SUPPLY CHAINS FACING ATYPICAL DEMAND: OPTIMAL OPERATIONAL POLICIES AND BENEFITS UNDER INFORMATION SHARING

Baruah, Pundarikaksha

Wayne State University, Department of Industrial and Manufacturing Engineering

21 December 2006

SUPPLY CHAINS FACING ATYPICAL DEMAND: OPTIMAL OPERATIONAL POLICIES AND BENEFITS UNDER INFORMATION SHARING

by

PUNDARIKAKSHA BARUAH

DISSERTATION

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

2006

MAJOR: INDUSTRIAL ENGINEERING

Approved by

Ratna Babu M. Ch 11/30/2006

Advisor Date

K. Park

A. Korostelev

L. Monplaisir

UMI Number: 3283917

ProQuest Information and Learning Company
300 North Zeeb Road
P.O. Box 1346
Ann Arbor, MI 48106-1346

DEDICATION

To my parents Mrs. Sonmai Baruah and Mr. Manindra Kumar Baruah

ACKNOWLEDGMENTS

Thanks to values of our society, that gives utmost importance to education and learning. I am very grateful to my family members and relatives that have always encouraged scholarly pursuit.

Without the guidance of Prof. Ratna Babu Chinnam this feat would not have been possible. I have no words to express my gratitude to Prof. Chinnam.

I am thankful to my committee members Prof. Alexander Korostelev, Prof. Lesli Monplaisir , and Prof. Namkyu Park for their suggestion for improvement. Thanks to Prof. Kenneth Chelst, Prof. Richard Darin Ellis of IME for their support and enthusiasm to accomplish this goal. I am thankful to Dr. Dimitre P. Filev of Ford, whose encouragement has boosted my confidence tremendously. Thanks to Dr. Alper Murat and Dr. Jia Shu of IME who helped me in various instances with their expertise. Thanks to Ms. Sara Tipton of Dept. of English for helpful feedback on my technical writing.

Thanks to all my friends for supporting me and helping me in going through this long period of dissertation research. Mr. Sunil Sheoran has helped me shape my initial understanding of supply chain management. Several reading recommendations by Dr. Ramakrishna Govindu were extremely helpful in broadening the understanding of industrial engineering. Advice from Mr. Rajdeep Patgiri was invaluable in deciding whether to take a research track or not. My brother, Dr. Pranab Jyoti Baruah has provided valuable guidance in learning the research process.

Finally, thanks to Wayne State University for providing such excellent resources to conduct research.

TABLE OF CONTENTS

DEDICATION ii

ACKNOWLEDGMENTS iii

LIST OF TABLES viii

LIST OF FIGURES ix

CHAPTERS

1. INTRODUCTION 1

1.1 Background 1

1.2 Characterizing atypical demand 4

1.3 Example of atypical demand: seasonal and promotional sales 5

1.4 Atypical demand and supply chain management 6

1.5 Supply chain setting for this research 8

1.5.1 Characterization of a buyer facing atypical demand 10

1.5.3 Characterization of a supplier that replenishes the above buyer 11

1.6 Supply chain planning and information sharing 11

1.7 Research focus and questions 12

2. BENEFITS OF ISSUING SOFT-ORDERS UNDER ATYPICAL DEMAND TO SUPPLIERS WITH CAPACITY UNCERTAINTY 15

2.1 Abstract 15

2.2 Introduction 16

2.3 Literature review 20

2.3.1 Information sharing under atypical demand and capacity uncertainty 20

2.3.2 Soft-order revision process 20

2.3.3 Production planning under soft-order revision 22

2.3.4 Production planning under capacity uncertainty 22

2.4 Model formulation 23

2.4.1 Two scenarios: Information sharing vs. no sharing 24

2.4.2 Soft-order revision model 27

2.4.3 Modeling capacity uncertainty 28

2.4.4 Production-scheduling model for the no-IS case 30

2.4.5 Production model for the IS case 31

2.4.6 Modeling forecast inflation and information degradation 32

2.4.7 Performance measures for comparison of information sharing scenarios 35

2.5 Numerical experiments 36

2.5.1 Aggregate production plan for stages 38

2.5.2 Framework for numerical analysis 39

2.5.3 Effect of lead-times (l and Δl) 42

2.5.4 Effect of order variability (m_σ) 46

2.5.5 Effect of correlation between successive soft-order forecasts (m_ρ) 48

2.5.6 Effect of intentional but systematic soft-order inflation (m_m) 48

2.5.7 Effect of capacity severity and uncertainty (μ_n and σ_n) 49

2.5 Conclusion 50

3. AN OPTIMAL SOFT-ORDER REVISION POLICY FOR A VENDOR FACING SUPPLY UNCERTAINTY AND UPSTREAM INFORMATION 52

3.1 Abstract 53

3.2 Introduction 52

3.3 Literature Review 57

3.3.1 Optimal ordering policy under demand and supply uncertainty .. 57

3.3.2 Optimal ordering policy under forecast revision and supply uncertainty for short life-cycle products 60

3.3.3 Value of upstream supply chain information for buyers 63

3.4 Model formulation 67

3.4.1 Two scenarios: Information sharing vs. no sharing 67

3.4.2 Modeling the forecast revision process 69

3.4.3 Modeling the supply uncertainty 69

3.4.4 Cost structure for the buyer 75

3.4.5 Model to make optimal Y_1 and Y_2 decisions 76

3.5 Establishing the benefits of upstream information sharing 78

3.6 Numerical analysis 81

3.6.1 Framework for numerical analysis 81

3.6.2 Structural properties of optimal decisions and costs 86

3.6.3 Numerical assessment of the benefits of information sharing 91

3.6.3.1 The impact of k_1, k_2 and CV on expected percentage benefit........91

3.6.3.2 The impact of unit deposit cost z on expected percentage benefit........95

3.6.3.3 The impact of c_0 and c_u on expected percentage benefit........96

3.7 Conclusion........98

4. CONCLUSION AND FUTURE RESEARCH

4.1 Conclusion........100

4.2 Research contributions........102

4.2.1 Contributions from supplier model........102

4.2.1 Contributions from buyer model........104

4.3 Future research........105

REFERENCES........108

ABSTRACT........118

AUTOBIOGRAPHICAL STATEMENT........120

LIST OF TABLES

Table 2.1 Summary of key supplier model variables and parameters 23

Table 2.2 Common framework for all numerical experiments..................... 40

Table 3.1 Summary of key retailer model variables and parameters.......... 65

LIST OF FIGURES

Figure 1.1 Consumer response to out-of-stock event 7

Figure 1.2 Supply chain configuration for this research 9

Figure 2.1 Schematic showing time-lines for the no information sharing case and the information sharing case with three soft-orders 25

Figure 2.2 Illustration of soft-order revision process with four stages 29

Figure 2.3 Relationship between capacity uncertainty and production uncertainty given a particular release (R_j) 29

Figure 2.4a,b Information degradation models 34

Figure 2.4c Forecast inflation model 34

Figure 2.5a Period level release policy 37

Figure 2.5b Aggregate stage level release policy 37

Figure 2.6 Effect of time between order forecast revisions on supplier’s cost 41

Figure 2.7 Effect of total order lead-time on supplier’s cost 41

Figure 2.8 Effect of (soft) order variability on supplier’s cost 43

Figure 2.9 Effect of (soft) order variability on order fill-rate 43

Figure 2.10 Effect of correlation between successive (soft) orders on supplier’s cost 45

Figure 2.11 Effect of correlation between successive (soft) orders on supplier’s cost 45

Figure 2.12 Effect of systematic soft-order inflation on supplier’s cost 47

Figure 2.13 Effect of systematic soft-order inflation on order fill-rate 47

Figure 2.14 Effect of capacity severity and uncertainty on supplier's cost ... 50

Figure 3.1 Schematic showing timeline of events for the buyer 65

Figure 3.2 Illustrating the forecast revision process for buyer 70

Figure 3.3a Causal relationship between the (soft) order quantities and the production quantity in information sharing (IS) case 70

Figure 3.3b Causal relationship between the (soft) order quantities and the production quantity in no information sharing (No-IS) case 69

Figure 3.4a Illustrating the feasible region for P_1 and P_2 and combination of values of P_1 and P_2 that results in $Q=P_1+P_2$ 73

Figure 3.4b Probability of $P_1 \geq Y_2$ obtained from conditional probability of $P_1|Y_1$ 73

Figure 3.5 Illustrating the relationship between stage-2 capacity uncertainty and stage-2 production uncertainty 82

Figure 3.6 Structure of the optimal decision (soft-order) in IS and No-IS case in the beginning of stage-1 84

Figure 3.7 Structure of the optimal cost for IS and No-IS case in the beginning of stage-1 84

Figure 3.8 Structure of the optimal decision (final order) for No-IS case based in the beginning of stage-2 85

Figure 3.9 Structure of the optimal cost at the beginning of stage-2 cost for No-IS case 85

Figure 3.10 Structure of the optimal decision (final order) in the beginning

of stage-2 for IS case for P_1=1 and P_1=100 87
Figure 3.11 Structure of the optimal cost in the beginning of stage-2 for IS case for P_1=1 and P_1=100 87
Figure 3.12 Expected cost for buyer under No-IS case decreases with increase in capacity of second stage 90
Figure 3.13 Expected cost for buyer under IS case decreases with increase in capacity of second stage 90
Figure 3.14 Expected percentage cost benefit for buyer *w.r.t.* k_2 and CV when k_1 = 1 92
Figure 3.15 Expected percentage cost benefit for buyer *w.r.t.* k_2 and CV when k_1 = 0.4 92
Figure 3.16 Expected percentage cost benefit for buyer for different c_0 and c_u when unit deposit cost is z=0 94
Figure 3.17 Expected percentage cost benefit for buyer for different c_0 and c_u when unit deposit cost is z=7 94
Figure 3.18 Effect of increase in z on expected percentage cost benefit for different c_0 and c_u = 9 97
Figure 3.18 Effect of increase in z on expected percentage cost benefit for different c_u and c_0 = 10 97

CHAPTER I

Introduction

1.1 Background

Management of supply chains facing atypical demand settings is challenging. Demand during events such as promotional sale, seasonal sale and or short life cycle product introduction is notoriously uncertain and therefore very difficult to predict. Demands arising from such events are called atypical demand. However, these events bring huge financial opportunity to the supply chain players.

In industries such as fashion, toys, and high-tech electronics, time-to-market and product turnover are vital; product has very short life and is sold in brief and well-defined selling seasons (Christopher 2004, Johnson 2001). Demand faced by such industries are extremely volatile and seasonal in nature, and highly unpredictable (Wong et al 2005). In addition, with a lot of this manufacturing being outsourced to distant countries, transit times are longer, creating additional constraints. The end result being higher costs of obsolete inventory, lost sales and markdowns. Early on, Reinmuth and Geurts (1972) labeled similar settings combined with promotions atypical. We particularly define atypical demand settings to be those settings where construction of a predictive time-series model for demand forecasting is difficult, consistent with observations by Hausman (1969).

Effective ways of managing atypical demand situation are: (a) Modeling the uncertainty, (b) improve visibility and, (c) decision making based on predictive updates. Modeling the uncertainty would need establishing methods and practices to monitor different source of market events and explore relationship between factors that can generate a demand estimate. Revised estimates based on recent market information should in turn be used to revise operational decisions. Market events are typically more visible to players closer to the final customer. Demand predictions or transformation of such information (e.g. soft orders), should be shared by downstream player through collaborative planning or information sharing framework with key supply chain partners. This improves downstream visibility for upstream players and enables them to efficiently position their resources and plan activities to hedge against uncertainty. In addition to downstream information, upstream information from supplier to buyer could potentially increase the supply side visibility. Increased supply side visibility helps reduce supply uncertainty and enables buyer to take action in case of possible supply shortage or supply disruption. Research done by AMR Research found that, ability to share information faster and more accurately among players allows them to see trends sooner and it is the real value of supply chain enablers (Koch 2004). Particularly in atypical demand situations, early planning through better visibility can make a huge difference; for example, a supplier that plan early and initiate necessary activities will benefit from better utilization of his resources and facilities where last minute ramp ups are usually very expensive. Similarly, a vendor gets a better assessment of supply uncertainty if supplier is updated with the order inventory position; for example, in case of possible supply shortage, she can go for an alternative supplier (such as a subcontractor) and or plan for a substitute product to hedge the possibility of lost-revenue due to lost sales.

However, the challenge is, to reap the benefit from superior predictive methods, forecasting updating technique, immediate information sharing and early warning about possible revenue opportunity, players will need custom operations planning policies in place that are sophisticated enough to incorporate extra information that are more frequently updated and finally generate recommendations that allows them to make intelligent decisions. This combined set: more predictive power, framework for sharing information and tools/policies to help make operational decisions can position the supply chains facing atypical demand in a competitive advantage against their competitors.

A supply chain player facing atypical demand, before beginning any initiatives in terms of investment for a information sharing system or bringing innovation in their operational policies need to investigate the return on investment and effort that it plan to put for change. Some of the key questions they face while performing this step are: what benefit sheared-information brings to the company or the supply chain as a whole, will it reduce cost, what are the options, which information to share, what operational changes are necessary, do we even have data to explore all these questions objectively etc. In this dissertation, we try to explore some of these important questions in the context of atypical demand situations. In this chapter, we characterize atypical demand, present a short literature about impact of atypical demand, more specifically, seasonal and promotional sales in industry and then explore questions based on industry need and driven by gaps in literature. We have identified information that can be shared between players, we have detailed discussion on the benefit of sharing them and presented operational policies and analysis that work with those information.

1.2 Characterizing atypical demand

'Atypical demand' situation has the following characteristics:

(i) A type of demand situation with high uncertainty and, forecasting through time series model does not result in good predictions. In such situations, demand is modeled through distributions or histograms based on experts' opinion or past data and forecast are updated as new market information becomes available.

(ii) Example of atypical demands are demand for a short life cycle product or a seasonal item under promotion that depends on numerous complex market activities such as weather, demand of substitute product, competitor's behavior, market price, overall economy etc.

(iii) Demand is usually intense in a short period due to its seasonal nature, promotional push and/or because product life cycle is relatively short. Demand could be so volatile that sales may jump to several times higher than any typical sales day.

(iv) Usually supply chain players near to the final customer face such demand.

The assumption that construction of a time series model (stationary or non-stationary) for predictive purpose is difficult in atypical situation has been researched by Hausman (1969). He provides evidence of such demand scenarios.

Reinmuth and Geurts (1972) also studied a similar demand situation. They are the first to discuss ‘atypical *situation*’. We use the phrase ‘atypical *demand*’ for the purpose of brevity, and depict demand characteristics outlined above.

1.3 Example of atypical demand: seasonal and promotional sales

One example of atypical demand situation is seasonal and promotional sales. Here we present a literature review of the significance of such demand situations. A recent survey that explored the format of customer shopping and spending across retail chains found that that on an average a grocery store sells 18.2% on promotion, a mass merchandiser sells 13.9% on promotion, and a drug store sells 24.3% sells on promotion (Fox 2004). According to the National Christmas Tree Association (NCTA 2000a), about 28 million natural Christmas trees were purchased for the holiday in 2001, nearly $1 billion in retail sales. Ann Taylor, a U.S. women’s apparel retailer with over 580 stores nationwide, reported a year on year increase in sales by 26% over the Christmas period of 2003 (Liu and Ryzin 2005). Wal-Mart, the world’s largest retailer, reports that, holiday season sales - including Thanksgiving and post-Christmas season sales events - account for close to 20% of total annual sales (Rozhon 2005). Retailers have recognized the potential of pricing and promotion as tools to boost seasonal sales. A study by Fearne et al (1999) done in UK on alternative promotion strategies in spirit category, found that impact of tactical promotions to increase share and volume growth in this sector is significant and essential even during the Christmas period. Larson (2004) states that retailers and producers can boost sales of Christmas trees by application of promotion and price tactics. If natural Christmas tree growers and seller do not use promotion as a sales leverage assuming it's a seasonal item, then plastic trees may eat away their market share; in 2001, only 24% house hold has natural trees and 52% has artificial trees (NCTA 2002b).

1.4 Atypical demand and supply chain management

Objective of a retailer during promotional and seasonal sales is to generate store traffic and help communicate image (Blattberg et al 1990), to increase revenue and profit in the short-term as well the long-term. Seasonal and promotional sales events however generate largest swings in demand, and as a result, they face the majority of out-of-stock, excess inventory, and unplanned logistics costs (VICS 2004). The ill effects of such events propagate beyond the boundary of the retailer's business. These events are one of the root causes of bullwhip effect (Lee *et al* 1997). Supply chain inefficiencies caused by bullwhip are: excessive inventory investment, poor customer service, lost revenue, misguided capacity plans, ineffective transportation, and missed production schedule (Lee *et al* 1997). Every day low price (EDLP) is prescribed as a counter measure for high-low pricing (HLP) to alleviate the detrimental effect of bullwhip (Lee et al 1997).

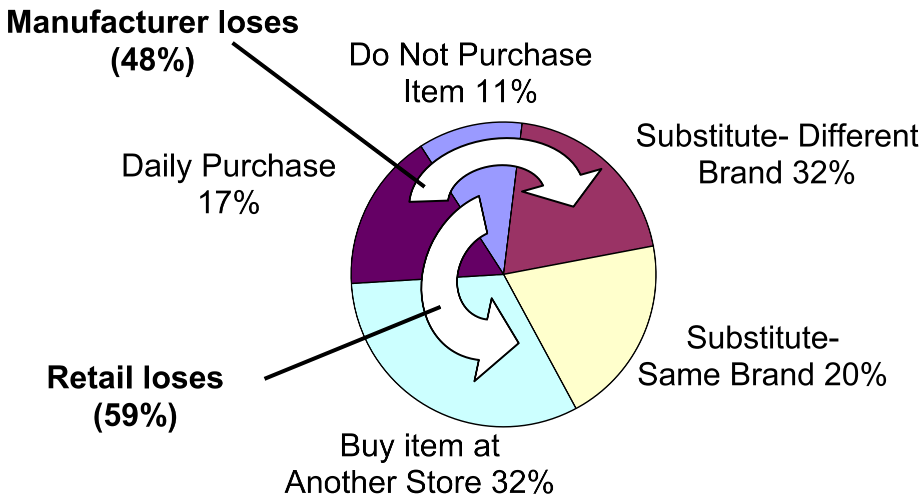


Figure 1.1 Consumer response to out-of-stock event. Source: GMA/FMI retail out-of-stock study (Gruen et al. 2002)

While such a prescription can dampen the bullwhip effect, not every retailer is embracing it. Based on a survey conducted among 86 grocery stores for 26 product categories, Hoch *et al* (1994) finds that an EDLP policy reduced profit by 18%, and HLP increased profit by 15%. A recent article by Lee (2004a) states “by applying tools such as pricing and promotions companies can influence demand and better manage their partnerships”.

These researches imply that the promotional and seasonal sales deserve more attention, because they come with huge financial opportunity but with notorious uncertainty. Strategies like price promotion at the front-end of the supply chain with improved logistics on the back-end can be a defensible competitive advantage (Hoch *et al* 1994). Given that the repercussions of these front-end supply chain events go beyond retailer’s business, some of the effective ways to reap the benefits while taking care of the uncertainty are increased collaboration and information sharing between retailers and suppliers of seasonal products, superior forecasting with forecast update techniques, and replenishment and inventory/manufacturing policies specifically designed to cope with such events. Seasonal and promotional events hold opportunities for both front-end seller as well as manufacturers of seasonal items. On the other hand, out-of-stock are also more common during such events, just as the customer demand peaks. Both the manufacturer as well as the retailer lose out during these out-of-stock conditions. For example, according to a recent retail out-of-stock study (Gruen et al. 2002), as illustrated in figure 1.1, retailers are likely to lose more than one-half of the intended purchases when a consumer confronts an out-of-stock, and manufacturers lose about one-half of the intended purchases. Pushing more inventories into the supply chain as a remedy to the stock-out problem however is not the solution (VICS 2004). Obsolete inventory management in case of overstock through clearance pricing is a major challenge for retail chains (Smith and Achabal 1998). For products like greeting cards, that has a finite selling season and uncertain demand, end of the season clearance pricing may not even work.

1.5 Supply chain setting for this research

This dissertation concentrates on a two-player supply chain facing a seasonal and/or a promotional sale. Among the two-players is a *buyer* (retailer/distributor/vendor) that makes ordering decision(s) in the presence of upstream supply uncertainty and demand forecast revision(s).

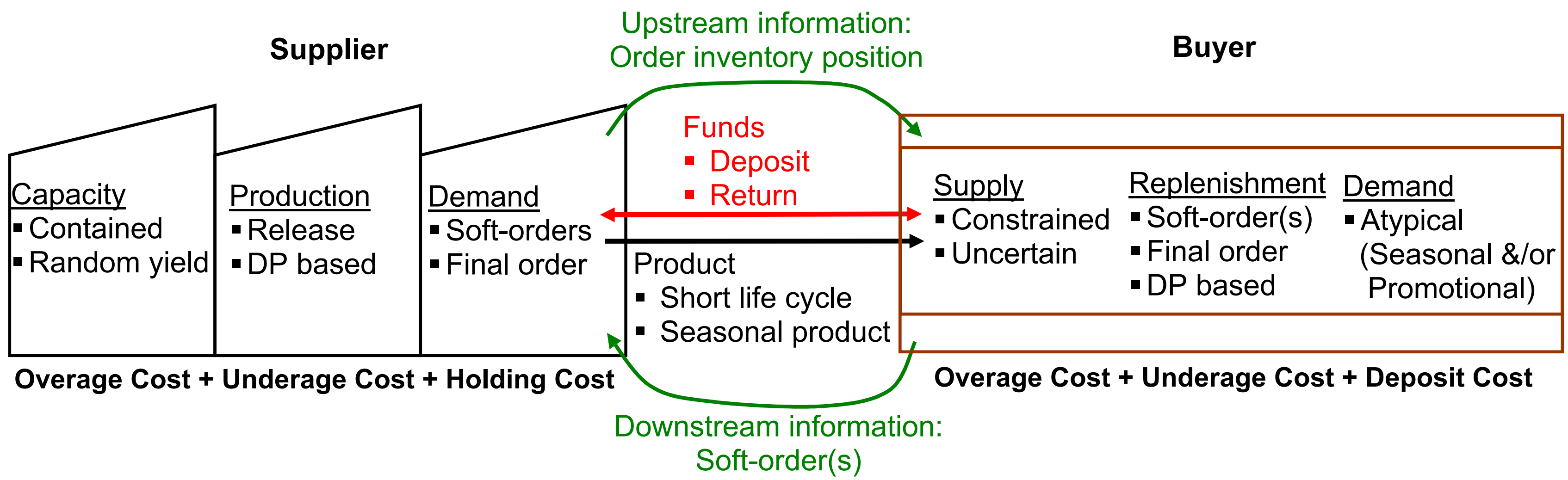


Figure 1.2: Supply chain configuration with a buyer and a supplier, along with theirs operating policies and uncertainties they face. Arrows represent direction of information, product, and fund flows.

Second player is a manufacturer that supplies the buyer; demand for this *supplier* is buyer's replenishment orders. Figure 1.2 illustrates the supply chain configuration with uncertainties that the players face and the decisions they need to make. Direction of arrows represent product, information and fund flows.

1.5.1 Characterization of a buyer facing atypical demand

(i) Buyer faces an atypical demand setting and must receive the only order shipment from the supplier before the start of the sale.

(ii) Buyer knows the date of the sale and plans for the sale quite early in time.

(iii) Buyer incurs no holding cost for the order is received just before the sale starts. She faces an underage cost for every unit short and an overage cost for every unit of excess at the end of the sales event.

(iv) Buyer carries no substitute product for the product on sale and replenishment decisions need to be made for one product.

(v) Demand forecasts are generated based on early market information and revised subsequently as time approaches the sale. Buyer has some prior knowledge of the demand uncertainty either in the form of past demand data or expert knowledgebase.

(vi) Supplier's delivery quantity never exceeds the size of the final order. From past knowledge, buyer knows the degree of supply uncertainty. Replenishment decisions are made considering both demand and supply uncertainty.

1.5.3 Characterization of a supplier that replenishes the above buyer

(i) Manufacturer of the seasonal product.

(ii) Does not build inventory unless he is notified about a possible purchase by buyer or he is sent a final purchase order.

(iii) His capacity is constrained and faces random yield. Capacity is considered inflexible and last minute ramp-up to satisfy an order is not a possibility.

(iv) Supplier lacks independent forecasting capability for market demand and relies on retailer's orders and soft-order revisions.

(v) Supplier has history of past orders and soft-order revisions from the same customer for the same or related product, and uses it for making production release decisions.

1.6 Supply chain planning and information sharing

This dissertation concentrates on a decision model with a time-frame which is within the time between the buyer sending a signal about a planned sale to the time the actual demand is observed by the retailer. This period is typically from a quarter and a year. Based on Chopra and Meindl (2004), we may classify this research to fall under the category of *supply chain planning*. As illustrated in figure 2, the flow of information, products, and funds between these two players occur in both directions. The information we consider in this research is as follows:

(i) <u>*Soft-order(s)*</u>: Based on early forecast of atypical demand, buyer generates a soft-order and sends it to the supplier. In doing so, it has to submit a deposit per unit of soft-order. The soft-order is later revised to become a final order. However, buyer has the option of not sending soft-order(s) and only issuing the final order when forecasts are more accurate. Note that these soft-orders are not legally binding final orders. They are early signals of probable purchase orders.

(ii) <u>*Supplier's inventory position*</u>: If the supplier receives soft-order(s), he may start building inventory or wait until receiving the final order. He has the option of disclosing his order inventory position with the buyer before receiving the final order.

In the context of information sharing, soft-order(s) can be considered as downstream information and supplier's inventory position as upstream information, by the buyer and supplier, respectively.

1.7 Research focus and questions

The research focuses on production-inventory management and role of cooperative information sharing on cost efficiency and fill rate for the two-player supply chain described above. We model a supplier that faces soft-order(s) and effective capacity uncertainty and compares her to a supplier that is not given the early soft-orders, instead only received the final order under similar capacity circumstances. The order fulfillment costs for these two suppliers are compared to assess the benefit of transmitting soft-order(s). These two supplier models and cost comparisons are used to answer the following specific questions:

(i) How to plan on production release(s) when soft-orders are received and subsequently revised before receiving the final order, in the presence of effective capacity uncertainty?

(ii) What is cost benefit to the supplier from receiving soft-order(s)?

(iii) What are the benefits to the retailer in terms of order fill-rate for sharing soft-order(s)?

(iv) How does per unit underage cost, overage cost and holding cost effect the decision making and cost-benefit tradeoffs?

These questions are explored in chapter-2.

On the buyer's side, we model a buyer that faces atypical demand and supply uncertainty. The problem considered here is how to generate soft-order(s) and a final order given the demand forecast evolution and supply uncertainty. Under upstream information sharing case, same replenishment decisions are made using additional information regarding supplier's order inventory position. We investigate the following questions:

(i) How does a buyer facing atypical demand optimally generate soft–order(s) and a final order given demand forecast revisions, supply uncertainty, and deposit cost?

