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SIMULATION OF THE IMPACT OF FORECASTING ACCURACY ON SUPPLY CHAIN PERFORMANCE: THE BIAS EFFECT

By

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ABSTRACT

SIMULATION OF THE IMPACT OF FORECASTING ACCURACY ON SUPPLY CHAIN PERFORMANCE: THE BIAS EFFECT

By

Alexandre Medeiros Rodrigues

Historically, most firms have operated in an anticipatory manner. Today, supply chain design focuses on agility and responsiveness. Regardless, forecasts are often still necessary because of longer and more uncertain lead times, service requirements, and capital constraints.

This dissertation investigates the impact of Forecasting Accuracy on Supply Chain Performance. Specifically, this research evaluates the effects of Forecast Bias, Forecast Skewness, Transit Lead Time Variability, and Demand Variability on Order Fill Rate, Case Fill Rate, and Average System Inventory.

Results from dynamic simulation experiments indicate that Forecast Bias is the primary factor, substantially affecting all performance measures. This impact is amplified at higher levels of demand and transit lead time variability. Lead Time Variability has a substantial impact on service, while Forecast Skewness has medium impact on inventory. Additionally, results suggest a trade-off impact of Forecast Bias on service and inventory.

Managerial guidelines are developed after a cost trade-off analysis is conducted. The framework identifies acceptable levels of Forecast Bias, and advises which actions can be taken to control and minimize its effects.

Dedicated to my wife and soul mate ***Moema***
for her love, time, support, and encouragement.

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1 Introduction

Forecasting can be formally defined as the method for predicting the future by extrapolating information from the past. In business, it is a process that synthesizes the quantitative and qualitative information from different functional departments to generate a prediction of periodic sales for the firm as a whole. Each forecast represents a prediction or estimate of the actual demand volume for a future period. Supply chain decision makers particularly need forecasts to plan for future uncertainty. Forecasts are critical to firm functions, including financial planning, facility openings and closings, new equipment purchases, production schedules, raw materials procurement, staffing allocation, and marketing planning.

Historically, most firms have operated their supply chain in an anticipatory basis. Products are produced to meet sales forecasts and are moved through the distribution channel in anticipation of end-customer requirements. Such a speculative strategy is used to achieve effective economies of scale. Increasingly, however, specific product requirements are difficult to forecast, due primarily to greater complexity in product offerings and supply chain alternatives. Today, supply chain design focuses on agility and responsiveness to reduce the need to forecast consumer demand. Partnerships, information sharing, and automation can also be used to reduce supply chain uncertainty and allow rapid flow of information and physical goods.

Even though companies are moving toward responsive supply chains, forecasts are often still necessary. Decisions about product acquisition, manufacturing, and transportation must be made prior to demand, so that customers can have instant product availability where and when desired. Longer and more uncertain lead times result in a greater need for demand forecasts. Responsive systems also require extensive coordination and information exchange between supply chain partners. Service requirements and capital constraints can limit a firm's ability to move from an anticipatory to a responsive system, and forecasting thus continues to be relevant for today businesses.

The primary objective of this dissertation is to investigate the impact of Forecasting Accuracy on supply chain performance. The ultimate test of any forecast is how it supports supply chain performance. Decision makers have a wide choice of ways to forecast, ranging from purely intuitive or judgmental approaches to highly structured and complex quantitative methods. Forecasting Accuracy is defined here as the difference between a specific forecast and corresponding customer demand. The goal of any forecasting process is to minimize this difference.

History shows that decision makers tend to develop predictions that are systematically lower or higher than actual demand. This is generally called Forecast Bias. It occurs because even when systematic methods are used, planners and managers often refine the generated forecasts, based either on their perceptions regarding the business environment or on a mean that will enhance their performance metrics.

Although the impact of Forecast Accuracy has been examined in the manufacturing literature, it has received less attention from logistics and supply chain researchers. It is important to understand the impact of different patterns of Forecast Accuracy in a supply chain environment, where complexity and dynamics are greater than in a single manufacturing system. It is also important to examine the impact at different levels of supply chain uncertainty.

Specifically, the primary research objective is to investigate how Forecast Bias affects supply chain service and inventory. This will be studied under different customer demand patterns and transit lead time scenarios. As a secondary objective, managerial guidelines are developed to suggest ways to reduce or manage bias in forecasts. Acceptable levels of Forecast Bias will be identified, and actions to control and minimize its effects will be described.

This introductory chapter covers a number of topics. First, it characterizes the role of forecasting in supply chain management and defines the boundaries of the study. Second, it explains why forecasting issues are important for not only supply chain researchers but also practitioners. Third, the chapter details the concept of Forecasting Accuracy and introduces the notion of Forecast Bias. Fourth, research objectives and specific research questions are reviewed. Fifth, the research procedure is presented. Finally, the potential contributions of this dissertation are noted.

1.1 What Is Forecasting?

Forecasting can be formally defined as the process for predicting the future by extrapolating information from the past (Morton 1999). It transforms historical time-series data and/or qualitative assessments into a prediction of future events. The process combines quantitative, analytical data with qualitative, subjective inputs. As a result of this process, forecasts are generated. Each forecast represents a prediction or estimate of an actual value in a future period. The more effectively quantitative and qualitative information are combined, the better the quality of the generated forecasts.

Planning is an integral part of decision making, but uncertainties make it quite difficult to plan effectively. Forecasts can help reduce some of the uncertainty, which enables managers to develop more meaningful plans than they might otherwise. Another reason to use forecasts is that, in general, there is a delay of time between awareness of an event and its occurrence. This lead time is the main reason for planning on an anticipatory basis. If the lead time is zero or very small, there is no need for planning. If the lead time is long or uncertain, planning can perform an important role. In such situations, forecasting is needed to determine when an event will occur or a need will arise, so that appropriate actions can be taken beforehand (Makridakis et al. 1983).

Different classifications are used to categorize forecasting approaches, based on either the time horizon (the period covered by the forecast) or the underlying method used. In terms of time horizon, the common categories are long term, intermediate term and short term (Martinich 1997). Short term forecasts usually look no more than three months ahead. They are used for tactical decision making, such as job sequencing and production scheduling, machine assignments, personnel scheduling, purchasing and inventory planning, and maintenance planning. Intermediate term forecasts have a time frame of three months to two years. They are commonly used for aggregate production planning, including decisions that alter short-term production capacity, such as subcontracting and overtime. Long term forecasts usually cover two to five years. Their most common use is for planning the introduction of new products and major capital expenditures.

Makridakis & Wheelwright (1989) propose a forecast classification according to the underlying method used: qualitative (subjective), quantitative (objective) and technological. Qualitative (subjective) methods are based on human judgment. Such forecasts are most often made by individuals or by committee agreements. Quantitative (objective) methods employ formulas based on historical patterns and relationships to develop forecasts. Technological methods address long term issues of a technological, societal, economic, or political nature.

Table 1 lists the forecasting methods most commonly used and major areas of business where they are applied. Despite differences, the various methods share certain characteristics (Stevenson 1990). First, all assume that the same underlying causal system will continue to exist in the future, as historical data are generally the starting point. Second, all admit that forecasts are rarely perfect and allowances should be made for inaccuracies. Third, all agree that forecasts tend to be more accurate for groups of items than for individual items because forecast errors among groups of items cancel one another. Finally, all concur that forecast accuracy decreases as the time horizon increases. Shorter range forecasts are typically more accurate than longer range forecasts less uncertainty is involved.

			Major Area of Business Aplication																			
									Sales													
									Aggregate			Disaggregate										
Forecasting Method			Production Planning	Production Scheduling	Inventories	Material Requirements	Personnel Scheduling	Personnel Planning	Short Term	Medium Term	Long Term	Short Term	Medium Term	Long Term	Pricing	Advertising and Promotion	Annual Budgeting	New Products	R&D Projects	Capital Budgeting	Competitive Analysis	Strategy
Quantitative	Time Series	Naive			X							X			X							
		Smoothing	X	X	X	X	X	X				X										
		Decomposition	X	X			X	X		X			X				X					
		Autoregressive Moving Average	X	X			X	X	X													
	Explanatory	Vector Autoregressive							X	X					X	X	X					
		Regression							X	X					X	X	X					
		Econometrics							X	X					X	X	X					
	Monitoring Approaches			X	X	X	X					X										
Qualitative	New Products Forecasting								X	X	X				X	X	X	X	X		X	X
	Individual	Individual Judgment	X				X		X	X	X				X	X	X	X	X	X	X	X
		Decision Rules		X	X	X	X															
	Group	Sales Force Estimates										X	X				X					
		Juries of Executive Opinion								X					X	X	X	X	X	X	X	X
		Role Playing																			X	
	Aggregate	Anticipatory Surveys								X							X					
		Market Research										X	X		X	X		X	X			
		Pilot Programs and pre-Market Tests										X	X	X	X	X		X				
Technological	Extrapolative	Growth Curves												X					X	X	X	X
		Time-independent Comparisons												X					X	X	X	X
		Historical and other Analogies												X					X	X	X	X
	Expert Based	Delphi											X					X	X	X	X	
		Futurists											X					X	X	X	X	
		Cross-impact Matrices											X					X	X	X	X	

Table 1 - Classification of Forecasting Methods (Makridakis & Wheelwright 1989)

Forecasting methods are applied in a number of business areas, but the generation of sales estimates is especially important. These forecasts attempt to predict customer demand either in an aggregate (sales by region, by state, by family of products) or disaggregate way (sales by specific products for specific customers). The information is important because it drives different operational processes across the company. Marketing, for example, predicts sales for new product lines in order to make strategic plans, and forecasts for existing product lines in order to provide feedback on whether current sales techniques are working well. Production and operations managers need forecasts for both product line and individual stock-keeping units (SKU) to order raw materials, plan and schedule production, and plan warehousing and deployment of finished goods.

The primary focus of this dissertation is short term business demand forecasting, but there is no emphasis on any specific method. As previously stated, the process commonly involves different departments of the organization and combines alternative approaches to generate forecasts. Decision makers then generally modify the estimates to reach a final forecast. Because the process is complex, this dissertation focuses on the final forecast, the estimate generated in the last step of the entire process. Specifically, our interest is in the accuracy of the forecasting process.

Forecasting Accuracy can be defined as the difference between the forecast value and the actual value. It can be understood as a measure of forecast error. Forecasting processes differ depending upon how the company uses the information, departments involved, and the approaches used. Each process will result in a different accuracy level. Also, accuracy is affected by the time horizon, the rate of technological change in the industry, entry barriers to the industry, the rate of information dissemination, demand characteristics, industry characteristics, the availability of historical data, and even the ability of decision makers to use forecasting methods correctly. The assumption in this dissertation is that each process, no matter how simple or complex, will generate a specific pattern of Forecasting Accuracy. For our purposes, the choice of forecasting method is not important. In this research, what is important is the effect of different patterns of errors.

1.2 The Relevancy of Forecasting

In the past, firms relied heavily on forecasts to drive planning. Most operations were designed on an anticipatory basis, and most activities were initiated before demand occurred. By planning in advance, firms can allocate resources and design operations in a cost efficient way, achieving economies of scale. This strategy operates well when demand is somewhat predictable, but the anticipatory model is not the best in all situations. Throughout the 1980s, IBM downplayed the personal computer market and maintained its focus on mainframes, which cost it a large part of market share before it modified that strategy. Similarly, in the 1960s and 1970s, the U.S. automotive industry underestimated the competitive threat of imported cars, which were smaller, more fuel efficient, highly reliable, and inexpensive. Detroit lost market share dramatically. In both cases, the anticipatory model was not able to adapt to the dynamic market.

To reduce the need to forecast consumer demand, many firms are enhancing supply chain agility and responsiveness. By improving relationships among supply chain partners (customers, suppliers, service providers) and investing in measurement and information systems, companies are creating highly responsive logistical operations and are reducing levels of anticipatory inventory so that they can meet increasing demand for customization.

Bowersox et al. (1999) identify this trend in a comprehensive study that relates supply chain competencies to firm performance. The competencies reflect integration and relationship management among supply chain partners, investment in technology and planning systems, and measurement systems development. There is evidence that firms with higher levels of delivery speed and inventory turn demonstrate higher performance levels.

These results might imply that all supply chains should move from an anticipatory (push) system, which seeks to supply predictable demand efficiently at the lowest possible cost, to a responsive (pull) system, which focuses on quick response to unpredictable demand in order to maximize sales. The responsive system reduces the need for reliance on forecasts, but variations in product demand patterns and consumer requirements make it impossible to prescribe one solution for all supply chains.

Fisher (1997) presents a conceptual framework for improved management by suggesting a match between product demand characteristics and supply chain capabilities. He proposes that products fall into two main categories: *functional* products have long life cycles, low profit margins, and stable demand; *innovative* products have short life cycles, high profit margins, and unstable demand. In his framework, *push* systems better match *functional* products, and *pull* systems better match *innovative* products. Hirakawa et al. (1992) support the relationship between product type and forecasting needs. In their article, although limited to a manufacturing environment, the authors propose a hybrid solution between *push* and *pull* supply chain systems to attain a higher degree of effectiveness.

Financial constraints may prevent the move from an anticipatory to a responsive supply chain design, which involves substantial capital investments. Responsive systems not only are technically sophisticated in terms of planning but also are information dependent, both internally as well as externally to the company. The advantage of the anticipatory model, at least in a stable and predictable demand environment, is the ease of operational planning and the minimal information needed to operate it.

Lead time constraints also may limit the ability of a company to operate in a responsive manner. There are lead times associated with the purchase of raw material, manufacture of goods, and transportation to end customers. Many companies have operations around the world, which increases not only lead times but also supply chain uncertainty. In this case, they cannot simply wait for demand to emerge and then react to it. Instead, they must anticipate and plan so that they can fill customer orders immediately. This is true even when efforts to reduce uncertainty and increase agility and responsiveness are implemented. The longer and more uncertain the lead time, the more important is an accurate forecast of customer demand.

One implication of the preceding discussion is that firms should have a combination of supply chain operations (anticipatory and responsive) to accommodate requirements for different product types, capital investment constraints, uncertainty and long lead times.

Furthermore, researchers continue to maintain the relevancy of forecasting in today's business environment. Makridakis et al. (1983), for example, believe that organizational complexity (number of markets and products) and dynamic environments (changes in technology and demand structures) make it more difficult for decision makers to see ahead, which highlights the importance of accurate forecasts and planning.

Mentzer (1999) develops a model of the impact of improved forecasting accuracy on shareholder value. Unless accurate forecasts can be translated into higher levels of customer service and lower supply chain costs, they have little influence on corporate profitability. The model translates forecasting accuracy into improved operational plans and execution and improved service to customers. The former results in lower costs per dollar and the latter results in increased sales.

In a more recent work, Lapide (2000) maintains that closer supply chain relationships and information sharing do not eliminate the need for forecasts. His primary point is that integration may reduce, but will not totally eliminate uncertainty. This opinion is shared by Parker (2001), who offers a managerial perspective on forecasting. He supports the view that although companies are migrating toward responsiveness, forecasting is still needed. The goal, according to him, is not to optimize the supply chain but to obtain better information from distribution channels.

There is also empirical evidence of a relationship between forecasting improvements and improved performance. Lee et al. (1993), for example, present the effects of forecast errors on the total cost of operations. Results from a study by Teach (1993) point to a strong connection between the ability to predict outcomes and the firm's performance. Shoesmith & Pinder (2001) provide additional evidence that improvements in forecasting lead to cost reductions. Richardson & Hicks (2003) provide a number of examples on how improved forecasting and inventory management can yield substantial supply chain performance improvements.

In summary, forecasting is still an important part of business decision making. Specific requirements for different product types imply that firms should have a combination of anticipatory and responsive supply chain operations. Even with increasing pressures for supply chain agility, forecasts are still needed. They are particularly relevant for operations with relatively long lead times and great uncertainty. In addition, there is both theoretical and empirical evidence for the association between improved forecasting accuracy and better performance.

1.3 Forecasting Accuracy: The Importance of Bias

The most important test for a forecasting model is Forecasting Accuracy (Armstrong 1985), commonly termed as forecast error, or the difference between estimates and actual values. Alternative measures of Forecasting Accuracy are used in the literature, and each captures different information. A single measure of accuracy may not be adequate, since each one makes an assumption regarding the loss function, which relates forecast error to its associated cost effect.

Table 2 offers mathematical definitions for the most common measures of Forecasting Accuracy. A consistent notation is used, assuming that forecasts are intended to predict customer demand: *D* is actual demand, *F* is the forecast, *t* is the time interval, and *n* is the number of periods in the forecast horizon.

Forecasting Accuracy Measure	Mathematical Definition
Mean Error (ME)	$\sum_{t=1}^{n}(D_t - F_t)/n$
Mean Absolute Deviation (MAD)	$\sum_{t=1}^{n}\lvert D_t - F_t\rvert/n$
Root Mean Square Error (RMSE)	$\sqrt{\sum_{t=1}^{n}(D_t - F_t)^2 / n}$
Mean Percentage Error (MPE)	$\sum_{t=1}^{n}[(D_t - F_t)/D_t](100)/n$
Mean Absolute Percentage Error (MAPE)	$\sum_{t=1}^{n}[\lvert(D_t - F_t)/D_t\rvert(100)]/n$

Table 2 – Common Measures of Forecast Error

The Mean Error (ME), also referred to as bias, is primarily a test of systematic error, that is, a tendency to forecast systematically values that are either greater or less than actual demand. It should not be used alone because it provides no measure of error variance, the extent of dispersion of errors around the mean.

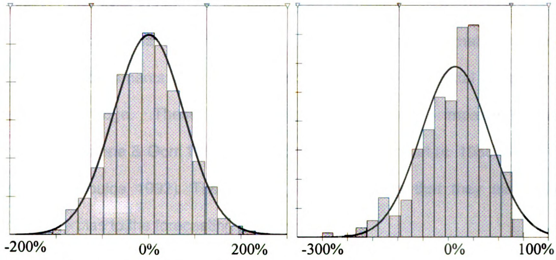
The Mean Absolute Deviation (MAD) reflects the typical error. It does not distinguish between variance and bias, and it is appropriate when the cost function is linear.

The Root Mean Square Error (RMSE) is very similar to MAD but is preferred when a quadratic loss function is assumed.

The Mean Percentage Error (MPE) and the Mean Absolute Percentage Error (MAPE) are, respectively, similar to ME and to MAD, but they are measured in percentage terms. Both are appropriate when the cost of errors is more closely related to the percentage error than to the unit error.

Additional accuracy measures exist in the literature and are primarily modifications of these common formulations. All attempt to summarize the performance of the forecast method, and none is perfect. Each fails to capture all dimensions of the difference between forecasts and actual demand.

One way to overcome this limitation is to analyze the histogram of forecast errors. A histogram is a bar chart representing a frequency distribution. The x-axis represents values, and the y-axis represents observed frequencies. The forecast error histogram is built by calculating a measure of error for each time interval and plotting them in one graph. Figure 1 provides two hypothetical histograms of Percentage Errors, defined as the difference between the actual and the forecast demand divided by actual demand. Each histogram provides complete information regarding errors patterns, including systematic errors, variance, and symmetry. An analysis of histograms helps minimize the limitations of using a single measure.



Case 1: Unbiased Forecasts
Mean = 0, Mode = 0
Standard Deviation = 0.65
Skewness = 0

Case 2: Biased Forecasts
Mean = -0.35, Mode = 0
Standard Deviation = 0.65
Skewness = -0.6

Figure 1 – Examples of Histograms of Percentage Errors

In the first case in Figure 1, there is an equal probability that the percentage errors will be either positive (underestimate demand) or negative (overestimate demand). The average error of zero means that errors tend to cancel one another, and there is no tendency to inflate or deflate forecast numbers, when compared to actual demand. In the second case, the mean of the distribution is -35%, so there is a systematic tendency for the forecast to be greater than actual demand.

In this dissertation, the focus is on the impact of different profiles of Forecasting Accuracy, represented as different distributions of forecast errors. Specifically, we are primarily interested in Forecast Bias (the mean of the distribution), which commonly occurs in business (Goodwin & Wright 1994). Anderson & Goldsmith (1994), found systematically biased decision making by business executives in nearly every industry studied.

The most probable sources for bias in forecasts are internal. In general, judgmental adjustments are made to incorporate environmental or product-specific knowledge. These subjective revisions potentially improve forecast accuracy (Carbone & Gorr 1985; Donihue 1993; Lawrence et al. 1985; Mathews & Diamantopoulos 1992). There is empirical evidence that they also bring undesirable bias to the forecasting process.

