | | **NIS** | **CDIS** | |
| ARIMA(0,0,0) | *113* | 11185 | 6375 | 43.0% |
| ARIMA(0,1,0) | *76* | 18003 | 8641 | 52.0% |
| AR(1) | *295* | 12002 | 6001 | 50.0% |
| AR(2) | *246* | 11199 | 6585 | 41.2% |
| ARMA(1,1) | *76* | 11012 | 6607 | 40.0% |
| MA(1) | *76* | 9986 | 3994 | 60.0% |
| MA(2) | *71* | 11403 | 4778 | 58.1% |
| ARMA(2,1) | *40* | 9605 | 5859 | 39.0% |
| ARMA(2,2) | *29* | 9223 | 5073 | 45.0% |
| ARMA(1,2) | *61* | 10252 | 6254 | 39.0% |
| ARIMA(1,1,0) | *195* | 13529 | 5411 | 60.0% |
| ARIMA(2,1,0) | *447* | 12901 | 7999 | 38.0% |

| **Demand Process** | **No. of series** | **Inventory Costs** | | **Percentage Reduction** |
|---|---|---|---|---|
| | | **NIS** | **CDIS** | |
| ARIMA(0,0,0) | *113* | 11194 | 3557 | 68.2% |
| ARIMA(0,1,0) | *76* | 18993 | 6447 | 66.1% |
| AR(1) | *295* | 12068 | 6963 | 42.3% |
| AR(2) | *246* | 11296 | 6812 | 39.7% |
| ARMA(1,1) | *76* | 11771 | 7898 | 27.9% |
| MA(1) | *76* | 10747 | 4514 | 58.0% |
| MA(2) | *71* | 11432 | 5213 | 54.4% |
| ARMA(2,1) | *40* | 9644 | 3000 | 68.9% |
| ARMA(2,2) | *29* | 9246 | 2698 | 70.8% |
| ARMA(1,2) | *61* | 10468 | 3081 | 70.6% |
| ARIMA(1,1,0) | *195* | 13630 | 4487 | 67.1% |
| ARIMA(2,1,0) | *447* | 12977 | 3983 | 69.3% |

# Appendix 9D: Effect of Smoothing Constant on Percentage Reduction in Inventory Cost by using CDIS

The following table indicates the average percentage reduction in inventory cost by using CDIS instead of NIS, averaged over all twelve demand processes analysed in the empirical analysis of this research.

| alpha | Percentage Reduction in inventory Cost by using CDIS instead of NIS |
|---|---|
| 0.1 | 35.0% |
| 0.3 | 72.2% |
| 0.8 | 78.8% |

# Appendix 9E: Effect of Number of Terms in SMA on Percentage Reduction in Inventory Cost by using CDIS

The following table indicates the average percentage reduction in inventory cost by using CDIS instead of NIS, averaged over all twelve demand processes analysed in the empirical analysis of this research.

| Number of Terms (n) | Percentage Reduction in inventory Cost by using CDIS instead of NIS |
|---|---|
| 3 | 38.7% |
| 6 | 56.3% |
| 12 | 75.6% |