(ii) How does she make the same decisions if supplier's order inventory position is known?

(iii) Is knowledge of supplier's inventory position beneficial to the buyer?

(iv) How do benefits very depending on the level of supply uncertainty, demand uncertainty, and deposit cost?

These questions are explored in chapter-3.

Apart from these specific questions, we also study the interactions of various cost parameters, level of demand and supply/capacity uncertainties, on the costs incurred by the two supply chain players.

CHAPTER 2

BENEFITS OF ISSUING SOFT-ORDERS UNDER ATYPICAL DEMAND TO SUPPLIERS WITH CAPACITY UNCERTAINTY

2.1 Abstract

Demand patterns for products with seasonal demand and/or short life-cycles do not follow a clear discernible pattern for individual sales events due to such factors as product promotions and unforeseen marketplace events. Suppliers supporting such “atypical” demand patterns typically incur higher holding costs, lower capacity utilization, and lower order fill-rates, particularly under long lead-times and capacity uncertainty. Sharing of order forecasts, also known as “soft-orders”, in advance by the buyer could be beneficial to both parties involved. To investigate, we model two information sharing scenarios: (1) Supplier receives “firm-orders” with a finite and deterministic lead-time; (2) Supplier receives an early soft-order with a deterministic due date, however, soft-order revisions are allowed at regular intervals. We formulate optimal production scheduling models for the supplier under these two scenarios using dynamic programming. We also compare the two scenarios through extensive Monte Carlo simulations. Key managerial insights offered by this analysis pertain to the impact of sharing early soft-orders on the supplier as a function of soft-order accuracy, volatility, timing, production capacity, capacity uncertainty, and costs (overage, underage, holding). We also look into scenarios where buyers intentionally inflate soft-orders and study the consequences for both parties involved.

Keywords: Information sharing, soft-orders, atypical demand, production planning.

2.2 Introduction

In recent years, researchers and practitioners alike seem to view effective supply chain management and information sharing technology as inextricably linked. They are motivated by the possibilities of efficient supply chain planning and execution introduced by the information technology (IT) enabler. IT has enabled companies to engage in various information-sharing practices, such as exchanging sales data, demand forecasts, inventory levels, ordering policies, and capacity forecasts with different stages of the supply chain. While the reported benefits of information sharing vary considerably (Cachon and Fisher 2000, Lee et al 2000), these technologies have substantially lowered the time and cost to process orders, leading to impressive improvements in supply chain performance (Chen 2003, Sahin and Robinson 2002, Cachon and Fisher 1997, Clark and Hammond 1997, Kurt Salmon Associates 1993). More recently, we have even seen initiatives such as Collaborative Planning, Forecasting, and Replenishment (CPFR), launched to create more effective and collaborative relationships between buyers and sellers through shared information (VICS 2004a). Despite all this, information sharing still suffers from problems in practice and is not so prevalent outside the retail and grocery industries. The major exception is the routine exchange of manufacturing resources planning information in supply chains through electronic data interchange systems.

Demand patterns for product with seasonal demand and/or short product life-cycles (such as styled goods and trendy consumer electronics) are normally “atypical” and do not follow a clear discernible pattern for individual events or seasons due to such factors as product promotions and unforeseen marketplace events (Reinmuth and Geurts 1972). In particular, for all those cases where construction of a predictive time-series model for demand forecasting is difficult (Hausman, 1969), we term the demand situation atypical. Suppliers supporting such atypical demand patterns typically incur higher holding costs, lower capacity utilization, and lower order fill-rates, particularly under long lead-times and capacity uncertainty. While they are labeled as atypical situations, they hold opportunity for business; increased collaboration between buyer and seller in the form of sharing early demand and/or order forecasts and their revisions can reduce the likelihood of performance shortfalls. Further motivation comes from the knowledge that demand from promotional sales are higher compared to usual sales for many product segments (Blattberg and Neslin 1990) and out-of-stock problems are more severe during promotional events (VICS 2004b).

Under atypical demand situations, Terwiesch et al (2005) points out that information such as demand forecasts are continually updated as the buyer receives new market information that effects demand. Buyer can also share order forecasts, also knows as “soft-orders”, and their revisions in advance with the supplier. Soft orders are a reflection of buyer’s purchase intent and are not legally binding “firm” purchase orders. Supplier may use them to achieve better order fulfillment rate without high investment in capacity and inventory. However, there is a tradeoff: suppliers that act prematurely through production on any given soft-order might face significant future adjustment costs. If the supplier happens to be a contract manufacturer, apart from final order uncertainty it faces during production decision making, it also needs to consider uncertainty in “effective production capacity”. Effective capacity uncertainty can be attributed to inevitable preemptive and non-preemptive factors (such as machine breakdowns, preventive maintenance, and yield) as well as uncertainty associated with allocation of line/facility capacity to different buyers. Usually, safety inventory is used to protect firms against both sources of uncertainty. However, using inventory as a hedge against demand and capacity uncertainty can be an expensive proposition, especially when holding costs are high (Hu 2003). This option may not even be relevant for contract manufacturers that do not build the ‘same’ product twice.

While there is a large body of literature regarding the benefits of sharing demand information, there is very little literature pertaining to benefits associated with sharing soft-orders, in particular, under atypical demand settings. On the contrary, there is more literature that studies advanced firm orders (Karesmen et al 2004). Raghunathan (2001) argues that information sharing regarding retailer’s actions such as planned promotions, price reductions, and advertising are greatly beneficial to the supplier. Our research inquires whether sharing of promotional and demand information in the form of order forecasts are beneficial to suppliers under capacity uncertainty. While at first glance the answer might seem obvious, our results indicate that the accuracy of information being shared (earlier forecasts being less reliable than later forecasts), degree of capacity severity (i.e., shortage), and capacity uncertainty dictate the final benefits. We quantify the potential performance improvements for a supplier under different settings and constraints. In particular, we model the supplier facing capacity uncertainty under two information sharing scenarios: (1) supplier receives firm-orders for seasonal or promotional events with a finite and deterministic lead-time; (2)

supplier receives an early soft-order with a deterministic due date, however, soft-order revisions are allowed at regular intervals, with a final firm-order issued with a deterministic lead-time. We formulate optimal production-scheduling models for the supplier under these two scenarios using stochastic dynamic programming. Hausman (1969) has provided justification for using a dynamic program framework in a problem of this setting. This problem involves sequential decision-making (deciding on production release quantity at the beginning of each period), which has a property that later decision (release of next period) may be influenced not only by the previous decisions (previous release), but also by observable stochastic parameters (such as inventory positions based on actual production and (soft) order). We also compare the two scenarios through extensive Monte Carlo simulations. Key managerial insights offered by this analysis pertain to the impact of sharing early soft-orders on suppliers cost as a function of soft-order accuracy, volatility, timing, production capacity, capacity uncertainty, and costs (overage, underage, holding). We further quantify the benefit of this information sharing on the buyer through calculation of order fill-rates. We also look into scenarios where buyers intentionally inflate demand while issuing soft-order forecasts and study the consequences for both parties involved.

While it is tempting to consider these buyer supplier interactions in the form of a stackelburg game with buyer as a stackelburg leader, the factors under investigation (multiple soft-order revisions, capacity uncertainty, demand uncertainty, and holding costs) make the problem intractable (see also Metters

(1998)). Hence, we choose to take the buyer's soft-order signals as exogenous information. In addition, the insights offered by our analysis are very compelling.

Relevant existing literature is reviewed in section 2.3. Detailed formulations of the models are presented in section 2.4. The experimental framework for assessing the benefits is outlined in section 2.5. Section 2.5 also presents results and insights. Section 5 offers some concluding remarks.

2.3 Literature review

The following sections review related literature and are roughly grouped into the following categories: Information sharing under atypical demand and capacity uncertainty; Soft-order revision process; Production planning under soft-order revision; and Production planning under capacity uncertainty.

2.3.1 Information sharing under atypical demand and capacity uncertainty

Chen (2003) and Sahin and Robinson (2002) provide a good review of literature regarding the benefits of information sharing in supply chains. For literature on production-inventory policies and benefits when sharing advanced "firm-orders" in capacitated environments, see Karenmen et al (2004), Simchi-Levi and Zhao (2004), and Ozer and Wei (2004). There is essentially no literature that looks into atypical demand settings combined with capacity uncertainty (besides capacity severity).

2.3.2 Soft-order revision process

Given that the buyer is issuing advanced soft-orders that are revised at regular intervals, any optimal production scheduling model should account for the soft-order revision process. Based on the type of signal, the revision process could be modeled as a time-series model (if significant inter-temporal correlation exists, e.g. Johnson and Thomson 1975) or through a state-space model (e.g. Aviv 2003). However, as argued by Hausman (1969), not all patterns exhibit properties that allow use of a time-series model or a state-space model. This is particularly the case for “atypical” demand settings where order forecasts are based on new market signals (Reinmuth and Geurts 1972).

Literature in general assumes that consecutive soft-orders follow a particular distribution with parameters estimated from historical data. As new information becomes available, the parameters are revised. For example, Terwiesch et al (2005) surveyed a soft-order revision process in a semiconductor industry supply chain where the buyer of semiconductor equipment sends soft-orders to equipment manufacturer and revises it periodically as new information is obtained (before issuing a final firm-order). In terms of modeling the soft-order revision process, two approaches are common. The revision process is assumed to follow a probability distribution whose parameters can be updated using: 1) Bayesian forecast update techniques or 2) through conditional probability distribution (CPD) of future order forecasts. An example of Bayesian techniques is Reinmuth and Geurts (1972), who present a forecast conditioning model for a farm facing atypical demand. Eppen and Iyer (1997) analyze a quick response system in the fashion industry through Bayesian updates of the demand distribution. There is more literature that employs the CPD technique (e.g., Raman and Kim 2002, Gurnani and Tang 1999, Fisher and Raman 1996 and Hausman and Peterson 1972). Majority of this literature exploits CPD technique based forecast revision for sequential production/inventory management or ordering policy optimization. With the exception of Hausman and Peterson (1972) that model the ratios of successive soft-order forecasts (log-normally distributed), all the others use a bivariate density model (particularly Gaussian) for successive forecasts.

2.3.3 Production planning under soft-order revision

Among the earliest of papers that has incorporated a soft-order revision process with production scheduling for seasonal demand goods is Hausman and Peterson (1972). It is a multi-period and capacitated model with terminal demand where the successive order forecast update ratios follow a log-normal process. Kaminsky and Swaminathan (2001) consider a forecast generation process that depends on forecast bands refined over time for a terminal demand capacitated case. Raman and Kim (2002) combine model features from Hausman and Peterson (1972) and Fisher and Raman (1996) to demonstrate the impact of holding cost and reactive capacity on supplier's profitability with a real world example.

2.3.4 Production planning under capacity uncertainty

Suppliers generally face uncertainty in their effective capacity (Lin and Terdif 1999, Hwang and Singh 1998). Production planning under usual demand uncertainty coupled with capacity uncertain is a concern in management science literature (e.g. see Ciarallo et al 1994 and Weng and Yigal 1996). Karabuk and Wu (2003) have described capacity uncertainty as a critical factor in capacity planning in semiconductor industry. Lin and Terdif (1999) consider capacity as uncertain while formulating a component partitioning scheme for a printed-circuit-board assembly. Recently, Jemai et al (2006) developed a contracting scheme for a two-stage supply-chain in which a supplier facing uncertain capacity sells to a retailer facing a newsvendor problem. However, for atypical demand scenarios, literature primarily deals with the task of optimal production scheduling of seasonal goods, and we are aware of no work that incorporates capacity uncertainty along with inventory holding costs under soft-orders.

2.4 Model formulation

This section describes the following: The two scenarios considered for evaluating the benefits of information sharing and the sequence of events (section 2.4.1); Soft-order revision process (section 2.4.2); Modeling capacity uncertainty (section 2.4.3); Production scheduling model for both scenarios (section 2.4.4); Model for forecast inflation and information degradation (section 2.4.5); Performance measures used to compare the two scenarios (section 2.4.6). Table 2.1 lists all the key model variables and parameters.

Table 2.1: Summary of key model variables and parameters

J	Number of periods in the total time horizon
N	Number of forecast revisions; leads to N+1 stages
j	Period index, $j = 1,2,\ldots,J$
n	Stage index, $n = 1,2,\ldots,N+1$
Δl	Time (number of periods) between two order revisions
l	Time (number of periods) between final order and shipment
Y_n	Soft order received at the beginning of stage n
Y_j	Most recently received soft-order (or final order) in the beginning of period j (State Variable)
Y_F	Final order sent in the beginning of stage $N+1$ (State Variable)
C_j	Production capacity for period j
C_n	Production capacity for stage n

μ_j	Average per period capacity
σ_j	Standard deviation of per period capacity
μ_n	Average per stage capacity
σ_n	Standard deviation of per stage capacity
f_{Cj}	Probability density function of C_j
R_j	Production release quantity at the beginning of period j (Decision Variable)
P_j	Realized production quantity at the end of period j
I_j	Inventory position at the beginning of period j (State Variable)
h	Per unit inventory holding cost per period
c_0	Per unit overage cost incurred on the day of shipment
c_u	Per unit underage cost incurred on the day of shipment
$g_{shipment}$	Actual cost incurred (also called terminal cost) on the day of shipment
g_j	Optimal expected cumulative cost from period j to the day of shipment (Objective function)
f_{Y_{n+1},Y_n}	Joint probability density of two successive (soft) orders, Y_n and Y_{n+1}
$\boldsymbol{\mu}_{n+1,n}$	Mean vector of f_{Y_{n+1},Y_n}
$\Sigma_{n+1,n}$	Covariance matrix of f_{Y_{n+1},Y_n}
$\rho_{\Delta I}$	Correlation coefficient between two successive (soft) orders issues ΔI interval apart
σ_D	Standard deviation of demand uncertainty on the day of shipment
σ_n	Standard deviation of demand uncertainty at the beginning of stage n
m_m	Linear rate of inflation of average soft-order w.r.t. time
m_σ	Linear rate of inflation of standard deviation of soft-order w.r.t. time
m_ρ	Liner rate of degradation of correlation coefficient $\rho_{\Delta I}$ w.r.t. time
$\mathbb{N}$	Normal probability distribution
$E(X)$	Expected value of random variable X
Ind	Indicator function
$\delta(x)$	Dirac's delta function

2.4.1 Two scenarios: Information sharing vs. no sharing

A buyer (a retailer or a distributor) plans for a seasonal or promotional event. Based on market information, the buyer updates its demand forecast for the product. Given that forecasts made quite early in time are prone to more error, buyer has the option of waiting a while to decide on a firm-order quantity to the

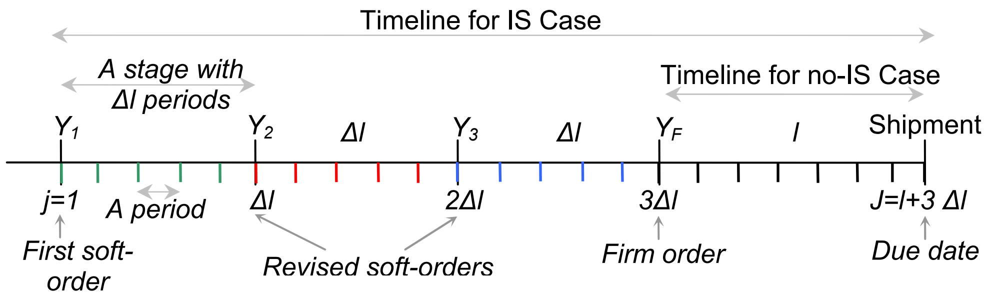


Figure 2.1: Schematic showing time-lines for the no information sharing (no-IS) case and the information sharing (IS) case with three soft-orders.

supplier. Alternatively, based on early assessment of demand, transmit soft-order(s) before placing a final firm-order. The motivation for issuing soft-orders is to improve the odds of receiving a full order by providing the supplier a longer lead-time for building the order. In case-1, the "no information sharing" (no-IS) case, the buyer does not provide the supplier with order forecasts; rather only issues a firm-order quantity with a finite lead-time. In case-2 however, the "information sharing" (IS) case, the supplier is provided with an early soft-order with a deterministic due date. The initial soft-order is then revised several times before giving the supplier a final firm-order with the same finite lead-time. Without loss of generality, we assume transportation lead-time to be zero.

Figure 2.1 offers a schematic that summarizes the time-lines for both the scenarios. It is assumed that the final firm-order, Y_F, is provided with a lead-time of l. In the no-IS case, soft-orders are updated N times (Y_1, Y_2, Y_3, …, Y_{N+1}) and transmitted to the supplier at finite time intervals, Δl, before the final order ($Y_F = Y_{N+1}$) is placed (N=3 in figure 2.1). The total timeline is J periods, where $J = N\Delta + l$. A stage is defined here as the duration between successive forecasts and the last stage entails the lead-time between issuing the final firm-order and the due date (figure 2.1 involves $N+1=4$ stages).

Thus, the sequence of events for the No-IS case is:

Step-1: Buyer sends a final order Y_F with a due date. Due date is l periods away.

Step-2: Supplier sends a production release R_j to its production plant on period j=1.

Step-3: Realized production is $P_j \leq R_j$ and inventory position is $I_j = I_{j-1}+P_j$ at end of period $j=1$.

Step-4: Supplier repeats *step-2* and *step-3* for all the available periods (j=2 to l) until either: (a) inventory position reached Y_F or (b) time for shipment reaches.

Step-5: At the end of period l, supplier ships an amount $I_{l+1} \leq Y_F$ (there can be no overage in the no-IS case).

The sequence of events for the IS case:

Step-1: Buyer sends a soft-order Y_1 with a due date. Due date is $l+N\Delta l$ periods away.

Step-2: Supplier sends a production release R_j to its production plant on period $j=1$.

Step-3: Realized production is $P_j \leq R_j$ at end of period $j=1$. Inventory position becomes $I_j = I_{j-1}+P_j$.

Step-4: Supplier receives soft-order updates (Y_{n+1}) during periods $j = n\Delta l+1$, for all n=1,2,..,N-1. Based on updated soft-orders and inventory position, supplier repeats *step-2* and *step-3* until either: (a) inventory reaches the final firm-order quantity (Y_F) or (b) due date is reached.

Step-5: At the end of period $l+N\Delta l$, supplier ships an amount less than or equal to Y_F.

2.4.2 Soft-order revision model

Demand forecasting for an atypical setting is a complex interaction of a number of largely unpredictable events or activities such as, overall economic condition, competitor's sales push, emergence of new substitute product etc. It is expected that as the buyer comes closer to the planned sale event, more reliable demand forecasts emerge. This results in soft-orders more reliable to the supplier. We assume that historical data is available to the supplier to construct a model of soft-order revision process. In order to couple the soft-order revision model to a decision model, we must also assume that the forecasting method used by the buyer has not changed significantly and that the underlying stochastic process relating to forecast information sources will not change significantly. This implies that the forecast data generation model is not going to significantly change in the next planning period and hence the soft-order revision model. Having stated that, our soft-order data generation model is assumed to be known and we consider it exogenous for our analysis of benefits of information sharing. As for the structure of the soft-order revision model, we model each pair of consecutive soft-orders as a joint distribution; mathematically, we have f_{Y_{n+1},Y_n}. Given f_{Y_{n+1},Y_n}, the decision maker can predict the next possible soft-order (i.e. Y_{n+1}) given the current stage soft-order through $f_{Y_{n+1}|Y_n}$. A quasi-Markovian property is assumed between successive forecasts, $f_{Y_{n+1}|Y_n,\ldots,Y_1} = f_{Y_{n+1}|Y_n}$. Hausman (1969) justifies this assumption and provides empirical evidence supporting this property. Hausman (1969) also states that a quasi-Markovian property is important because it allows us to formulate a sequential decision problem using a dynamic program without having to handle a large number of state variables. This soft-order revision model is flexible enough to represent many forecast-generation models discussed in literature. For example, the log-normal order forecast revision process model proposed by Hausman and Robinson (1972), where the ratio of two consecutive order signals follows a lognormal distribution, is a special case of this model. So is the demand evolution model proposed by Raman and Kim (2002) that models successive demands as Gaussian.

An important characteristic we seek in our soft-order revision process model is its applicability for achieving a fair comparison of the two information-sharing scenarios. It is therefore necessary to ensure that the final firm-orders from the buyer to the supplier follow an identical pattern irrespective of sharing early soft-orders. The process is illustrated in figure 2.2, including the estimation of $f_{Y_{n+1}|Y_n=y_n}$. In all numerical experiments, we generate the complete soft-order sequence of $Y_1, Y_2, \ldots, Y_F$ and use only Y_F for the no information sharing case.

2.4.3 Modeling capacity uncertainty

We assume supplier's production capacity as constrained and random. Without loss of generality, per period capacity, C_j, is assumed to be *i.i.d.* for all *j* with density f_{C_j}. Based on f_{C_j}, the production yield density (P_j) for a given release R_j is as follows:

$$f_{P_j=p_j} = f_{C_j}\,\mathrm{Ind}(0 \le p_j < R_j) + \left(\int_{R_j}^{\infty} f_{C_j}\, dC_j\right)\delta_{Rj}(p_j) \qquad (1)$$

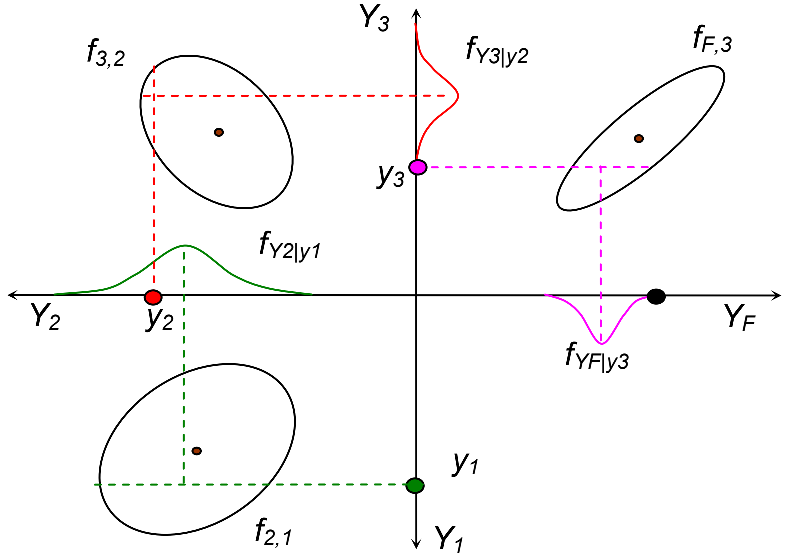


Figure 2.2: Illustration of soft-order revision process with four stages (N=3). Ellipses denote joint density contours of successive soft-orders, while the bell curves denote conditional density of next soft-order given a soft-order. Capital Y denotes soft-order random variable where as y denotes a realization during a particular season.

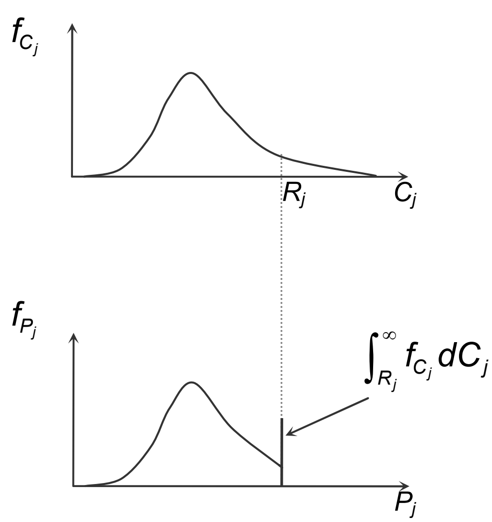


Figure 2.3: Relationship between capacity uncertainty and production uncertainty given a particular release (R_j).

where, Ind is the indicator function and δ is the Dirac's delta function with the following properties:

$$\begin{aligned}\mathrm{Ind}(0 \le p_j < R_j) &= 1 \quad \textit{if} \quad 0 \le p_j < R_j \\ &= 0 \quad \textit{elsewhere}\end{aligned} \tag{2}$$

$$\delta_{Rj}(p_j) = \begin{cases} \infty, & p_j = Rj \\ 0, & p_j \neq Rj \end{cases} \tag{3}$$

These mechanics are illustrated in figure 2.3. It shows that the probability of producing R_j is the sum of all the probabilities of realizing a capacity more than or equal to R_j. On the other hand, the probability of producing less than R_j is equal to the probability of realizing that much capacity to produce. Right hand side of the equation 1 is integral to the cost formulation presented in the next sections.

2.4.4 Production-scheduling model for the no-IS case

Supplier makes one final shipment and a unit underage cost of c_u is incurred on the day of shipment. In addition, a unit holding cost of h per period is incurred based on the production pattern. Over production is not a possibility in the no-IS case for the supplier initiates production after receiving the final order. With the presence of capacity uncertainty, we can optimally schedule production (i.e., determine releases) for the *I* periods using backward dynamic programming. Let, I_j denote inventory position at the beginning of the j^{th} period and P_j is the actual production of the j^{th} period. The (underage) cost incurred at the end of shipment (end of period *J*) holds the following relationship:

$$g_{shipment}(I_J + P_J) = c_u[Y_F - (I_J + P_J)]^+ \tag{4}$$

where P_J denotes the quantity produced during period *J*.

At the beginning of period *J*, the expected cumulative cost from the beginning of period *J* to the end of shipment is $\int_{C_J=0}^{R_J} g_{shipment}(I_J + C_J) f_{C_j} dC_J + g_{shipment}(I_J + R_J)\int_{C_J=R_J}^{\infty} f_{C_j} dC_J$, where R_J denotes the "production release' quantity for period *J* and actual production yield (P_J) less than or equal to R_J. There is obviously no holding cost term given that the order is being shipped at the end of the period. The task is to determine the optimal production release quantity R_J that minimizes this cost:

$$g_J(I_J) = \underset{R_J}{\text{Min}}\left[\int_{C_J=0}^{R_J} g_{shipment}(I_J + C_J) f_{C_j} dC_J + g_{shipment}(I_J + R_J)\int_{C_J=R_J}^{\infty} f_{C_j} dC_J\right] \quad (5)$$

The general recurrence relation for any period j (including the last period) is:

$$g_j(I_j) = \underset{R_j}{\text{Min}}\begin{bmatrix} \int_{C_j=0}^{R_j}\left(g_{j+1}\left(I_j + C_j\right) + HC_j(C_j)\right) f_{C_j} dC_j \\ +\left(g_{j+1}(I_j + R_j) + HC_j(R_j)\right)\int_{C_j=R_j}^{\infty} f_{C_j} dC_j \end{bmatrix}, \quad j = 1,..,J \quad (6)$$

where, the holding cost function HC_j is defined as cost incurred for producing a quantity *x* in the period *j* and carrying to the day of shipment (i.e. period *J*). Note that this way of defining holding cost doesn't incur a holding cost for the period in which the product is produced:

$$HC_j(x) = hx(J - j) \quad (7)$$

2.4.5 Production model for the IS case

As in the no-IS case, supplier incurs an underage cost of c_u or unit overage cost of c_0 based on mismatch between realized production and final order. A unit holding cost of *h* per period is incurred based on production pattern. Let, I_j and Y_j denote inventory position and the most recently received soft-order forecast or final order quantity, respectively, at the beginning of period *j*. While the production planning is done on a period by period basis, the revised forecasts are available only on a stage by stage basis. Therefore, $Y_{j+1} = Y_j$ for those successive periods with no new forecast update. Overall, two sets of recursive equations are necessary for these two cases in deriving the optimal release orders.