In a survey of 134 executives, Dalrymple (1987) found that the majority of companies used subjective forecasting methods. Fildes (1991), in controlled laboratory experiments, observed systematic bias during forecast formulation. Sanders (1992) and Lawrence et al. (2000) also found that judgment creates biased forecasts. Sanders & Manrodt (1994) surveyed 500 companies, and 80 percent of respondents relied on such adjustments. Furthermore, 70 percent of the managers underestimated demand. The direction of bias, however, depends on the forecaster's role in the company (Cyert & March 1961). The use of judgmental adjustments also varies by industry type or firm specifics (Mentzer & Cox 1984; Parkash et al. 1995). Consumer product firms tend to use more quantitative methods than do industrial firms (Kahn & Mentzer 1995).

It appears that judgmental adjustments can improve forecasts under certain conditions. Forecasting performance is influenced by such variables as the desirability, imminence, time period, and perceived controllability of the event to be forecast (Wright & Ayton 1986). On the other hand, judgment is better than quantitative techniques at estimating the magnitude, onset, and duration of a temporary change. Quantitative methods provide superior performance during periods of no change, or constancy, in the data pattern (Sanders & Ritzman 1991).

In addition to judgmental adjustments, other possible internal causes for bias are the reward system (bonuses or salary increments) and company politics. If departments are rewarded strictly on a revenue basis, forecasts tend to be systematically higher than actual demand. The rationale is that optimistic estimates will protect sales from possible stockouts. If the reward system is based on cost efficiency, forecasts tend to be closer to or less than actual demand. The rationale is that conservative predictions accommodate sales at the minimum total cost. Political pressures on the forecasting process can lead to unrealistic goals (Chase 1992; O'Clock & O'Clock 1989). This is evident when decision makers develop forecasts based on enterprise or corporate needs rather than actual market conditions. A good example is the pressure from stockholders for financial target results.

External factors, such as stockouts and promotions, also may create bias in forecasts. Wecker (1978), for example, found a direct relationship between stockouts and bias. The greater the stockout, the higher is the downward bias in the sales forecast.

In summary, the literature provides support for a match between product characteristics and supply chain type (anticipatory and responsive). Even with increasing pressures for supply chain agility, forecasts are still necessary. Forecast Bias is an important dimension to consider when investigating Forecast Accuracy, as it is common in business environments due to internal or external causes. There is little information, however, concerning the effect of bias on supply chain performance. In addition, there is a gap in the literature regarding the influence of different distributions of forecast error. Histograms can be a better representation of Forecasting Accuracy as compared to single measures of accuracy.

1.4 Research Objectives

The primary objective is to investigate the impact of Forecast Bias on Supply Chain performance. Two dimensions of performance are considered: customer service, measured by fill rates, and average system inventory. Specifically, this research investigates the influence of accuracy under different contexts of uncertainty, on daily customer demand and on transit lead times.

This primary objective results in four specific research questions. Each question is presented and discussed below.

The impact of different profiles of forecast errors has been investigated in the manufacturing literature. Rresearch suggests that Forecast Bias and Forecast Variability affect manufacturing performance in different ways. On a histogram of forecast percentage errors, the mean value of the distribution represents the level of Forecast Bias. This is a typical or central value that best describes the error pattern. Forecast Variability, commonly measured as the variance or standard deviation of the histogram, refers to the extent of dispersion of forecast errors around the mean. Studies have found that the impact of bias is relatively larger than the impact of variability. This suggests that different profiles of Forecast Accuracy (different histograms of forecast error) may affect supply chain performance in different ways.

The relationship between bias and variability has been researched. The focus here is on a different dimension of the histogram distribution of forecast errors: skewness. Skewness is a measure of symmetry or, more precisely, the lack of symmetry. A distribution is symmetric if it is equally divided to the left and right of the center point. In our case, the center point is the average of forecast errors, or simply the level of Forecast Bias. Therefore, we are interested in the relative influence of Forecast Bias and Forecast Skewness on performance.

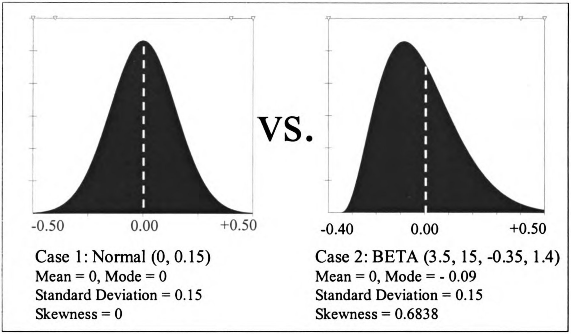


Figure 2 - Examples of Different Skewness Patterns

Figure 2 illustrates the previous discussion. Suppose that two different patterns of forecast percentage errors are plotted in histograms. In the first case in Figure 2, the profile of errors follows a Normal distribution, with a mean of 0% and a standard deviation of 15%. Notice that errors are distributed in a symmetric way around the mean. There is no Forecast Bias in this case, as the average value is zero, and there is equal probability for a forecast to be either greater than or lesser than actual demand. In the second, the error distribution follows a generalized form of the Beta distribution. It also has a mean of 0% and a standard deviation of 15%. In contrast to the first case, there is a higher probability that percentage errors will be lower than the average. Although the two cases have the same measures of central tendency (mean) and variability (standard deviation), their histograms reveal two distinct patterns. It is expected that these two patterns will affect operations and ultimately performance in different ways.

This dissertation will explore the relative impact of different forecast Percentage Error distributions on performance. Specifically, the first research question is: What are the impacts of Forecast Bias on supply chain performance, compared to the impacts of Forecast Skewness?

In addition, there is a need to evaluate any interaction between Forecast Bias and Forecast Skewness. In Figure 2, for example, the two distributions have the same mean and standard deviation. Does the impact of bias on performance change with the skewness of the distribution? It is possible that at higher degrees of skewness the impact of bias is amplified. Therefore, the second research question is: Are there any significant interaction effects between Forecast Bias and Forecast Skewness?

Earlier, the concept of a fit between product characteristics and supply chain design was presented. This notion implies that, the relative importance of forecasts differs with the level of uncertainty in demand and operations. It is expected that the impact of Forecast Accuracy on performance will be amplified for products with higher variation in daily requirements. Thus, the third research question is: In what circumstances and to what extent does the variability in daily demand offset or compound the impacts of Forecast Bias and Forecast Skewness?

The last research question considers the impact of Forecast Bias and Forecast Skewness under different levels of lead time variability. As previously discussed, as companies go global, transit lead times tend to be longer and more uncertain. The relative impact of Forecast Bias and Forecast Skewness on performance is potentially different at lower and higher levels of transit lead time uncertainty. The final research question is: In what circumstances and to what extent does the variability in transit lead times in the supply chain network offset or compound the effects of Forecast Bias and Forecast Skewness?

The second major objective of this dissertation is to generate guidelines that can help executives determine the relative influence of Forecast Bias under different levels of customer demand and transit lead time variability. Such insight can enhance supply chain performance through better forecasting by prescribing when efforts to reduce or eliminate Forecast Bias should be pursued.

1.5 Research Procedure

It is difficult to isolate the parameters characterized in the research questions in actual business systems due to the many interactions and lack of control. This research requires a controlled environment under which experiments can be conducted and evaluated. The analysis of actual operations or a survey study could not provide the experimental environment or the necessary level of control.

This research uses simulation methodology, as it is capable of representing controllable environments and of modeling stochastic uncertainty. General system characteristics are translated to a conceptual model that captures common operations typical of the consumer electronics industry. Using the Arena simulation package, a model is developed and validated with realistic parameters.

A full factorial design is conducted, with data collected from 30 replications of 150 treatments, from combinations of 4 factors (Demand Variability, Lead Time Variability, Forecast Bias and Forecast Skewness). As performance variables, Order Fill Rate, Case Fill Rate, and Average System Inventory are recorded.

The statistical technique of multivariate analysis of variance (MANOVA) is employed to analyze collected data for hypotheses testing.

1.6 Potential Contributions

The primary research contribution is a better understanding of how Forecasting Accuracy, and specifically Forecast Bias and Forecast Skewness, impact supply chain performance. This investigation is conducted for different levels of demand and transit lead time, which have not yet been explored in the literature.

The secondary research contribution is a set of managerial guidelines to provide insights regarding the benefits of reduced Forecast Bias. Specifically, a framework is provided to guide management efforts. This framework can be cost effective, as capital investments are required to improve forecast accuracy through management training and data collection equipment.

1.7 Organization of Chapters

This introductory chapter has stated the primary issues and the relevancy of the research, as well as specific research questions and potential contributions.

In chapter two, the literature will be reviewed from three perspectives. The first section addresses general forecasting research. The second section covers the role of forecasting in supply chain management. The final section reviews previous applications of simulation methods. At the end of the chapter, formal hypotheses are presented.

Chapter three discusses research methods. First, the conceptual model is presented. Second, the simulation environment is described. Third, details of the experimental design, including experimental factors, fixed parameters, and performance variables, are presented. Finally, the data analysis technique is discussed.

Chapter four examines the major assumptions related to the statistical technique and presents formal hypothesis tests.

In chapter five, the conclusions of this research are stated, along with implications (both academic and managerial), research contributions, and directions for future research.

2 Literature Review

This chapter reviews past research related to forecast in a supply chain context. Gaps in the literature will be identified and support for the relevancy of this dissertation will be provided.

Section one of this chapter covers the general research on forecasting. The second section describes previous research that addresses forecast issues in supply chain management. This includes an analysis of past research in both manufacturing and supply chain management literatures. The third section includes previous applications of simulation methodology for supply chain analyses.

Summaries from each section are then provided and conclusions are presented. In addition, the hypotheses to be tested using the simulation environment are formally stated.

2.1 Research on Forecasting

This section reviews the relevant literature of forecasting. The discussion focuses on forecasting articles that review the body of knowledge and attempt to identify research needs in the area. As a result, a historical perspective of the field is presented and gaps in the forecasting literature are identified.

Armstrong et al. (1984) developed one of the first reviews of forecasting literature. This article reviews twenty-five years of research and concludes that the field is highly focused in the comparison of alternative methods for short term forecasting.

Another comprehensive review is developed by Makridakis (1986). In this article, the author assesses forecasting performance, evaluates accomplishments, and proposes directions for future research. This review also offers an interesting historical perspective regarding forecasting.

According to Makridakis (1986), the foundations of forecasting were laid in the late 1930's when the first forecasting models were proposed. Between 1950 and 1970, five parallel and independent subfields were developed in the field of quantitative forecasting, including: (1) econometric models used by economists to explain macroeconomic phenomena; (2) filtering methods used by engineers to eliminate 'noise' from patterns; (3) models used by statisticians to generate time series and forecasts; (4) decomposition techniques used by the government to uncover seasonality and trend-cycles in macroeconomic time series; and (5) exponential smoothing methods used by operation researchers to forecast production scheduling and inventory control.

The personal computer brought computational power to the fingertips of researchers and practitioners. The 1970's and 1980's were dominated by research focused on the assessment of forecasting performance, and the comparison of alternative methods.

Makridakis (1986)'s research also proposes directions for future research. As a conclusion, the author suggests the development of new methods and the modification of the existing ones as the primary focus for new research efforts.

Armstrong (1988) conducts another comprehensive review of forecasting research. The author identifies research needs of practitioners and academics using a survey instrument. Results of this survey are presented on Table 3.

Field	Practitioners	Academics
Economics	Causal models; survey research	Causal models; uncertainty
Finance & Accounting	Environmental forecasting; seasonal variations	Expert systems; uncertainty
Marketing	Implementation; computerization; combine methods; competitive actions; evaluation	Incorporate judgment in models; competitive actions; combine forecasts; compare alternative methods; implementation
Planning	Impact on decision-making; expert systems; judgmental forecasting; computerization; compare alternative models; implementation; scenarios; uncertainty	Compare alternative methods; monitor forecast
Production	New product forecasting; combine methods; quality of data vs. method; seasonality	Combine alternative methods; uncertainty; combine forecasts; compare alternative methods
Research & Development	New product forecasting; outliers; causal models; computerization	Combine alternative methods; compare alternative methods; impact on decision-making; scenarios
Other Areas	Expert systems; compare alternative methods; impact on decision-making; implementation; monitor forecasts	Compare the alternative methods; quality of data vs. method; impact on decision-making; scenarios; uncertainty

Table 3 – Research Needs in Forecasting (Armstrong 1988)

After identifying the most important areas for research, Armstrong (1988) compares the identified research needs with the literature published up to that moment. Table 4 summarizes the conclusions developed from the review.

Topic	Past Research Conclusions	Future Research Prospects
Decomposition (Predict parts, then aggregate)	- Helpful where uncertainty is high	Good
Extrapolation	- Seasonal factors useful - Trends should be dampened - Minor differences in accuracy among methods	Modest
Intentions	- Ways to reduce response and non-response bias	Modest
Expert Opinion	- Limited value of expertise in forecasting large changes - Role-playing accurate for conflict situations	Excellent
Expert Systems (Bootstrapping)	- Less expensive & a bit more accurate	Excellent
Causal Methods (Econometrics)	- Simplicity is a virtue - Econometric methods better for large changes	Modest
Combined Forecasts	- Combination yield substantial gains	Modest
Uncertainty	- Judgmental estimates are typically overconfident argue against your forecast	Good
Implementation	- Scenarios can help to gain prior commitment	Excellent
Audit Process	- Guidelines needed	Excellent

Table 4 – Comparison of Research Needs and Research Supply in Forecasting (Armstrong 1988)

Table 4 presents an identification of gaps between the reported research and the identified research needs. Potential topics suggested by this analysis include: (1) identification of standards for acceptable practice in forecasting; (2) improvement of forecasting under conflict situations; (3) identification of best methods for estimating uncertainty associated with forecasts; and (4) identification of effective ways to gain managerial perspective of unfavorable forecasts.

Dawes et al. (1994) discuss the past and the future of forecasting research. In this article, a panel of four research experts presents a brief response to two issues: (1) identification of the major development in forecasting over the past decade, and (2) identification of the area with most promise for the future. According to the authors, the future did not appear to lie in bigger or smarter models. Rather it may be in the implementation of models, in the development of a better understanding of the practical forecasting process, and by the better use of the data resources made available by increasing automation.

Finally, Winklhofer et al. (1996) developed a recent review of empirical studies on forecasting. One conclusion is that although considerable empirical research has focused on the forecasting practices of firms, not all issues have received equal attention. While questions concerning the utilization of forecasting methods have attracted a lot of study, issues such as the role and level of forecasting have been relatively neglected. While variables such as company size and industry type have been linked to some aspects of forecasting practice (resources available and forecasting accuracy), such linkages have been left unexplored for other aspects (data sources utilized). According to the authors, future research should take three broad directions: (1) to relate organizational and environmental variables known to affect forecasting to a wider range of issues; (2) to explore the impact of additional firm-specific and environment-specific variables on forecasting; and (3) to examine neglected linkages between different aspects of organizational forecasting.

The preceding discussion provides interesting insight about the research focus on forecasting. Initially, efforts were focused on analyzing the performance of alternative forecasting techniques under different contexts. The primary research motivation in the past was to investigate alternatives to improve existing forecasting techniques and to identify a match between such techniques and different environmental characteristics.

Most recent reviews of the forecasting literature provide support for the need of a better understanding of the managerial side of the forecasting process. The current research motivation is to gain a better understanding of the practical issues involving the forecasting process. It also aims to gather a better knowledge regarding the impact of forecasting on operations and decision-making processes.

2.2 Forecast Issues in Supply Chain Management

This section reviews previous research that addresses forecast issues in supply chain management. The first part of this section presents an analysis of past research related to forecasting in the manufacturing literature. The second part presents a review of past research in the supply chain management literature.

2.2.1 Manufacturing Literature

Early efforts investigating the impact of forecast error on operations are reported in the manufacturing literature. There is considerable research that reports the response of production scheduling and resource planning performance resulting from various levels of forecast error. Previous research in this area generally considers a single unit of analysis, such as a single company or a single manufacturing facility.

In an interesting simulation study, Biggs & Campion (1982) investigate the relative impact of forecast error on a production system. This study is different from previous research that attempts to minimize forecast error by improving forecasting techniques. The results of the paper indicate that manipulating forecast error bias may be the better managerial strategy as opposed to going to great lengths to minimize forecast error. This article is one of the first to conceptually consider separate dimensions of forecast accuracy.

Lee & Adam (1986) and Lee et al. (1987) support the importance of forecast bias on manufacturing performance. While forecast bias and standard deviation significantly affect the Master Requirements Planning (MRP) performance, bias has a more significant impact. Both studies are limited to a single plant operation. These two studies were motivated by the similar findings of the Lee (1982) doctoral dissertation.

Lin & Krajewski (1992) and Lin et al. (1994) explicitly address forecasting in manufacturing environments. The authors evaluate the impact of three scheduling parameters: replanning interval, schedule freezing period, and forecast window. In their analytical model, forecasts are considered unbiased, and its variance increases as the time interval between the forecast date and the production date increases. The authors present the effects of these three parameters on cost and performance of the manufacturing system.

Ritzman & King (1993) use a simulation approach to investigate the impact of forecast error on manufacturing performance. Two components of forecast error are examined in this article: variability and bias. The study, limited to a single plant environment, considers the analysis of two lot size techniques under alternative levels of resource use (workers, capacity, inventory), demand uncertainty and forecast error. Results regarding the manufacturing performance indicate that reducing forecast bias is preferred to reducing forecast variability.

In another simulation approach, Zhao & Lee (1993) evaluate the impact of scheduling freezing parameters on the total cost, schedule instability and service levels in MRP systems under alternative conditions of demand uncertainty. Two different forecasting models are compared to the case where no forecast errors exist in the system. The results indicate that forecast errors significantly increase total costs and schedule instability, and reduce the service level in MRP systems.

Toktay (1998) considers an analytical model of a capacitated production-inventory system operating under a stationary demand process and using forecast updates to determine production order releases. The author assesses the impact of information quality on total cost. Results show that forecast model misspecification and forecast bias lead to significant cost increases.

Masuchun (2002) compares the performance of an anticipatory and a responsive strategy on a manufacturing system. The author investigates the impact of the two strategies on total inventory, production throughput, and customer service. The simulation environment tests the manufacturing system under different levels of forecast error and inventory targets. Results support the concept of fit between environmental characteristics (demand uncertainty, forecast error, target inventory levels) and either the push or pull strategies.

In a recent study, Sloyer (2003) researches the effect of forecast error on a production system. Specifically, the author uses a simulation model to evaluate different methods for adjusting inventory targets in the presence of forecast bias. Results of this study help decision makers determine the most appropriate safety stock method using characteristics that match a particular environment.

From the previous discussion, most research in the manufacturing literature addresses a single production facility. The relevant part of this literature is in the study of multiple stage production systems. Those systems could, by analogy, be viewed as a supply chain network with multiple partners.

Bookbinder & Heath (1988) identify this limitation and extend the investigation to a distribution network. The authors use a simulation model to study the relationships between network structures, demand, forecast errors, and their impact on costs. The research compares the performance of alternative lot size methods and parameters.

In a more contemporary work, Krajewski & Wei (2001) explore the value of integrated production schedules in supply chains involving buyer and supplier firms. Basically, the article extends the manufacturing environment to outside its borders. A stochastic cost model is developed to evaluate the total supply chain cost with integrated purchasing and scheduling policies. Although forecasts are unbiased in their analytical model, results support that forecast accuracy plays a critical role in realizing the benefits of schedule integration between supply chain partners.

Forecast error thus plays an important role on the performance of manufacturing systems. These relevant manufacturing studies consider the specific dimension of forecast bias. Results support that bias significantly and substantially impacts manufacturing performance. One limitation is that the majority of these studies addresses a single production environment, and rarely considers the operational impact of forecast bias outside the plant borders.

2.2.2 Supply Chain Management Literature

The previous section presented a review of relevant articles on the manufacturing literature. Although the preceding discussion offers interesting insights, the most relevant literature for this dissertation is found on inventory management studies in the supply chain literature.

In general, these studies evaluate the performance of a supply chain system under different environmental contexts. They generally investigate the relationship between inventory target levels and customer service.

Gullu (1997) explores the effects of incorporating forecasts in a two-echelon network. The analytical model considers a central depot and several retailers. The article investigates the possible benefits on system costs and inventory level, when information is shared between supply chain partners. When information is not shared, higher forecast errors result, the system requires higher inventory and results in higher system costs.

Other authors focus on evaluating the impact of information sharing on demand variability across supply chain partners. This impact is commonly referred as the *bullwhip effect*, a situation where demand order variability is amplified as one move up a supply chain. In other words, when there are multiple levels in a supply chain (supplier, manufacturer, distributor, and customer), the farther from the customers, the less predictable are the order quantities.

Lee et al. (1997), for example, demonstrate through analytical models the existence of the bullwhip effect. The authors conclude that the effect is a consequence of strategic interactions among supply chain members.

Metters (1997) quantifies the impact of the bullwhip effect on profitability. The analytical model uses multiple companies operating in a serial supply chain network. Results indicate that the importance of the bullwhip effect to a firm differs greatly depending on the specific business environment. Tan (1999) reaches similar conclusions. The research accesses the impact of information sharing on different supply chain structures, product structures, and demand mix. The conclusion is that there is no overall information sharing policy that has superior performance in all scenarios.

Other studies also use analytical approaches to quantify the impact of improved information sharing on demand, inventory, and costs. Raghunathan (1999), for example, quantifies the benefits of a collaborative supply chain network. Baganha & Cohen (1998) propose conditions to promote supply chain stabilization on demand variability. Lee et al. (2000) find from their analytical formulation that the value of information sharing is high, especially when demands are significantly correlated over time. Finally, Cachon & Fisher (2000) include transit lead time variability and compares its impact to information sharing. According to the authors, there are situations where it is more valuable to reduce uncertainty on transit lead times than to improve information sharing.

A common trait of the previously presented studies is to consider demand variability, but not to explicitly consider forecasts.

Chen et al. (2000) identify this limitation and extend the work developed by Metters (1997) by incorporating forecast error in its analytical formulation. Among its findings, the research demonstrates that the bullwhip effect can be reduced, but not completely eliminated by centralizing demand information. The results suggest that management policies can have a destabilizing effect by increasing the volatility of demand as it passes up through the chain.

Yao (2001) also explicitly considers forecasts in his dissertation research. The author compares the bullwhip ratio under three different forecasting methods and demonstrates that the optimal forecast scheme has advantages over other traditional quantitative techniques.

Ganeshan et al. (2001) study the impact of selected inventory parameters on supply chain performance. In addition to forecast error, two inventory parameters are modeled: mode of communication between echelons and planning frequency. The results are consistent with previous research: increasing forecast error and replanning frequency decreases service, return on investment, but increases cycle time. The use of a communication mode facilitating exchange of information between echelons results in increased service, when compared to the scenario where there is lack of information sharing between supply chain partners.

Xu et al. (2001) develop an analytical study with similar objectives to Raghunathan (1999). In the former case, forecast error is explicitly modeled. Independent actions by members of a conventional supply chain are shown to impact overall performance negatively by increasing order release variability and forecast error variability. The proposed analytical model is useful to assess when and to what extent such fluctuations can be controlled through supply chain collaboration.

In a simulation study, Zhao et al. (2002b) explore the value of practicing early order commitment in the supply chain. Early order commitment represents a situation where a retailer commits to purchase a fixed-order quantity and delivery time from a supplier before the real need takes place. The authors investigate the complex interactions between early order commitment and forecast errors by simulating a supply chain with one supplier and multiple retailers under demand uncertainty. One of the findings is that different components of forecast error have different cost implications.

In a follow-up study, Zhao et al. (2002a) examine demand forecasting and inventory replenishment decisions by the retailers, and production decisions by the supplier under different demand patterns and capacity tightness. Analysis of the simulation output indicates that the selection of the forecasting model significantly influences the performance of the supply chain and the value of information sharing.

The preceding discussion supports that most of the research on the supply chain management literature addressed indirectly the impact of forecast errors on performance. In general, this impact is assessed by investigating issues related to supply chain information sharing. In these studies, forecast error is considered, but it is treated much more as a control variable or parameter rather than a primary factor in the study. There is a gap in the literature to investigate the direct impact of forecast errors in a supply chain context. More specifically, there is a lack of studies that consider the direct impact of Forecast Bias on supply chain performance.

2.3 Simulation in Supply Chain Management

Previous sections in this chapter reviewed the relevant research on the manufacturing and supply chain literatures. Now we review previous studies in supply chain management that used simulation as a methodological tool.

Three model categories are frequently used in logistics and supply chain planning: (1) analytic, (2) heuristic, and (3) simulation. Analytical models use mathematical methods to identify an "optimal" solution to the problem under analysis. In contrast, models that utilize heuristic or simulation approaches utilize numerical techniques to quantify specific problem solutions. Both analytic and heuristic solutions are typically deterministic in that the recommended course of action will be identical, if the procedure is repeated using the same data and assumptions. The distinguishing feature of simulation is its capability to include stochastic situations, where uncertainty can be better considered.

One of the first reviews of the use of simulation in supply chain problems is developed by Bowersox & Closs (1989). In the article, the authors compare simulation with other methodologies and also present the most commonly used applications. Common applications are categorized in terms of structural design and operational questions. Structural analysis typically considers the number of facilities and channel design relationships facilities and/or channel participants. The second category of planning and evaluation is tactical in nature. Operational analysis considers spatial and temporal product positioning. The typical operational analysis is concerned with the integration of raw material and finished goods inventory, service levels and production planning. These two categories and typical problems are summarized on Table 5.

Category	Type of Problem	Observation
Structural Analysis	Facility Analysis	Focuses on the geographical location and arrangement of production, warehouse and to a lesser extent retail stores.
Structural Analysis	Channel Structure	Focuses upon the efficiency and effectiveness of alternative channel members such as raw material suppliers, manufacturers, distributors, wholesalers and retailers.
Operational Analysis	Inventory Management	Analysis of the impact of inventory policies on cost, service and performance.
Operational Analysis	Forecasting	What is the effect of forecast accuracy on inventory required to meet service level objectives.
Operational Analysis	Distribution	What are the cost/service benefits of alternative timing and transportation strategies.
Operational Analysis	Production Scheduling	How do current policies regarding production scheduling impact inventory.
Operational Analysis	Functional Integration	Impact of increased internal integration on cost, service level and performance.
Operational Analysis	Supply Chain Integration	Impact of increased integration across partners in the supply chain on cost, service level and performance.

Table 5 – Categories of Logistics Applications (Bowersox & Closs 1989)

To be able to assess how the methodology has been used in academic research on supply chain management, a focused literature review was conducted for this dissertation. Eight journals were evaluated: *Journal of Business Logistics, International Journal of Physical Distribution & Logistics Management, International Journal of Logistics Management, Journal of Operations Management, International Journal of Operations & Production Management, European Journal of Operational Research, Decision Sciences* *and Management Science*. The period of this review covers from 1980 to the current date. The period is not consistent for all selected journals. Table 6 provides the number of articles found per publication. Keywords used in the literature search were: simulation, supply chain, logistics, transportation, and inventory.

Journal	Period Evaluated	Articles Found
European Journal of Operational Research	1981-2003	20
Journal of Business Logistics	1987-2003	19
Decision Sciences	1982-2003	18
Journal of Operations Management	1980-2003	15
International Journal of Physical Distribution & Logistics Management	1992-2003	14
International Journal of Operations & Production Management	1981-2003	14
Management Science	1981-2003	13
International Journal of Logistics Management	1998-2003	2

Table 6 – Simulation Articles in Logistics and Supply Chain Management

A total number of 115 references were collected from these journals. Two criteria were used for the selection of articles: first, the article should use primarily simulation as a methodological tool and second, the article should address one of the types of problems proposed by Bowersox & Closs (1989). Each article was reviewed related to its content and then allocated to a single type of problem. Table 7 has a summary of this categorization process.

Category	Type of Problem	Articles
Structural Analysis	Facility Analysis	No articles found
Structural Analysis	Channel Structure (9 articles)	Berry et al. 1994; Evers 1996; Hammant et al. 1999; Harrington et al. 1992; Landeghem & Vanmaele 2002; Petrovic et al. 1998; Swaminathan et al. 1998; Taylor & Closs 1993; Vorst et al. 2000
Operational Analysis	Inventory Management (39 articles)	Bagchi et al. 1986; Barnes-Schuster & Bassok 1997; Bashyam & Fu 1998; Benton & Krajewski 1990; Biddle & Martin 1986; Bradley & Glynn 2002; Bregman et al. 1989; Chien 1993; Choi et al. 1984; Chyr 1996; Clark et al. 1983; Disney et al. 1997; Ebrahimpour & Fathi 1985; Etienne 1987; Garg et al. 2002; Glasserman & Liu 1996; Hong-Minh et al. 2000; Humphrey et al. 1998; Jackson 1988; Jacobs & Whybark 1992; Kabir & Al-Olayan 1996; Kumar & Chandra 2002; Li & Qi 1995; McClelland & Wagner 1988; Mohan & Ritzman 1998; Okogbaa et al. 1994; Petrovic et al. 1982; Pfohl et al. 1999; Rosenbaum 1981; Rutten & Bertrand 1998; Takahashi et al. 1997; Teulings & Vlist 2001; Towill et al. 1992; V. Daniel R. & Srivastava 1998; Waller et al. 1999; Walter & Bowersox 1988; Wemmerlov 1989; Zinn & Marmorstein 1990; Zinn et al. 1992
Operational Analysis	Forecasting (8 articles)	Biggs & Campion 1982; Flowers 1980; Hsu & El-Najdawi 1991; Karmarkar 1994; Lee & Adam 1986; Ritzman & King 1993; Zhao et al. 2002a; Zhao et al. 2002b

Table 7 – Articles Categorized by Type of Problem

Category	Type of Problem	Articles
Operational Analysis	Distribution (21 articles)	Akaah & Jackson 1988; Andreussi et al. 1981; Bagchi 1988; Bielli 1992; Bookbinder & Heath 1988; Evers 1999; Fujiwara et al. 1987; Gomes & Mentzer 1988; Guimaraes & Kingsman 1989; Higginson 1995; Higginson & Bookbinder 1994; Ho 1992; Jansen et al. 2001; Kamoun & Hall 1996; Legato & Mazza 2001; Mentzer & Gomes 1991; Pooley & Stenger 1992; Powers & Closs 1987; Shabayek & Yeung 2002; Strasser 1992; Waller 1995
Operational Analysis	Production Scheduling (33 articles)	Akkan 1997; Ardalan 1997; Benton & Whybark 1982; Berkley & Kiran 1991; Bott & Ritzman 1983; Chakravorty & Atwater 1995; Chan et al. 2001; Chan & Smith 1993; Christy & Kanet 1988; Cruickshanks et al. 1984; Ding & Yuen 1991; Goyal et al. 1993; Heuts et al. 1992; Ho 1993; Huang et al. 1983; Huq & Huq 1995; Kanet 1986; Kern & Wei 1996; Klitz 1983; Krajewski et al. 1987; Leachman & Gascon 1988; Lee & Seah 1988; Mapes 1993; McClelland 1988, 1992; Morris & Tersine 1990; Schartner & Pruett 1991; Scudder & Hoffman 1985; Seagle & Fisk 1982; Sridharan & LaForge 1990, 1994; Suresh & Meredith 1994; Tardif & Maaseidvaag 2001
Operational Analysis	Functional Integration	No articles found
Operational Analysis	Supply Chain Integration (4 articles)	Closs et al. 1998; Kia et al. 2000; Raghunathan 2001; Towill & McCullen 1999

Table 7 – Articles Categorized by Type of Problem (Continued)

Some interesting conclusions can be developed from the review of simulation studies in supply chain management. First, research has focused on operational issues. A total of 106 articles were categorized as operational analysis. Considerable effort in this area has been done in the study of Inventory Management, Production Scheduling and Distribution problems. Second, there is limited research investigating Forecasting, Functional Integration and Supply Chain Integration issues. Only twelve simulation studies were found that addressed such issues. Finally, the structural level of analysis has also received limited research. Only nine simulation studies were found on this area, dealing with problems related to the channel structure.

The preceding discussion supports that while a considerable effort has been done to study supply chain operational characteristics, few articles used simulation to address more tactical or strategic type of problems. Furthermore, there is limited number of simulation studies that addressed forecast as the primary issue. There is a need to investigate the impacts of the different dimensions of forecast error on supply chain performance.

2.4 Conclusions from Literature Review

The previous sections discussed how issues related to forecast error were addressed in the forecasting, manufacturing and supply chain literatures. In addition, the preceding section discussed how simulation was used to investigate supply chain related problems.

From the insights provided by the forecasting literature review, it is clear that most of the efforts were focused on the evaluation and improvement of competing forecasting techniques. The literature review indicates that there is a need for an evaluation of the role of Forecast Bias and its impact on operations.

Three conclusions result from the review of forecasting literature related to supply chain management research. First, there is substantial need for the development of research on this topic, as the prior research regarding the impact of forecast errors on supply chain performance is relatively new and it is mostly studied in a manufacturing context. Second, there is a need for better conceptualization of forecast errors, making clear the distinctive dimensions of error (bias, variability, etc.). Third, although some issues regarding information sharing and demand amplification are addressed in the literature, there is a need for better assessment regarding the impact of forecast errors in complex supply chain environments. This dissertation fills these three gaps by distinctly modeling different dimensions of forecast accuracy and by representing supply chain networks with stochastic lead times.

In conclusion, the review of the use of computer simulation as a methodological tool shows that most of the previous efforts were focused on the study of inventory management systems, the evaluation of alternative rules for production scheduling, and the study of alternative distribution systems, This dissertation extends previous research by considering the effect of forecast errors on supply chain performance.

Table 8 presents a summary of the primary gaps identified as a results of the literature review.

Topic	Gaps
General Research on Forecasting	• Efforts focused in the **improvement and evaluation of competing forecasting methods**. • Potential room for the study of the **role of forecast accuracy and its impact on operations.** • Potential room to **relate organizational and environmental variables** that **affect forecasting** and to explore the impact of additional firm-specific and environment-specific variables
Forecast issues: Manufacturing & Supply Chain Management	• There is a **need for better conceptualization of forecasting accuracy** in supply chain management research. • Although some issues regarding information sharing and demand amplification were addressed, there is a **need for better assessment regarding the impact of forecast accuracy on supply chain performance.** • There is a **gap concerning the interaction of components of the forecasting accuracy distribution and its combined impact on supply chain operations**
Previous applications of simulation methodology	• Most of the effort was **focused on operational issues.** • Limited research investigating Forecasting, Functional Integration and Supply Chain Integration

Table 8 – Literature Review: Primary Gaps

This section reviewed previous literature and summarized the primary existing gaps. The next section formally states the hypotheses to be tested using the simulation environment.

2.5 Hypotheses

Using results from the literature review and the research questions proposed earlier, eight hypotheses can be formally stated.

The literature review supports the need for research of the impact of forecast errors on supply chain performance. Specifically, there is a need for a better conceptualization of the different dimensions of forecast error and analysis of their different impacts. In this dissertation, two aspects of the forecast error distribution are investigated: Forecast Bias and Forecast Skewness.

The first research question considers the investigation of the different impacts of Forecast Bias and Forecast Skewness on performance. Therefore, the first set of hypotheses considers the individual impacts of Forecast Bias and Forecast Skewness on performance as well as their combined effect. From insights of the manufacturing literature, it is assumed that both Forecast Bias (H1a) and Forecast Skewness (H1b) individually affect supply chain performance. The second research question expects the impact of Forecast Bias on performance to be altered depending on the level of Forecast Skewness. Therefore, an interaction effect between these two factors is assumed (H1c). Finally, results from the manufacturing literature suggest that the individual effect on performance of Forecast Bias is relatively larger (H1d). Thus, the first set of hypotheses is:

Hypothesis H1a: Forecast Bias has a significant impact on Supply Chain Performance.

Hypothesis H1b: Forecast Skewness has a significant impact on Supply Chain Performance.

Hypothesis H1c: There is a significant interaction effect between Forecast Bias and Forecast Skewness.

Hypothesis H1d: Forecast Bias has a relatively greater impact than Forecast Skewness on Supply Chain Performance.

The third research question investigates the extent that the variability on daily demand offsets or compounds the impacts of Forecast Bias and Forecast Skewness on performance. The fourth research question investigates the extent that the variability on transit lead times offsets or compounds the impact of Forecasting Bias and Forecasting Skewness.

It is expected that the higher the level of daily demand variability, the higher the individual impact of Forecasting Bias (H2a). In an analogous way, it is also expected that the higher the variability in transit lead times, the higher the impact of Forecasting Bias on performance (H2b). The second set of hypotheses is stated as follows:

Hypothesis H2a: There is a significant interaction effect between Forecast Bias and Demand Variability.

Hypothesis H2b: There is a significant interaction effect between Forecast Bias and Lead Time Variability.

In an analogous way, when higher levels of demand variability (H3a) and transit lead time variability (H3b) are present, the higher the individual impact of Forecasting Skewness on performance. Thus, the last set of hypotheses is:

Hypothesis H3a: There is a significant interaction effect between Forecast Skewness and Demand Variability.

Hypothesis H3b: There is a significant interaction effect between Forecast Skewness and Lead Time Variability.

The eight hypotheses previously presented will bring additional understanding about the separate impacts of Forecast Bias and Forecast Skewness on supply chain performance. In addition, the formal test of these hypotheses will contribute to the existing literature by considering these impacts under different environmental contexts of customer demand and transit lead time.

This chapter reviewed the literature from three perspectives and presented formal statements of the hypotheses to be tested. The following chapter will discuss details about the research methodology.

3 Research Methodology

This chapter describes the research methodology used for this study. The first section presents the chosen methodology: computer simulation. The second section discusses the conceptual model, providing a summary of the various events modeled and how model validity was assessed. The next four sections describe model assumptions, experimental factors, fixed parameters, and performance measures. Finally, the last section explains the data analysis technique used for formal hypotheses testing.

3.1 Computer Simulation

This research requires a controlled environment under which experiments can be conducted and evaluated. The analysis of actual operations or a survey study could not provide the experimental environment or the necessary level of control. This dissertation uses simulation methodology, as it is capable of representing controllable environments and of modeling stochastic uncertainty.

Law & Kelton (2000) define computer simulation as the process of designing a model of a real system and conducting experiments. This approach is used whenever a complete mathematical formulation of the problem does not exist or an analytical method of solving the mathematical model does not exist.

According to Martin (1968), computer simulation is indicated for 27 different types of applications, including evaluation of operations, evaluation of business strategy, test of strategy and tactics and analysis of decision-making processes. Simulation is well suited for supply chain and logistics applications, because of the interactions and dynamics existent in such problems (Carson et al. 1997). In addition, it is a viable technique for modeling systems characterized by great complexity, probabilistic or stochastic processes, and whose variables are difficult to analyze in precise mathematical terms. Simulation is also quite tractable for experimentation in that, after a computer model has been developed and validated, the model may be sampled under different input conditions. Computer simulation is, therefore, an appropriate methodology for this dissertation.

3.2 Conceptual Model

This section describes the conceptual model of the supply chain for the distribution of consumer goods. The conceptual model is the mathematical, logical or verbal representation of the phenomena to be investigated. It relates the entities, activities, and factors used in this research.

The conceptual model considered in this research is a dynamic multi-echelon structure that considers production and distribution functions, product and information flows, and customer demand and forecasting activities. Figure 3 illustrates the conceptual model.

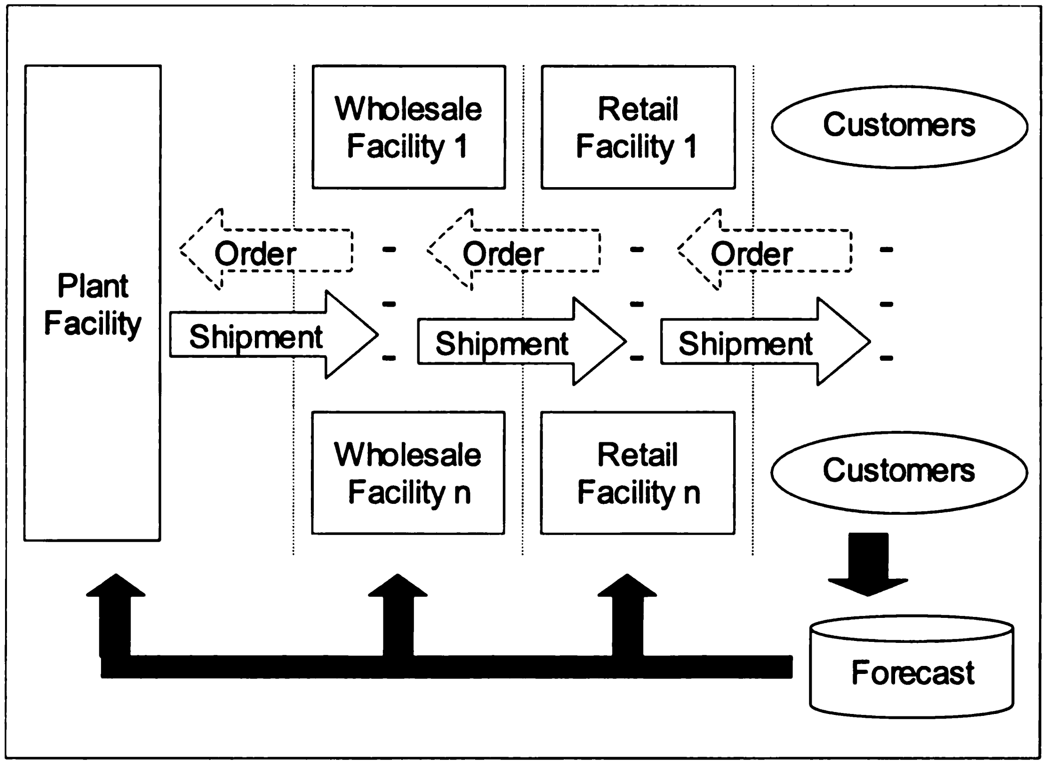


Figure 3 – Conceptual Model

The conceptual model assumes independent policy and inventory operations for each facility. Retail facilities obtain inventory supply from wholesale facilities, which in turn replenishes inventory from the plant facility.