Similar to (4), the sum of overage and underage costs incurred at the end of shipment is:

$$g_{shipment}(I_J + P_J, Y_F) = c_o\left[(I_J + P_J) - Y_F\right]^+ + c_u\left[Y_F - (I_J + P_J)\right]^+ . \qquad (8)$$

Once again, using backward dynamic programming, one can derive the following recurrence relations for determining the optimal production release quantities for all periods. For all $j = n\Delta I - 1$, $n = 1, 2..., N$, the recurrence relations involve soft-order revision and can be expressed as follows:

$$g_j(I_j, Y_j) = \underset{R_j}{\mathrm{Min}}\left[\int_{C_j=0}^{R_j} G_j(I_j + C_j, Y_j) f_{C_j} dC_j + G_j(I_j + R_j, Y_j)\int_{C_j=R_j}^{\infty} f_{C_j} dC_j\right] \qquad (9)$$

where

$$G_j(I_j + P_j, Y_j) = hP_j(J - j) + \int_{Y_{j+1}=0}^{\infty} g_{j+1}(I_j + P_j, Y_{j+1}) f_{Y_{j+1}|Y_j} \mathrm{d}Y_{j+1} \qquad (10)$$

For all $j \neq n\Delta I - 1$, $n = 1, 2..., N$, the recurrence relations involve no soft-order revision and can be expressed as follows:

$$g_j(I_j, Y_j) = \underset{R_j}{\mathrm{Min}}\left[\begin{array}{l}\int_{C_j=0}^{R_j}\left(g_j(I_j + C_j, Y_j) + hC_j(J - j)\right) f_{C_j} dC_j \\ +\left(g_j(I_j + R_j, Y_j) + hR_j(J - j)\right)\int_{C_j=R_j}^{\infty} f_{C_j} dC_j\end{array}\right] \qquad (11)$$

2.4.6 Modeling forecast inflation and information degradation

In the context of sharing early soft-order forecasts, poor forecasting on the part of the buyer induces forecast volatility to the supplier (Terwiesch et al 2005). Forecast volatility also arises as soft-orders based on preliminary information are transmitted to supplier at a point when the buyer still faces substantial uncertainty about the market demand (market volatility). While forecast volatility could be an unavoidable condition, forecast inflation or manipulation can be considered an opportunistic behavior: buyer places inflated soft-orders hoping to obtain a higher order fill-rate. We investigate the impact of these two elements, degree of forecast volatility and degree of forecast inflation, on the supplier as well as the buyer, with two objectives. First, we study the cost and order fill-rate consequences to supplier and buyer, respectively. Secondly, we investigate the extent to which the above dynamic programming model can compensate the behavior of soft-order inflation, in particular, under the condition that the supplier possesses historical knowledge that buyer inflates soft-order forecasts and is aware of the degree of inflation in an expected sense.

It is a commonly accepted notion that longer forecast horizons lead to forecasts that are more uncertain. As illustrated in figure 2.4, a linear model is employed here to model forecast volatility and degradation of certainty with time. Amplitude of standard deviation of the soft-order forecast distribution (Y_j) is used as a measure of forecast uncertainty and is modeled as $\sigma_n = \sigma_D + m_\sigma\left((N-n+1)\Delta l + l\right)$, where σ_n denotes the standard deviation of the soft-order forecast distribution at the beginning of stage *n*, σ_D the standard deviation of demand uncertainty on the day of shipment, and m_σ the slope of the degradation model. In estimating σ_n, it is necessary to use the standard deviation of demand uncertainty on the day of shipment, σ_D, as a base for facilitating a fair comparison between the two information sharing scenarios (for the duration of the last stage, *l*, is common to both cases). Given that our formulation models the joint density of successive soft-orders, it is also necessary to address the effect of correlation between two consecutive soft-orders. We assume that this correla-

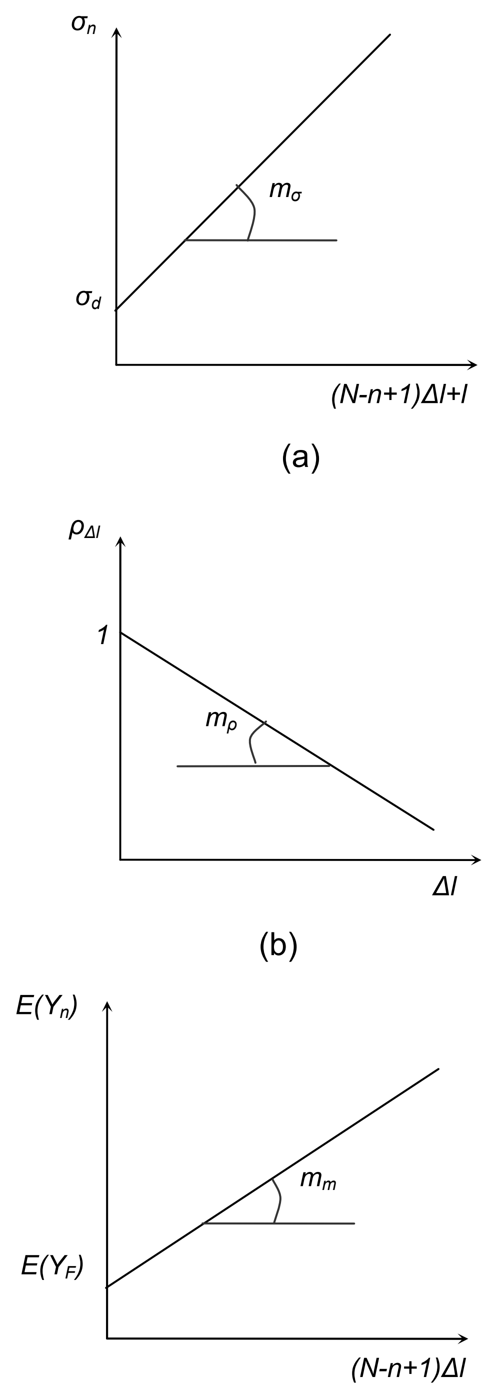


Figure 2.4: Forecast inflation (c) and information degradation models (a and b).

-tion strictly depends on the stage duration, i.e. Δl , and is also modeled linearly as $\rho_{\Delta l} = 1 - m_{\rho}(\Delta l)$, where $\rho_{\Delta l}$ is the correlation coefficient. This model implies the following: Correlation coefficient is one if two successive soft-orders are issued at the same instant and correlation degrades linearly with time at a rate of m_{ρ}.

As for intentional order inflation, we once again employed a linear model: $E(Y_n) = E(Y_F) + m_m\left((N - n + 1) \cdot \Delta l\right)$, where $E(Y_n)$ denotes the mean of the soft-order distribution at the beginning of stage n, $E(Y_F)$ the mean of final firm-order distribution, and m_m the slope of soft-order mean inflation. These relations are also illustrated in figure 2.4.

2.4.7 Performance measures for comparison of information sharing scenarios

The different information sharing scenarios will be compared based on supplier's expected costs (holding, overage, and underage costs) as well expected order fill-rates to the buyer (fraction of the final firm-order). It is assumed that the supplier makes one final shipment on the due date asked by the buyer. Holding cost is incurred for keeping finished goods and overage and underage costs are incurred on the day of shipment. Overage costs are possible only when forecasts are updated; therefore, for no-IS case, this cost component is not applicable. Costs are denoted as follows: c_o for unit cost of overage, c_u for unit cost of underage, and h for holding cost per unit per time-period. The expressions for the cost performance measures are as follows. For the No-IS case:

$$E(TC) = E\left(c_u[Y_F - (I_J + P_J)]^+ + HC_j(P_j)\right) \tag{12}$$

For the IS case, the cost expression is:

$$E(TC) = E\Big(c_o\left[(I_J + P_J) - Y_F \right]^+ + c_u\left[Y_F - (I_J + P_J) \right]^+ + HC_j(P_j) \Big) \tag{13}$$

where, $HC_j(P_j)$ is defined in equation (7).

For both the cases, the expected order fill-rate is:

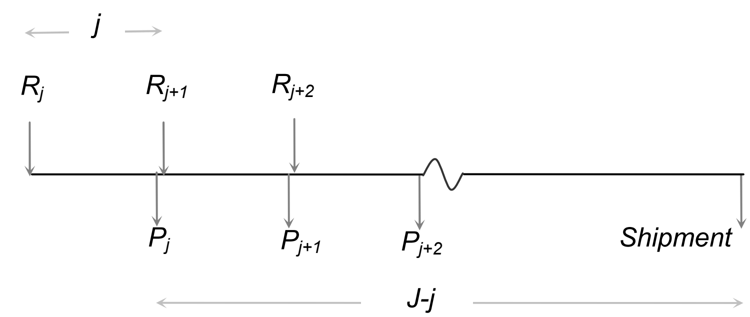
$$E(FR) = E\left(\begin{array}{ll} \dfrac{\sum_j P_j}{Y_F} & \text{if} \quad Y_F > \sum_j P_j,\ Y_F \neq 0 \\ 1 & \text{if} \quad Y_F \leq \sum_j P_j \end{array} \right) \tag{14}$$

In expressions (12), (13) and (14) the expectation is taken over all possible variations on soft-orders and production yield coupled with the decision being taken at each period of the production process. In the numerical evaluation section of this research, the expected values are computed through Monte Carlo simulations of optimal release policies.

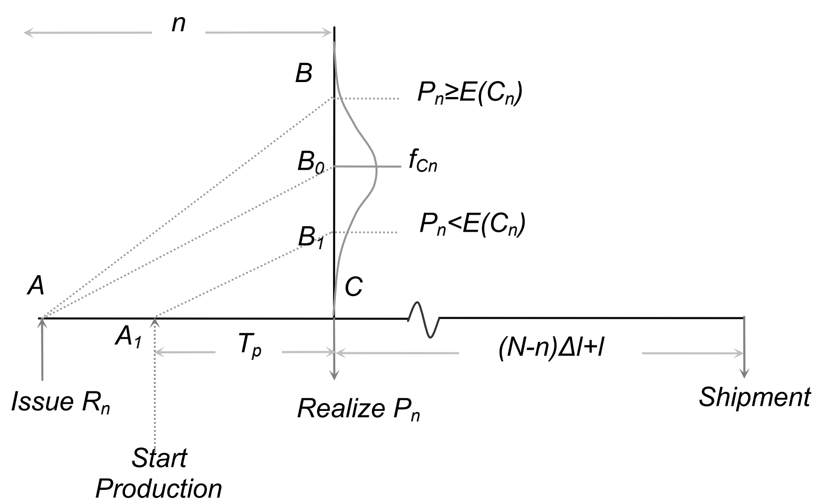
2.5 Numerical experiments

In this section, we numerically analyze how modification of different cost parameters, lead-time, forecast uncertainty/inflation, and capacity shortage/uncertainty affect the two players (i.e., the supplier as well as the buyer). The supplier's order fulfillment cost and the order fill-rate it delivers to the buyer depends on all these parameters.

Numerical evaluation involves the following steps. First, optimal production scheduling models for all the selected combinations of parameters are executed and the resulting optimal policies are stored. Then, the Monte Carlo simulation is performed that primarily involves two tasks: i) Generation of soft-order forecasts and final firm-order quantities based on the selected soft-order revision process. ii) Determination of optimal production release orders based on stored optimal policies, and in turn, computation of supplier's expected cost and order fill-rate.



(a)



(b)

Figure 2.5: (a) Period level release policy. (b) Aggregate stage level release policy. While holding cost is ignored for production during the period of production for the period level policy, this is not the case in the stage level model.

Given the nature of the dynamic programming formulations, modeling capacity uncertainty and production at an aggregate level for stages rather than individual periods offers significant advantage in terms of computing time (resulting in three to four fold reduction in some cases). While this approximation leads to a small bias in determining holding costs, for ease of simulation, we have adopted the aggregate optimization and simulation strategy.

2.5.1 Aggregate production plan for stages

Firstly, we derive the capacity per stage (C_n) from the capacity per period model (C_j) (assuming capacity per period is independent). Then, we compute an optimal aggregate release order R_n for every stage of production instead of every period of production. However, without the detailed production schedule for every period, it becomes necessary to approximate the computation of holding cost. The assumption that holding cost is not incurred during the "stage" of production but incurred during subsequent stages will introduce significant bias in assessing the difference between expected total cost of IS case and No-IS case, since No-IS case contains a single stage. Hence, a reasonable holding cost approximation for a stage is derived as follows. Given the realized production for any stage as P_n , we assume that it is realized through uniform production over duration T_p. Here, we define T_P as the time taken to produce an amount P_n in a stage of length Δl:

$$\begin{aligned} T_P &= \frac{P_n}{E(C_n)}\Delta l \quad \text{if} \quad P_n < E(C_n) \\ &= \Delta l \qquad\qquad \text{if} \quad P_n \geq E(C_n) \end{aligned} \tag{15}$$

These relations are illustrated in figure 2.5 (b) and can be best visualized by comparing triangles A_1B_1C, AB_0C, and ABC. The resulting holding cost expression is:

$$HC_n(P_n) = \frac{h}{2} T_P P_n + hP_n\left((N-n)\Delta l + l\right) \tag{16}$$

In this expression, the first term is the holding cost for that stage and the second term is the holding cost for remaining periods (with due date $J-(N-n)\Delta l$ periods into the future). This modified formulation is implemented for deriving the optimal production "release" patterns. For the No-IS case, we no more need a dynamic program. Optimal policy becomes a rule that can be stated as follows: release quantity R_l is equal to the order quantity Y_F. Assuming R_l units are produced during the lead-time l, supplier's expected cost under this policy becomes:

$$E(TC) = E(c_u[Y_F - P_N]^+ + HC_N(P_N)) \tag{17}$$

In the IS case, as periods are aggregated into stages, unlike in period by period scheduling, we no longer need to derive two sets of recursive expression for in

$$g_n(I_n, Y_n) = \underset{R_n}{\mathrm{Min}}\left[\int_{C_n=0}^{R_n} G_n(I_n + C_n, Y_n) f_{C_n} dC_n + G_n(I_n + R_n, Y_n)\int_{C_n=R_n}^{\infty} f_{C_n} dC_n\right] \tag{18}$$

where,

$$G_n(I_n + P_n, Y_n) = HC_n(P_n) + \int_{Y_{n+1}=0}^{\infty} g_{n+1}(I_n + P_n, Y_{n+1}) f_{Y_{n+1}|Y_n} \mathrm{d}Y_{n+1}\,. \tag{19}$$

Modifications in the expressions for performance measures are straightforward; we simply replace number of periods J with number of stages N and period index j with stage index n in equations (13)-(15).

2.5.2 Framework for numerical analysis

All numerical evaluations presented here are based on 1.5 million simulation runs. Table 2.2 provides the common framework for all the simulations while the subsections below discuss the framework for studying the different effects. During optimization and simulation of various scenarios, we approximate the continuous probability distributions functions with probability mass functions defined over a set of discrete values. Capacity is always bounded between

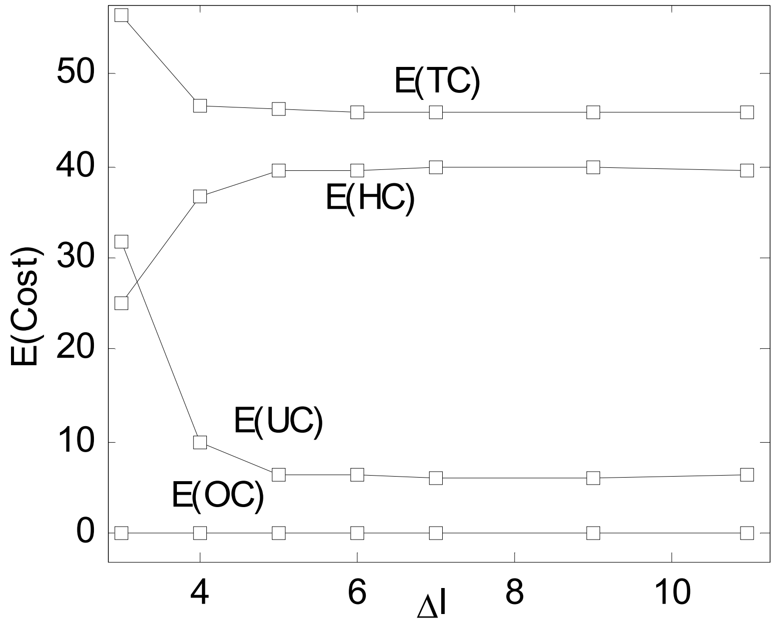
$[0, \mu_n + 4.5\sigma_n]$, where μ_n is the expected capacity per stage and σ_n the standard deviation of stage capacity.

Table 2.2: Common framework for all numerical experiments

		Information Sharing Case (IS)	No Information Sharing Case (No-IS: Δl=0)
Number of revisions (N)		3	0
Number of stages (N+1)		4	1
Final order lead-time		l	l
Total number of periods (J)		$N\Delta l+l$	l
Soft-order revision model		$f(Y_1, Y_2) \sim \mathbb{N}(\boldsymbol{\mu}_{12}, \Sigma_{12})$ $f(Y_2, Y_3) \sim \mathbb{N}(\boldsymbol{\mu}_{23}, \Sigma_{23})$ $f(Y_3, Y_F) \sim \mathbb{N}(\boldsymbol{\mu}_{3F}, \Sigma_{3F})$	N.A.
Production capacity	Per period	$\mathbb{N}(\mu_j, \sigma_j^2)$	$\mathbb{N}(\mu_j, \sigma_j^2)$
	Per stage	$\mathbb{N}(\mu_n, \sigma_n^2) = \sum_{periods} \mathbb{N}(\mu_j, \sigma_j^2)$	$\mathbb{N}(\mu_N, \sigma_N^2) = \sum_{l} \mathbb{N}(\mu_j, \sigma_j^2)$
	Bounds	$[0,\ \mu_n + 4.5\sigma_n]$	$[0,\ \mu_N + 4.5\sigma_N]$
Final order		Y_F	Y_F

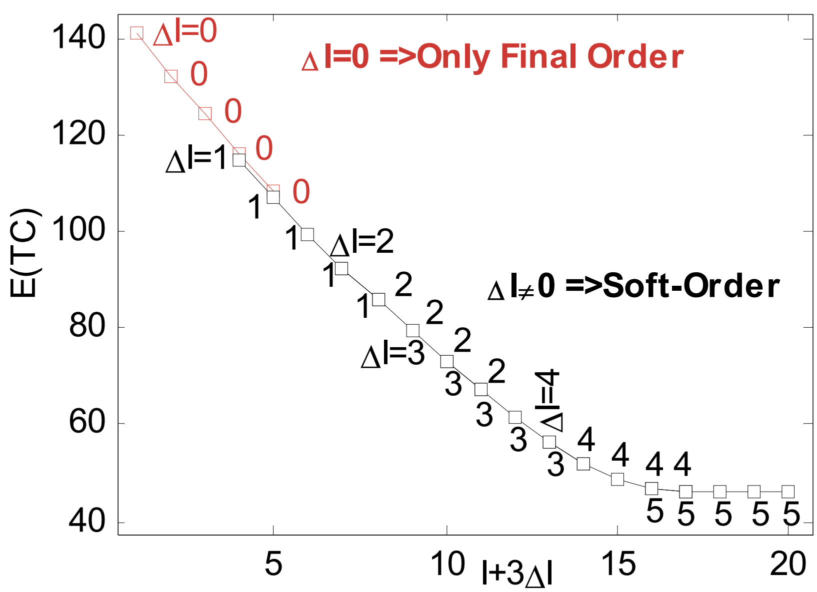
We caution here that while care has been exercised in conducting these numerical experiments to best extract and illustrate the dynamics at play, all the while coping with a large number of parameters, the patterns/effects reported can change somewhat as a function of the parameter levels. However, the essential dynamics/insights from these results are expected to hold strongly in most settings.

The rest of this section is organized as follows: Section 2.5.3 outlines the effect of firm-order lead-times as well as soft-order revision lead-times on supplier's total order fulfillment cost as well as order fill-rate to buyer. Sections 2.5.4 and 2.5.5 jointly study the impact of soft-order quality degradation with lead-times.



Parameters: $E(Y_F)$=100, σ_d=7, l = 4, μ_C=6, σ_C=2, c_o=1, c_u=1.5, h=0.05, m_m=0, m_σ=0.3, m_ρ=0.045.

Figure 2.6: Effect of time between order forecast revisions on supplier's cost.



Parameters: $E(Y_F)$=100, σ_d=7, l=[1,2,3,4,5], μ_C=6, σ_C =2, c_o=1, c_u=1.5, h=0.05, m_m=0, m_σ=0.3, m_ρ=0.045.

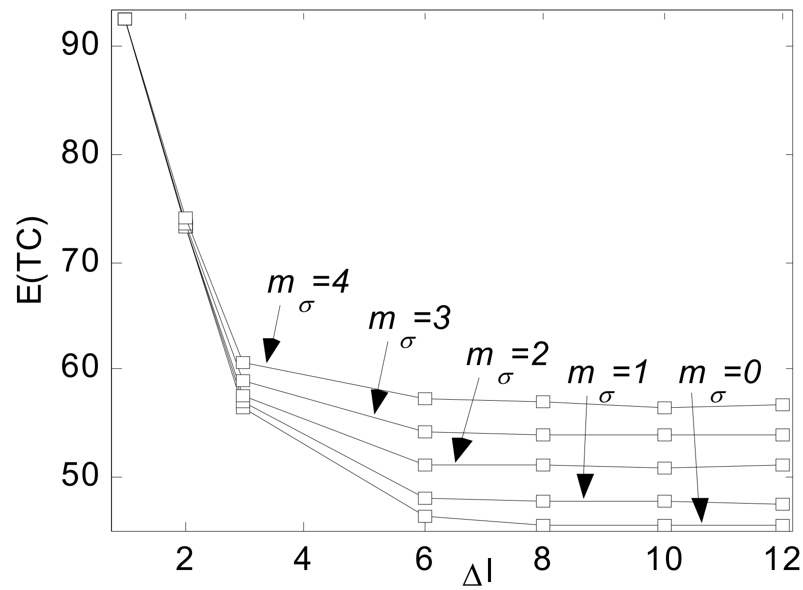
Figure 2.7: Effect of total order lead-time on supplier's cost.

While section 2.5.4 studies the impact of degradation of standard deviation of soft-orders, section 2.5.5 studies the impact of degradation in correlation between soft-orders and final firm-order. Section 2.5.6 studies the impact of "intentional" efforts by the buyer to deceive the supplier through systematic soft-order inflation. Lastly, section 2.5.7 studies the impact of capacity uncertainty.

2.5.3 Effect of lead-times (l and Δl)

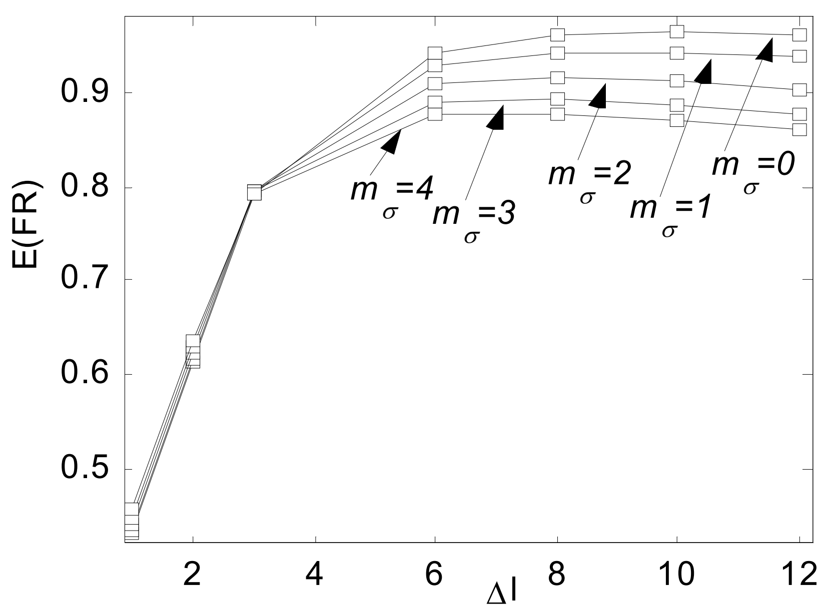
While longer order lead-times are preferred by suppliers for the ability to reduce underage costs without having to commit large amounts of capacity to individual buyers and/or resort to overtime, they expose increased risk to buyers, attributable to placing orders based on early demand forecasts. While sharing soft-order forecasts can partially address this dilemma, relying too heavily on very early soft-order forecasts (large number of revisions (N) and/or large durations between revisions (Δl)) also increases suppliers risk (attributable to potential for over production). This section investigates these tradeoffs through a variety of experiments. For example, while increasing Δl effectively increases capacity of a stage, it also degrades the correlation between two adjacent soft-orders, and hence, increasing the uncertainty associated with final firm-order. These affects captured through numerical evaluations are illustrated in figures 2.6 and 2.7.

Figure 2.6 illustrates the effect of Δl on expected total order fulfillment cost to the supplier. It can be seen that increase in Δl decreases the total cost initially, attributable to significant reduction in underage costs from extra capacity. However, beyond a certain point, the marginal benefit is zero, and the cost can actually increase due to increased forecast volatility. As expected, holding cost



Parameters: $E(Y_F)$=100, σ_d=7, l=4, μ_j=6, σ_j=2, c_o=1, c_u=1.5, h=0.05, m_m=0, m_ρ=0.05.

Figure 2.8: Effect of (soft) order variability on supplier's cost.