Daily customer demands can be created using stochastic distributions, such as Normal and Gamma. Each daily order volume has a defined mean and variance. This actual demand is then used to create weekly forecasts.

Instead of using a quantitative technique to generate forecasts, controlled forecast errors are imposed on the actual generated demand at the retail level to create forecasts. Thus, different patterns of forecast error can be imposed on the actual demand when generating forecasts. The forecasted demand is then used as the primary information for planning of replenishment orders in the system. If no forecast error is defined, actual demand is used for planning purposes. This allows forecast error to be controlled and enables the simulation of a supply chain environment with different patterns of error.

Customer demand and forecasted demand are then used to trigger daily events in the simulation model, which is presented in the following section.

3.2.1 List of Events

The conceptual model assumes that the behavior of the system changes as time advances. In this dissertation, therefore, a dynamic simulation model is considered. During a particular simulated day, a sequence of activities is performed, updating the status of the entire system before time is advanced. Each activity is responsible for coordinating flows of information and products in different ways. This section describes in detail each major activity. Figure 4 summarizes all events present in the conceptual model.

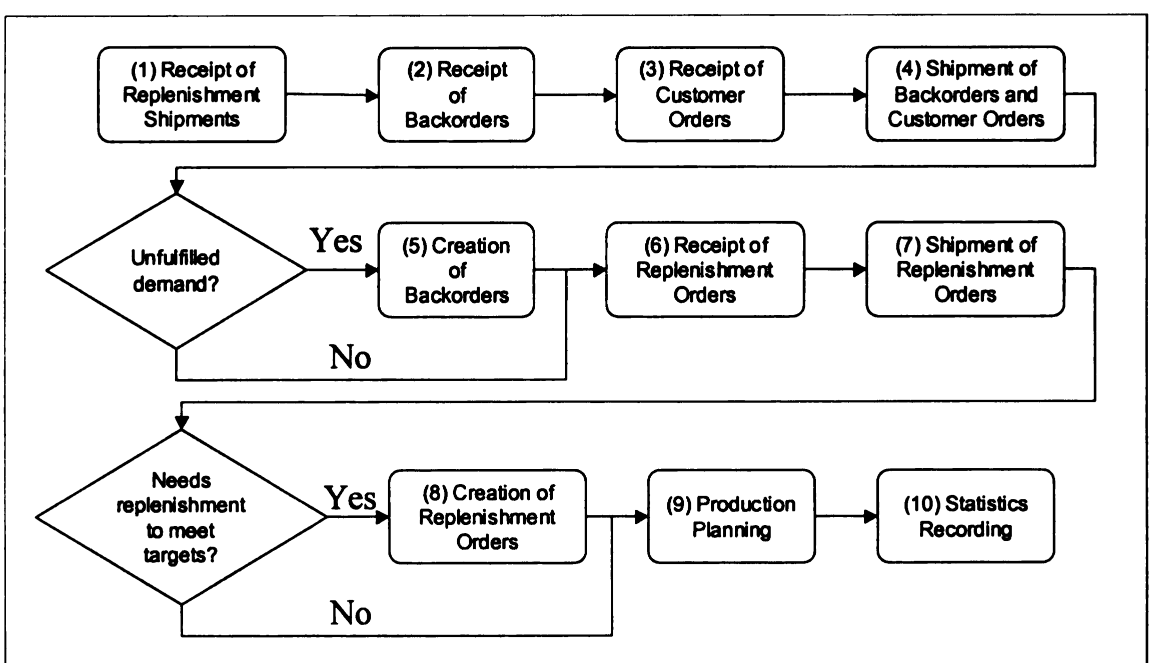


Figure 4 – Conceptual Model: List of Events

The first event to occur is the receipt of replenishment shipments. Those shipments represent in-transit inventory that was scheduled to arrive in the beginning of the day. Inventory positions are then updated to reflect the additional inventory received.

The second and third events to occur are the receipt of backorders (from past unfulfilled demand) and new customer orders at retail locations. Backorders can be allowed only at the retail level. The simulation user decides if backorders exist in the system. When backorders are allowed, all customer orders are eventually fulfilled. If not, then demand that is not filled is lost, and stockouts are recorded at the retail level. In this dissertation, the choice is to record stockouts instead of allowing for backorders.

After that, the next event takes place: the shipment of backorders and customer orders. If the required quantity in an order is fully available, a complete shipment is sent to customers. If some quantity is missing, a partial order is shipped. Stochastic lead times are imposed to represent transportation delays. If an order is left unfulfilled, the remaining quantity is considered a backorder and is left to be filled on the next day, constituting the fifth event. When replenishment requests are not fully shipped, stockouts are calculated instead. The same occurs at the retail level if backorders are not allowed, the case in this dissertation.

In the following event, replenishment orders are received at the sourcing locations after stochastic delays of order transmittal are completed. These replenishment orders represent requests from retail facilities to wholesale facilities and requests from wholesale facilities to the plant. Such replenishment orders are processed in the same ways as the customer order fulfillment process. After inventory evaluation, replenishment shipments are created as the seventh event. Replenishment quantities not fulfilled are discarded, and stockouts are recorded. Such requirements are reflected in the next planning cycle.

After the completion of both customer and replenishment order fulfillment processes, replenishment requirements are evaluated, constituting the eighth event. Requirements are evaluated under a daily order-up policy. Maximum levels of inventory are defined in each location for each specific product.

These target inventory levels are defined in days of demand. This means that targets are dynamically calculated based on demand forecast information. During every review period, average daily forecast is recalculated. The average daily forecast is then multiplied by the defined target level (in days) to obtain a specific quantity to be maintained at the facility. This procedure allows the system to dynamically adapt to seasonality periods. Inventory requirements are then evaluated taking into account not only current inventory position, but also transit inventory and backorders. If the planned inventory is below the maximum target, a replenishment order is created. The order quantity is the necessary amount of products needed to build the maximum target.

The ninth event to occur is production planning. Production lead time is represented as a stochastic delay. The plant facility also has target inventory levels to maintain. If quantities are required, a delay is applied to represent the manufacturing time required to build such requirements. After this delay is completed, these quantities are moved automatically to stock and are ready to be shipped. This research assumes infinite capacity at the plant. A second assumption is that the production lead time, although stochastic, does not depend on the size of the replenishment order. Finally, for modeling purposes, the production lead time was incorporated as the transit time from plant to wholesale facilities.

The last event to occur is the collection of statistics. Service statistics are collected only in the first pass. Fill rates, average inventory and costs are computed for each facility. Individual statistics are then aggregated to compute performance for the entire supply chain.

After the last event occurs, time advances and the system returns to the first event, repeating the same sequence until the simulation period is over.

The conceptual model is thus translated to a simulation model. The next section details steps taken to assure the simulation model validity.

3.2.2 Model Validation

Before information derived from simulation models can be used, the primary concern is whether results can be considered valid. This concern is addressed through model verification and validation. This section describes major issues regarding validation and details of how the simulation model was evaluated before experiments could be conducted and results could be analyzed.

In a comprehensive article, Sargent (2000) discusses verification, validation, and accreditation of simulation models. In this article, model verification is defined as "ensuring that the computer program of the computerized model and its implementation are correct". Model validation is defined as "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Schlesinger et al. 1979). Finally, model accreditation determines if a model satisfies specified criteria. The author presents different approaches to deciding model validity and defines different validation techniques.

The determination of whether a model is valid or not is usually part of the entire model development process. It is often too costly and time consuming to determine whether a model is absolutely valid over the complete domain of its intended applicability. Instead, sample tests and evaluations are conducted until sufficient confidence is obtained that the model can be considered valid.

Sargent (2000) presents a simplified version of the modeling process (Figure 5). He defines the *problem entity* as the system, idea, situation, policy, or phenomena to be modeled. The *conceptual model* can be viewed as the mathematical/logical/verbal representation of the problem entity. Finally, the *computerized model* is the conceptual model implemented on a computer.

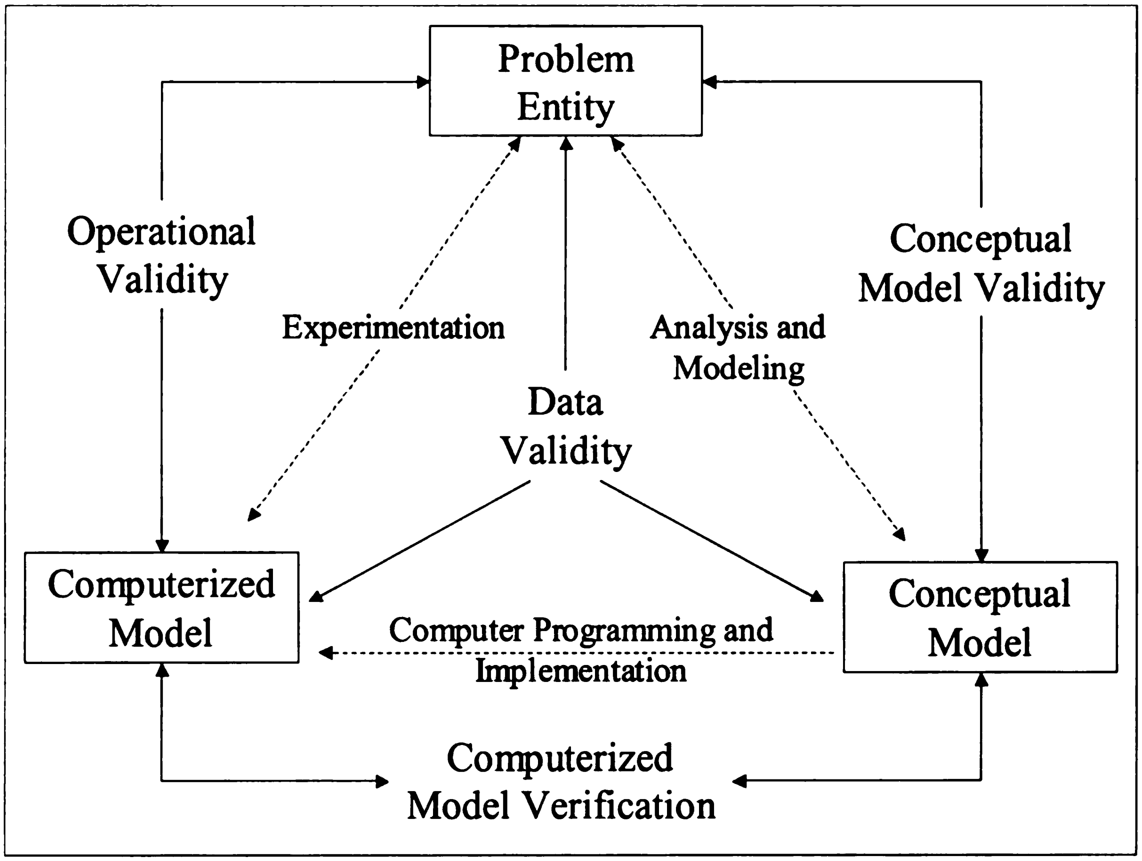


Figure 5 – Simplified Version of the Modeling Process (Sargent 2000)

During the modeling process, four types of validity should be ensured. The first one, *conceptual model validity*, is defined as determining that the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is "reasonable" for the intended purpose. The second dimension of validity, *computerized model verification*, is defined as ensuring that the computer programming and implementation of the conceptual model is correct. The third dimension, *operational validity,* is defined as determining that the model's output behavior has sufficient accuracy. Finally, *data validity* is defined as ensuring that the data necessary for model building, model evaluation and testing, and conducting the model experiments are adequate and correct.

Sargent (2000) presents sixteen validation techniques that can be used to ensure the different types of validity. These techniques can be used either subjectively or objectively (by using some type of statistical test or mathematical procedure). Generally, a combination of techniques is used.

To assess *conceptual model validity*, an evaluation of the model is required to ensure its correctness for the intended purpose. This procedure includes determining if the appropriate detail and aggregate relationships are used and if the appropriate structure, logic, and mathematical and causal relationships are employed. To assess this type of validity, two techniques are used: face validation and traces.

Face validation requires that experts on the problem entity evaluate the conceptual model to determine if it is correct and reasonable for its purpose. This technique can be used in determining if the logic in the conceptual model is correct and if a model's input-output relationships are reasonable. In this research, each event proposed on the conceptual model was analyzed and evaluated by managers of four different companies. The conceptual model was considered reasonable when an agreement was reached in terms of the logical relationships described in the conceptual model.

In addition to face validation, traces were used to track orders and shipments throughout the simulation model. A log file was created with every single activity that was generated during initial experiments. The file recorded customer orders, shipments to customers, replenishment orders, replenishment shipments, and inventory positions throughout the simulation. Using this technique, information and product flows were tracked and analyzed. The objective was to determine if the logic was correct and if the necessary accuracy was maintained. The model was concluded to operate according to the proposed logic.

The trace technique was also useful to assure the second dimension of validity, *computerized model verification*. The use of a special purpose simulation language generally results in fewer errors than if a general purpose simulation language is used. In this case, a special-purpose language is used (Arena Simulation Package) and verification is primarily focused on testing if the model has been programmed correctly in the simulation language. By analyzing the log file, the second type of validity is considered achieved.

The third type of validity, *operational validity,* is concerned with determining that the model's output behavior has the accuracy required for the model's intended purpose. This is where most of the validation testing and evaluation took place. A subjective approach was used to ensure operational validity. Three techniques were used: Parameter Variability–Sensitivity Analysis, Degenerate Tests, and Internal Validity Check.

The Parameter Variability–Sensitivity Analysis technique consists of changing the values of the input and internal parameters of a model to determine the effect upon the model's behavior and its output. Initial simulation runs generated outputs with reasonably low variance under different uncertainty environments. In our case, inventory and lead time parameters where changed and its effect on performance variables were observed. For example, when inventory levels were lowered, service levels and average inventory went down. When lead times were increased, transit inventory and cycle time went up. After different tests, the model's behavior is concluded to be satisfactory.

The second technique used was Degenerate Tests. The degeneracy of the model's behavior was tested by appropriate selection of values of the input and internal parameters. As an example, production times and lead times were increased, with the objective to replicate a constrained environment. As an effect, backorders were increased and service variables went substantially down.

Finally, the last technique used was Internal Validity. In this case, several replications (runs) of the model were made to determine the amount of (internal) stochastic variability. One way to assess the variability was to calculate the coefficient of variation (CV), defined as the standard deviation of a distribution divided by its mean. For the performance variables considered in this research, the average CV across scenarios stayed between 0.01 and 0.02, giving support for a low amount of variability across different replications. Therefore, the model's internal validity was considered appropriate.

Finally, *data validity* was ensured by testing the collected data using internal consistency checks, and screening for extreme values. Reviews were conducted with company experts. When problems were found, the source of data was contacted and errors were eliminated from data used.

3.3 Simulation Model

As presented in the discussion of the conceptual model, this research incorporates manufacturing lead time, distribution inventory policies, stochastic demand patterns, stochastic lead times, and measurements of inventory levels and fill rates into a simulation model. This section describes major model assumptions.

The general supply chain network structure presented in the conceptual model was adapted to model a typical network. Figure 6 illustrates the network environment used for the analysis.

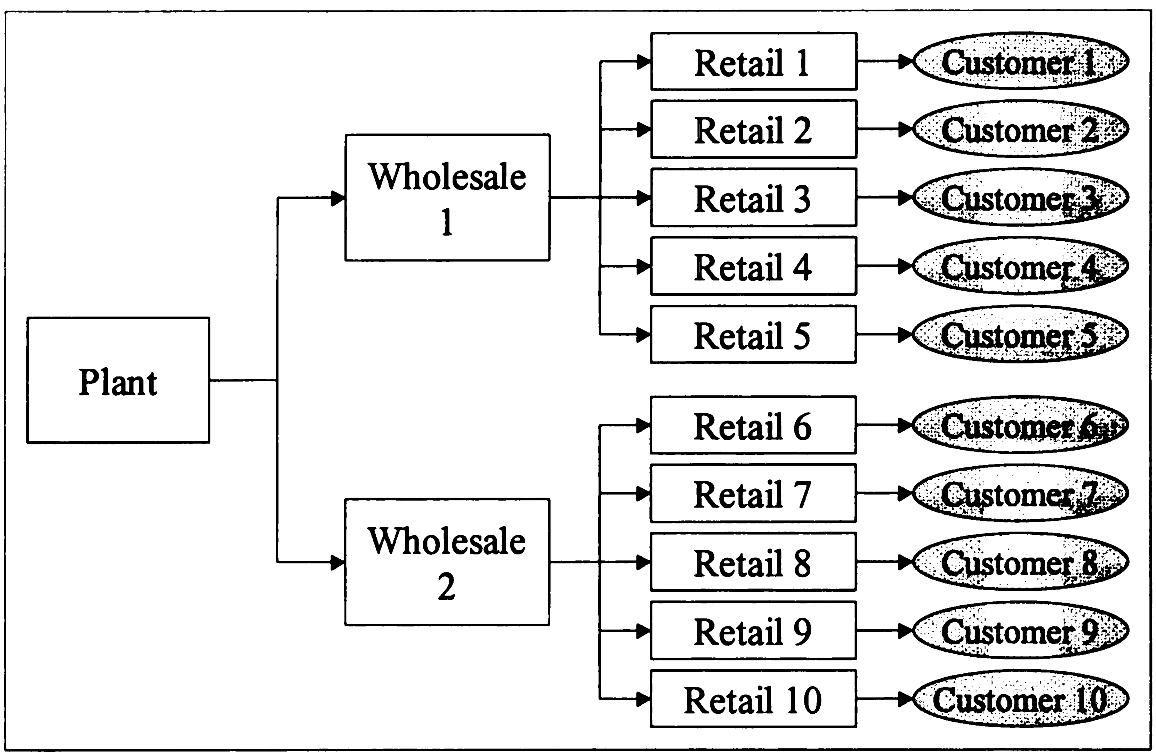


Figure 6 – Typical Supply Chain Network

The network assumes direct shipments from the plant to two different wholesale locations. Each one of the wholesale facilities is responsible for replenishing five different retail locations. Each individual retail location has equally defined and independent demand patterns. The demand for the wholesale level is equal to the sum of each of the five individual retail facilities.

The network is considered typical of a consumer electronics firm with operations in the United States. It assumes two regional distribution centers, for example one in the east coast and another in the west coast, and five local distribution centers in each region. For simplification purposes, a single production source is considered. Although generalization for all types of businesses is limited, the network was considered typical after reviews were conducted with company experts.

3.4 Experimental Factors

The purpose of an experimental design is to provide a method for measurement of changes made in the factors and not other random fluctuations, which might occur during the experimental runs. Hunter & Naylor (1970) point out that a variety of experimental designs may be employed in simulation experiments when the objective is to explore the reaction of a system to changes in factors affecting the system. Those designs considered to be particularly relevant include the full factorial, fractional factorial, and response surface designs. This research employed a full factorial design with a structured approach for studying the research questions and hypotheses.

A factorial experiment is one in which the effects of all the factors and factor combinations in the design are investigated simultaneously (Cohran & Cox 1957). Each combination of factor levels is used the same number of times. The experiments were designed to reflect the dynamic process of market demand and supply chain activities. Four groups of experimental factors included are: (1) Demand Variability, (2) Lead Time Variability, (3) Forecast Bias and (4) Forecast Skewness.

The first experimental factor, Demand Variability, represents the level of variability in customer daily demand. This factor is introduced as a way to investigate the impact of Forecast Accuracy under different levels of demand instability. Three different levels of Demand Variability are considered: low, medium and high.

Customer demand is assumed to follow a Triangular distribution. This type of statistical distribution is commonly used in situations in which the exact form of the distribution is not known, but estimates for the parameters are available. This approach represents transit lead times in a very general form. The Triangular distribution can be defined as symmetric or asymmetric. In addition, it is bounded at minimum and maximum defined values, minimizing the problem of occurrence of extreme values during simulation runs.

At the low Demand Variability level, customer demand in each retail location is assumed to follow a Triangular distribution with minimum value of 75 units per day, a mode of 100 units per day, and a maximum value of 125 units per day. As presented before, the coefficient of variation (the standard deviation of a distribution divided by its mean) is the measure of variability. At this level, CV is equal to 10%.