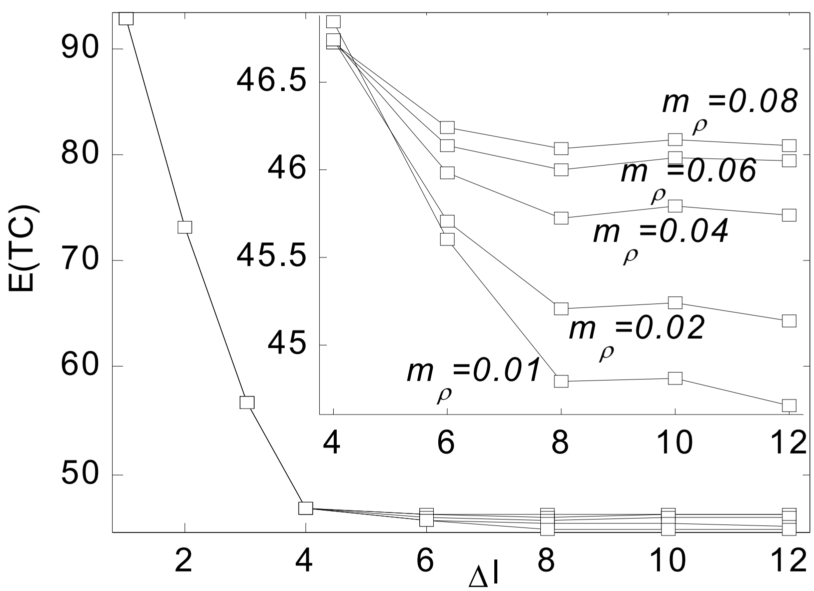


Parameters: $E(Y_F)$=100, σ_d=7, l=4, μ_j=6, σ_j=2, c_o=1, c_u=1.5, h=0.05, m_m=0, m_ρ=0.05.

Figure 2.9: Effect of (soft) order variability on order fill-rate.

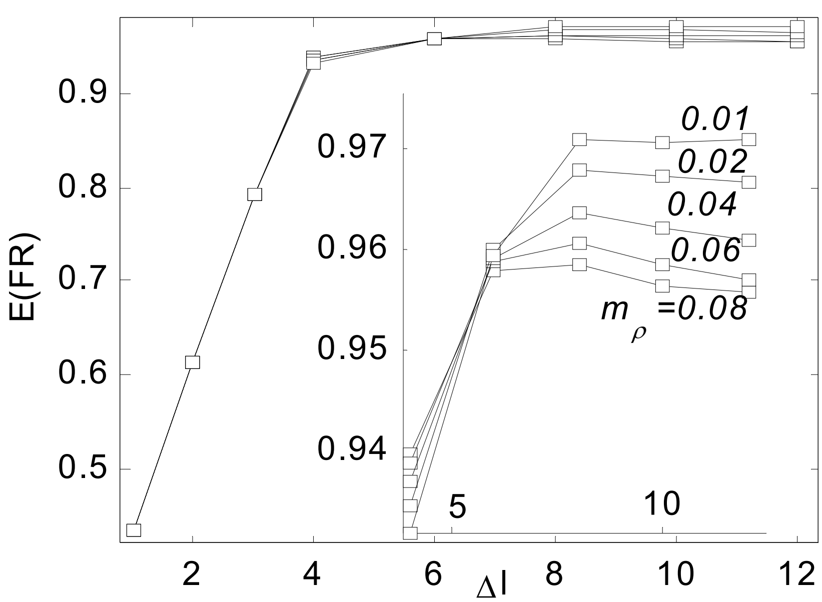
increases with Δl while underage cost decreases. Given the underage cost trend, it can be easily inferred that the order fill-rate would increase with Δl, however, with diminishing returns. The zero overage cost for experiments reported in figure 2.6 can be attributed to the fact that, on average, final demand is $E(Y_F)$=100 and only 24% of that demand (i.e., $E(C)/\ E(Y_F)$) can be produced after receiving the final order. Therefore, to incur overage, the volatility of the soft-orders has to be so huge that the supplier produces more than 100% of the order before receiving the final order. Such behavior can be introduced by increasing the values of m_σ and m_ρ.

Figure 2.7 plots the expected order fulfillment cost to the supplier as a function of total order lead-time ($l+\Delta l$). Unlike results from figure 2.6, here we also study the impact of final order lead-time (l). It shows that increasing the total lead-time ($l+\Delta l$) decreases supplier's cost. Also, receiving soft-orders (i.e. cases when $\Delta l \neq 0$) are always beneficial. However, the marginal benefit of increasing total lead-time beyond a certain point is zero. It could even be negative, as we will see in subsequent sections. Another observation from figure 2.7 is that expected cost for certain combinations of l and Δl are found to be same (e.g., consider the pair (l=4, Δl=1) and (l=1, Δl=2)). This implies that providing a final order with a sorter lead-time could be just as effective as issuing soft-orders earlier. Thus, these experiments are able to reveal the dynamics in play. The plots clearly demonstrate the benefit of sharing early soft-orders, at least, at the specified parameter levels. Obviously, significantly increasing the final order lead-time will diminish the value of soft-orders. However, as explained earlier, this is not necessarily acceptable to buyers that have to place orders based on very early



Parameters: $E(Y_F)$=100, σ_d=7, l = 4, μ_j=6, σ_j=2, c_o=1, c_u=1.5, h=0.05, m_m=0, m_σ=0.3.

Figure 2.10: Effect of correlation between successive (soft) orders on supplier's cost



Parameters: $E(Y_F)$=100, σ_d=7, l=4, μ_j=6, σ_j=2, c_o=1, c_u=1.5, h=0.05, m_m=0, m_σ=0.3.

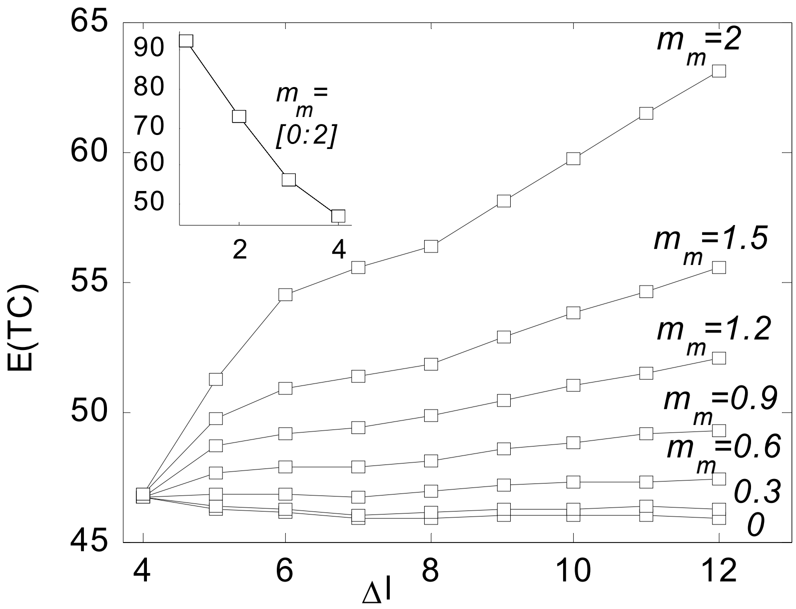
Figure 2.11: Effect of correlation between successive (soft) orders on supplier's cost

demand forecasts.

2.5.4 Effect of order variability (m_σ)

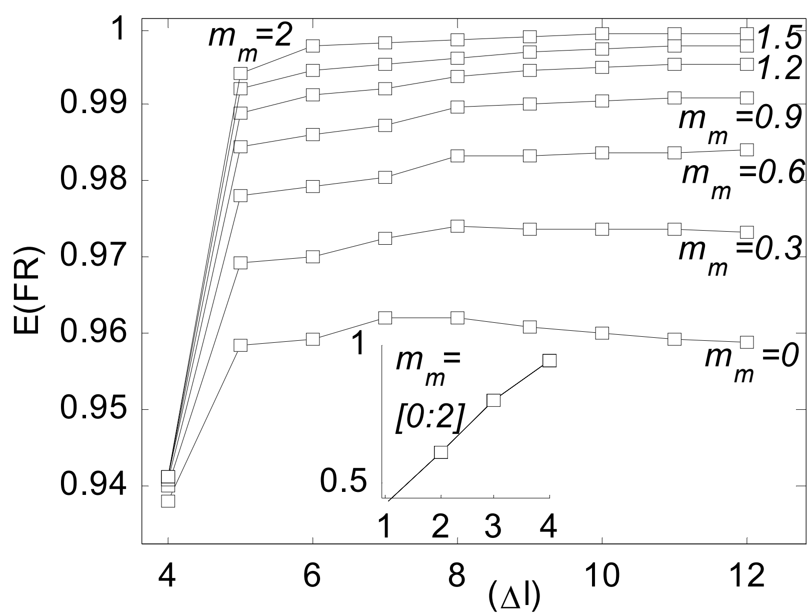
Our experiments investigate the impact of forecast uncertainty on supplier's order fulfillment cost as well as buyer's order fill-rates by varying the m_σ (increasing m_σ linearly increases the standard deviation or uncertainty of order forecasts as a function of lead-times). Overall, as expected, both performance measures de grade with increasing m_σ for a given Δl. Figures 2.8 and 2.9 illustrate cost and order fill-rate effects, respectively.

It is already evident from section 2.5.3 that short soft-order revision lead-times (given a fixed number of revisions) does increase supplier's order fulfillment cost while reducing order fill-rates to the buyer. This explains the overall trends in figures 2.8 and 2.9. Figure 2.9 also illustrates that the cost is indifferent to m_σ at low levels of Δl (e.g., Δl ≤2). The reason being that cost is so severely dominated by the low capacity constraint, that the effect of m_σ becomes secondary. Further comparison of figures 2.8 and 2.9 reveals that while order fulfillment costs are insensitive to low levels of Δl(≤2), order fill-rates are insensitive even at slightly higher levels of Δl(≤3). This implies that while total cost is dominated by the capacity constraint, the order fill-rate is favored by higher variability level if capacity is highly constrained. Another important observation from figure 2.9 is the downward trend in the order fill-rate as Δl increases beyond a certain limit. This can be attributed to the fact that the corruptive influence of order volatility begins to outweigh the benefits of increased effective capacity from a larger Δl.



Parameters: $E(Y_F)$=100, σ_d=7, l = 4, μ_j=6, σ_j=2, c_o=1, c_u=1.5, h=0.05, m_σ=0.3, m_ρ=0.05.

Figure 2.12: Effect of systematic soft-order inflation on supplier's cost



Parameters: $E(Y_F)$=100, σ_d=7, l=4, μ_j=6, σ_j=2, c_o=1, c_u=1.5, h=0.05, m_σ=0.3, m_ρ=0.05.

Figure 2.13: Effect of systematic soft-order inflation on order fill-rate

2.5.5 Effect of correlation between successive soft-order forecasts (m_ρ)

As noted earlier, correlation between successive soft-order forecasts strongly affects the predictability of final firm-order based on earlier soft-orders. The affects of degradation in this correlation are illustrated in figures 2.10 and 2.11. As expected, stronger correlations (lower m_ρ values) are favorable for both the supplier and the retailer. It is clear that both the cost and fill-rate graphs are fanning out at higher levels of Δl, meaning that the interaction between Δl and m_ρ is significant at higher soft-order revision lead-times. These behaviors can be explained in a manner similar to that of figures 2.8 and 2.9. A small Δl implies a higher correlation but with a lower capacity. Therefore, the cost (order fill-rate) is high (low). From the production planning point of view, low correlation is never good whether capacity is constrained or not (figure 2.10). However, the order fill-rate seems to improve with lower correlation in the region between $4 \leq \Delta l \leq 6$.

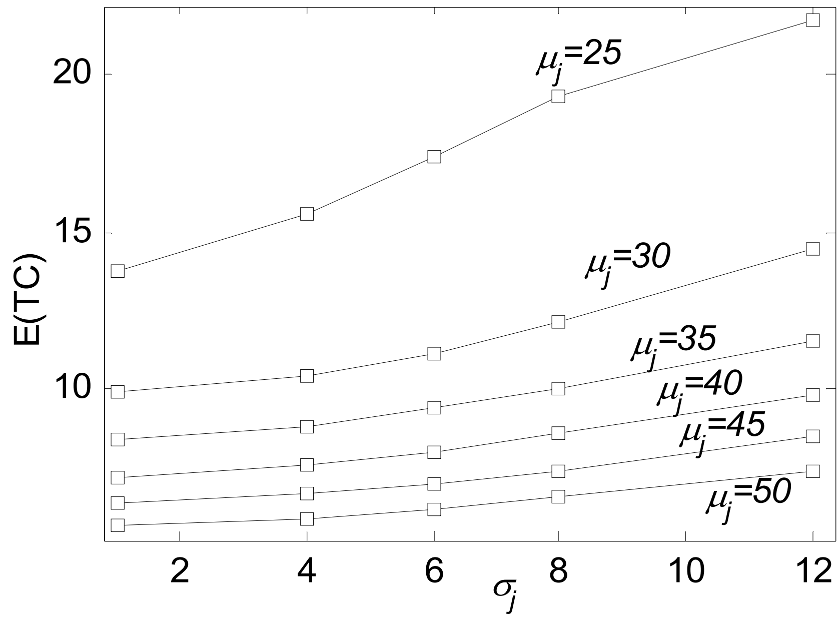
2.5.6 Effect of intentional but systematic soft-order inflation (m_m)

From figures 2.12 and 2.13, it can be seen that systematic soft-order inflation has no effect when capacity is tight. With no forecast inflation (i.e. $m_m = 0$), increasing capacity decreases cost; however, from order fill-rate point of view, there exist an optimal Δl for which the order fill-rate is maximum ($\Delta l = 7$ for $m_m = 0$). For high degree of inflated soft-orders (e.g. $m_m \geq 1.5$), the supplier's cost goes up dramatically after passing a point of minimum (e.g. for $m_m = 1.5$, the cost is least at $\Delta l = 4$).

Two important insights can be drawn from these graphs. Firstly, for a given Δl, increasing the degree of inflation increases the order fill-rate while also increasing the order fulfillment cost to the supplier. This implies that the buyer always benefits (receives a better order fill-rate) from issuing inflated soft-orders, while it hurts the supplier. Secondly, the proposed dynamic programming formulation is not robust enough to fully compensate for these soft-order inflations, in spite of the systematic (linear) pattern, and is fully appropriate only when the soft-orders are not inflated. The overall difficulty can be attributed to the interaction between soft-order inflation and order volatility. We hypothesize that the dynamic programming formulation is likely to more effectively counter systematic soft-order inflation at lower levels of order volatility. In addition, we believe that the ability of dynamic programming technique to counter soft-order inflation will also be a function of the inflation pattern. While we only investigated a particular type of systematic inflation pattern (linear), other patterns such as step-shifts will be considered for further study.

2.5.7 Effect of capacity severity and uncertainty (μ_n and σ_n)

As expected, figure 2.14 illustrates that increasing the expected capacity decreases the expected order fulfillment cost to the supplier. This is because increasing the capacity allows the supplier to postpone production without incurring any increase in underage cost, while decreasing the holding cost. The plot also illustrates that the detrimental effect of capacity uncertainty is more when the mean effective capacity is less (or when capacity is constrained). Moreover, the marginal benefit of increasing capacity decreases as we keep increasing capacity.



Parameters: $E(Y_F)$=100, σ_d=7, l = 1, Δl=1, c_o=1, c_u=1.5, h=0.05, m_m=0, m_σ=0.5, m_ρ=0.25

Figure 2.14: Effect of capacity severity and uncertainty on supplier's cost

2.6 Conclusion

Our analysis reveals that suppliers supporting "atypical" demand patterns, arising say from promotional marketing efforts, seasonal and/or short product life-cycles, and contract manufacturing, can benefit from receiving early soft-order forecasts from the buyer. Our analysis also reveals that such information sharing is also beneficial to the buyer in terms of order fill-rate. The dynamic programming formulations offered allow for soft-order revisions and can determine optimal production release targets for individual production periods under capacity uncertainty. We also identify several different dynamics at play, as a function of order lead-times, soft-order volatility, and reliability of soft-orders. The benefit of receiving soft-orders depends primarily on the degree of capacity shortage and uncertainty. Volatility in soft-orders is detrimental to both the players, resulting in increased order fulfillment costs while lowering order fill-rates. Although receiving early soft-orders improves the supplier's ability to complete the order, early forecasts are often more uncertain, increasing the risk of over production. An optimal lead-time for sharing soft-orders can be determined based on the levels of effective capacity, demand forecast uncertainty, and the different cost parameters.

We also demonstrate that the dynamic programming technique cannot fully account for intentional soft-order inflation by the buyer, even under conditions of a stable and linear order inflation pattern. The analysis reveals that the buyer has an incentive to inflate soft-orders at a cost to the supplier. This suggests that any contract offered by the supplier to the buyer should incorporate penalties for soft-order inflation. Future studies will look into optimal penalty structures for inflation.

Presently, efforts are also under way to study the optimal soft-ordering policy for a retailer facing atypical demand and supply uncertainty. In addition, we will study the benefits of upstream information sharing (such as production inventory) for such retailers.

CHAPTER 3

AN OPTIMAL SOFT-ORDER REVISION POLICY FOR A VENDOR FACING SUPPLY UNCERTAINTY AND UPSTREAM INFORMATION

3.1 Abstract

Atypical demands are highly volatile and unsuitable for regular forecasting. In such cases, vendors utilize market signals to do demand forecast updating. Early soft-orders are transmitted to the supplier to avoid supply shortages. We determine an optimal soft-order revision policy for a vendor facing atypical demand and supply uncertainty in a single selling season based on a stochastic dynamic program. The decision variables are soft-order(s) and final firm-order quantities to be transmitted to the supplier. We also demonstrate the value of upstream information sharing, such as a supplier sharing order inventory information at regular intervals with the vendor. The contributions of this paper are: (i) A decision model for vendor to optimally revise soft-orders with or without supplier's order inventory position. (ii) We establish the relationship between optimal soft-orders and final firm-order under demand forecasts, demonstrating that optimal orders may be inflated, deflated, or match the forecast. (iii) We identify circumstances under which sharing of supplier's order inventory information is beneficial to vendor. A detailed analysis explores the structure of the optimal ordering policies and the effect of cost parameters and the different sources of uncertainty on vendor performance.

Keywords: Soft-orders; supply uncertainty; upstream information sharing; atypical demand

3.2 Introduction

In the current global and highly competitive marketplace, the product lifecycle is continually shortening. Vendors selling short life cycle products (such as styled goods and trendy consumer electronics) face increasing pressure in determining replenishment order quantities for their seasonal sales and promotion events. Although everyday low price (EDLP) strategy is being promoted by retailer Walmart and others as the solution to tame the highly detrimental bullwhip effect in supply chains, instruments like promotion and price reduction during seasonal sales are a commonplace. Demand patterns of style products during seasonal sales are rather “atypical” attributable to complex interactions between many intractable events, resulting in such demand behaviors that may not exhibit a clear discernible pattern (Reinmuth and Geurts 1972). Today software vendors are providing a myriad of packages to cope with uncertain situations and sales planning for promotional and seasonal events. However, every competing vendor has access to such tools. Only those vendors capable of squeezing every bit of inefficiency and customer dissatisfaction out of the system through better forecasting and planning to best match supply and demand are going to win in the marketplace.

The replenishment decision making for vendors becomes difficult if such unpredictability down-stream is supported by an up-stream supply source that is geographically distant, resulting in longer replenishment lead-times. To start the planning process early in time, vendors should involve experts/expert methods that assimilate all the complex yet relevant market information and estimate an early sales forecast. Early forecasts in such situations are extremely helpful for both the vendor and the supplier. By issuing reasonable soft-orders based on these early forecasts, long before the start of the sale, vendor allows the supplier to better plan for and support the sales event. These soft-orders are tentative orders from buyer to supplier; they are reflection of buyer's purchase intent but not legally binding "firm" purchase orders. Those suppliers that do not have in-house forecasting capability or do not have forecasting capability for that particular product are completely dependent on such signals for early production planning. Moreover, if the supplier happens to be a contract manufacturer that does not build the same product twice, these signals become even more important. If the vendor is a trustworthy player or commits a deposit amount for every soft-order she submits, the supplier may even start building inventory based on such soft-order. Such early information sharing in terms of soft-ordering is beneficial for the supply chain in terms of achieving higher order fill-rates for the vendor as well as increasing sales for the supplier. Higher order fill-rates without soft-ordering would have been otherwise possible only through either investing in huge reactive capacity capable for last minute "just in case" production ramp-ups or through building up inventory that may have to be marked down with loss if demand does not occur.

Replenishment decisions become more difficult with increase in uncertainty (both supply uncertainty as well as demand uncertainty). In case of atypical demand situations that we just described, construction of a predictive time series model based on simple observation of demand is difficult (Hausman 1969). In such cases, we depend on simple statistical models such as joint distributions of consecutive demand forecasts and basic statistics such as correlations for decision support. We have seen that this way of capturing demand uncertainty for atypical situation has gained preference in the literature (see literature review by Raman and Kim 2002). Although literature predominantly focuses on demand side uncertainty, supply side uncertainty is relevant in many industries and not very well explored in developing optimal procurement policies. As stated by Lee (2002), supply uncertainty results from supplier source capability; elements and activities associated with a supply system are not free from frequent breakdowns, unpredictable and low yields, poor quality, limited supply capacity, inflexible capacity, evolving production process, and life cycle position of product. Heightened alertness towards quality control in production process and superior condition based maintenance practice may lower uncertainty due certain factors like frequent breakdown, unpredictable low yields, and poor quality. In contrast, increased complexity in production system, frequent overhauling of assembly system due to change in product design, thrust towards flexible production system, reconfigurable production, frequent change of suppliers for components and raw materials due to better visibility of market price will have a negative impact on supply uncertainty. Today, computing power allows us to build models capable of optimizing a policy considering more sources of uncertainty that we could not have done few decades earlier. Therefore, policies should incorporate supply source uncertainty, which if not considered, results in a suboptimal decisions and hence negatively influence the profit potential.

One of the key topics of investigation in this research is the way soft-ordering decisions are made in atypical demand situations described above. We have shown earlier that soft-orders decrease supplier's cost and increases buyer's fill-rate (Baruah and Chinnam 2006). We now ask the following follow up questions: Is there any information the supplier can share that will help the vendor better assess its demand or supply? While the supplier can collaborate in developing demand forecasts for the buyer, this is not our focus. Considering that the supply side uncertainty is mostly a result of supplier's production and operational processes, we seek opportunities for upstream information sharing to reduce this uncertainty. One paper has investigated the effect of upstream inventory information sharing in reducing bullwhip effect through simulation modeling of a serial supply chain (Croson and Donohue 2005). In our modeling framework, we investigate the effect of the sharing supplier's production information on vendor's replenishment policy and show how this information interacts with optimal soft-ordering behaviors: What soft-order is optimal based on her early assessment of the demand and supply uncertainty? What final order to place. To model this scenario, we employ a two-stage stochastic dynamic program framework that generates optimal soft-order and final firm-order given a demand evolution model and supply uncertainty model. A slightly modified model answers the same set of questions when supplier shares his inventory position while buyer makes the decision on final order. We have shown that sharing production information by supplier helps the vendor reduce its expected cost.

Subsequent sections are organized as follows. Section 3.3 reviews the related literature. Section 3.4 presents the dynamic programming model for soft-order and final firm-order determination. Section 3.5 presents mathematical analysis that establishes the benefits of upstream inventory information sharing. Section 3.6 presents results and insights from numerical analysis followed by conclusion in section 3.7.

3.3 Literature Review

3.3.1 Optimal ordering policy under demand and supply uncertainty

While the production/inventory models have been studied in the operations/production management literatures for decades, involving uncertainties in the environment, the attention however has been mostly focused on probabilistic modeling of demand side uncertainty (Yano and Lee 1995, Gullu et al 1999). Many sophisticated procedures are developed to determine procurement quantities and their timings optimally or near optimally while demand is uncertain. In actuality, considering realization of sure delivery times and/or receipt of exact quantity ordered may not be proper assumptions (Gullu et al 1999). There may be many reasons why supply could be uncertain (Lee 2002): frequent breakdown, unpredictable and low yields, poor quality, limited supply capacity, inflexible capacity, evolving production process, and life cycle position of product. Industries where random yield is known are: electronic fabrication and assembly (Karabuk and Wu 2003), chemical processes, and finally procurement from suppliers that produce imperfect products are common across any industry.

In fact, it is a common occurrence in a wide range of manufacturing and service scenarios (Vollmann et al. 1997). A good literature review on supply/yield uncertainty can be found in Yano and Lee (1995) and Mohebbi (2004). For some related work in microeconomics, see Amihud and Mendelson (1983).

There is a long history for this research, starting with earlier works by Karlin (1958) and Silver (1976). Karlin (1958) considered a periodic review model with random yield where ordering was restricted to a fixed amount. Silver (1976) studied an EOQ model where the quantity received is a random proportion of the quantity requisitioned and finally derived an EOQ formula that accounts for such supply uncertainty. This concept of proportional supply uncertainty is used by Shih (1980) and Ehrhardt and Taube (1987) to study single period inventory model with random demand and random replenishment. An optimal order-up-to policy is studied by Henig and Gerchak (1990) considering periodic review model where the quantity received is random multiple of the order size. Ciarallo et al. (1994) showed optimality of order-up-to type policies for a stochastic demand production/inventory model with random available capacity. Similar capacity uncertainty model is used by Gullu (1997) that contracts an order-up-to level through the use of queuing systems. Parlar and Berkin (1991) formulated an EOQ model where supply is available or disrupted for random duration in planning horizon. In another study, Parlar et al. (1995) consider a periodic review model with Markovian supply availability structure in which supply is either fully available or completely unavailable.

More recently, Kouvellus and Minler (2002) studied the interplay of demand and supply uncertainty in capacity and outsourcing decisions in multistage supply chains. One of the important findings of this paper is that greater supply uncertainty increases the need for vertical integration while greater demand uncertainty increases the reliance on outsourcing. Wu and Lin (2004) have studied an (*r*, *Q*) inventory model under lead-time and ordering cost reductions when the receiving quantity is different from the ordered quantity. They simultaneously optimize the order quantity, reorder point, ordering cost, and lead-time with the objective of minimizing the total relevant costs. Mohebbi (2004) considers a continuous-review inventory system with compound Poisson demand, hyper-exponentially distributed lead-time, and lost sales where the supply process maybe randomly interrupted depending on the availability of a supplier. He assumed that the supplier’s availability can be modeled as an alternating renewal process in which the on and off periods are independent random variables following general and hyper-exponential distributions, respectively. Bopllapragada et al. (2004) has modeled two-stage serial inventory systems under demand and supply uncertainty and customer service level requirements. Their supply model incorporates both quantity and timing uncertainty. Yang and Malek (2004) extended the newsvendor approach to study multi-supplier sourcing with random yields. A double-layered supply chain is considered where a buyer (vendor) facing the end users has the option of selecting among a cohort of suppliers; suppliers have different yield rates and unit costs. Kim et al (2004) propose a decision model for ordering quantity considering uncertainty in supply-chain logistics operations. They model uncertainty due to unforeseeable disruption or various types of defects (e.g., shipping damage, missing parts and misplacing products). Given that commonly used ordering plans developed for maximizing expected profits do not allow retailers to address concerns about contingencies, their research proposes two improved procedures with risk-averse characteristics towards low probability and high impact events. While all the papers we have discussed so far models production/inventory systems to cope with supply/ yield uncertainty, Lin and Hou (2005) have considered an inventory system with random yield in which both the set-up cost and yield variability can be reduced through capital investment. Objective is to determine the optimal capital investment and ordering policies that minimize the expected total annual costs for the system.