At the medium level of Demand Variability, customer demand in each retail location follows a Triangular distribution with minimum value of 40 units per day, a mode of 100 units per day, and a maximum value of 160 units per day, resulting in a CV of 25%.

Finally, at the high level of Demand Variability, customer demand follows a Triangular distribution with minimum value of 0 units per day, a mode of 100 units per day, and a maximum value of 200 units per day, resulting in a CV of 40%.

It is important to notice that each retail location has independent patterns of demand defined with equal distributions. No transshipments are allowed in the simulation environment, implying that if there is no inventory at a particular retail location to fulfill demand then demand is lost and stockouts are recorded. All levels of Demand Variability follow the same type of statistical distribution, with the same mode, but different variability parameters. The mode value of 100 units per day is typical of a consumer electronics industry. This approach was chosen because there are neither capacity constraints nor economies of scale imposed in the simulation model. The focus here is to address different levels of variability at the same base level of average demand, not the impact of different daily volumes.

The second experimental factor is called Lead Time Variability. This factor is introduced to investigate the impact of Forecast Accuracy under different levels of transit lead time instability. Two different levels were considered: low and high. The physical network, presented in the previous section, has a single plant that supplies products to two different wholesale locations. Each wholesale location is responsible for supplying products to five retail locations.

Transit lead times also follow Triangular distributions. Parameters of the specific Triangular distributions were defined with the objective to model a typical cycle time of a consumer products company. Davis & Drumm (2003) conduct an annual survey that benchmarks cost and service among logistics companies in the United States. Total cycle time is the amount of time it takes to complete a business process between receiving and shipping orders to customers. The average cycle time for the simulated network is 7 days, consistent with the benchmark value presented in this survey.

At the low level of Lead Time Variability, deterministic lead times are considered. In this case, average lead times are used but no variability is present. Every shipment takes the exact amount of time to occur and no delays exist. This level is introduced to represent a situation where transit lead times are very controllable. At this level, the transit lead time from plant to any wholesale takes exact 4 days to occur, while the transit lead time from any wholesale to any retail location takes exact 3 days to occur.

At the high Lead Time Variability level, stochastic lead times are considered by using Triangular distributions. This research assumes asymmetric Triangular distributions to represent transit lead times, where maximum values are farther from the mode and minimum values are closer to the mode. This approach is chosen because on practice, when shipments do not arrive in the expected time, they have a higher probability to arrive *after* the expected time rather than *before* the expected time.

At this level of high Lead Time Variability, the transit lead time from plant to any wholesale location follows a Triangular distribution with a minimum value of 3 days, a mode of 4 days and a maximum value of 6 days. The transit lead time from any wholesale to any retail location is defined using a Triangular distribution with a minimum value of 2 days, a mode of 3 days and a maximum value of 5 days.

The last two experimental factors represent the primary focus of this research, Forecast Accuracy. In this dissertation, two parameters of the forecast error distribution are investigated: Forecast Bias and Forecast Skewness.

As previously addressed, this dissertation's approach to model Forecasting Accuracy does not consider any specific forecasting method. Statistical distributions are used to control the pattern of forecast error. Forecast errors for each time period are randomly selected from the specified distribution and are then imposed to actual demand to generate forecasts. This is a common approach in simulation studies that consider forecast errors.

Researchers generally consider two assumptions: that forecasts are unbiased and that forecasts follow a Normal distribution. Generally, the distribution of forecast errors is assumed to follow a Normal distribution with mean of zero and some level of standard deviation. Researchers that use this approach are interested on investigating the impact of the variability of errors on system performance.

The choice of the Normal distribution as a representation for the forecast error distribution has two limitations. First, the Normal distribution is unbounded in its extremities. This implies that extreme values can occur when errors are randomly selected from the distribution. These extreme values can compromise the simulation results, as they do not represent likely values that would occur in practice. The second limitation is that the Normal distribution is symmetric, constraining the researcher's ability to investigate the impact of more general types of forecast patterns. Lefrancois (1989), for example, asserts that forecast errors are commonly non-stationary (correlated between consecutive time periods) and asymmetric. Bassin & Bilchak (1995) identify the limitations of the Normal distribution and propose a modification of its form as a way to improve the realism of forecast errors.

This dissertation approach avoids such limitations by using a different type of statistical distribution. Our choice is to use a generalized form of the Beta distribution as a way to represent patterns of forecast error. The Beta distribution describes a family of curves that are unique in that they are nonzero only on the interval between zero and one. The shape of the Beta distribution is quite variable depending on the values of the two shape parameters: $\alpha 1$ and $\alpha 2$, as illustrated on Figure 7.

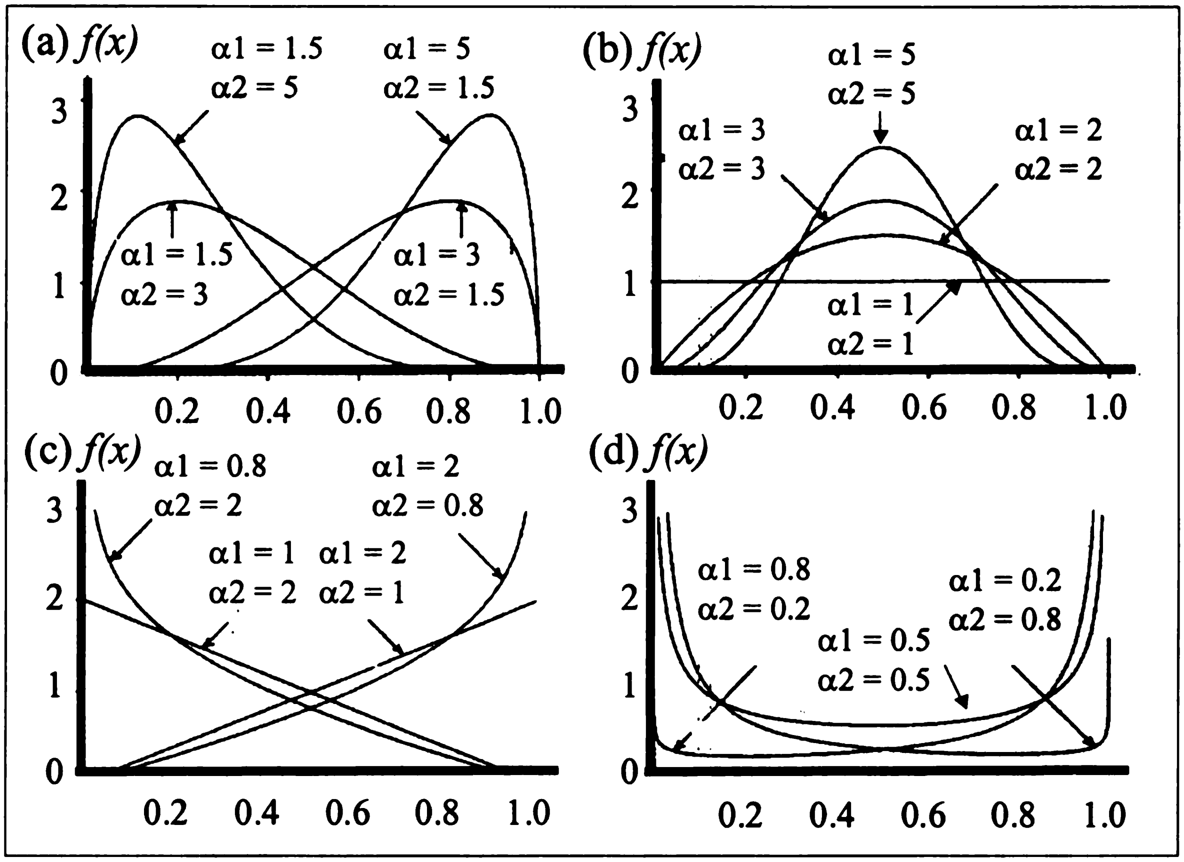


Figure 7 – Examples of BETA (α1, α2) Distributions

In addition to the shape parameters, the generalized form of the Beta function assigns parameters to the end-points of the interval. Thus, for the generalized Beta, four parameters are defined: α1, α2, Min (minimum endpoint of the interval) and Max (maximum endpoint of the interval).

Different patterns of Forecast Bias and Forecast Skewness can be tested during simulation experiments by choosing alternative parameters for the generalized Beta distribution. The mean of the distribution corresponds to the level of bias. Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it is equally distributed to the left and right of the center point. The skewness for a Normal distribution is zero, and any symmetric data should have skewness near zero. When equal shape parameters of the Beta distribution are utilized, the distribution is symmetric around the mean.

Forecast Bias is manipulated at five levels: -40%, -20%, 0%, +20% and +40%. These levels are chosen to represent typical examples of average of the distribution of percentage errors. Benchmark studies of forecasting accuracy reported that average MAPE ranges from 5% to 40%, varying by industry, level of aggregation and forecasting horizon (Jain 2003b, 2003a; Kahn 1998; Kahn & Mentzer 1995; Makridakis et al. 1982; Makridakis & Hibon 1979; Peterson 1993).

Five treatments are used for Forecast Skewness: -1.3693, -0.6838, 0.0, +0.6838 and +1.3693. Values of two standard errors of skewness (SES) or more (regardless of sign) are probably skewed to a significant degree. The SES for the Normal distribution was estimated using the formula provided by Tabachnick & Fidell (1983). The value 0.6838 was obtained for two SES after applying this formula. Therefore, these skewness levels are chosen to represent mild to strong asymmetric patterns in the distribution of percentage errors.

Manipulations of these two factors result in twenty-five alternative distributions of forecast percentage error, as seen on Table 9. Each distribution has a specified level of Forecast Bias and Forecast Skewness. These distributions are then used to conduct experiments.

ID	Distribution	Mean	Standard Deviation	Skewness	Kurtosis
1	BETA (3.5, 3.5,-0.9,+0.1)	- 40%	0.17678	0.0000	2.4000
2	BETA (3.5,3.5,-0.7,+0.3)	- 20%	0.17678	0.0000	2.4000
3	BETA (3.5,3.5,-0.5,+0.5)	0%	0.17678	0.0000	2.4000
4	BETA (3.5, 3.5,-0.3,+0.7)	+20%	0.17678	0.0000	2.4000
5	BETA (3.5,3.5,-0.1,+0.9)	+40%	0.17678	0.0000	2.4000
6	BETA (3.5,15,-0.79 ,+1.25)	- 40%	0.18093	+0.6838	3.3896
7	BETA (3.5,15,-0.59,+1.45)	- 20%	0.18093	+0.6838	3.3896
8	BETA (3.5,15,-0.39,+1.65)	0%	0.18093	+0.6838	3.3896
9	BETA (3.5,15,-0.19 ,+1.85)	+20%	0.18093	+0.6838	3.3896
10	BETA (3.5,15,+0.01,+2.05)	+40%	0.18093	+0.6838	3.3896
11	BETA (15,3.5,-2.05,-0.01)	- 40%	0.18093	-0.6838	3.3896
12	BETA (15,3.5,-1.85,+0.19)	- 20%	0.18093	-0.6838	3.3896
13	BETA (15,3.5,-1.65,+0.39)	0%	0.18093	-0.6838	3.3896
14	BETA (15,3.5,-1.45,+0.59)	+20%	0.18093	-0.6838	3.3896
15	BETA (15,3.5, -1.25,+0.79)	+40%	0.18093	-0.6838	3.3896
16	BETA (1.5,20.5,-0.63,+2.75)	- 40%	0.17764	+1.3693	5.4602
17	BETA (1.5,20.5,-0.43,+2.95)	- 20%	0.17764	+1.3693	5.4602
18	BETA (1.5,20.5,-0.23,+3.15)	0%	0.17764	+1.3693	5.4602
19	BETA (1.5,20.5,-0.03,+3.35)	+20%	0.17764	+1.3693	5.4602
20	BETA (1.5,20.5,+0.17,+3.55)	+40%	0.17764	+1.3693	5.4602
21	BETA (20.5,1.5,-3.55 ,-0.17)	- 40%	0.17764	-1.3693	5.4602
22	BETA (20.5,1.5,-3.35,+0.03)	- 20%	0.17764	-1.3693	5.4602
23	BETA (20.5,1.5,-3.15,+0.23)	0%	0.17764	-1.3693	5.4602
24	BETA (20.5,1.5,-2.95,+0.43)	+20%	0.17764	-1.3693	5.4602
25	BETA (20.5,1.5,-2.75,+0.63)	+40%	0.17764	-1.3693	5.4602

Table 9 – Distributions of Forecast Percentage Error

Histograms of the resulting distributions are presented on Figure 8. The number in the upper right corner of each histogram corresponds to the distribution number presented on Table 9. Each graph has a fixed scale: the boundaries of the x-axis are –100% and +100%, while the boundaries of the y-axis are 0 and 3.5.

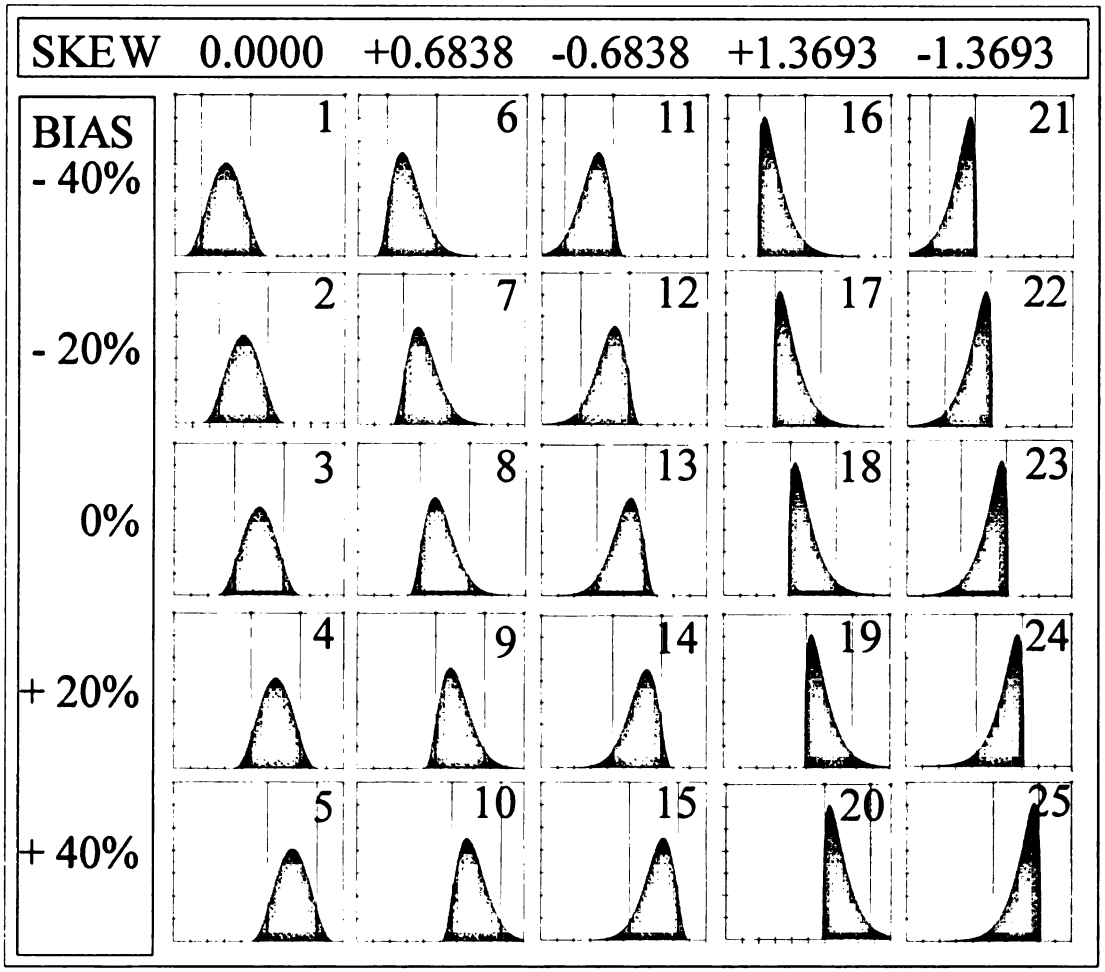


Figure 8 – Histograms of BETA Distributions of Forecast Percentage Error

Distributions 1 to 5 represent situations were errors are symmetric around the mean, resulting in skewness of zero.

Kurtosis is a measure of whether the data are peaked or flat relative to a Normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. The kurtosis for a standard Normal distribution is three. For this reason, most statistical packages report the "excess kurtosis", defined as the original measure of kurtosis minus three. By doing that, the standard Normal distribution then has a kurtosis of zero.

Distributions 1 to 5 have kurtosis measures close to 3. Therefore, these first five distributions represent cases that are similar to the common approach of modeling forecast errors assuming Normal distributions.

Distributions 6 to 10 represent cases where there exists a slight skew to the left, while distributions 11 to 15 represent cases where the distribution is slightly skewed to the right.

Finally, distributions 16 to 20 represent cases where the distributions are strongly skewed to the left, while distributions 21 to 25 represent cases where they are strongly skewed to the right.

Notice that all twenty-five distributions have similar measure of variability. The standard deviation is approximately 0.18 for all distributions. The purpose of this approach is to investigate the effects of Forecast Bias and Forecast Skewness on performance variables at a fixed and controlled level of Forecast Variability.

Also notice that all twenty-five distributions are bounded between -100% and +100%. This is a reasonable assumption if daily volumes of demand are moderate to high, the case in this dissertation.

Specific details of the experimental factors and corresponding levels are summarized on Table 10.

Experimental Factor	Details
(1) Demand Variability 3 Levels	(a) Low - Demand: TRIANGULAR (75,100,125), CV=10% (b) Medium - Demand: TRIANGULAR (40,100,160), CV=25% (b) High - Demand: TRIANGULAR (0,100,200), CV=40%
(2) Lead Time Variability 2 Levels	(a) Low - Transit Time from Plant to Wholesale: 4 days - Transit Time from Wholesale to Retail: 3 days (b) High - Transit Time from Plant to Wholesale: TRIANGULAR (3,4,6) days - Transit Time from Wholesale to Retail: TRIANGULAR (2,3,5) days
(4) Forecast Bias 5 Levels	(a) - 40% (Strongly Negative Bias) (b) - 20% (Negative Bias) (c) 0% (No Bias) (d) +20% (Positive Bias) (e) +40% (Strongly Positive Bias)
(3) Forecast Skewness 5 Levels	(a) 0 (No Skew) (b) +0.6838 (Positive Skew) (c) -0.6838 (Negative Skew) (d) +1.3693 (Strongly Negative Skew) (e) -1.3693 (Strongly Positive Skew)

Table 10 – Experimental Factors

3.5 Fixed Parameters

The previous section detailed experimental factors that are manipulated during simulation experiments. This section presents parameters that are modeled, but considered constant across treatments.

Fixed parameters are defined as part of the inventory management technique. As previously stated, a daily order-up policy is used to model inventory policy in all facilities. Every day, inventory levels are evaluated and the necessity for replenishment orders is determined. The model uses a fifteen-day planning horizon to determine average forecasts. This average value is then multiplied by the maximum inventory target in each facility, defined as 4 days for retail locations and 5 days for wholesale locations. These parameters are summarized on Table 11.

Fixed Parameter	Details
Inventory Management Technique	- Policy: Order-up - Revision Period: Daily - Planning Horizon: 15 days - Maximum Inventory Target: o Retail: 4 days of demand o Wholesale: 5 days of demand

Table 11 – Fixed Factors

3.6 Performance Variables

Three output variables are measured to evaluate the performance of the supply chain: Order Fill Rate, Case Fill Rate, and Average System Inventory. Separate measurement of service and inventory performance allow collection of empirical data through which the basic relationships between inventory and service can be investigated independent of arbitrary cost parameters.

The first two performance variables are measures of availability used to establish the extent to which a firm's inventory strategy is accommodating customer demand.

Order Fill Rate is the most exacting measure of performance in product availability. It is analogous to orders shipped complete. Failure to provide even one item on a customer's order results in that order being recorded as *zero*, not a complete shipment.

Case Fill Rate measures the magnitude or impact of stockouts over time. It is defined here as the total number of units shipped to a customer divided by the total number of units requested. For example, if a customer wants 100 units of an item and only 97 are available, the Fill Rate is 97%. Backorders are not considered for the calculation of Fill Rate. Both fill rate measures are calculated only at the retail level.

Average System Inventory is calculated using the weighted average inventory based on the cumulative daily inventory level. This statistic considers not only storage inventory, but also transit inventory. This performance measure is calculated not only for the retail level, but also for the wholesale and plant levels. Table 12 summarizes the key performance variables.