None of the papers discussed above have researched ordering policies under forecast revision. This is because research on soft-ordering is very recent. To the best of our knowledge, we are the first to study optimal soft-ordering under demand and capacity uncertainty, and in particular, under upstream information sharing.

3.3.2 Optimal ordering policy under forecast revision and supply uncertainty for short life-cycle products

Analytical models for managing inventory for short lifecycle products share these common features, according to Fisher et al. (2001): First, all are stochastic models, because they consider uncertainty explicitly. Second, they consider a finite selling period at the end of which unsold inventory is marked down in price and sold at a loss. These models are similar to the classic newsvendor model. Third, they model multiple commitments such that sales information is obtained and used to update demand forecasts between planning periods. The “finite-selling periods” and “multiple production commitments” are two unique characteristics of style goods inventory models that differentiate them from stochastic inventory models.

Style goods inventory problems are studied by Murry and Silver (1966), Hausman and Peterson (1972), Bitran et al. (1986), Matsau (1990), Fisher and Raman (1996) and Raman (1999). While these papers capture the demand side uncertainty through a forecast revision model initially proposed by Hausman (1966), Baruah and Chinnam (2006) have proposed a modified model that captures capacity uncertainty through probability distributions.

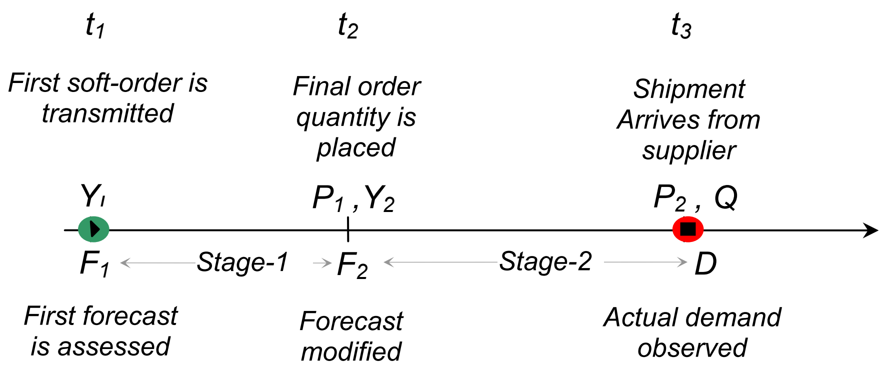
Research that specifically relates to replenishment decision by the vendor in atypical demand situations is sparse. Four papers are of interest: Bradford and Sugre (1990), Eppen and Iyer (1997a), Eppen and Iyer (1997b) and the most recent one being Raman et al. (2001). Bradford and Sugre (1990) present a model of the two-period style-goods inventory problem for a firm, which stocks many hundreds of distinctive items having heterogeneous Poisson demands. The model uses Bayesian procedure for forecast and probability revisions based on an aggregate-by-item scheme. They derive optimal inventory stocking policies, which maximize expected profit during the season based on revised forecasts. They have used negative binomial distribution for modeling aggregate demand behaviors. Eppen and Iyer (1997a) developed an updated Newsboy heuristic based on Bayesian updates of demand to derive an optimal inventory policy that determines an original order based on a demand forecast, and later, how much to divert to the other sources of distribution when actual demand is observed. A stochastic dynamic program framework is used to model this for individual item demand case. Eppen and Iyer (1997b) model a backup agreement for a catalog retailer. Backup agreement is a scheme to provide upstream sourcing flexibility for fashion merchandise. In a backup agreement, retailer places an initial order before the start of the season and reorders during the selling season based on actual demand and customer return rate. This agreement uses a penalty cost for not buying a unit in the second period that is committed in the first period. Raman et al (2001) optimize initial and replenishment order quantities that manimize cost of lost sales, back orders, and obsolete inventory through a two-stage stochastic dynamic program. Their model is an upgrade of Bradford and Sugre (1990). While Bradford and Sugre do not consider the impact of replenishment lead times, Raman et al do. In addition, solution procedure of Bradford's model is through complete enumeration, which works efficiently for smaller problems.

None of these models consider a scenario where a soft-order is issued in the first stage and final order in the second stage with a finite lead-time. The model we present incorporates them. We have incorporated a deposit scheme associated with the soft-order that is different from Eppen and Iyer's (1997b) backup agreement penalty cost. Compared to these above models, our model provides insights in three new dimensions: 1) impact of soft-orders on vendor performance, 2) allowing supply uncertainty as opposed to deterministic supply system, and 3) assessing the value of upstream production information sharing.

3.3.3 Value of upstream supply chain information for buyers

Supply chain management literature on information sharing typically studies scenarios when information comes from demand side, typically, a downstream supply-chain player sharing the information with upstream supply chain player. According to Chen (2003), upstream information sharing research has received relatively little attention. Examples of upstream information sharing studied in literature are supplier cost, lead-time information, supplier's capacity information, and inventory information.

Chen (2001) has studied the procurement problem faced by a buyer who has multiple suppliers to select from and shows the potential for supply chain improvement if suppliers are willing to share cost information. Chen and Yu (2005) have quantified the value of lead-time information sharing in a single-location inventory system. A typical supplier knows the lead-time of order fulfillment, when the retailer submits a replenishment order. They show that sharing it with the retailer whose replenishment orders are based on periodic review inventory model with an infinite planning horizon has benefits. Chen and Yu (2001) have studied value of upstream capacity information based on a one retailer one supplier model. This single selling season has uncertainty in supplier's capacity. The model permits two orders, one early in time when supplier possesses infinite capacity and a second order during which capacity is assumed uncertain. They compare two scenarios based on supplier's willingness to share its future capacity forecast with the buyer. Another study by Swaminathan et al (1997) studies the influence of sharing supplier capacity information (available-to-promise capacity) on the performance of a supply chain. Their model is a manufacturer who orders raw materials from two alternative suppliers differing in cost and capacity. They have studied different information sharing scenarios based on optimal inventory policy for the manufacturer facing stochastic demand while exact capacities of supplier are unknown. One of their findings is that while information sharing is beneficial to overall supply chain performance, it can be detrimental to individual entities. They have found trade offs between benefit of extra information versus cost of adoption of information system. The study by Croson and Donohue (2005) is the only paper we found that is related to our findings regarding upstream inventory information sharing. Although their simulation modeling framework is not at all related to the scenario we model, one of their inferences is similar to ours. They have shown that access to upstream inventory information provides a forewarning of when suppliers are running short of inventory and thus lessen a decision maker’s tendency to overreact when the order he receives from his supplier falls short of his original order request. Thus, it helps in reducing bullwhip effect. They state that benefits from sharing upstream inventory information are not as significant when compared to benefits from sharing downstream inventory information, as far as bullwhip is concerned. This result however could be dependent on the level of demand versus supply uncertainty a process faces.



Control	Y_1	Y_2
No information sharing (No-IS)	F_1	F_2
Information sharing (IS)	F_1	F_2, P_1

Figure 3.1: Schematic showing timeline of events for the buyer. P_1 is known to buyer only if shared by supplier.

Table 3.1: Summary of key model variables and parameters

t_i	Time stamp at the beginning of a stage
F_1	First demand forecast made by the buyer (State variable)
F_2	Second demand forecast (State variable)
D	Actual demand for the sales event or season
Y_1	Soft-order sent to the supplier (Decision variable)
Y_2	Final order (Decision variable)
P_1	Supplier's production during the first stage after receiving Y_1 (State variable in IS case)
C_2	Supplier's capacity in the second stage
P_2	Supplier's production during the second stage after receiving Y_2 (State variable in IS Case)
Q	Supplier's shipment order quantity
c_0	Unit overage cost

c_u	Unit underage cost
z	Unit deposit cost that accompanies a soft-order
g_3	Actual cost incurred after realizing actual demand
g_j	Optimal expected cumulative cost from stage j to realization of actual demand in No-IS case (Objective function)
g_j^s	Optimal expected cumulative cost from stage j to realization of actual demand in IS case (Objective function)
G_j	An intermediate cost function used in No-IS case for ease of manipulation
G_j^s	An intermediate cost function used in IS case for ease of manipulation
FR	Order fill-rate to the buyer
R_d	Portion of deposit amount returned to buyer
N_d	Net deposit amount paid by buyer after receiving the order
$\boldsymbol{\mu}_{21}$	Mean vector of F_1 and F_2
Σ_{21}	Covariance matrix of F_1 and F_2
$\boldsymbol{\mu}_{21}$	Mean vector of F_2 and D
Σ_{21}	Covariance matrix of F_2 and D
k_1	Ratio of average production in stage-1 to soft-order Y_1
CV_1	Coefficient of variation of production in stage-1
k_2	Coefficient of variation of capacity in stage-2
CV_2	Ratio of average capacity in stage-2 to shortage $Y_2 - P_1$
$\mu_{P1\|Y1}$	Mean production during stage-1 given the soft-order
$\sigma_{P1\|Y1}$	Standard deviation of production during stage-1 given the soft-order
$\mu_{P2\|Y2,\, P1}$	Mean capacity of stage-2 given the final order and production of stage-1
$\sigma_{P2\|Y2,\, P1}$	Standard deviation of capacity at stage-2 given final order and production of stage-1
$\mathbb{N}$	Normal probability distribution
f_X	Probability density function for random variable X
$E_{X,Y}(U)$	Expected value of function U *w.r.t.* random variables X and Y
Ind	Indicator function
$\delta(x)$	Dirac's delta function

3.4 Model formulation

3.4.1 Two scenarios: Information sharing vs. no sharing

A buyer (a vendor or a retailer or a distributor) plans for seasonal or promotional event. Buyer does forecasting (F_1) based on market information and sends the supplier a tentative soft-order quantity (Y_1). Supplier produces a quantity P_1 based on this order before receiving a final firm-order. The buyer updates her forecast based on new market information, F_2. The time between receiving Y_1 and Y_2 is denoted stage-1. Once F_2 is known, buyer sends the supplier a final order of Y_2. Based on this final order, supplier produces P_2 before the order is due. This production quantity depends on whether $Y_2 > P_1$ or not. If $Y_2 \leq P_1$, then $P_2=0$ with probability 1. Within a finite period of receiving Y_2, supplier ships a quantity Q that can never exceed what has been ordered (Y_2).

In the so called *information sharing case* (abbreviated as IS case), the supplier shares how much he had produced in stage-1 (i.e. P_1) in response to buyer's soft-order (Y_1). This information is transmitted to the buyer at the end of stage-1. Buyer now can estimate the amount to be produced in stage-2 (i.e. P_2) by subtracting the Q from P_1. In addition, he can estimate $f_{P_1|Y_1}$ and $f_{P_2|Y_2,P_1}$ based on historical information and uses them to model the supply uncertainty (detailed below). This model along with the demand uncertainty model (described below) allows the retailer to determine the optimal Y_1 and Y_2 based on optimal cost computation.

In the *no information sharing case* (abbreviated as No-IS case), supplier does not reveal P_1 to the buyer. Hence, the buyer cannot estimate $f_{P_1|Y_1}$ and $f_{P_2|Y_2,P_1}$.

However, he estimates $f_{Q|Y_1,Y_2}$ and the demand uncertainty model as in IS case to determine optimal Y_1 and Y_2 order quantities.

Figure 3.1 offers a schematic that summarizes the time-lines for both these scenarios. The sequence can be described as follows. For the No-IS Case:

Step-1: Buyer determines and issues an optimal soft-order (Y_1) to the supplier based on her initial forecast (F_1) of the demand.

Step-2: Within a finite time period, based on new market information, buyer adjusts her forecast (F_2) of the demand and places a final order (Y_2) to the supplier with a due date.

Step-3: Supply is received ($Q \leq Y_2$) on the due date and actual demand (D) is observed.

The sequence of events for the IS Case is as follows:

Step-1: Buyer determines and issues an optimal soft-order (Y_1) to the supplier based on her initial forecast (F_1) of the demand.

Step-2: Within a finite time period, based on new market information, buyer adjusts her forecast (F_2) of the demand. Supplier reveals to buyer how much he has produced (P_1) based on her soft-order (Y_1). Buyer places a final order (Y_2) to the supplier with a due date.

Step-3: Supply is received ($Q \leq Y_2$) on the due date and actual demand (D) is observed.

3.4.2 Modeling the forecast revision process

It is typically the case that forecasts are updated based on new market information with individual forecasts for a particular season, in the beginning of each stage (say F_1 and F_2). We assume that F_1 and F_2 are average point forecasts of the actual demand D. The forecast evolution is modeled as follows: (F_1,F_2) and (F_2, D) are assumed to follow joint Gaussian distribution f_{F_2,F_1} and f_{D,F_2} with known parameters, and are assumed to be independent $f_{F_2,F_1} \perp f_{D,F_2}$. Historical information will be necessary to estimate these distributions. Figure 3.2 illustrates how the conditional order ($f_{F_2|F_1}$) and conditional demand ($f_{D|F_2}$) are computed for a given season given the joint densities.

3.4.3 Modeling the supply uncertainty

In the presence of soft-order revision process, supplier will attempt to use some type of an optimal production planning process to decide on the production release quantities, based on the transmitted (soft) orders. However, the buyer could only see the supplied quantity as a response to its (soft) orders. From the history of such responses, buyer can assess the model of *supply uncertainty* given the orders i.e. $f_{Q|Y_1,Y_2}$. If supplier shares how much he has produced in stage-1 in response to Y_1, then buyer's belief about the supplier's *production uncertainty* in each stage can also be assessed, i.e. $f_{P_2|Y_2,P_1}$ and $f_{P_1|Y_1}$. It is clear that the marginal uncertainty associated with the shipment quantity (f_Q) given no P_1 information sharing should perfectly match the IS Case. In another words, the

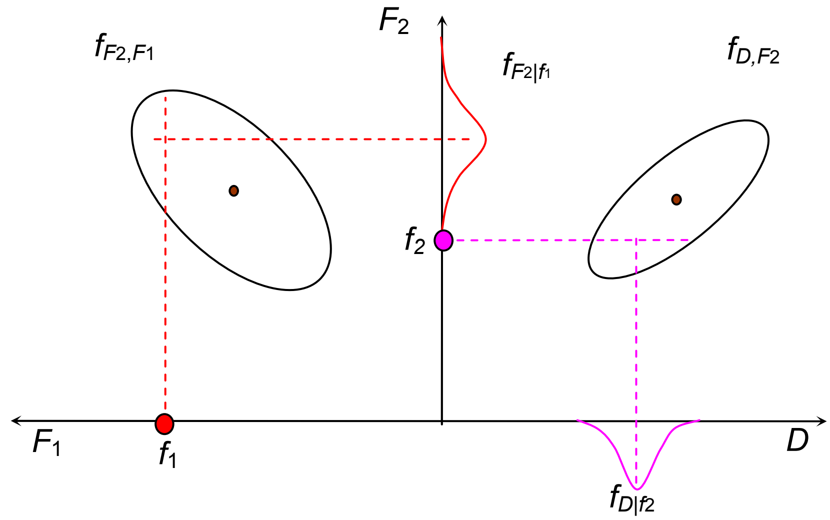
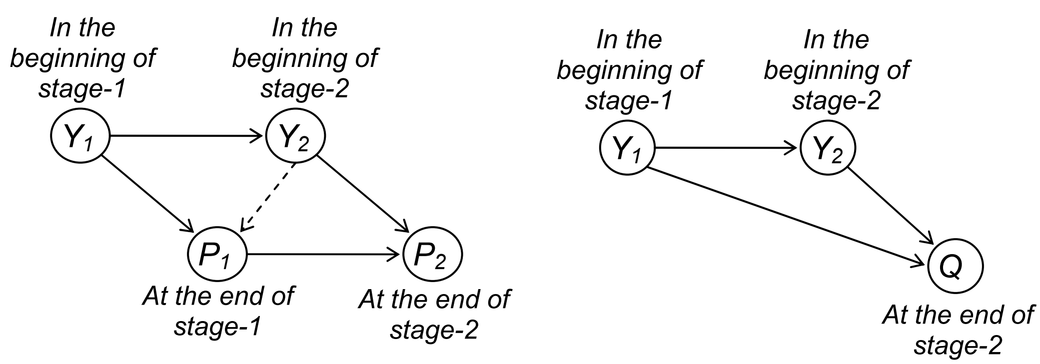


Figure 3.2: Illustrating the forecast revision process. The joint density contour of (Y_1, Y_2) and (Y_2, D) are shown by ellipse, while the conditional densities are shown through the bell curves. The capital Y's represent random variable and small y's represent a particular value for a season.



(a)Production uncertainties

(b)Supply uncertainty

Figure 3.3: Causal relationship between the (soft) order quantities and the production quantity are shown in (a). The belief diagram in (b) shows the no information sharing case

model of supply uncertainty ($f_{Q|Y_1,Y_2}$) should be logically related with production uncertainties ($f_{P_2|Y_2-P_1}$ and $f_{P_1|Y_1}$). The goal of this section is to establish this relationship.

Proposition 1: P_1 and P_2 are conditionally independent: $f_{P_1|Y_1} \perp f_{P_2|P_1,Y_2}$.

Proof and explanation: The cause and effect relationships between (soft) orders transmitted from buyer and the supplier production is graphically illustrated as a causal model in figure 3.3. The network represents how soft-orders are responsible for production response. Arcs between nodes denote the existence of a direct relationship. Direction of arc represents the flow of effect. This network is the buyer's perception of supplier's response. In figure 3.3(a), we have shown arcs between Y_1 and Y_2 and between Y_2 and P_1. However, for the buyer, these two relationships cannot be estimated from historical data.

From figure 3.3(a) we get,

$$f_{Y_1,P_1,Y_2,P_2} = f_{Y_1}.f_{Y_2|Y_1}.f_{P_1|Y_1,Y_2}.f_{P_2|P_1,Y_2} \tag{1}$$

where,

$$f_{P_1|Y_1,Y_2} = \frac{f_{P_1,Y_1,Y_2}}{f_{Y_1,Y_2}} = \frac{f_{P_1|Y_1}.f_{Y_2|P_1,Y_1}.f_{Y_1}}{f_{Y_1,Y_2}} \tag{2}$$

That results in,

$$f_{Y_1,P_1,Y_2,P_2} = f_{Y_1}.f_{P_1|Y_1}.f_{Y_2|P_1,Y_1}.f_{P_2|P_1,Y_2} \tag{3}$$

From equation (2) we get $f_{P_1|Y_1} \perp f_{P_2|P_1,Y_2}$. (In the above equations, we can replace $f_{P_2|P_1,Y_2}$ with $f_{P_2|Y_2-P_1}$ given the fact that P_2 is strictly dependent on order shortage Y_2-P_1only and nothing else. Therefore, $f_{P_2|Y_2,P_1} = f_{P_2|Y_2-P_1}$.)

Now, we establish the relationship between $f_{Q|Y_1,Y_2}$, $f_{P_1|Y_1}$ and $f_{P_2|P_1,Y_2}$.

Proposition 2:

$$f_{Q=q|Y_1,Y_2} = \left(\int_{P_1=0}^{P_1=q} f_{P_1|Y_1} . f_{(q-P_1)|(Y_2-P_1)} dP_1 \right) \mathrm{Ind}(0 \le q \le Y_2) + \left(\int_{P_1=Y_2}^{P_1=\infty} f_{P_1|Y_1} dP_1 \right) \delta_{Y_2}(q)$$

Proof and explanation:

Following inequalities holds:

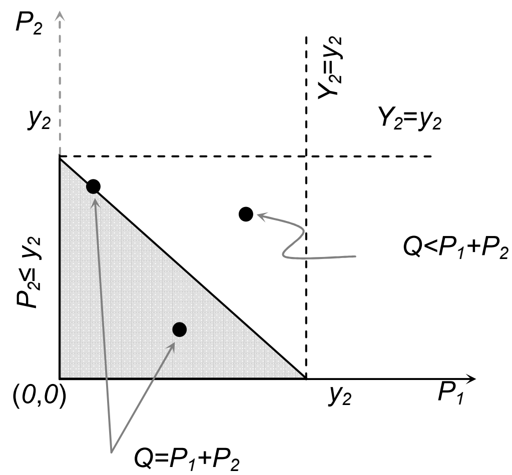
$$Q \le Y2 \tag{4}$$

$$Q = P1 + P2 \text{ if } Y2 > P1 \tag{5}$$

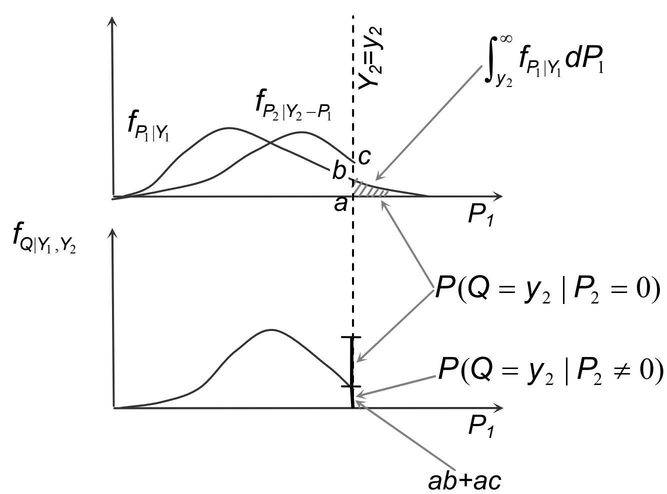
$$Q \le P1 \quad \text{if } Y2 \le P1 \tag{6}$$

From the above three relationships, we can graphically plot the relationships between Y_1, Y_2, P_1, P_2 and Q as in figure 3.4. Now, from probability theory, if Q=P_1+P_2 and $f_{P_1|Y_2} \perp f_{P_2|Y_2,P_1}$

$$\begin{aligned} F_{P_1+P_2 \le Y_2}(Q=q) &= P\{P_1 + P_2 \le q\} \\ &= \int_{P_1=0}^{P_1=q} \int_{P_2=0}^{P_2=q-P_1} f_{P_2|Y_2,P_1} dP_2 f_{P_1|Y_1} dP_1 \\ &= \int_{P_1=0}^{P_1=q} F_{q-P_1|Y_2,P_1} f_{P_1|Y_1} dP_1 \end{aligned} \tag{7}$$



(a) Triangle ($0y_2y_2$) is the region where possible combination of P_1 and P_2 values lie that satisfies $Q=P_1+P_2$.



(b) Probability of $P_1\geq y_2$ so that a point (P_1,P_2) falls within the triangle ($0y_2y_2$) and its effect on $P(Q)$

Figure 3.4: Illustrating (a) the feasible region for P_1 and P_2 and combination of values of P_1 and P_2 that results in $Q=P_1+P_2$; (b) Probability of $P_1\geq Y_2$ obtained from conditional probability of $P_1|Y_1$.

By differentiating,

$$
\begin{aligned}
f_{P_1+P_2\le Y_2}(Q=q) &= P\{P_1+P_2\le q\} \\
&= \int_{P_1=0}^{P_1=q}\frac{d}{dq}F_{q-P_2|Y_2,P_1}f_{P_1|Y_1}dP_1 \\
&= \int_{P_1=0}^{P_1=q}f_{q-P_1|Y_2,P_1}f_{P_1|Y_1}dP_1
\end{aligned}
\tag{8}
$$

Note: The above expression is not a convolution between $f_{q-P_1|Y_2,P_1}$ and $f_{P_1|Y_1}$ given the fact that for a given $Y_1=y_1$, the shape of $f_{P_1|Y_1}$ and $f_{q-P_1|Y_2,P_1}$ changes. We can visualize it as a dynamic convolution of two conditionally independent distributions.

We also know that manufacturer's second stage production does not exceed final order Y_2, i.e. $P_2 \le Y_2$. Therefore, the only way $P_1+P_2 \ge Y_2$ is possible is if $P_1 \ge Y_1$ and $P_2=0$. If $P_1 \ge Y_1$, then at the beginning of second stage $P(Q=Y_2)=1$. Mathematically,

$$
f_{Q=Y_2|P_2=0} = \left(\int_{P_1=Y_2}^{P_1=\infty} f_{P_1|Y_1}dP_1\right)\delta_{Y_2}(q) \tag{9}
$$

From equations (8) and (9) we clearly see that $Y_2=P_1+P_2$ can happen in two ways: (a) $P_1+P_2 = Y_2$ such that $P_2=0$ or (b) $P_1 \ge Y_2$ with $P_2=0$. Now we can write the expression for supply uncertainty as:

$$
f_{Q=q|Y_1,Y_2} = \left(\int_{P_1=0}^{P_1=q} f_{P_1|Y_1}.f_{(q-P_1)|(Y_2-P_1)}dP_1\right)\mathrm{Ind}(0\le q\le Y_2) + \left(\int_{P_1=Y_2}^{P_1=\infty} f_{P_1|Y_1}dP_1\right)\delta_{Y_2}(q) \tag{10}
$$

where, Ind is the indicator function and δ is the Dirac's delta function with the following properties:

$$\mathrm{Ind}(0 \le q \le Y_2) = 1 \quad if \quad 0 \le q \le Y_2 \qquad (11)$$
$$= 0 \quad elsewhere$$

$$\delta_{Y_2}(q) = \begin{cases} \infty, & q = Y_2 \\ 0, & q \ne Y_2 \end{cases} \qquad (12)$$

3.4.4 Cost structure for the buyer

Buyer incurs following costs in our models. For every unit unsold at the end of the season or promotional sale, buyer incurs an overage cost of c_0. For every unit of unmet demand, buyer also incurs an underage cost of c_u. Shipment from supplier is received on the day of sale and therefore buyer incurs no holding costs.

Our model also incorporates a stylized deposit scheme associated with the soft-order Y_1 to ensure that buyer places a reasonable soft-order (and not intentionally inflate the soft-order to improve order fill-rate). In this scheme, a deposit of z dollars is made to the supplier for every unit of soft-order. Paying this amount upfront ensures that the buyer has no incentive for making highly inflated soft-orders. While this deposit should act as a deterrent for inflated soft-orders by buyers, it should not be a panelizing factor for buyers that are conservative in issuing soft-orders. In addition, deposit should not result in situations where supplier simply takes a soft-order and earns a deposit without finally shipping any good. To counter all these limitations, we have devised a deposit return scheme as follows. If deposit with soft-order Y_1 is zY_1, then the return to the buyer on the day of the shipment is R_d,

$$R_d = zY_1 - z.FR.(Y_1 - Y_2)^+ \qquad (13)$$

$$FR = \begin{cases} \dfrac{Q}{Y_2} & \text{if} \quad Y_2 > 0 \\ 1 & \text{if} \quad Y_2 = 0 \end{cases} \tag{14}$$

FR stands for fill rate for the buyer. Time value of money is not accounted here.

The overall scheme works as follows:

I. If the final firm-order exceeds the soft-order, $Y_2 \geq Y_1$, buyer gets credit for the complete deposit, i.e. $R_d = kY_1$.