Performance Variable	Details
Order Fill Rate	Analogous to Orders Shipped Complete, it is defined as the number of orders shipped complete divided by the total number of orders originally requested
Case Fill Rate	Total number of units shipped to a customer divided by the total number of units originally requested
Average System Inventory	Sum of end of day position of inventory (storage and transit) divided by number of days

Table 12 – Performance Variables

3.7 Number of Replications

The previous section presented the performance variables that are analyzed in this study. A specified precision is important for estimating the mean of performance variables. Law & Kelton (2000) present a procedure to calculate the required number of replications to achieve a specified level of precision for these mean estimates.

The procedure calculates the number of replications (n) required to estimate the population mean (μ) with a specified error or precision (β). From previous research experience, the estimated range of service measurements falls between 0.7 and 1.0 (Closs & Law 1983). Therefore, an estimated standard deviation value equals one-fourth of the observed range, or 0.075. Assuming a population variance $S^2(n)$ of 0.0056, an absolute error β of 0.05, and a confidence level α of 90%, about 12 replications would be required per experimental cell. This dissertation assumes 30 replications for each experiment.

3.8 Data Analysis

Measuring the inexact nature of the relationship between forecast uncertainty and performance requires the utilization of a statistical technique. Such a statistical tool can then separate the systematic component from the random component of the relationship. The six hypotheses presented previously are tested using multivariate analysis of variance (MANOVA).

MANOVA is an extension of analysis of variance (ANOVA) to accommodate more than one dependent variable (Hair et al. (1998). It is a dependence technique that measures the differences for two or more metric dependent variables (supply chain performance measures) based on a set of categorical variables acting as independent variables (experimental factors).

MANOVA is concerned with differences between groups (experimental treatments). It is classified as a multivariate procedure because it assesses group differences across dependent variables simultaneously. In the case where the dependent variables are not independent of one another, MANOVA is the most appropriate test. A series of univariate ANOVA tests would ignore the correlations among dependent variables and thus use less than the total information available for assessing overall group differences.

This chapter reviewed the research methodology. The conceptual model was presented along with the simulation environment and details of the experimental design, including experimental factors, fixed parameters, performance variables, and data analysis. The next chapter presents and discusses results from simulation experiments.

4 Results and Analysis

This chapter discusses the results of the simulation experiments and the statistical analyses. The first section reviews the critical assumptions necessary for the use of MANOVA. The second section reviews the results from the perspective of the conformity to these assumptions. The third section of the chapter presents the hypothesis test results from MANOVA, followed by multiple comparisons of the results.

4.1 MANOVA Assumptions

MANOVA is a dependence technique that measures the differences for two or more metric dependent variables based on a set of categorical independent variables. For the multivariate test procedures of MANOVA to be valid, four assumptions must be met: (1) units (persons, families, or countries) are randomly sampled from the population of interest, (2) observations are statistically independent of one another, (3) dependent variables must follow a multivariate Normal distribution within each group, and (4) the variance-covariance matrices must be equal for all treatment groups (Bray & Maxwell 1985).

Although these four assumptions are mathematical requirements for MANOVA, in practice it is unlikely that all of them will be met precisely (Bray & Maxwell 1985). Fortunately, under many conditions, violating the assumptions does not necessarily invalidate the results. The technique is relatively robust to violations of all except the first two assumptions.

Simulation studies were conducted to investigate the extent to which test statistics are strong to violations of the other two assumptions: multivariate normality and equality of covariance matrices (Ito 1969; Mardia 1971; Olson 1974).

Departures from multivariate normality generally have only very slight effects on the Type I error rates of the four test statistics. In a hypothesis test, a Type I error occurs when the null hypothesis is rejected when it is in fact true. The sole know exception to this rule is that Roy's greatest characteristic root test may lead to too many Type I errors when only one of several groups has a distribution with high positive kurtosis.

The effects of failing to meet the equality of covariance matrices assumption are more complicated. When sample sizes are unequal, none of the four test statistics is consistent. When sample sizes are equal, all of the test statistics tend to be robust unless sample sizes are small, or the number of variables is large, and the difference in matrices is quite large. Olson (1974) has found that the Pillai-Barlett trace is stronger across a wide range of population configurations than any of the other three statistics.

Characteristics of the different MANOVA tests of statistical significance are summarized on Table 13.

Test Statistic	Description	Characteristics	When to Use
Wilks' Lambda	Product of the unexplained variances on each of the discriminant variates.	Determines whether the groups are different without worrying about linear combinations of dependent variables.	Good balance between power and assumptions. Use if assumptions appear to be met.
Pillai-Barlett's Trace	Sum of explained variances on the discriminant variates.	Minor differences from Wilks' Lambda	Most robust when assumptions are not met. Particularly useful is sample sizes are small, cell sizes are unequal, or covariances are not homogeneous.
Hotelling's Trace	Sum of ratios of explained variances on the discriminant variates.	Minor differences from Wilks' Lambda	Safely ignored in most cases
Roy's Largest Root	Based only on the first discriminant variate.	Measures the difference only on the first canonical root.	Appropriate and very powerful when the dependent variables are strongly interrelated on a single dimension. Most likely to be affected by violations of assumptions. Use cautiously.

Table 13 – MANOVA Tests of Statistical Significance

4.2 Conformity to Assumptions and Data Transformations

The experimental design for this study used independent replications in sample collection, thus satisfying the first two assumptions. Then one must check the validity of the last two assumptions: conformity to multivariate normality and equality of covariance matrices.

Before the last two assumptions are evaluated, some descriptive statistics of the dependent variables will be analyzed. Table 14 presents Pearson's correlation coefficients for the dependent variables. Pearson's correlation coefficient is a measure of linear association. Two variables can be perfectly related, but if the relationship is not linear, the correlation coefficient is not an appropriate statistic for measuring their association.

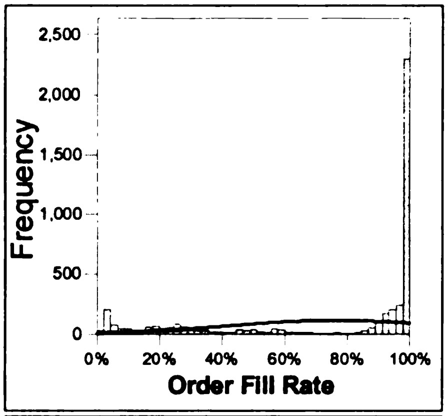
	Order Fill Rate	Case Fill Rate	Avg System Inventory
Order Fill Rate	1.000	0.996	0.798
Case Fill Rate	0.996	1.000	0.775
Avg System Inventory	0.798	0.775	1.000

Table 14 – Correlations among Dependent Variables

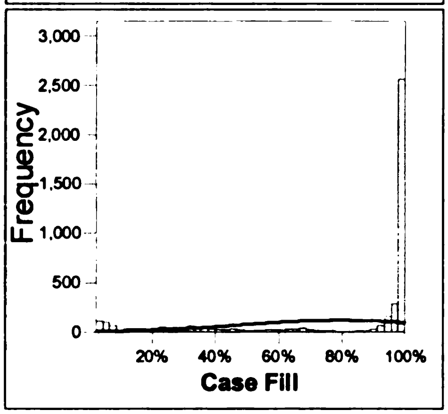
All correlation measures are statistically significant at the $p<0.01$ level (2-tailed). Both measures of fill rate are, as expected, highly correlated. There is a significant and strong correlation between Order Fill Rate and System Inventory. The correlation between Case Fill Rate and System Inventory is analogous. Thus, the dependent variables are not independent of one another. This finding is not surprising. As inventories go down, product availability becomes an issue, affecting the measures of service. MANOVA is then the most appropriate test, compared to an alternative series of univariate ANOVAs.

An Exploratory Factor Analysis among the dependent variables was conducted to assess the number of dimensions. Principal component analysis was chosen as the extraction method, using Varimax rotation. Only one component was extracted, responsible for 90.5% of the variance. This result supported that the dependent variables are strongly interrelated in a single dimension.

To check for multivariate normality, this research's strategy is to ensure univariate normality, a necessary but not sufficient condition.



	Skewness		Kurtosis	
	Statistic	Std Error	Statistic	Std Error
Order Fill Rate	-1.144	0.037	-0.389	0.073
Case Fill Rate	-1.285	0.037	0.023	0.073
Avg System Inventory	0.024	0.037	-1.311	0.073



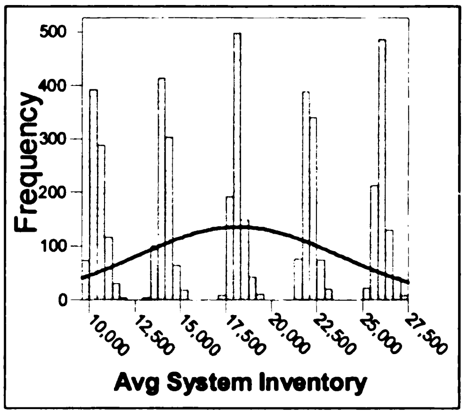


Figure 9 – Histograms and Statistics for the Dependent Variables

Figure 9 presents histograms for the three dependent variables. It also presents statistics of skewness and kurtosis.

Order Fill Rate has substantial departures from normality, with a skewness value of -1.144 and a kurtosis value of –0.389. Case Fill Rate also has departures from normality (skewness of –1.285 and kurtosis of 0.023). Average System Inventory also departs from normality, with a skewness of 0.024 and a kurtosis of -1.311.

The multivariate Box's M test is a test for the equality of the group covariance matrices. For sufficiently large samples, a non-significant p-value means that there is insufficient evidence that the matrices differ. The test is sensitive to departures from multivariate normality. The null hypothesis that the observed covariance matrices of the dependent variables are equal across groups is rejected at $p<0.001$. It is important to notice that the test is sensitive to departures from multivariate normality.

Because of such departures, the original variables were transformed in an attempt to reach univariate normality and equality of covariance matrices. The chosen strategy is to work with ratios of the original variables, dividing the service variables by the system inventory. This procedure resulted in two transformed variables: Order Fill Rate / Average System Inventory and Case Fill Rate / Average System Inventory. By adapting this strategy no original variable is discarded and two different dimensions of efficiency are captured (service, as measured by fill rates, divided by investment, as measured by inventory). Figure 10 presents histograms containing statistics of skewness and kurtosis for the two transformed dependent variables.

	Skewness		Kurtosis	
	Statistic	Std Error	Statistic	Std Error
Order Fill / Inventory	-0.658	0.037	0.145	0.073
Case Fill / Inventory	-0.688	0.037	0.553	0.073

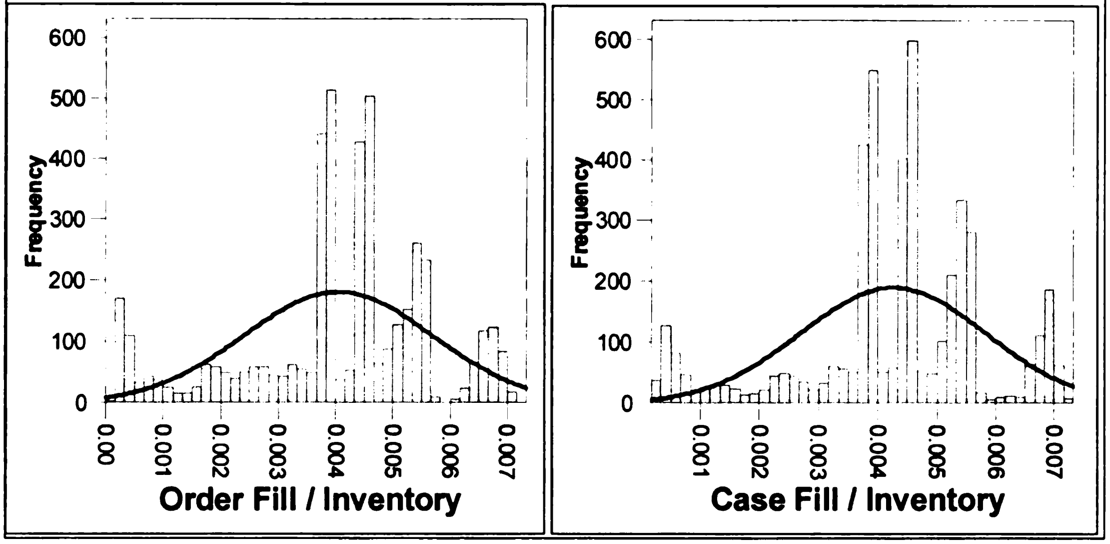


Figure 10 - Histograms and Statistics for the Transformed Dependent Variables

By using the ratios of the original variables, the problem of violating univariate normality is minimized. The two transformed variables are slightly departed from the Normal distribution, with measures of skewness and kurtosis closer to zero. In addition, both distributions are more continuous (no gaps between histogram cells) when compared to the original ones.

Nevertheless, results of the Box's M test for the transformed variables are analogous to the original variables case. The null hypothesis that the observed covariance matrices of the transformed dependent variables are equal across groups is also rejected at $p<0.001$.

Since MANOVA is relatively strong to slight departures from the last two assumptions when all treatment groups have equal sample size (the case in this research), the decision was to proceed with MANOVA for significance testing.

4.3 Hypothesis Testing

The previous section discussed data conformity to assumptions and transformations. The objective of this section is to present the hypotheses test results as well as to develop multiple comparisons of the results. Multivariate followed by univariate results are presented and discussed. Next, the proposed hypotheses are formally tested. Finally, relationships are discussed and findings that were not expected are presented.

4.3.1 Results of Multivariate Tests

A four-way multivariate analysis of variance was performed on the two transformed dependent variables: Order Fill Rate / Average System Inventory and Case Fill Rate / Average System Inventory. Demand Variability (three levels), Lead Time Variability (two levels), Forecast Bias (five levels) and Forecast Skewness (five levels) resulted in a total of one hundred and fifty different treatments. For each treatment, data were collected from thirty replications. Thus, the total sample size consists of 4,500 observations.

SPSS MANOVA was used for conducting the analysis. MANOVA performs multivariate tests of significance using four testing criteria (Pillai's Trace, Hotteling's Trace, Wilk's Lambda and Roy's Largest Root Criterion). Although all testing criteria are reported, special attention is given to Pillai's Trace test. This is the most robust test criterion when assumptions are not met. It is particularly useful when covariances are not homogeneous. Table 15 reports multivariate tests results for the two transformed dependent variables.

Effect	Value		F	df	Sig.	Partial Eta Squared	Observed Power
Intercept	Pillai's Trace	0.992	276354.895	2	0.000	0.992	1.000
	Wilks' Lambda	0.008	276354.895	2	0.000	0.992	1.000
	Hotelling's Trace	127.089	276354.895	2	0.000	0.992	1.000
	Roy's Largest Root	127.089	276354.895	2	0.000	0.992	1.000
Demand Variability	Pillai's Trace	0.006	6.255	4	0.000	0.003	0.989
	Wilks' Lambda	0.994	6.262	4	0.000	0.003	0.989
	Hotelling's Trace	0.006	6.270	4	0.000	0.003	0.990
	Roy's Largest Root	0.006	12.496	2	0.000	0.006	0.996
Lead Time Variability	Pillai's Trace	0.761	6908.458	2	0.000	0.761	1.000
	Wilks' Lambda	0.239	6908.458	2	0.000	0.761	1.000
	Hotelling's Trace	3.177	6908.458	2	0.000	0.761	1.000
	Roy's Largest Root	3.177	6908.458	2	0.000	0.761	1.000
Forecast Bias	Pillai's Trace	1.655	5211.632	8	0.000	0.827	1.000
	Wilks' Lambda	0.011	9184.265	8	0.000	0.894	1.000
	Hotelling's Trace	28.817	15661.974	8	0.000	0.935	1.000
	Roy's Largest Root	26.581	28906.767	4	0.000	0.964	1.000
Forecast Skewness	Pillai's Trace	0.006	3.176	8	0.001	0.003	0.971
	Wilks' Lambda	0.994	3.180	8	0.001	0.003	0.971
	Hotelling's Trace	0.006	3.183	8	0.001	0.003	0.971
	Roy's Largest Root	0.006	6.143	4	0.000	0.006	0.988
Demand Variability * Lead Time Variability	Pillai's Trace	0.002	1.696	4	0.148	0.001	0.525
	Wilks' Lambda	0.998	1.697	4	0.148	0.001	0.525
	Hotelling's Trace	0.002	1.697	4	0.148	0.001	0.525
	Roy's Largest Root	0.002	3.375	2	0.034	0.002	0.638
Demand Variability * Forecast Bias	Pillai's Trace	0.079	22.397	16	0.000	0.040	1.000
	Wilks' Lambda	0.921	22.778	16	0.000	0.040	1.000
	Hotelling's Trace	0.085	23.160	16	0.000	0.041	1.000
	Roy's Largest Root	0.081	44.121	8	0.000	0.075	1.000
Lead Time Variability * Forecast Bias	Pillai's Trace	1.387	2458.835	8	0.000	0.693	1.000
	Wilks' Lambda	0.067	3103.645	8	0.000	0.741	1.000
	Hotelling's Trace	7.112	3865.607	8	0.000	0.781	1.000
	Roy's Largest Root	5.985	6509.202	4	0.000	0.857	1.000
Demand Variability * Lead Time Variability * Forecast Bias	Pillai's Trace	0.080	22.668	16	0.000	0.040	1.000
	Wilks' Lambda	0.920	23.094	16	0.000	0.041	1.000
	Hotelling's Trace	0.087	23.520	16	0.000	0.041	1.000
	Roy's Largest Root	0.084	45.645	8	0.000	0.077	1.000
Demand Variability * Forecast Skewness	Pillai's Trace	0.000	0.052	16	1.000	0.000	0.070
	Wilks' Lambda	1.000	0.052	16	1.000	0.000	0.070
	Hotelling's Trace	0.000	0.052	16	1.000	0.000	0.070
	Roy's Largest Root	0.000	0.089	8	1.000	0.000	0.075
Lead Time Variability * Forecast Skewness	Pillai's Trace	0.001	0.437	8	0.899	0.000	0.209
	Wilks' Lambda	0.999	0.437	8	0.899	0.000	0.209
	Hotelling's Trace	0.001	0.437	8	0.899	0.000	0.209
	Roy's Largest Root	0.001	0.853	4	0.492	0.001	0.275
Demand Variability * Lead Time Variability * Forecast Skewness	Pillai's Trace	0.000	0.026	16	1.000	0.000	0.059
	Wilks' Lambda	1.000	0.026	16	1.000	0.000	0.059
	Hotelling's Trace	0.000	0.026	16	1.000	0.000	0.059
	Roy's Largest Root	0.000	0.036	8	1.000	0.000	0.060

Table 15 – Results of Multivariate Tests: Transformed Dependent Variables

Effect	Value		F	df	Sig.	Partial Eta Squared	Observed Power
Forecast Bias * Forecast Skewness	Pillai's Trace	0.031	4.216	32	0.000	0.015	1.000
	Wilks' Lambda	0.970	4.220	32	0.000	0.015	1.000
	Hotelling's Trace	0.031	4.225	32	0.000	0.015	1.000
	Roy's Largest Root	0.022	5.988	16	0.000	0.022	1.000
Demand Variability * Forecast Bias * Forecast Skewness	Pillai's Trace	0.001	0.080	64	1.000	0.001	0.119
	Wilks' Lambda	0.999	0.080	64	1.000	0.001	0.119
	Hotelling's Trace	0.001	0.080	64	1.000	0.001	0.119
	Roy's Largest Root	0.001	0.147	32	1.000	0.001	0.147
Lead Time Variability * Forecast Bias * Forecast Skewness	Pillai's Trace	0.031	4.304	32	0.000	0.016	1.000
	Wilks' Lambda	0.969	4.329	32	0.000	0.016	1.000
	Hotelling's Trace	0.032	4.354	32	0.000	0.016	1.000
	Roy's Largest Root	0.030	8.161	16	0.000	0.029	1.000
Demand Variability * Lead Time Variability * Forecast Bias * Forecast Skewness	Pillai's Trace	0.002	0.141	64	1.000	0.001	0.196
	Wilks' Lambda	0.998	0.141	64	1.000	0.001	0.196
	Hotelling's Trace	0.002	0.141	64	1.000	0.001	0.196
	Roy's Largest Root	0.002	0.258	32	1.000	0.002	0.255

Table 15 – Results of Multivariate Tests: Transformed Dependent Variables (Continued)

The first column on Table 15 details the source of the effect, either a main factor or an interaction. The second column presents values for the four MANOVA tests of statistical significance. The third column presents the values for the F statistic, the ratio of two mean squares. The fourth column provides information regarding the degrees of freedom used to obtain the observed significance level. The next column details the significance level (p-value), the conditional probability that a relationship as strong as the one observed in the data would be present if the null hypotheses were true. The sixth column presents the proportion of the total variability in the dependent variable that is accounted for by variation in the independent variable (Partial Eta Squared). The Partial Eta Squared is a measure of effect size. Finally, the last column reports the Power of the test, computed assuming an alpha value of 0.05. The Power of a statistical hypothesis test measures the test's ability to reject the null hypothesis when it is actually false.