II. If supplier shipped nothing, $Q = 0$, buyer gets credit for the complete deposit.

III. If $Y_2 < Y_1$, supplier gets to keep a part of the deposit based on what he has supplied:

- if supplied 100% of Y_2, i.e. $FR = 1$, $R_d = zY_2$
- if supplied x% of Y_2, i.e. $FR = x$, $R_d = zY_1 - z.(Y_1 - Y_2)$
- if supplied 0% of Y_2, i.e. $FR = 0$, $R_d = zY_1$, same as (ii)

Now, net deposit cost that is incurred to the buyer is $kY_1 - R_d$ i.e.

$$N_d = z.FR.(Y_1 - Y_2)^+ \tag{15}$$

3.4.5 Model to make optimal Y_1 and Y_2 decisions

The sum of overage, underage, and net deposit costs incurred by the buyer at the end of shipment is:

$$g_3(Q, D, Y_1, Y_2) = c_0(Q - D)^+ + c_u(D - Q)^+ + N_d \tag{16}$$

Based on the sequence of events, it is clear that the decisions to be made (Y_1 and Y_2) depend on the information available at time instants $t_1$and t_2. It is evident that information at t_2 includes all the information of t_1, however, the reverse may not be true; in other words, no information is lost in progression of time. Our cost optimization model is in the form of a backward dynamic program (DP) because the DP paradigm fits perfectly to this kind of a decision-making problem.

Making decision Y_2 at t_2

Expected cost *w.r.t.* demand at t_2 is written as:

$$G_2(Q,F_2,Y_1,Y_2) = \int_{D=0}^{D=\infty} g_3(Q,D,Y_1,Y_2) f_{D|F_2} dD \tag{17}$$

Now, the expected cost *w.r.t.* both demand and supply at t_2 depends on whether $f_{P_2|Y_2-P_1}$ (IS case) is known or $f_{Q|Y_1,Y_2}$ (No-IS case) is known.

In the No-IS Case, the expected cumulative cost is minimized:

$$g_2(Y_1,F_2) = \underset{Y_2}{Min} \int_{Q=0}^{Q=Y_2} G_2(Q,F_2,Y_1,Y_2) f_{Q|Y_1,Y_2} dQ \tag{18}$$

For the IS-Case, the cost becomes:

$$g_2^s(Y_1,F_2,P_1) = \underset{Y_2}{Min} \begin{cases} \int_{P_2=0}^{P_2=Y_2-P_1} G_2(Q,F_2,Y_1,Y_2) f_{P_2|Y_2-P_1} dP_2, & if \quad Y_2 > P_1 \\ G_2(Q,F_2,Y_1,Y_2), & if \quad Y_2 \le P_1 \end{cases} \tag{19}$$

Here, the upper suffix *s* in *g* denotes the IS-Case (*s* stand for “shared information”).

Making decision Y_1 at t_1

Expected cost based on demand forecast at t_1 for the No-IS-Case is,

$$G_1(Y_1,F_1) = \int_{F_2=0}^{F_2=\infty} g_2(Y_1,F_2) f_{F_2|F_1} dF_2 \tag{20}$$

and for the IS-Case,

$$G_1^s(P_1,F_1,Y_1) = \int_{F_2=0}^{F_2=\infty} g_2^s(P_1,F_2,Y_1) f_{F_2|F_1} dm_2 \tag{21}$$

The minimization based on whether $f_{P_1|Y_1}$ is known or not becomes:

$$g_1(F_1) = \underset{Y_1}{Min}\, G_1(Y_1, F_1) \tag{22}$$

$$g_1^s(F_1) = \underset{Y_1}{Min} \int_{P_1=0}^{P_1=\infty} G_1^s(P_1, F_1, Y_1) f_{P_1|Y_1} dP_1 \tag{23}$$

3.5 Establishing the benefits of upstream information sharing

This section investigates the benefit of sharing P_1. We show that, in comparison with the no information sharing case, optimal Y_1 and Y_2 with sharing P_1 do not worsen the expected cost of the retailer.

Proposition 3: Let the initial demand forecast be F_1, soft-order sent to supplier be Y_1, and P_1 the production during the first stage. Based on whether P_1 is shared or not shared, for a given value of F_2, expected optimal total cost incurred by retailer at time t_2 holds the following relationship: $g_2 \geq g_2^s$.

Proof:

<u>Case-1</u>: $Y_2 > P_1$

Partitioning the integral in g_2 as:

$$\int_{Q=0}^{Q=Y_2} G_2 f_{Q|Y_1,Y_2} dQ = \int_{Q=0}^{Q=P_1} G_2 f_{Q|Y_1,Y_2} dQ + \int_{Q=P_1}^{Q=Y_2} G_2 f_{Q|Y_1,Y_2} dQ \tag{24}$$

where, G_2 stands for $G_2(Q, F_2, Y_1, Y_2)$.

For any fixed P_1, LHS and the two parts of the RHS are positive.

$$\therefore \underset{Y_2}{Min} \int_{Q=0}^{Q=Y_2} G_2 f_{Q|Y_1,Y_2} dQ \geq \underset{Y_2}{Min} \int_{Q=P_1}^{Q=Y_2} G_2 f_{Q|Y_1,Y_2} dQ \tag{25}$$

For $Y_2 > P_1$, $Q = P_1 + P_2$, therefore,

$$\int_{Q=P_1}^{Q=Y_2} G_2 f_{Q|Y_1,Y_2} dQ = \int_{P_2=0}^{P_2=Y_2-P_1} G_2 f_{P_2|Y_1,Y_2,P_1} dQ \tag{26}$$

From the physics of the production process, we know that P_2 is independent of Y_1 if Y_2 and P_1 is known. From the graph in figure 3.4

$$f_{P_2|Y_1,Y_2,P_1} = \frac{f_{P_1,P_2,Y_1,Y_2}}{f_{P_1,Y_1,Y_2}} = \frac{f_{Y_1}.f_{Y_2|Y_1}.f_{P_1|Y_1,Y_2}.f_{P_2|P_1,Y_2}}{f_{Y_1}.f_{Y_2|Y_1}.f_{P_1|Y_1,Y_2}} = f_{P_2|P_1,Y_2} \tag{27}$$

Hence,

$$\underset{Y_2}{Min} \int_{Q=0}^{Q=Y_2} G_2 f_{Q|Y_1,Y_2} dQ \geq \int_{P_2=0}^{P_2=Y_2-P_1} G_2 f_{P_2|Y_2-P_1} dQ \tag{28}$$

<u>Case-2</u>: $Y_2 \leq P_1$

When $Y_2 \leq P_1$, the supply quantity becomes $Q = Y_2$. This is true whether P_1 is shared or not.

We know that for any function $f(X, Y)$, the following is true:

$$\underset{Y}{Min}\, E_{Q|Y} f(Q,Y) \geq \underset{Y}{Min}\, f(Q,Y) \tag{29}$$

Hence,

$$\underset{Y_2}{Min} \int_{Q=0}^{Q=Y_2} G_2(Q,F_2,Y_1,Y_2) f_{Q|Y_1,Y_2} dQ \geq \underset{Y_2}{Min}\, G_2(Q=Y_2,F_2,Y_1,Y_2) \tag{30}$$

Proposition 4: Expected total optimal cost under upstream production inventory information sharing is always less than or equal to total optimal cost under no information sharing, i.e. $E_{\forall}(g_3) \geq E^s_{\forall}(g_3)$, where $E_{\forall}$ and $E^s_{\forall}$ stand for expectation over all possible variations in No-IS and IS cases, respectively.

Proof:

We know the following:

$$E_{\forall}(g_3) = E_{F_1}(g_1) \tag{31}$$

$$E^s_{\forall}(g_3) = E_{F_1}(g^s_1) \tag{32}$$

Therefore, if we prove $g_1 \geq g^s_1$, proves the proposition.

We have, $E_{F_2|F_1}(g_2) \geq E_{F_2|F_1}(g^s_2)$. Then, using Proposition 3,

$$\underset{Y_1}{Min}\, E_{P_1|Y_1}\left(E_{F_2|F_1}(g_2)\right) \geq \underset{Y_1}{Min}\, E_{F_2|F_1}(g^s_2) \tag{33}$$

If the above is true for all possible values of F_1, then,

$$E_{F_1}\left[\underset{Y_1}{Min}\, E_{P_1|Y_1}\left(E_{F_2|F_1}(g_2)\right)\right] \geq E_{F_1}\left[\underset{Y_1}{Min}\, E_{F_2|F_1}(g^s_2)\right] \tag{34}$$

Or, $g_1 \geq g^s_1$.

The above discussion and results clearly show that upstream production inventory information sharing by the supplier cannot deteriorate the performance of the soft-ordering policies for the buyer.

3.6 Numerical analysis

In this section, we numerically analyze how modification of different cost parameters, forecast uncertainty, and capacity shortage/uncertainty affect the expected total cost of the buyer. Numerical evaluation involves the following steps. First, optimization models for all the selected combinations of parameters are established and optimal policies are stored. Then, the expected total cost is computed by taking expectation over the all possible variations.

The section is organized as follows: section 3.6.1 discusses the framework for numerical analysis; section 3.6.2 illustrates the optimal decision surfaces and optimal costs *w.r.t* different state variables; section 3.6.3 outlines the performance measures used for comparing the IS Case with the No-IS case; section 3.6.4 discusses the effect of different policy parameters on expected costs.

3.6.1 Framework for numerical analysis

The section describes specific statistical models used to model demand revision process and the capacity uncertainty in the supply side. The demand revision process are assumed to follows joint Gaussian model with known parameters; i.e. parameters of $f_{F_2,F_1} \sim \mathbb{N}(\boldsymbol{\mu}_{21}, \Sigma_{21})$ and $f_{D,F_2} \sim \mathbb{N}(\boldsymbol{\mu}_{D2}, \Sigma_{D2})$ are known. Stage 1 production uncertainty is assumed to follow a conditional Gaussian distribution $f_{P_1|Y_1} \sim \mathbb{N}(\mu_{P_1|Y_1}, \sigma^2_{P_1|Y_1})$ with following parameters:

$$\mu_{P_1|Y_1} = k_1 Y_1 \tag{35}$$

$$\sigma_{P_1|Y_1} = \mu_{P_1|Y_1} CV_1 \tag{36}$$

This model of production in stage-1 depends on the order size Y_1. This represents a scenario when the supplier will setup a capacity for the first stage based on the retailer's soft-order. k_1 = 1 will be equivalent to a supplier who believes in the buyer's soft-order and installs a capacity that is on an average sufficient to make the full soft-order Y_1. Assuming that the uncertainly linearly adds up as the size of the production capacity is increased, we use a constant coefficient of variation in production CV_1. Please note that the model of stage-1

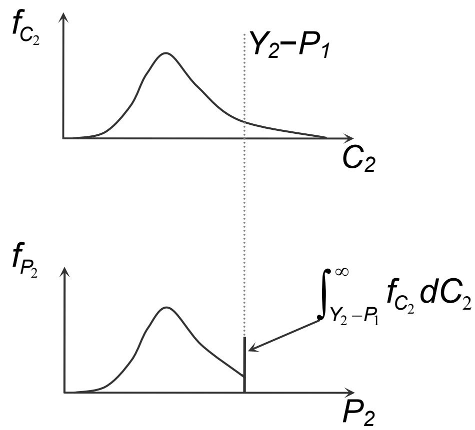


Figure 3.5: Illustrating the relationship between stage-2 capacity uncertainty and stage-2 production uncertainty

production is such that production quantity P_1 can be equal to, less than or more than Y_1. However, while modeling the stage-2 production we have to model it such that $P_2 \le Y_2 - P_1$, since supplier will never produce more than the shortage amount, if $Y_2 \ge P_1$. To derive such a production model we first model the capacity of stage-2 as a Gaussian model and derive the production model out of it. Stage-2 capacity is assume to follow $f_{C_2} \sim \mathbb{N}(\mu_{C_2|Y_2,P_1}, \sigma^2_{C_2|Y_2,P_1})$ with following parameters:

$$\mu_{C_2|Y_2,P_1} = k_2(Y_2 - P_1) \quad (37)$$

$$\sigma_{C_2|Y_2,P_1} = \mu_{C_2|Y_2,P_1} CV_2 \quad (38)$$

This model of capacity model is constrained and random. Based on f_{C_2}, the production yield density (P_2) would be:

$$f_{P_2|Y_2,P_1} = f_{C_2} \mathrm{Ind}(0 \le P_2 < Y_2 - P_1) + \left(\int_{Y_2-P_1}^{\infty} f_{C_2} dC_2 \right) \delta_{Y_2-P_1}(P_2) \quad (39)$$

where, Ind is the indicator function and δ is the Dirac's delta function with following properties:

$$\begin{aligned}\mathrm{Ind}(0 \le P_2 < Y_2 - P_1) &= 1 \quad \textit{if} \quad 0 \le P_2 < Y_2 - P_1 \\ &= 0 \quad \textit{elsewhere}\end{aligned} \tag{40}$$

$$\delta_{Y_2 - P_1}(P_2) = \begin{cases} \infty, & Y_2 - P_1 = P_2 \\ 0, & Y_2 - P_1 \ne P_2 \end{cases} \tag{41}$$

Meaning of the equation 39 is illustrated in the figure 3.5. It shows that probability of producing as much as the shortage quantity $Y_2 - P_1$ is sum of all the probabilities of realizing a capacity more than or equal to the shortage. On the other hand probability of producing less than shortage is equal to probability of realizing that much capacity to produce.

Capacity C_2 and production P_1 is bounded between $[0, \mu_{P_1|Y_1} + 4.5\sigma_{P_1|Y_1}]$ and $[0, \mu_{C_2|Y_2,P_1} + 4.5\sigma_{C_2|Y_2,P_1}]$ respectively. Demand forecasts, capacity, and production are always whole numbers. During optimization of various scenarios, we approximate the continuous probability distributions functions with probability mass functions defined over a set of discrete values. We caution here that while great care has been exercised in conducting these numerical experiments to best extract and illustrate the dynamics at play, all the while coping with a large number of parameters, the patterns/effects reported throughout the manuscript

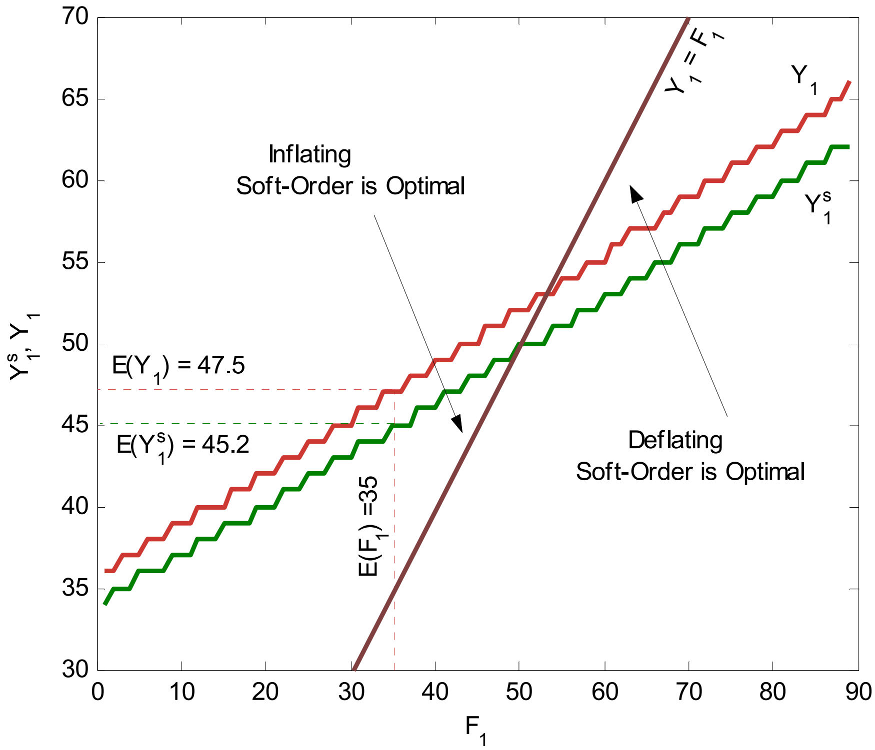


Figure 3.6: Structure of the optimal decision (soft-order) in IS and No-IS case in the beginning of stage-1.

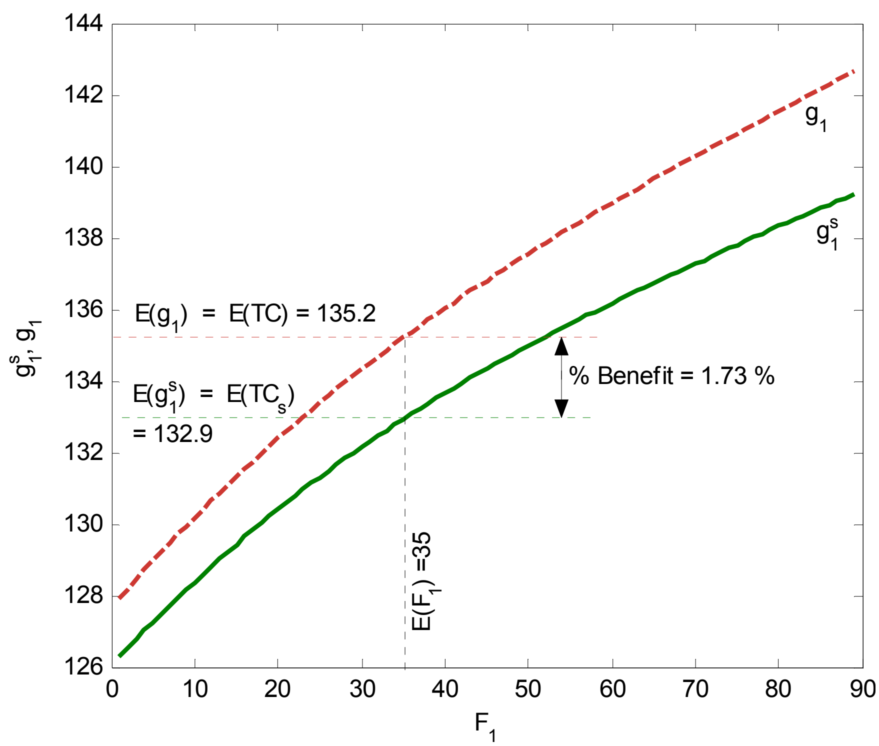


Figure 3.7: Structure of the optimal cost for IS and No-IS case in the beginning of stage-1. In this particular case, the expected benefit of information sharing is 1.73%.

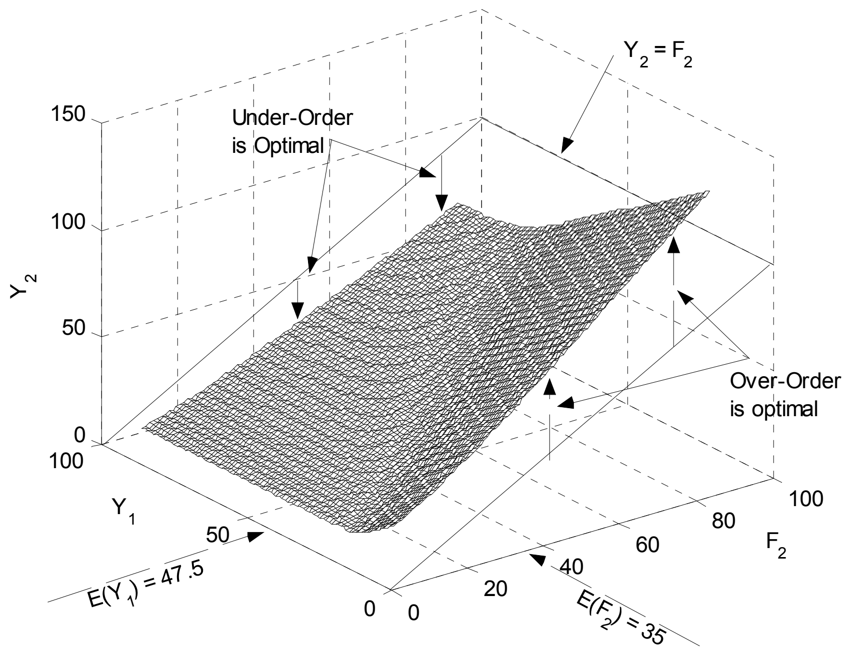


Figure 3.8: Structure of the optimal decision (final order) for No-IS case based in the beginning of stage-2.

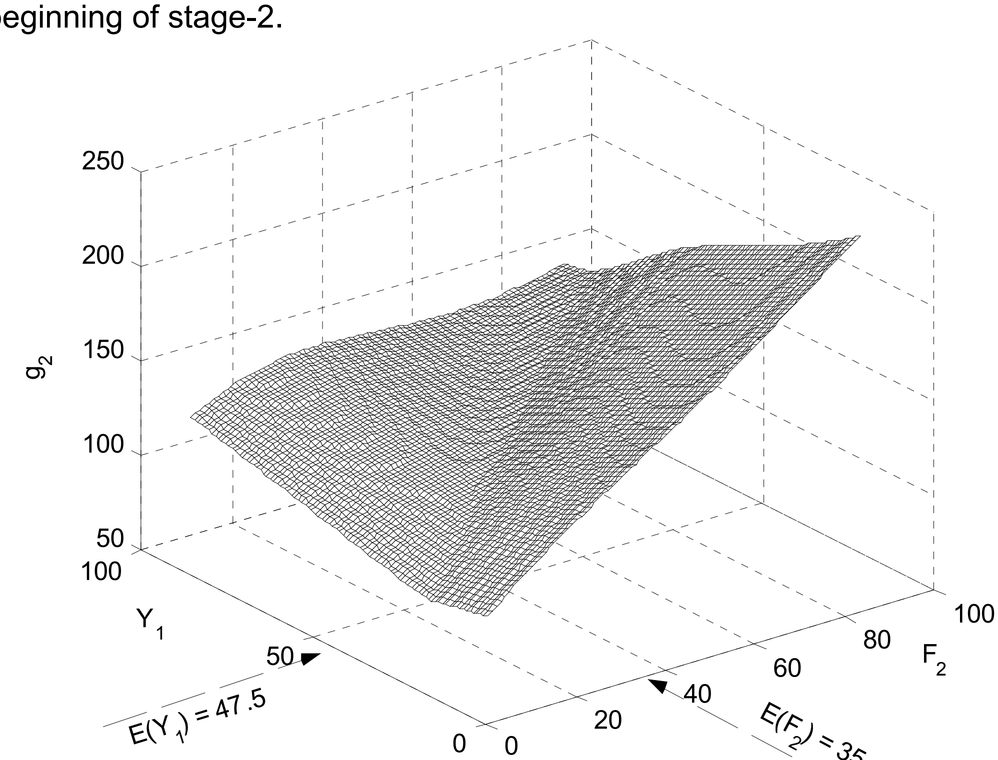


Figure 3.9: Structure of the optimal cost at the beginning of stage-2 cost for No-IS case

can change as a function of the parameter levels. However, the essential dynamics/insights from these results are expected to hold strongly in most settings.

3.6.2 Structural properties of optimal decisions and costs

In this section, we outline the structure of the optimal costs and optimal decision surfaces with or without information sharing. Following parameter set is used to generate the plots: $c_0 = 10$, $c_u = 15$, z = 0.5, $k_1 = 0.5$, $CV_1 = 0.3$, $k_2 = 0.5$, $CV_2 = 0.3$, $E(F_1) = 35$, $\sigma(F_1) = 15$, $E(F_2) = 35$, $\sigma(F_2) = 10$, $E(D) = 35$, $\sigma(D) = 10$, $\rho(F_1, F_2) = 0.5$, $\rho(F_2, D) = 0.5$.

From the above parameter set, we see that supplier respond to the soft-order by installing a production capacity of 50% of the size of the soft-order in stage-1. Also in stage-2, he installs a capacity of 50% of the size of the final-order. In both cases, the variability in effective production (measured in standard deviation) is 30% of mean. If soft-order is at least as high as the final order, this scenario does not represent a capacity-constrained case, since on total (combining stage-1 and stage-2) average capacity is more than equal to the final order. We have set mean of point forecasts as unbiased to the final average demand. $\sigma(F_1)$ is set higher than $\sigma(F_2)$; it is an accepted notion that forecasts with higher lead-time have more variability.