The three-way interaction of Demand Variability, Lead Time Variability and Forecast Bias is statistically significant at the $p<0.001$ level. The three-way interaction of Lead Time Variability, Forecast Bias and Forecast Skewness is also statistically significant at the $p<0.001$ level.

The two-way interactions between Demand Variability and Forecast Bias, between Lead Time Variability and Forecast Bias, and between Forecast Bias and Forecast Skewness are all significant at the $p<0.001$ level.

Finally, the main effects of Demand Variability, Lead Time Variability, Forecast Bias and Forecast Skewness are all significant at the $p<0.001$ level. The presence of significant interactions suggests that testing results on main effects should be interpreted with caution.

Table 16 reports multivariate tests results for the three original dependent variables (Order Fill Rate, Case Fill Rate and Average System Inventory). The results in terms of statistical significance are analogous to the transformed variables case.

Once a significant overall MANOVA has been found, the next step is to investigate the specific differences between groups (Bray & Maxwell 1985). As in ANOVA, this involves determining which groups are responsible for the significant omnibus test. In addition, the follow-up analyses are used to evaluate which variables are important for group separation.

Historically, following a significant MANOVA with ANOVAs on each of the dependent variables was one of the first methods recommended for interpreting group differences. This method is often referred to as the Least Significant

Difference (LSD) test or protected F. The term "protected" comes from the idea that the overall multivariate test provides protection from an inflated alpha level on the dependent variables' univariate tests. Each univariate F test that reaches the specified alpha level is considered to be statistically significant and available for interpretation.

Effect	Value		F	df	Sig.	Partial Eta Squared	Observed Power
Intercept	Pillai's Trace	1.000	5811509.584	3	0.000	1.000	1.000
	Wilks' Lambda	0.000	5811509.584	3	0.000	1.000	1.000
	Hotelling's Trace	4009.781	5811509.584	3	0.000	1.000	1.000
	Roy's Largest Root	4009.781	5811509.584	3	0.000	1.000	1.000
Demand Variability	Pillai's Trace	0.012	8.518	6	0.000	0.006	1.000
	Wilks' Lambda	0.988	8.541	6	0.000	0.006	1.000
	Hotelling's Trace	0.012	8.564	6	0.000	0.006	1.000
	Roy's Largest Root	0.012	17.084	3	0.000	0.012	1.000
Lead Time Variability	Pillai's Trace	0.765	4705.677	3	0.000	0.765	1.000
	Wilks' Lambda	0.235	4705.677	3	0.000	0.765	1.000
	Hotelling's Trace	3.247	4705.677	3	0.000	0.765	1.000
	Roy's Largest Root	3.247	4705.677	3	0.000	0.765	1.000
Forecast Bias	Pillai's Trace	2.311	3646.200	12	0.000	0.770	1.000
	Wilks' Lambda	0.000	28754.645	12	0.000	0.952	1.000
	Hotelling's Trace	405.449	146862.539	12	0.000	0.993	1.000
	Roy's Largest Root	392.036	426339.346	4	0.000	0.997	1.000
Forecast Skewness	Pillai's Trace	0.254	100.455	12	0.000	0.085	1.000
	Wilks' Lambda	0.747	111.560	12	0.000	0.093	1.000
	Hotelling's Trace	0.337	121.978	12	0.000	0.101	1.000
	Roy's Largest Root	0.333	361.796	4	0.000	0.250	1.000
Demand Variability * Lead Time Variability	Pillai's Trace	0.002	1.265	6	0.270	0.001	0.505
	Wilks' Lambda	0.998	1.265	6	0.270	0.001	0.505
	Hotelling's Trace	0.002	1.266	6	0.270	0.001	0.505
	Roy's Largest Root	0.002	2.456	3	0.061	0.002	0.614
Demand Variability * Forecast Bias	Pillai's Trace	0.067	12.427	24	0.000	0.022	1.000
	Wilks' Lambda	0.933	12.663	24	0.000	0.023	1.000
	Hotelling's Trace	0.071	12.894	24	0.000	0.023	1.000
	Roy's Largest Root	0.066	36.137	8	0.000	0.062	1.000
Lead Time Variability * Forecast Bias	Pillai's Trace	1.348	886.948	12	0.000	0.449	1.000
	Wilks' Lambda	0.075	1589.165	12	0.000	0.578	1.000
	Hotelling's Trace	6.670	2416.071	12	0.000	0.690	1.000
	Roy's Largest Root	5.686	6182.983	4	0.000	0.850	1.000
Demand Variability * Lead Time Variability * Forecast Bias	Pillai's Trace	0.091	16.960	24	0.000	0.030	1.000
	Wilks' Lambda	0.910	17.461	24	0.000	0.031	1.000
	Hotelling's Trace	0.099	17.953	24	0.000	0.032	1.000
	Roy's Largest Root	0.096	52.073	8	0.000	0.087	1.000

Table 16 – Results of Multivariate Tests: Original Dependent Variables

Effect	Value		F	df	Sig.	Partial Eta Squared	Observed Power
Demand Variability * Forecast Skewness	Pillai's Trace	0.000	0.043	24	1.000	0.000	0.070
	Wilks' Lambda	1.000	0.043	24	1.000	0.000	0.069
	Hotelling's Trace	0.000	0.043	24	1.000	0.000	0.070
	Roy's Largest Root	0.000	0.091	8	0.999	0.000	0.076
Lead Time Variability * Forecast Skewness	Pillai's Trace	0.001	0.463	12	0.937	0.000	0.274
	Wilks' Lambda	0.999	0.463	12	0.937	0 000	0.241
	Hotelling's Trace	0.001	0.463	12	0.937	0.000	0.274
	Roy's Largest Root	0.001	1.238	4	0.292	0.001	0.392
Demand Variability * Lead Time Variability * Forecast Skewness	Pillai's Trace	0.000	0.024	24	1.000	0.000	0.061
	Wilks' Lambda	1.000	0.024	24	1.000	0.000	0.060
	Hotelling's Trace	0.000	0.024	24	1.000	0.000	0.061
	Roy's Largest Root	0.000	0.036	8	1.000	0.000	0.060
Forecast Bias * Forecast Skewness	Pillai's Trace	0.050	4.600	48	0.000	0.017	1.000
	Wilks' Lambda	0.951	4.617	48	0.000	0.017	1.000
	Hotelling's Trace	0.051	4.633	48	0.000	0.017	1.000
	Roy's Largest Root	0.030	8.241	16	0.000	0.029	1.000
Demand Variability * Forecast Bias * Forecast Skewness	Pillai's Trace	0.001	0.064	96	1.000	0.000	0.117
	Wilks' Lambda	0.999	0.064	96	1.000	0.000	0.117
	Hotelling's Trace	0.001	0.064	96	1.000	0.000	0.117
	Roy's Largest Root	0.001	0.153	32	1.000	0.001	0.153
Lead Time Variability * Forecast Bias * Forecast Skewness	Pillai's Trace	0.044	4.008	48	0.000	0.015	1.000
	Wilks' Lambda	0.957	4.056	48	0.000	0.015	1.000
	Hotelling's Trace	0.045	4.103	48	0.000	0.015	1.000
	Roy's Largest Root	0.042	11.486	16	0.000	0.041	1.000
Demand Variability * Lead Time Variability * Forecast Bias * Forecast Skewness	Pillai's Trace	0.003	0.122	96	1.000	0.001	0.209
	Wilks' Lambda	0.997	0.122	96	1.000	0.001	0.209
	Hotelling's Trace	0.003	0.122	96	1.000	0.001	0.209
	Roy's Largest Root	0.002	0.303	32	1.000	0.002	0.305

Table 16 – Results of Multivariate Tests: Original Dependent Variables (Continued)

As the results of multivariate tests for both the original and transformed dependent variables were analogous, we decided to investigate the specific differences between groups using the results from the original dependent variables.

MANOVA tests whether or not a set of means differs due to treatment effects. Therefore, it is relevant to present means and standard deviations of the dependent variables for the four different treatments. This information is presented on Table 17. Means are displayed as bold numbers, while standard deviations are displayed as italic numbers.

		Order Fill Rate	Case Fill Rate	Avg System Inventory
Demand Variability	Low	**77.13%**	**79.81%**	**18178.46**
		0.13%	*0.15%*	*7.57*
	Medium	**76.78%**	**79.47%**	**18173.92**
		0.13%	*0.15%*	*7.57*
	High	**76.02%**	**78.77%**	**18174.49**
		0.13%	*0.15%*	*7.57*
Lead Time Variability	Low	**83.68%**	**85.78%**	**18137.07**
		0.11%	*0.12%*	*6.18*
	High	**69.60%**	**72.92%**	**18214.18**
		0.11%	*0.12%*	*6.18*
Forecast Bias	-40%	**99.77%**	**99.87%**	**26026.07**
		0.17%	*0.19%*	*9.77*
	-20%	**99.43%**	**99.70%**	**22098.95**
		0.17%	*0.19%*	*9.77*
	0%	**96.03%**	**97.77%**	**18149.18**
		0.17%	*0.19%*	*9.77*
	+20%	**72.66%**	**78.75%**	**14136.86**
		0.17%	*0.19%*	*9.77*
	+40%	**15.33%**	**20.67%**	**10467.07**
		0.17%	*0.19%*	*9.77*
Forecast Skewness	-1.3693	**77.65%**	**80.32%**	**18431.53**
		0.17%	*0.19%*	*9.77*
	-0.6838	**77.07%**	**79.73%**	**18275.55**
		0.17%	*0.19%*	*9.77*
	0.0000	**76.83%**	**79.48%**	**18133.45**
		0.17%	*0.19%*	*9.77*
	+0.6838	**76.14%**	**78.93%**	**18077.47**
		0.17%	*0.19%*	*9.77*
	+1.3693	**75.53%**	**78.29%**	**17960.12**
		0.17%	*0.19%*	*9.77*

Table 17 – Estimated Marginal Means and Standard Deviations

Results are conceptually correct. When Demand Variability increases, both measures of service decrease. The same occurs when Lead Time Variability is increased. Also, service systematically decreases when Forecast

Bias moves from negative values to positive values. This occurs because negative bias represents situations where forecasts are systematically greater than actual demand. In this case, using an anticipatory replenishment strategy, inventories are built in excess of actual demand. Higher inventory allows better service in terms of customer fill rates.

Before the main effects can be analyzed, it is important to understand the impact of statistically significant interactions. The following sections discuss univariate results for statistically significant interactions and main effects.

4.3.2 Results of Univariate Tests: Interactions

The interaction term represents the joint effect of two (or more) treatments. It is the effect that must be examined first. Each treatment represents a unique combination of experimental factors. If the interaction effect is not statistically significant, then the main effects of the treatments are independent. Independence in factorial designs means that the effect of one treatment is the same for each level of the other treatments and that the main effects can be interpreted directly.

If the interaction term is significant, then the type of interaction must be determined. Interactions can be termed ordinal or disordinal. An ordinal interaction occurs when the effects of a treatment are not equal across all levels of another treatment, but the magnitude is always in the same direction. In a disordinal interaction, the effects of one treatment are positive for some levels and negative for other levels of the other treatment.

If the significant interactions are ordinal, the researcher must interpret the interaction term and ensure that its results are acceptable conceptually. If so, then the main effects of each treatment can be described (Hair et al. 1998). But if the significant interaction is disordinal, then the main effects of the treatments cannot be interpreted and the study must be redesigned. This stems from the fact that with disordinal interactions, the effects vary not only across treatment levels but also in direction. Thus, the treatments do not represent a consistent effect.

According to Table 16, two three-way interactions are significant at $p<0.001$: Demand Variability * Lead Time Variability * Forecast Bias and Lead Time Variability * Forecast Bias * Forecast Skewness.

Table 18 details the univariate tests for these interactions. In addition to statistical significance, the following discussion also focuses on effect size. The Partial Eta Squared measures the proportion of the total variability in the dependent variable that is accounted for by variation in the independent variable. Therefore, it is used as a measure of effect size.

According to Cohen (1988), it is possible to characterize the type of effect size depending on the measure for Partial Eta Squared. If the measure is smaller than 0.15, the effect is considered small or minimal. If the measure is close to 0.35, the effect can be considered medium or typical. When Partial Eta Squared is close to 0.5, the effect is considered large or substantial. Finally, for values of this statistic greater than 0.7, the effect is considered very large.

Source	Dependent Variable	df	F	Sig.	Partial Eta Squared	Observed Power
Demand Variability * Lead Time Variability * Forecast Bias	Order Fill Rate	8	2.775	0.005	0.005	0.944
	Case Fill Rate	8	1.622	0.113	0.003	0.725
	Avg System Inventory	8	0.129	0.998	0.000	0.088
Lead Time Variability * Forecast Bias * Forecast Skewness	Order Fill Rate	16	1.644	0.050	0.006	0.928
	Case Fill Rate	16	0.837	0.643	0.003	0.597
	Avg System Inventory	16	0.155	1.000	0.001	0.118

Table 18 – Univariate Tests (Three-way Interactions)

The univariate tests presented on Table 18 indicate that the three-way interaction of Demand Variability, Lead Time Variability and Forecast Bias is statistically significant for Order Fill Rate at $p<0.01$ level. This three-way interaction is responsible for a small variation on Order Fill Rate (about 0.5%). The interaction is not statistically significant for the other two performance variables.

The three-way interaction of Lead Time Variability, Forecast Bias and Forecast Skewness is statistically significant at $p<0.001$ (Table 16). According to Table 18, this three-way interaction is statistically significant for Order Fill Rate only at the $p<0.1$ level. The Partial Eta Squared statistic shows that the effect is also small, close to 0.6%. This interaction is not significant for the other two dependent variables.

Univariate results support that the impact of the three-way interactions is small on all dependent variables.

Three two-way interactions are statistically significant (Table 16): Demand Variability * Forecast Bias, Lead Time Variability * Forecast Bias, and Forecast Bias * Forecast Skewness.

Table 19 describes the univariate tests for these interactions. Results indicate that the three two-way interactions are statistically significant for all dependent variables at $p<0.01$. The only exception is the interaction between Demand Variability and Forecast Bias, which is not statistically significant for Average System Inventory.

Source	Dependent Variable	df	F	Sig.	Partial Eta Squared	Observed Power
Demand Variability * Forecast Bias	Order Fill Rate	8	6.067	0.000	0.011	1.000
	Case Fill Rate	8	2.774	0.005	0.005	0.944
	Avg System Inventory	8	0.213	0.989	0.000	0.117
Lead Time Variability * Forecast Bias	Rate	4	2632.046	0.000	0.708	1.000
	Case Fill Rate	4	1717.827	0.000	0.612	1.000
	Avg System Inventory	4	61.330	0.000	0.053	1.000
Forecast Bias * Forecast Skewness	Rate	16	4.461	0.000	0.016	1.000
	Case Fill Rate	16	3.359	0.000	0.012	1.000
	Avg System Inventory	16	2.845	0.000	0.010	0.998

Table 19 - Univariate Tests (Two-way Interactions)

Figure 11 presents a graphical display of the impact of the interaction between Demand Variability and Forecast Bias on Order Fill Rate. This interaction partially accounts for 1.1% of the variation for Order Fill Rate, a small effect. As Forecast Bias moves from -40% to +40%, the system shifts from a situation where forecasts are systematically higher than demand to a situation where forecasts are systematically lower than demand. When this happens, service decreases. This impact is slightly accentuated under higher levels of Demand Variability. Notice that, on Figure 11, the lines for different levels of Demand Variability are superimposed.

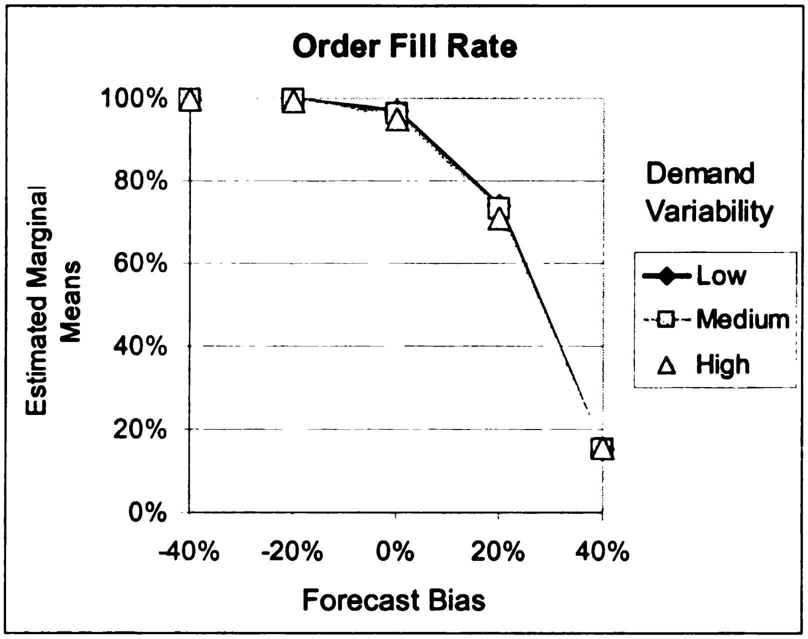


Figure 11 – Effect of Demand Variability * Forecast Bias on Order Fill Rate

Figure 12 presents a graphical display of the interaction between Demand Variability and Forecast Bias on Case Fill Rate. This interaction partially accounts for 0.5% of the variation for Case Fill Rate. This impact, thus, is small and the discussion is analogous to the impact on Order Fill Rate.

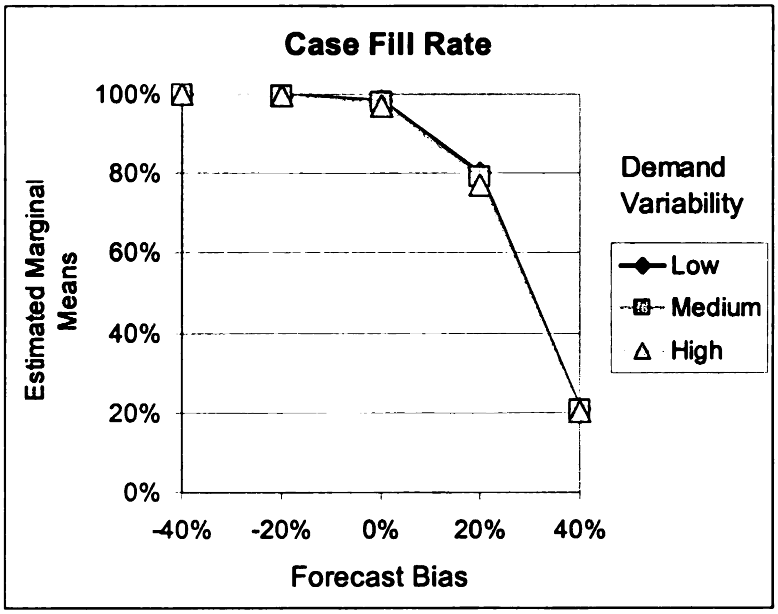


Figure 12 - Effect of Demand Variability * Forecast Bias on Case Fill Rate

The effect of this interaction on Average System Inventory is presented on Figure 13. The effect is not statistically significant, resulting in superimposed lines in the graph. This implies that the impact of Forecast Bias on Average System Inventory is not amplified at higher levels of Demand Variability.

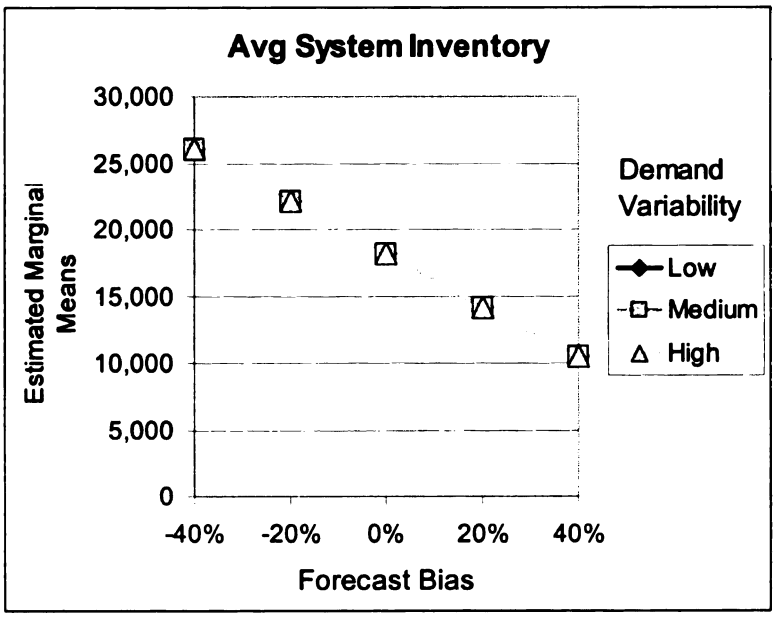


Figure 13 – Effect of Demand Variability * Forecast Bias on Avg System Inventory

The second statistically significant interaction is the combined impact of Lead Time Variability and Forecast Bias. The impact of this interaction on Order Fill Rate is presented on Figure 14. This impact is very large, as the interaction partially accounts for 70.8% of variation on Order Fill Rate. As Forecast Bias moves from -40% to +40%, service decreases. This loss in service is strongly accentuated at higher levels of Lead Time Variability.