Figure 3.6 shows the structure of the optimal soft-order Y_1 *w.r.t.* the forecast F_1 for both IS and No-IS case. As the figure shows the optimal soft-order for No-IS case (Y_1) is always higher than IS case (Y_1^s). The difference in the optimal

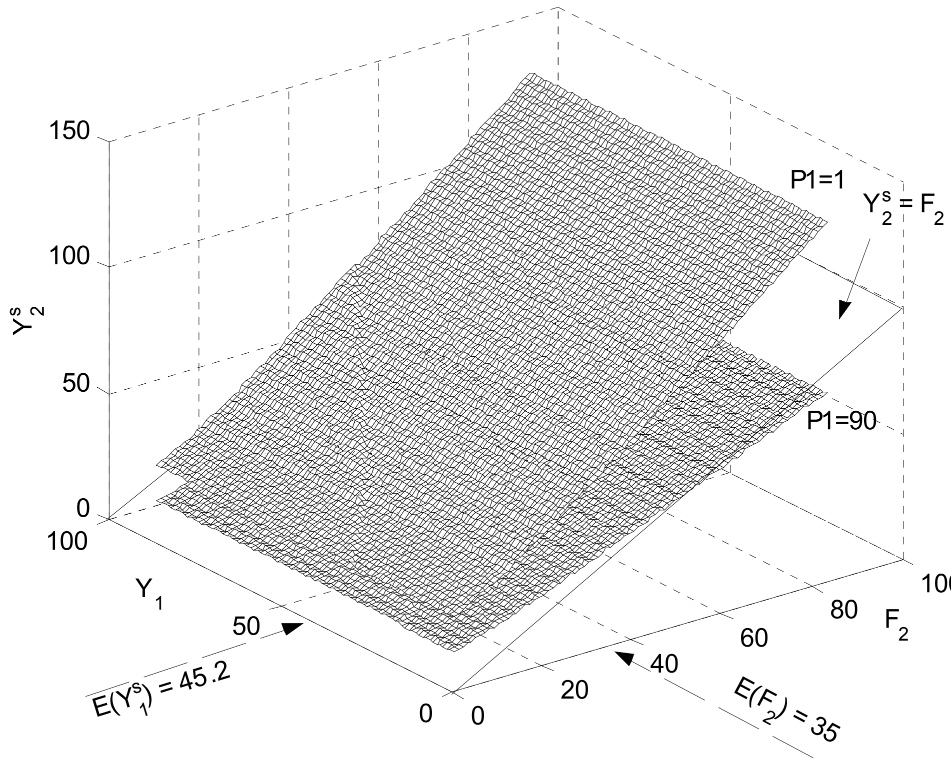


Figure 3.10: Structure of the optimal decision (final order) in the beginning of stage-2 for IS case for P_1=1 and P_1=100

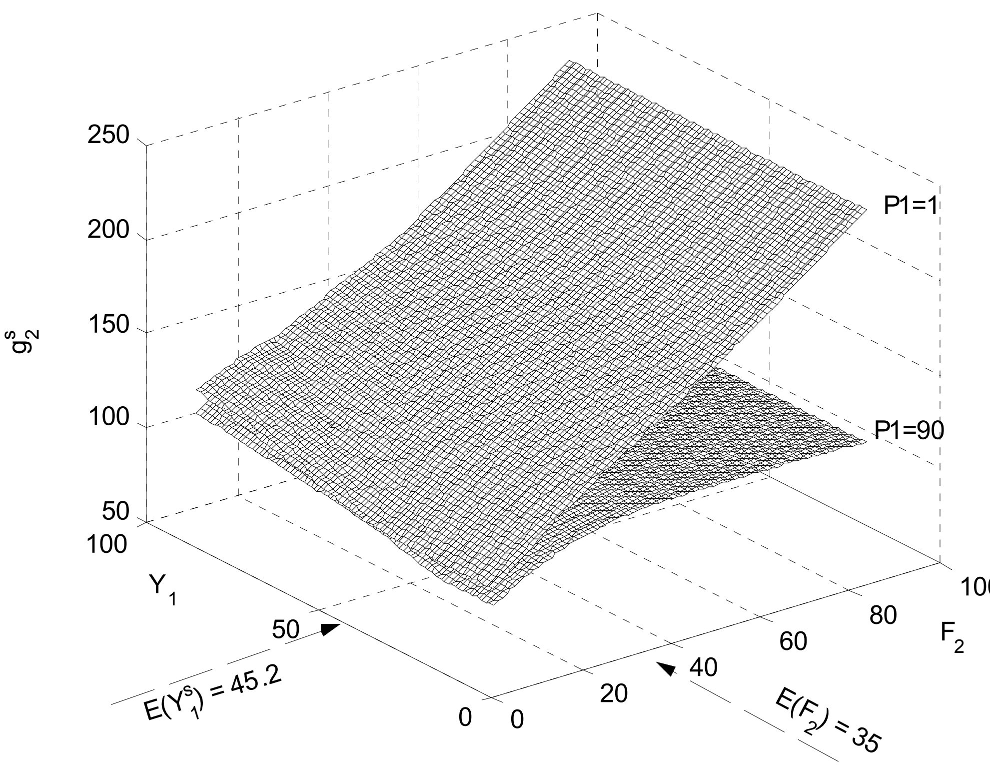


Figure 3.11: Structure of the optimal cost in the beginning of stage-2 for IS case for P_1=1 and P_1=100.

decision increases as the forecast F_1 increases. The expected difference between the two decisions are approximately 2 units. The important point to note in this figure is the difference between the optimal soft-order that minimizes the cost and forecast. Please note the difference between Y_1=F_1 and the optimal decision graphs $Y_1(F_1)$ and $Y_1^s(F_1)$. It clearly shows that there is a region where inflating the soft-order is an optimal decision, and in another region, the reverse is true. Although the buyer knows that supplier installs a higher capacity with linearly increasing variability is she transmits a high soft-order; this way she can make minimize the probability of under supply. However, presence of deposit cost does not allow her to do so. Therefore, a tradeoff between risking the deposit money versus the underage cost is the reason behind why over ordering or unerring is optimal. It is found that if the deposit cost per unit (z) is set to zero, then buyer always inflate and transmits a soft-order that is maximum possible. This way she makes the supplier produce so much in the first stage itself that supplier uncertainty becomes zero. Hence, implication is that there have to be a penalty associated with intentionally transmitting soft-orders, which are far higher that demand forecasts. Unless such a penalty is present, then optimal behavior is to deceive.

Figure 3.7 presents the corresponding costs associated with the optimal decisions in the beginning of the stage-1. It is clear that is the IS case always incurs lower cost then the No-IS case. The benefit of sharing information increases as with higher forecast F_1. From this graph, we can obtain the expected total cost of IS case and No-IS case by taking expectation of g_1 and g_1^s *w.r.t.* the distribution of F_1:

$$E(TC) = E_{F_1}(g_1) = \int_{F_1=0}^{\infty} g_1(F_1) f_{F_1} dF_1 \tag{42}$$

$$E(TC_s) = E_{F_1}(g_1^s) = \int_{F_1=0}^{\infty} g_1^s(F_1) f_{F_1} dF_1 \tag{43}$$

The benefit of information sharing (*i.e.* sharing P_1) is obtained by:

$$\%Benefit = \frac{E(TC) - E(TC_s)}{E(TC)} \tag{44}$$

The % benefit in this particular case is 1.73%.

Figure 3.8 shows the structure of optimal decision in the beginning of stage-2. Optimal Y_2 increases with increase in the demand forecast F_2. We also notice that for a given forecast F_2, optimal Y_2 in No-IS case decreases with increase in Y_1. This is obvious because, it is expected that a higher Y_1 will result in a higher average production in stage-1, and therefore a smaller Y_2 is optimal. The figure clearly shows the difference between the optimal final order and forecast, a similar observation when comparing a soft-order with a forecast. Depending on the state variable Y_1 and F_2 the optimal final order Y_2 is higher or lower than the forecast F_2. The corresponding optimal cost structure at the beginning of stage-2 for No-IS case is shown in figure 3.9.

Figure 3.10 illustrate the structure of the optimal final order in the beginning of the stage-2 for IS case for two specific values of information being shared: P_1 = 1 and P_1 = 100. Please not that, it appears that the optimal decision does not depend on the soft-order anymore; however with close notice the non-linearity along Y_1 is detectable on P_1 = 1 surface. This dependence is very clear in the

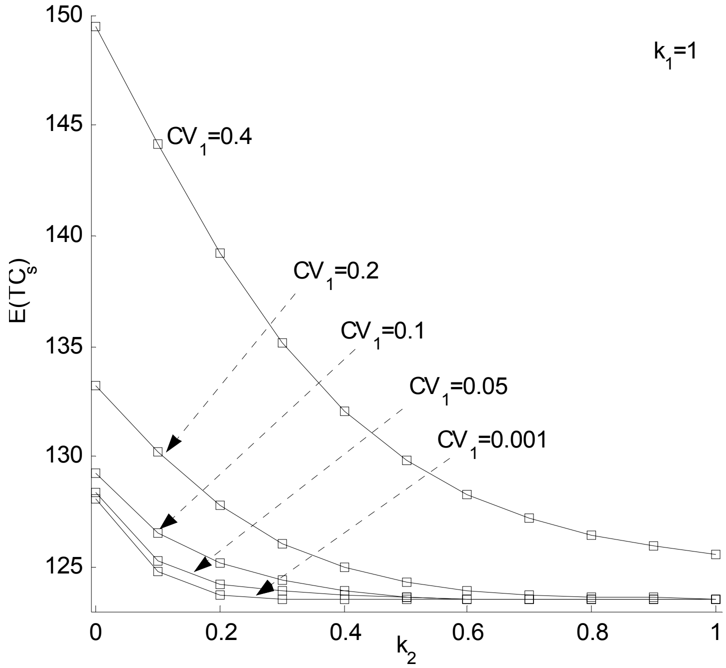


Figure 3.12: Expected cost for buyer under No-IS case decreases with increase in capacity of second stage. Cost is lower if capacity variability (CV_1) is lower.

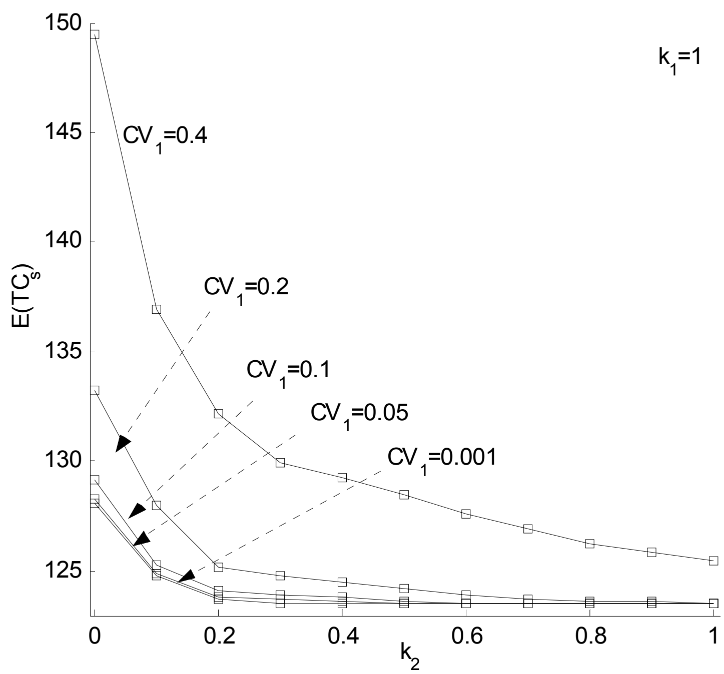


Figure 3.13: Expected cost for buyer under IS case decreases with increase in capacity of second stage. Cost is lower if capacity variability (CV_1) is lower.

corresponding optimal cost surface plotted in figure 3.11. As evident from figure 3.10, depending on value of P_1 being shared, the difference in optimal decisions can be as higher than 50%.

3.6.3 Numerical assessment of the benefits of information sharing

This section investigates effect of various factors on benefits of information sharing. In particular, we consider the impact of per unit deposit cost along with underage and overage cost and impact of supply uncertainty.

3.6.3.1 The impact of k_1, k_2 and CV on expected percentage benefit

Considering $CV_1 = CV_2$ the parameter set used for this section of analysis is as follows: $c_0 = 10$, $c_u = 15$, z = 0.5, $CV_1 = CV_2$, $E(F_1) = 35$, $\sigma(F_1) = 15$, $E(F_2) = 35$, $\sigma(F_2) = 10$, $E(D) = 35$, $\sigma(D) = 10$, $\rho(F_1, F_2) = 0.5$, $\rho(F_2, D) = 0.5$.

Increase in k_1 and k_2 represent suppliers expected capacity commitment in stage-1 and stage-2 respectively. Increase in CV_1 represents the increase in variability of the production system. From figure 3.12 and 3.13 we notice that increase in capacity commitment in stage-2 by supplier decreases the expected cost in both no IS case as well as IS case. This is obvious because if capacity in second stage is increase, then dependence on first stage production for a better fill rate decreases. In fact, if second stage capacity is high enough to produce the final order size in an expected sense, then soft-order transmission is of no value as well supplier need not have to produce anything in first stage. The effect of variability that is introduced through the CV_1 factors is as expected, lower CV_1 is

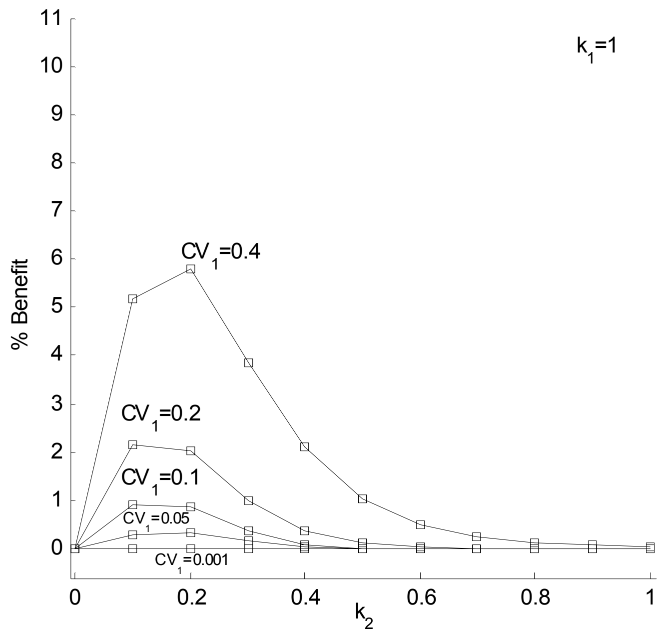


Figure 3.14: Expected percentage cost benefit for buyer is maximum for a particular second stage expected capacity set by the supplier. Benefit is negligible if expected capacity set by customer is zero irrespective of order size or when expected capacity set is same as the order size. Benefit is high when variability (CV_1) is high.

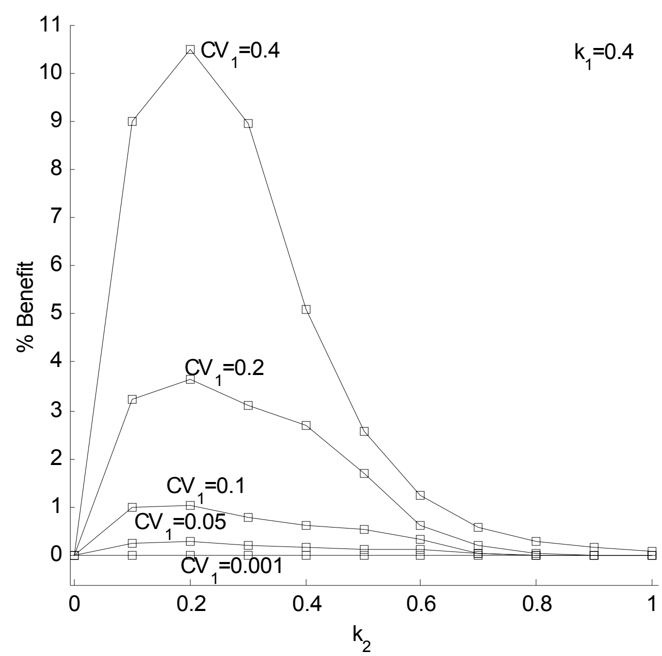


Figure 3.15: Expected percentage cost benefit for buyer increases with decrease in expected capacity commitment in first stage by supplier.

results in reduced cost. Although without plotting the % Benefit graph we may not comment on the cost difference between IS and No-IS case, we see a steeper decrease in $E(TC)$ compared to $E(TC_s)$. This effect is very pronounced when CV_1 is relatively higher (see 0.4 and 0.2) in both IS and No-IS case. This implies that marginal expected cost reduction for buyer through increasing capacity commitment in stage-2 by supplier has better effect when information is shared and when variation is high.

The % benefit graph for same k_1=1 is plotted in figure 3.14. As explained above the cost benefit for the buyer is high is CV_1 is high. There exist no benefit when CV_1 is very small (e.g. 0.001). The benefit is highest at a particular value of k_2. This is due to the way rate of decrease of $E(TC)$ and $E(TC_s)$ *w.r.t.* k_2. The inference from these graphs is that sharing of P_1 has little value if supplier's commitment to second stage capacity is either very small or very high when compared to the final order.

Figure 3.14 and 3.15 together illustrates the difference in % Benefit for different capacity commitment by supplier in stage-1. A smaller capacity commitment in stage-1 (k_1=0.4) is more capacity constrained compared to k_1=1. We saw that for same level of variability (CV_1's) the benefit of information sharing is higher when capacity in first stage is constrained. When variability is extremely small (CV_1=0.001), irrespective of the capacity commitment, the benefit is close to zero.

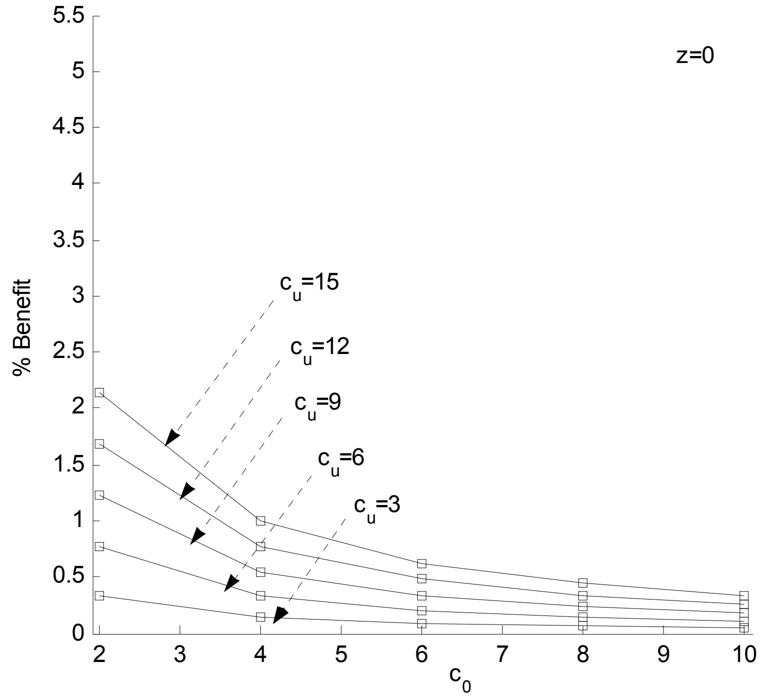


Figure 3.16: Expected percentage cost benefit for buyer for different c_0 and c_u when unit deposit cost is z=0. Benefit increases with increase in c_u, however decrease with increase in c_0.

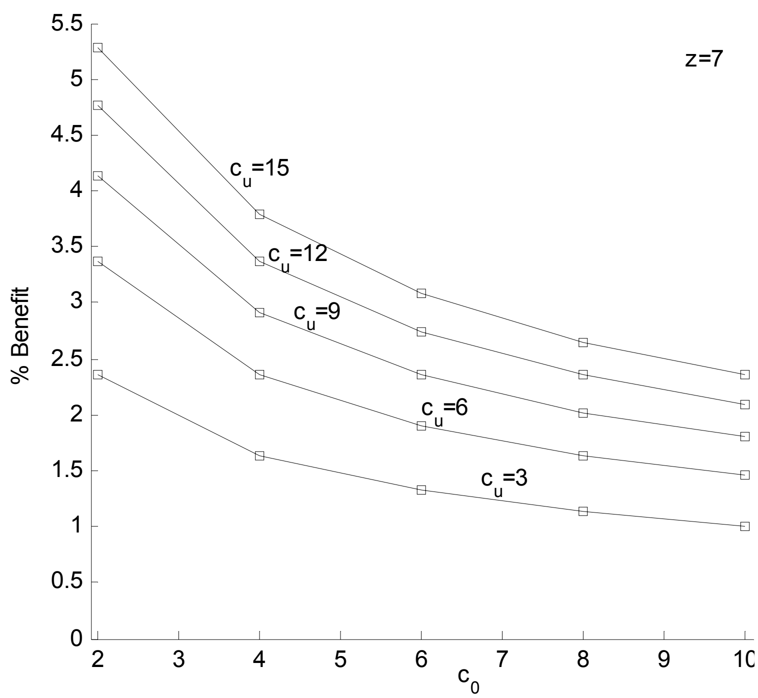


Figure 3.17: Expected percentage cost benefit for buyer for different c_0 and c_u when unit deposit cost is z=7. Comparing figure 3.16 and 3.17 we notice that benefit has increased when z is a positive value.

3.6.3.2 The impact of unit deposit cost z on expected percentage benefit

Considering $CV_1 = CV_2$ the parameter set used for this section of analysis is as follows: k_1=0.5, k_2=0.5, $CV_1 = CV_2$=0.3, $E(F_1)$ = 35, $\sigma(F_1)$ = 15, $E(F_2)$ = 35, $\sigma(F_2)$ = 10, $E(D)$ = 35, $\sigma(D)$ = 10, $\rho(F_1, F_2)$ = 0.5, $\rho(F_2, D)$ = 0.5.

The impact of z on expected % Benefit is illustrated in figure 3.16, 3.17, 3.18 and 3.19. Impact of z is illustrated here in comparison with per unit overage cost c_0 and per unit underage cost c_u. The effect of z on % Benefit is as seen in figure 3.18 and 3.19. We notice that for the same combination of overage and underage cost, a higher z=7 value results in higher % Benefit compared to z=0. Here, z=0 case corresponds to case when no deposit needed for submitting a soft-order. On the hand, a very high unit deposit cost for a unit of soft-order will make the buyer consider her soft-orders like a firm order. Had our cost model contain a purchase price, the value of z for which a soft-order becomes a firm one is when z become equal to purchase price. The transition of a pure soft-order (i.e. z=0) to a more firm one is shown in figure 3.18. From figure 3.18, there exist a unique value of z for a given c_u and c_0 when the % Benefit is maximal. This optimal vale is pronounced in c_0=2 compared to c_0=10. % Benefit becomes stable after certain value of z for a given combination of c_u and c_0. This imply that a very high deposit (z=5, 7) cost will increase the cost of soft-ordering without necessarily increasing the value of upstream information sharing.

3.6.3.3 The impact of c_0 and c_u on expected percentage benefit

Considering $CV_1 = CV_2$ the parameter set used for this section of analysis is as follows: k_1=0.5, k_2=0.5, $CV_1 = CV_2$=0.3, $E(F_1)$ = 35, $\sigma(F_1)$ = 15, $E(F_2)$ = 35, $\sigma(F_2)$ = 10, $E(D)$ = 35, $\sigma(D)$ = 10, $\rho(F_1, F_2)$ = 0.5, $\rho(F_2, D)$ = 0.5.

While it is obvious that increasing the value of c_0 or c_u will increase the expected cost for buyer under both upstream information sharing versus no sharing scenario, their effect on % Benefit however can not be guessed so straightforward. The effect of increasing c_0 is just the opposite of the effect of increasing c_u in terms of % Benefit of sharing upstream information. The trend sin figure 3.16, 3.17, 3.18 and 3.19 clearly show that increasing c_0 decreases the % Benefit while increasing c_u increases the % Benefit. One possible reason for such behavior is that the upstream information in this case effectively reduces the supply uncertainty in the beginning of stage-2 and hence reduces the possibility of underage. This is more pronounces when capacity is constrained and to get a better fill rate stage-2 production is necessary. We have chosen k_1=k_2=0.5 with z=0.5. This setting imply that capacity is more than necessary if soft-order is more than final order, but this will be restricted by deposit cost. Therefore, if she places a soft-order nearly same as the final order, average capacity that the supplier commits is barely enough to produce the full final order. On the other hand, the supplier does not supply more than what has been ordered. In this model, the information about how much has been produced by the end of stage-1 is needed only to prepare if case supplier has not produced enough. If he has produced more than enough then knowing P_1 has no value.

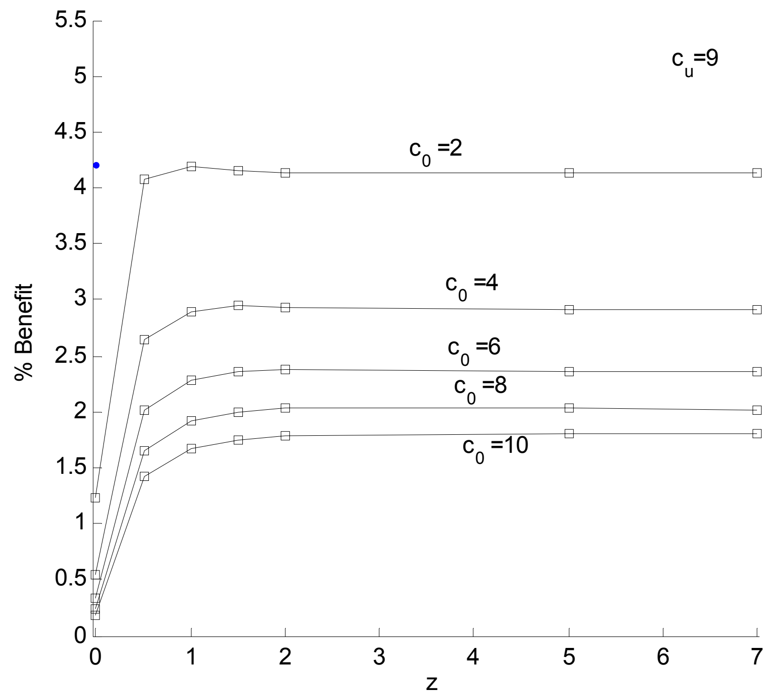


Figure 3.18: Effect of increase in z on expected percentage cost benefit is nonlinear; in cases like c_u = 9 above, the benefit increases abruptly initially and decrease slightly and flattens.

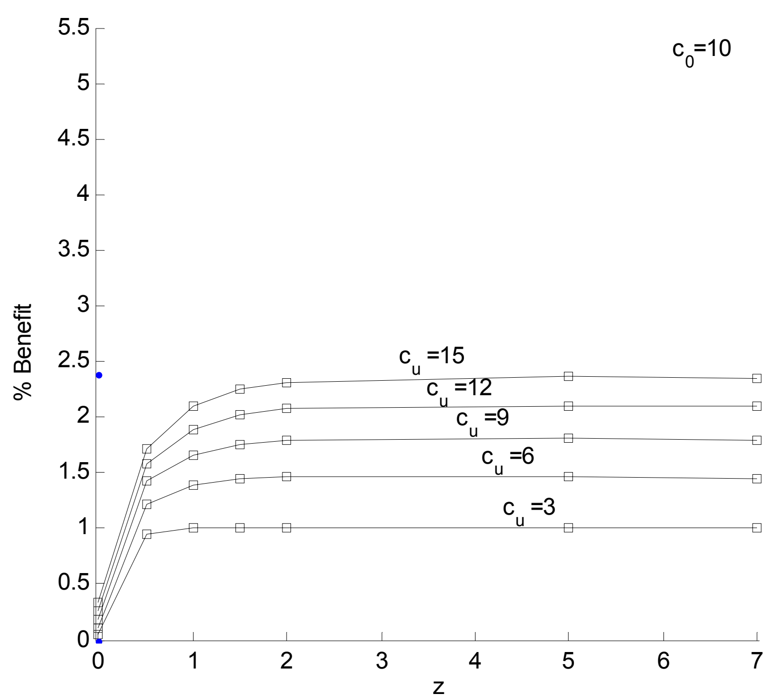


Figure 3.19: For a similar rate of change of c_u and z, a bigger value of c_0 reduces the benefits, while increase in c_u increase benefit.

The figure 3.19 shows it clearly sharing P_1 is beneficial if c_u is high. Now increasing c_0 makes the buyer to order less, effectively making her less concerted about underage, in other words effective c_u goes down if c_0 goes high. Therefore, increase in c_0 decreases the benefit.

3.7 Conclusion

We have presented a model to decide optimally on soft-order revisions in the presence of supply uncertainty and atypical demand. Our analysis reveals that the optimal soft-order and final frim-order are not necessarily the same as the demand forecast made during the time of issuing the order. While in some instances inflating a (soft) order compared to the demand forecast is optimal, deflating the orders is optimal in certain other cases. We have studied the impact of sharing upstream information such as the inventory position of supplier while revising the soft-order. A mathematical inequality is derived that states that vendor's expected cost would never deteriorate when this extra piece of information is received. Detailed numerical analysis reveals that expected cost benefit is significant, in some cases reaching 11%, when supply side variability is high and supplier's commitment to capacity is constrained compared to order size. Our model has also introduced a novel deposit scheme that forces the buyer not to issue unrealistically high soft-orders. This study reveals that increasing the deposit for a unit soft-order increases the benefit of information sharing. Another observation is that while increasing underage cost increases the benefit of information sharing, *w.r.t.* the overage cost, the effect is opposite.

The study has opened up several possibilities for future research. Firstly, the current supplier model is simplistic; the supply uncertainty model is exogenous in our case. Future study should conjoin this model with an optimal supplier model such as one proposed in Baruah and Chinnam (2006). Second, we have not studied the benefit for the supplier while he shares his inventory information. We hope that this question can be answered through an integrated model. Third, the proposed deposit scheme needs more research in terms of determining appropriate deposit per unit of soft-order. More investigation is also due in terms of how to model a deposit scheme if an initial soft-order is revised more than once before submitting the final order. Finally, in reality, modeling the uncertain demand and supply environments needs relevant data that is difficult to obtain. A few practical questions can be posed, if there exists no history to model distributions, while uncertainties do exist, how to go about making decisions? This last point in our view is most important if model needs to be implemented in the real world, and therefore, most challenging.

CHAPTER IV

Conclusion and Future Research

4.1 Conclusion

This research has studied supply chain operational planning in atypical demand situations and the impact of information sharing. The study uses a two-player supply chain configuration comprising a buyer and a supplier. The buyer faces atypical demand and supply uncertainty. The supplier faces effective capacity uncertainty and buyer's soft-order(s) and final order as his demand. A stochastic dynamic programming buyer model for optimal soft-order generation and revision is presented that accounts soft-order deposit costs. A stochastic dynamic programming supplier model for optimal production releases is also offered that accounts soft-order revisions and effective capacity uncertainty. Based on these two models, the effects of sharing soft-orders between the players as well as supplier's order inventory position on both parties involved are studied.

The supplier model shows that soft-order sharing is beneficial to supplier as well as the buyer. Structural relationship between several different factors that affect the benefit of information sharing is explored. We found that that benefit of downstream information sharing varies as a function of order lead times, soft-order volatility, and reliability of soft-orders. The benefit of receiving soft-orders depends primarily on the degree of capacity severity and uncertainty. Volatility in soft-orders is detrimental to both the players, resulting in increased order fulfillment costs while lowering order fill-rates. Although receiving early soft-orders improves the supplier's ability to complete the order, soft-orders are inherently uncertain, increasing the risk of over production. An optimal lead-time for sharing soft-orders can be determined based on the levels of effective capacity, demand forecast uncertainty, and the different cost parameters. We also demonstrate that stochastic dynamic programming technique cannot fully account for intentional soft-order inflation by the buyer, even under conditions of a stable and linear order inflation pattern. The analysis reveals that the buyer has an incentive to inflate soft-orders at a cost to the manufacturer, in the absence of an early soft-order deposit.

Not unlike the classic newsvendor model, our buyer’s model clearly shows the difference between optimal soft-order(s) and mean demand forecasts. In the newsvendor model, the order fractile is a function of unit overage and underage costs, and the order matches the mean expected demand only if these costs are the same. However, the mechanics are more complicated with our buyer’s model. While inflating the soft-order with respect to the average demand forecast is optimal in some cases, deflating it is optimal in some other cases. Both inflation and deflation can be optimal under given overage and underage costs, with the optimal action depending on the demand forecast besides others. As for the impact of sharing supplier’s order inventory position with the buyer before receiving the final firm order, a mathematical inequality is derived that states the following: buyer’s expected total cost would never deteriorate when this extra piece of information is received. Detailed numerical analyses reveal that expected cost benefit from receiving order inventory position is significant, in some cases reaching 11%, when supply side variability is high and supplier's capacity is constrained. Our model has also introduced a novel deposit scheme that forces the buyer not to issue unrealistically high soft orders. This study reveals that to some degree, increasing the deposit for a unit soft-order increases the benefit of information sharing. Another observation is that while increasing underage cost increases the benefit of upstream information sharing, with respect to the overage cost, the effect is opposite; increasing overage cost decreases the benefit of sharing upstream information.

4.2 Research contributions

This research has taken a holistic view to explore the effect of atypical demand on both retailers as well as suppliers (facing effective capacity uncertainty). Effect of information flow (soft-order(s) and supplier's order inventory position), effect of product flow decisions (release decisions under holding cost), and effect of flow of funds (early deposit with soft-order) has been studied in a single product setting. More specifically, this research explores the questions asked in section 1.7 in a supply chain setting that is described in section 1.5. We hope that these insights can help supply chain decision makers exploit opportunities that frequently arise in atypical demand environments.

4.2.1 Contributions from supplier model

Specific contribution of this research due to the supplier model based on stochastic dynamic programming:

(i) This is the first study to explore the benefits of sharing soft-order(s) with the supplier. The study shows that both the supplier as well as the retailer benefits by sharing soft-orders.

(ii) The study also investigates the effect of soft-order accuracy, volatility (e.g., due to lead-times), and intentional inflation on benefits to both parties involved.

(iii) Sensitivity analysis reveals several structural properties of the cost-benefit trade-off of information sharing versus no sharing with managerial insights.

(iv) A production-scheduling algorithm with forecast revision and capacity uncertainty is formulated for the study. Related model from the previous research (such as Housman and Peterson 1972, Raman and Kim 2002) accounted for capacity constraint, however, did not account for capacity uncertainty. This is critical for random production yield (which we term effective capacity uncertainty) is typical in the real word (Yano and Lee 1995). The study shows that the effect of effective capacity uncertainty is significant in influencing costs for both parties.

(v) The production-scheduling model for supplier measures the holding cost more accurately than that reported in Raman and Kim (2002). Raman and Kim (2002) do not account for holding cost for the stage in which the product is produced. We estimate holding cost for the stage of production as well.

4.2.2 Contributions from buyer model

The contribution of this research due to the buyer model based on stochastic dynamic programming:

(i) This is the first time an optimal soft-order revision model for retailer facing atypical demand and supply uncertainty is presented. Fisher et al's (2001) model on optimal inventory replenishment of retail fashion products is closet to ours, but does not optimize soft-orders; their model optimizes two firm orders sent in different time-periods.

(ii) Our model prescribes optimal soft-order revision both with and without upstream supplier's inventory position information.

(iii) We have modeled production uncertainty that degenerate into supply uncertainty. This allows us to relate effect of capacity commitment on different production stages by supplier on buyer's replenishment decisions. While demand uncertainty has gained lot of attention, no literature has previously studied production inventory system that accounts for supply uncertainty simultaneously accounting for atypical demand.

(iv) We have shown that upstream information sharing improves retailer's optimal soft-order revision policy in term of expected cost.

(v) This research has shown for the first time that while soft-order inflation is optimal under certain circumstances, deflation may also be optimal.

(vi) We have devised a fair deposit scheme that is incurred to buyer while soft-ordering. This novel scheme prevents unrealistic or fake soft-orders.

(vii) Detail numerical analysis is presented that explore structural properties of optimality and managerial insights are presented.

4.3 Future research

Author believes that more research is due to study problems on supply chain management facing atypical demand scenarios and uncertain supply. Development of better and practical forecasting-production-inventory-capacity policies is due. Here, we briefly discuss a few possible areas of future research that can possibly fill the gap in the present research:

(i) Cost of information sharing: None of our models presented here have accounted for cost of information sharing. Information sharing between two companied are possible only if there is necessary infrastructure in place. In addition, colleting the information also incurs costs. In context of this research, supplier can transmit soft-order in timely manner only if a system is in place to collect it, transmit it, and be received by supplier. Similarly, order inventory position sharing needs a system to accurately count inventory and data transmission capability. Unless benefits of information sharing outweigh cost of installing these systems, information sharing is not a value proposition.

(ii) Deposit scheme: The proposed deposit scheme need more research in terms of how to find out what an appropriate deposit per unit of soft-order. More research is due to optimally devise such a deposit for a scenario presented here. More investigation is due in terms of how to model a deposit scheme if an initial soft-order is revised more than once before submitting the final order.

(iii) Inaccurate information sharing: While the supplier's model in our research study the effect of intentional soft order inflation, the retailer's model has assumed that order inventory position shared by the supplier is a true signal. More investigation is necessary to analyze the impact of supplier' sharing a wrong order inventory position.

(iv) Incentive for sharing order inventory: Present retailer model does not shed light on 'why supplier should share order information with his retailer?' While benefit of soft-order information sharing is clear to both parties, supplier as well retailer, the benefit of sharing order inventory for supplier needs more investigation.

(v) Conjoined supplier-retailer model: The present supplier's model considers soft-orders evolution process as exogenously given for the supplier. On the retailer's side, the supplier model is very simplistic; the supply uncertainty model is exogenous in our case. Future study should conjoin these two models to gain more insight related to benefit of information sharing in terms a centralized versus decentralized way of planning a two-player supply chain.

(vi) Multi-product setting: The future study should incorporate a multi product setting and explore the computational complexity of a manufacturing scheduling algorithm and retailer's soft order revision policy. In multi product setting, brute search to find the optimal release or the optimal soft-order may be extremely time consuming; more research on heuristics to solve such problem is necessary.

(vii) Supply chain cost or profit: A more detailed analysis is needed to find out the benefit of information sharing in terms of supply chain profit.

(viii) Modeling uncertainty in absence of historical data: Modeling the uncertain demand and supply environments need relevant data that is difficult to obtain. A practical question is if there exists no history to model distributions, while uncertainties do exist, how to go about making decisions. This point in our view is most important if model needs to be implemented in real world and therefore most challenging.

REFERENCES

Aviv, Y. 2003. A time-series framework for supply-chain inventory management. *Operations Research*. **51** 210-227.

Baruah, P. and R. B. Chinnam. 2006. Benefits of Sharing Order Forecasts with Manufacturers facing Capacity Uncertainty. Working Paper. Wayne State University.

Bopllapragada, R., U. Rao, J. Zhang. 2004. Managing two-stage serial inventory systems under demand and supply uncertainty and customer service level requirements, *IIE Transactions*, **36**, 73-85.

Bitran G. R., E. A. Haas, H. Matsuo. 1986. Production planning of style goods with high setup costs and forecast revisions. *Operations Research* **34**, 226–236.

Blattberg, R. and S. Neslin. 1990. Sales promotion: concepts, methods, and strategy. Prentice-Hall Inc. New Jersey.

Bradford, J. W., and P. K. Sugrue. 1990. A Beyesian approach to the two-period style-goods inventory problem with single replenishment and heterogeneous Poisson demand. *Journal of the Operational Research Society*, **41(3)** 211-218.

Cachon, G. P. and M. Fisher. 1997. Campbell Soup's Continuous Product Replenishment Program: evaluation and enhanced decision rules. *Production and Operations Management*. **6** 266-275.

Cachon, G. P. and M. Fisher. 2000. Supply chain inventory management and the value of shared information. *Management Science*. **46(8)** 1032-1048.

Cachon, G. P. and M. A. Lariviere. 2001. Contracting to Assure Supply: How to Share Demand Forecasts in a Supply Chain. *Management Science,* **47(5)** 629-646.

Chen, F. 2003. Information sharing and supply chain coordination. Handbooks in Operations Research and Management Science: Supply Chain Management: Design, Coordination and Operation. **11**. Elsevier Publishing Company.

Chen, F. 2001. Auctioning supply contracts. Working paper, Columbia University.

Chen, F. and B. Yu. 2005. Quantifying the Value of Lead-time Information in a Single-Location Inventory System. *Manufacturing and Service Operations Management*, **7(2)**, 144–151

Chopra, S. and P. Meindl. 2004, Supply Chain Management- Strategy, Plannin, and Operation., 2nd edition. Prentice Hall.

Christopher, M, R. Lowson and H. Peck. 2004. Creating agile supply chains in the fashion industry. *International Journal of Retail & Distribution Management*, **32(8/9)**, pp. 367-376.

Ciarallo, F. W., R. Akella, T. E. Morton. 1994. A periodic review, production planning model with uncertain capacity and uncertain demand - optimality of extended myopic policies. *Management Science*. **40(3)** 320-332.

Clark, T.H. and J. Hammond. 1997. Reengineering Channel Reordering Processes to Improve Total Supply Chain Performance. *Production and Operations Management*. **6(3)** 248-265.

Croson R. and K. Donohue. 2005. Information and its Impact on the Bullwhip Effect. *System Dynamics Review*, **21(3)**, 249–260.

Donohue, K. L. 2000. Efficient Supply Contracts for Fashion Goods with Forecast Updating and Two Production Modes. *Management Science*. **46(11)** 1397-1411.

Eldridge, E. 2006. Motorists can soft-order new plug-in hybrid vehicle. The Examiner, Oct 17, 2006. URL: *http://www.examiner.com*

Ehrhardt, R. and L. Taube. 1987. An Inventory Model with Random Replenishment Quantities. *International Journal of Production Research*, **25**, 1795-1803.

Eppen, G. D. and A. V. Iyer. 1997a. Improved Fashion Buying with Bayesian Updates. *Operations Research*. **45(6)** 805-819.

Eppen, G. D. and A. V. Iyer. 1997b. Backup agreement in fashion buying- The value of upstream flexibility. *Management Science*. **43(11)** 1469-1484.

Fearne, A., A. Donaldson, P. Norminton. 1999. The impact of alternative promotion strategies on the spirits category: evidence from the UK. The *Journal of Product and Brand Management*, **8(5)** 430-442.

Fisher, M., K. Rajaram, A. Raman. 2001. Optimizing Inventory Replenishment of Retail Fashion Products, *Manufacturing and Service Operations Management*, **3(3)**, 230-241.

Fisher, M. and A. Raman. 1996. Reducing the cost of demand uncertainty through accurate re-sponse to early sales. *Operations Research*. **44(1)** 87-99.

Gruen, T. W., D. S. Corsten, S. Bharadwaj. 2002. Retail Out-of-Stock: A Worldwide Examination of Extent, Causes and Consumer Response. Grocery Manufacturers of America, The Food Marketing Institute and CIES – The Food Business Forum.

Gurnani, H. and C. S. Tang. 1999. Optimal ordering decisions with uncertain cost and demand forecast updating. *Management science*. **45** 1456-1462.

Gullu, R., E. Onol., N. Ekrim. 1999. Analysis of an inventory system under supply uncertainty. *International Journal of Production Economics*, **59**, 377-385.

Heath, D. C. and P. L. Jackson. 1994. Modeling the evolution of demand forecasts with application to safety stock analysis in production/distribution systems. *IIE Transactions*. **26(3)** 17-30.

Henig, M. and Y. Gerchak. 1990. The structure of periodic review policies in the presence of random yield, *Operations Research*, **38**, 634–643.

Hausman, W. and R. Peterson. 1972. Multiproduct production scheduling for style goods with limited production capacity, forecast revisions and terminal delivery. *Management Science*. **18(7)** 370-383.

Hausman, W. 1969. Sequential Decision Problems: A Model to Exploit Existing Forecasting. *Management Science*, **16(2)**, B93-B111.

Hu, H. 2003. Advanced demand information and safety capacity as a hedge against demand and capacity uncertainty. *Manufacturing & Service Operations Management*. **7(2)** 144-151.

Hwang, J. and M. Singh. 1998. Optimal production policies for multi-stage systems with setup costs and uncertain capacity. *Management Science*. **44(9)** 1279-1294.

Jemai, Z., N. K. Erkip, Y. Dallery. 2006. Contracting under uncertain capacity. *Proceedings of International Conference on Information Systems, Logistics and Supply Chain*, May 14-17, 2006, Lyon, France.

Johnson, M. E. 2001. Learning from toys: Lessons in managing supply chain risk from the toy industry. *California Management Review*. **43(3)**, pp 106-124.

Johnson, O. and H. Thomson. 1975. Optimality of myopic inventory policies for certain dependent demand process. *Management Science*. **21** 1303-1307.

Kaminsky, P. and J.M. Swaminathan. 2001. Utilizing Forecast Band Refinement for Capacitated Production Planning. *Manufacturing & Service Operations Management*. **3(1)** 68-82.

Kandel, E. 1996 The Right to Return, *Journal of Law and Economics*, **39(1)**, 329-356.

Karabuk, S. and S. D. Wu. 2003. Coordinating Strategic Capacity Planning in the Semiconductor Industry. *Operations Research*. **51(6)** 839-849.

Karlin, S. 1958. Studies in the Mathematical Theory of Inventory and Production, University Press, Stanford, California.

Karenmen, F., G. Liberopoulos, Y. Dallery. 2004. The Value of Advance Demand Information in Production/Inventory Systems, *Annals of Operations Research*. **126**, 135-157

Kouvellus, P., and J. M. Minler. 2002. Supply chain capacity and outsourcing decisions: the dynamic interplay of demand and supply uncertainty, *IIE Transactions*, **34**, 717-728.

Kim, H., J. C. Lu, P. H. Kvam. 2004. Ordering Quantity Decisions Considering Uncertainty in Supply-Chain Logistics Operations, Working Paper, School of Industrial and Systems Engineering, Georgia Institute of Technology.

Koch, C. 2004. Nike Rebounds, *CIO Magazine*, Jul. 24, Issue 2004.

Kurt Salmon Associates. 1993. Efficient Consumer Response: Enhancing Consumer Value in the Supply Chain. Washington D.C.: Kurt Salmon Associates.

Larson, R. B. 2004. Christmas Tree Marketing: Product, Price, Promotion, and Place Tactics. *Journal of Forestry*, **102(4)**, 40-45.

Lee, H. L., Padmanabhan, V., and Whang, S. 1997. The Bullwhip Effect in Supply Chains. *Sloan Management Review*, **38**, pp. 93-102.

Lee, H., K. C. So., C. S. Tang. 2000. The Value of Information Sharing in a Two-Level Supply Chain. *Management Science*, **46(5)**, 626-643.

Lee. H. L. 2002. Aligning Supply Chain Strategies with Product Uncertainties. *California Management Review*, Spring, 105-119.

Lin, W. and V. Tardif. 1999. Component partitioning under demand and capacity uncertainty in printed circuit board assembly. *International Journal of Flexible Manufacturing Systems*. **11** 159-176.

Lin, L. C., and K. L. Hou. 2005. An inventory system with investment to reduce yield variability and set-up costs, *Journal of the Operational Research Society*, **56**, 67-74.

Liu, Q and G. Ryzin. 2005. Strategic Capacity Rationing to Induce Early Purchases. Working Paper. Columbia Business School.

Matsuo, H. 1990. A Stochastic Sequencing Problem for Style Goods with Forecast Revisions and Hierarchical Structure. *Management Science*, **36(3)**, 332-347.

Metters, R. 1998. General rules for production planning with seasonal demand. *International Journal of Production Research*. **36(5)** 1387-1399.

Mohebbi, E. 2004. A replenishment model for the supply-uncertainty problem. *International Journal of Production Economics*, **87**, 25-37.

Murray, G. R. and E. A. Silver. 1966. Bayesian analysis of the style goods inventory problem. *Management Science* **12**: 785–797

NCTA. 2002a. Quic Tree Facts. *www.realchristmastrees.org*

NCTA. 2002b. Industry Statistics. *www.realchristmastrees.org*

Ozer, O. and W. Wei. 2004. Inventory Control with Limited Capacity and Advance Demand Information. *Operations Research*. **52(6)**, 988-1000.

Parlar, M., and D. Berkin. 1991. Future supply uncertainty in EOQ models, *Naval Research Logistics*, **38**. 107–121.

Parlar, M., Y. Wang, Y. Gerchak. 1995. A periodic review inventory model with Markovian supply availability: Optimality of (S, s) policies, *International Journal of Production Economics*, **42**, 131–136.

Padmanabhan, V. and I. P. L. Png. 1995. Returns Policies: Make Money by Making Good, *Sloan Management Review*, **37(1)**, 65-72.

Raghunathan, S. 2001. Information sharing in a supply chain: A note on its value when demand is non-stationary. *Management Science*. **47(4)** 605-610.

Raman, A. 1999. Managing inventory for fashion products. Quantitative Models for Supply Chain Management. S. Tayur, R. Ganeshan, and M. Magazine, eds. Kluwar Academic Publishers.

Raman, A. and B. Kim. 2002. Quantifying the impact of inventory holding cost and reactive capacity on an apparel supplier's profitability. *Production and Operations Management*. **11(3)** 358-373.

Reinmuth, J. E. and M. D. Geurts. 1972. A Bayesian Approach to Forecasting the Effect of Atypical Situations. *Journal of Marketing Research*. **9(3)** 292-297.

Rozhon, T. 2005. Before Christmas, Wal-Mart was stirring. http://www.nytimes.com/

Sahin, F. and E. W. Robinson. 2002. Flow coordination and information sharing in supply chains: Review, implications, and directions for future research. *Decision Sciences*. **33(4)** 505-536.

Shih, W. 1980. Optimal Inventory Policies When Stock outs Result From Defective Products. *International Journal of Production Research*, **18(6)**, 677-685.

Silver, E. A. 1976. Establishing the order quantity when the amount received is uncertain. *INFOR*, **14(1)**, 32-39.

Simchi-Levi and Y. Zhao. 2004. The Value of Information Sharing in a Two-stage Supply Chain with Production Capacity Constraints: The Infinite Horizon Case. *Probability in the Engineering and Informational Sciences*. **18(2)**, 247-274.

Smith, S. A. and D. D. Achabal. 1998. Clearance pricing and inventory policies for retail chains. *Management Science*. **44(3)**, 285-301.

Swaminathan, J., N. M. Sadeh, and S. F. Smith. 1997. Effect of Sharing Supplier Capacity Information. Working Paper. University of California, Berkeley and Carnegie Mellon University, Pittsburgh.

Tenser, J. 1997. Procter Gamble Revamps Retail Incentives (Streamlined '97 initiative to improve efficiencies), *Supermarket News*, **1**.

Terwiesch, C., Z. J. Ren, T. H. Ho and M. A. Cohen. 2005. An Empirical Analysis of Forecast Sharing in the Semiconductor Equipment Supply Chain. *Management Science*. **51(2)** 208-220.

Tokay, L. B. and L.. M. Wein. 2001. Analysis of a forecasting-production-inventory system with stationary demand. *Management Science*. **47(9)** 1268-1281.

Vollmann, T, W. L. Berry, and D.C. Whybark. 1997. Manufacturing Planning and Control Systems, 4th edition. Irwin/McGRaw-Hill, Boston, Massachusetts.

Wang, Y. and G. Yigal. 1996. Periodic review production models with variable capacity, random yield, and uncertain demand. *Management Science*. **42(1)** 130-137.

Wong, C. Y., J. S. Arlbjorn, and J. Johansen. 2005. Supply Chain Management Practices in toy supply chains. *Supply Chain Management*, 10(5), pp. 367-376.

Wu, K. and I. Lin. 2004. Extend (*r*, *Q*) Inventory Model Under Lead Time and Ordering Cost Reductions When the Receiving Quantity is Different from the Ordered. *Quality & Quantity* **38**, 771–786.

Yang, S. and L. Malek. 2004. Multi-Supplier Sourcing with Random Yields: A Newsvendor Approach. Working Paper. Seton Hall University, NJ and New Jersey Institute of Technology, NJ, USA.

Yano, C. A., and H. L. Lee. 1995. Lot sizing with random yields: A review, *Operations Research* **43**, 311–334.

VICS. 2004a. CPFR- An Overview. URL: http://www.vics.org/

VICS. 2004b. Retail Event Collaboration- Business Process Guide. URL: http://www.vics.org/

ABSTRACT

SUPPLY CHAINS FACING ATYPICAL DEMAND: OPTIMAL OPERATIONAL POLICIES AND BENEFITS UNDER INFORMATION SHARING

by

PUNDARIKAKSHA BARUAH

December 2006

Advisor: Dr. Ratna Babu Chinnam

Major: Industrial Engineering

Degree: Doctor of Philosophy

Demand patterns for products with seasonality and or short life-cycles do not follow a clear discernible pattern (to allow predictive time-series modeling of demand) for individual sales events or seasons due to such factors as considerable demand volatility, product promotions, and unforeseen marketplace events. Suppliers supporting such *atypical* demand patterns typically incur higher holding costs, lower capacity utilization, and lower order fill-rates, particularly under long lead-times and uncertainty in *effective capacity*. Retailers on the other hand struggle with product overages and supply shortages. On the other hand, atypical demand settings bring huge financial opportunity to supply chain players, and are pervasive. It is suggested in the literature that an effective means to reap these benefits is through increased information sharing between retailers and suppliers, superior forecasting with forecast update techniques, proper replenishment, and custom designed inventory/manufacturing policies. We also believe that sharing of order forecasts, also known as *soft-orders*, in advance by the buyer could be beneficial to both parties involved.

This dissertation in particular studies a two-player supply chain, facing atypical demand. Among the two-players is a buyer (retailer/distributor/vendor) that makes ordering decision(s) in the presence of upstream supply uncertainty and demand forecast revision(s). We propose a stochastic dynamic programming model to optimally deicide on soft-order(s) and a final firm-order under a deposit scheme for initial soft-order(s). While sharing of upstream soft-order inventory position information by the supplier before receiving a final order is not a common industrial practice, nor is it discussed in the literature, our analysis shows that such information sharing is beneficial under certain conditions.

Second player of the supply chain is a supplier (manufacturer) that makes production release decision(s) in the presence of limited and random effective capacity, and final order uncertainty. Our stochastic dynamic programming model for optimal production release decision making reveals that substantial savings in order-fulfillment cost (that includes holding, overage, and underage costs) can be realized in the presence of advance soft-order(s). Soft-orders can also be shown to improve order fill-rate for the buyer.

This research explores complex interactions of factors that affect the operational decision making process, such as costs, demand uncertainty, supply uncertainty, effective capacity severity, information accuracy, information volatility, intentional manipulation of information etc. Through extensive analysis of the operational policies, we provide managerial insights, many of which are intuitively appealing, such as, additional information never increases cost of an optimal decision; many are also counterintuitive, for example, dynamic programming models cannot fully compensate for intentional soft-order inflation by the buyer, even under conditions of a stable and linear order inflation pattern, in the absence of deposits.

AUTOBIOGRAPHICAL STATEMENT

NAME: PUNDARIKAKSHA BARUAH

EDUCATION

Ph.D. (Industrial Engineering): Wayne State University, U.S.A, 2006.

B.S. (Mechanical Engineering): National Institute of Technology, Mangalore, India, 2000.

RESEARCH AND DEVELOPMENT EXPERIENCE

09/01 – 04/02 Rumble Research Fellow, Wayne State University

04/02 – 04/06 Graduate Research Assistant, Wayne State University

04/06 – 08/06 Summer Dissertation Fellow, Wayne State University

08/06 – 12/06 Graduate Teaching Assistant, Wayne State University

INDUSTRY EXPERIENCE

08/00 – 08/01, Management Trainee, Ministry of Commerce, India

04/02 – 04/03 Ford Motor Company and WSU Collaborative project, MI

ACADEMIC ACTIVITIES

Founder, Industrial Eng. Annual Graduate Research Symposium

Lead Organizer, 1st Industrial Eng. Graduate Research Symposium, 2006.

PROFESSIONAL MEMBERSHIP

INFORMS, ASQ, IEEE

AWARDS

Thomas C. Rumble Fellowship, 2001-2002

ASQ Essay Writing Award, 2006

IEEE Travel Grant, 2006

Summer Dissertation Fellowship, 2006

PUBLICATIONS

I authored papers in International Journal of Production Research, International Journal of Material and Product Technology, International Journal of General Systems and in referred conference proceedings of IEEE, MFPT, FAIM, ISSAT-RQD etc.