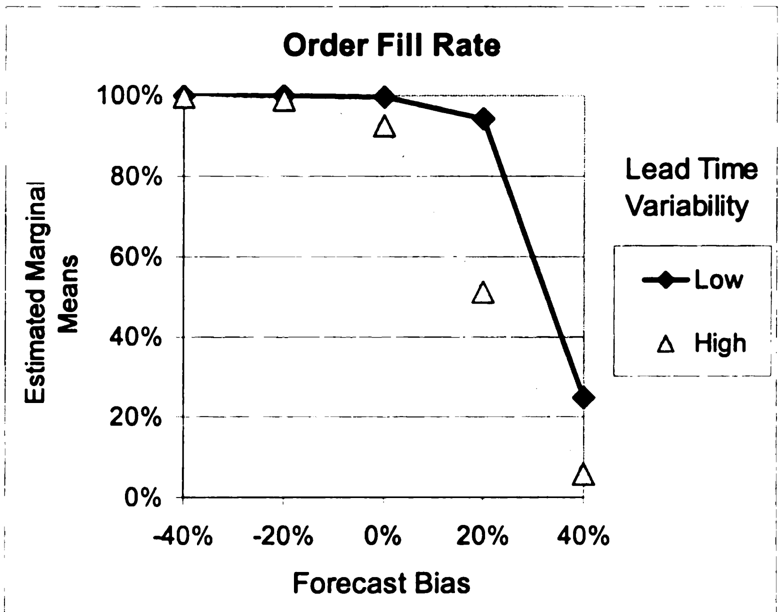


Figure 14 - Effect of Lead Time Variability * Forecast Bias on Order Fill Rate

The impact of the interaction between Lead Time Variability and Forecast Bias on Case Fill Rate is presented on Figure 15. This impact is large, partially accounting for 61.2% of variation on Case Fill Rate. The discussion is analogous to the Order Fill Rate case.

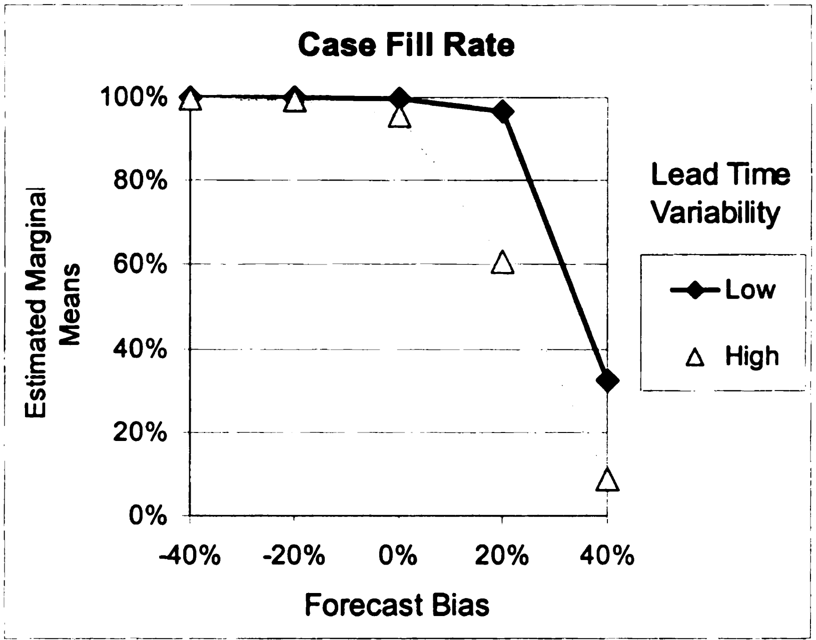


Figure 15 - Effect of Lead Time Variability * Forecast Bias on Case Fill Rate

The impact of the interaction between Lead Time Variability and Forecast Bias on Average System Inventory is presented on Figure 16. The impact is statistically significant, but the effect size is small. This interaction partially accounts for 5.3% of variation on Average System Inventory. Because of this small effect, lines on Figure 16 are superimposed.

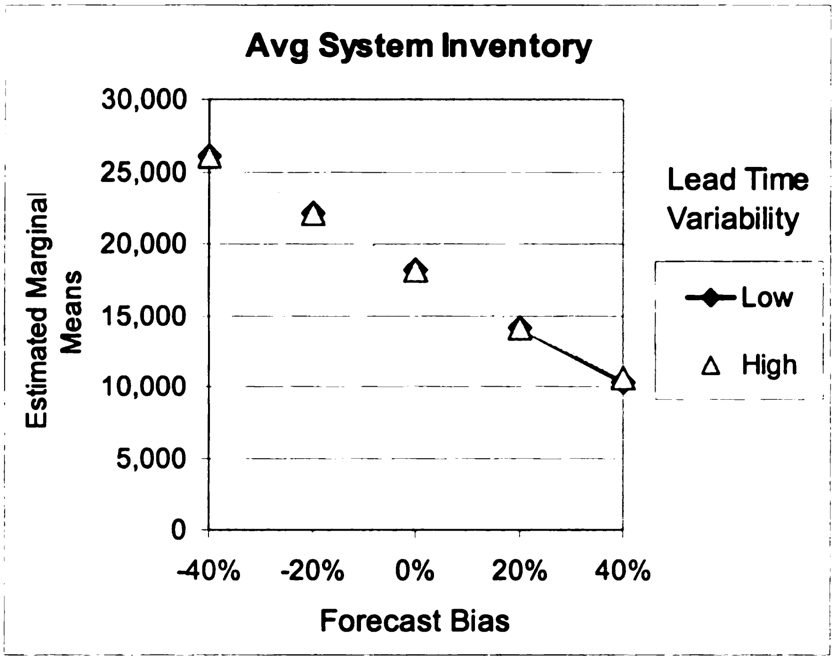


Figure 16 –Effect of Lead Time Variability * Forecast Bias on Avg System Inventory

The last statistically significant two-way interaction is the combined effect between Forecast Bias and Forecast Skewness. Figure 17 displays the effect of this interaction on Order Fill Rate. As Forecast Bias moves from -40% to +40%, service decreases in a non-linear way. This impact is slightly accentuated as Forecast Skewness moves from -1.3693 to +1.3693. The curve slightly shifts towards the origin. This shift is relatively small. It results in superimposed lines on Figure 17. The interaction partially accounts for 1.6% of the variation on Order Fill Rate.

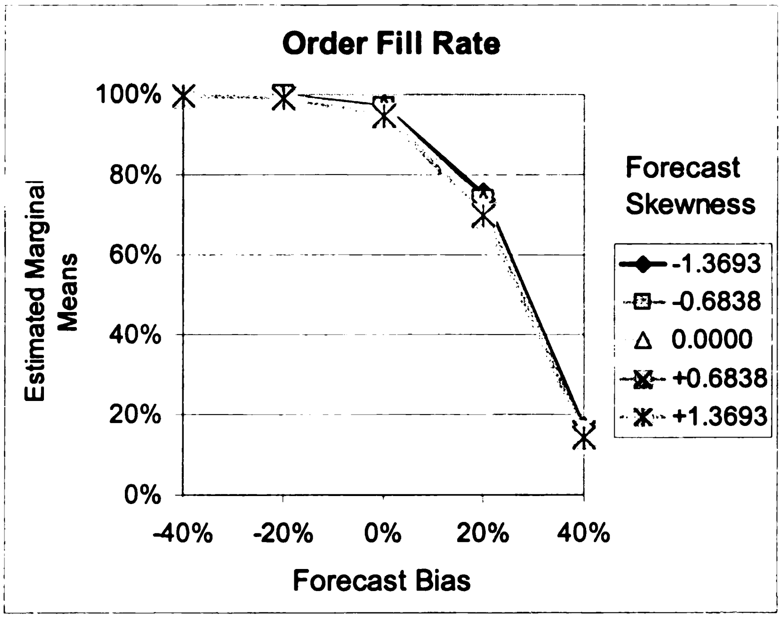


Figure 17- Effect of Forecast Bias * Forecast Skewness on Order Fill Rate

Figure 18 displays the effect of the interaction between Forecast Bias and Forecast Skewness on Case Fill Rate. The effect is similar to the one for Order Fill Rate. The impact is relatively small, as this interaction partially accounts for 1.2% of variation on Case Fill Rate.

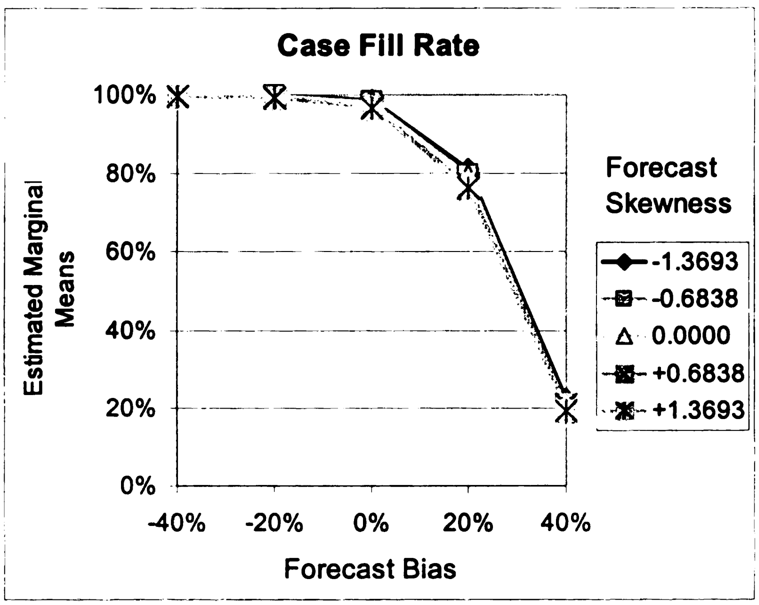


Figure 18 - Effect of Forecast Bias * Forecast Skewness on Case Fill Rate

Figure 19 displays the effect of this interaction on Average System Inventory. The discussion is similar to the ones for the service performance variables. As Forecast Bias moves from -40% to +40%, Average System Inventory decreases in a linear way. This impact is slightly accentuated as Forecast Skewness moves from –1.3693 to +1.3693. The line slightly shifts towards the origin. But the impact of this interaction is relatively small, partially accounting for 1% of the variation on Average System Inventory. The result is superimposed lines on Figure 19.

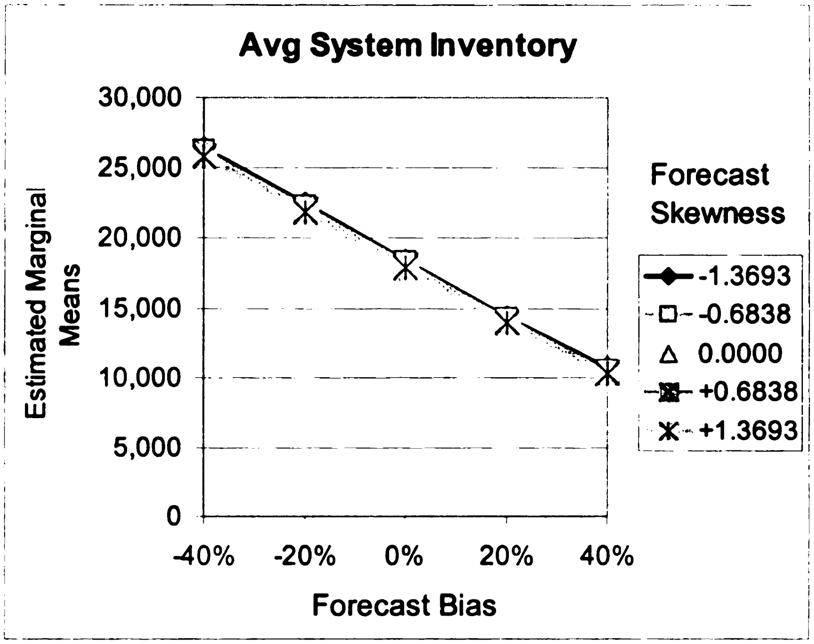


Figure 19 –Effect of Forecast Bias * Forecast Skewness on Avg System Inventory

Two conclusions can be developed from the analysis of the significant two-way interactions. First, the impact of Forecast Bias on service variables and inventory is strongly accentuated as variability in lead time increases. Second, the impact of Forecast Bias on performance variables is slightly accentuated under higher levels of Demand Variability and Forecast Skewness.

These conclusions support that Forecast Bias is the primary factor affecting service and inventory. Other experimental factors should not be discarded because they affect the impact of Forecast Bias on performance.

All significant interactions are ordinal and conceptually acceptable. Therefore, the main effects of each treatment can be further analyzed in the next section.

4.3.3 Results of Univariate Tests: Main Effects

Table 20 presents the univariate test results for the main effects. The first factor, Demand Variability, is statistically significant at $p<0.001$ for both Order Fill and Case Fill rates, but not for Average System Inventory. Demand Variability partially accounts for 0.8% of variation in Order Fill Rate and 0.6% of variation in Case Fill Rate. The effect size of this main factor is thus relatively small.

Source	Dependent Variable	df	F	Sig.	Partial Eta Squared	Observed Power
Demand Variability	Order Fill Rate	2	17.649	0.000	0.008	1.000
	Case Fill Rate	2	12.555	0.000	0.006	0.997
	Avg System Inventory	2	0.107	0.899	0.000	0.066
Lead Time Variability	Order Fill Rate	1	8243.868	0.000	0.655	1.000
	Case Fill Rate	1	5477.031	0.000	0.557	1.000
	Avg System Inventory	1	77.790	0.000	0.018	1.000
Forecast Bias	Order Fill Rate	4	43293.715	0.000	0.975	1.000
	Case Fill Rate	4	30602.036	0.000	0.966	1.000
	Avg System Inventory	4	399695.326	0.000	0.997	1.000
Forecast Skewness	Order Fill Rate	4	22.707	0.000	0.020	1.000
	Case Fill Rate	4	15.851	0.000	0.014	1.000
	Avg System Inventory	4	348.862	0.000	0.243	1.000

Table 20 - Univariate Tests (Main Effects)

Further evidence of this relatively small impact can be observed on the graphical display of this main effect. Figure 20, Figure 21 and Figure 22, respectively, present the effect of Demand Variability on Order Fill Rate, Case Fill Rate and Average System Inventory. As variability on daily demand increases, Order Fill Rate decreases from 77.1% to 76.0%, Case Fill Rate decreases from 79.8% to 78.8% and Average System Inventory decreases from 18,178 to 18,174.

Estimated marginal means of service variables for low and medium variability levels are not statistically different at the p=0.05 level. Statistical difference is reached only at the high variability level. There is no statistical difference at any variability level for Average System Inventory.

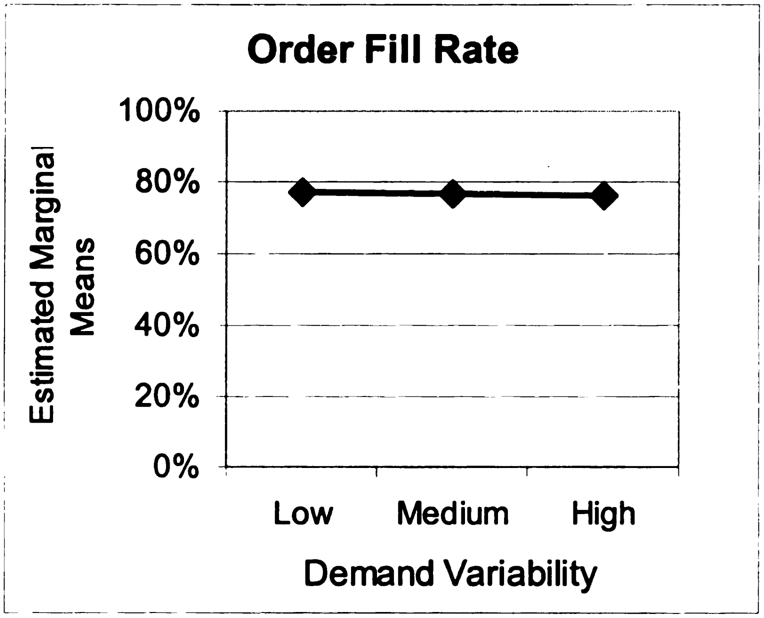


Figure 20 – Effect of Demand Variability on Order Fill Rate

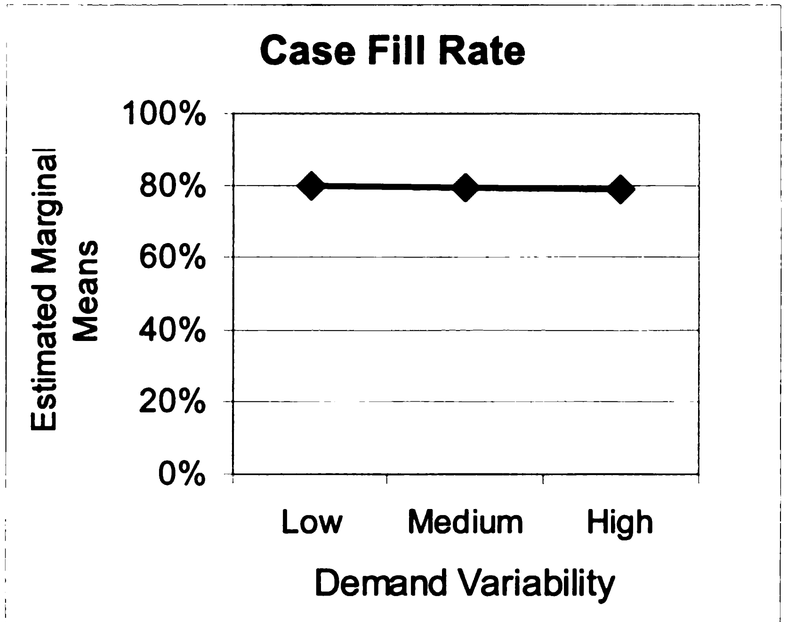


Figure 21 – Effect of Demand Variability on Case Fill Rate

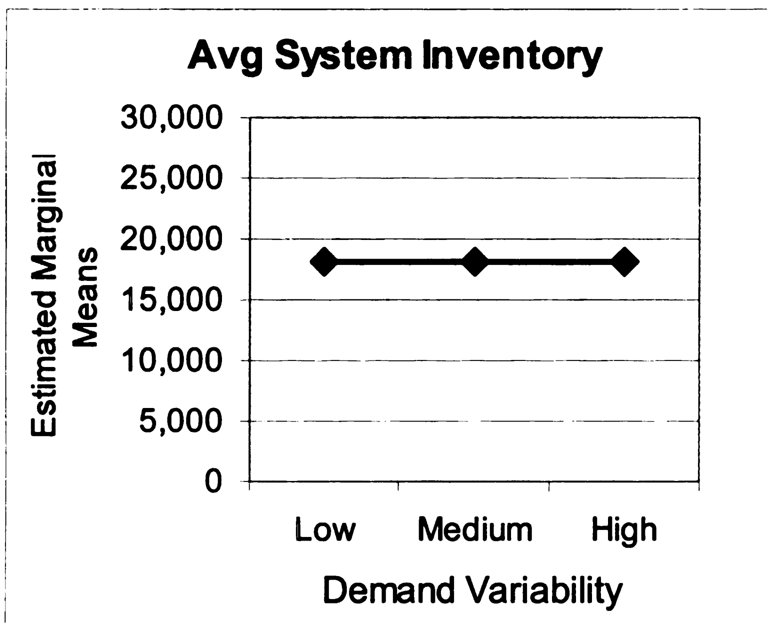


Figure 22 – Effect of Demand Variability on Avg System Inventory

The second factor, Lead Time Variability, is statistically significant at $p<0.001$ for all performance variables. Different from Demand Variability, Lead Time Variability has a substantial impact on service variables. According to Table 20, this factor partially accounts for 65.5% of variation in Order Fill Rate and 55.7% of variation in Case Fill Rate. The impact of Lead Time Variability on Average System Inventory is relatively small, as this factor accounts for only 1.8% of variation.

In an analogous way, further evidence can be observed by analyzing the graphical displays of these relationships. Figure 23, Figure 24 and Figure 25, respectively, present the effect of Lead Time Variability on Order Fill Rate, Case Fill Rate and Average System Inventory.

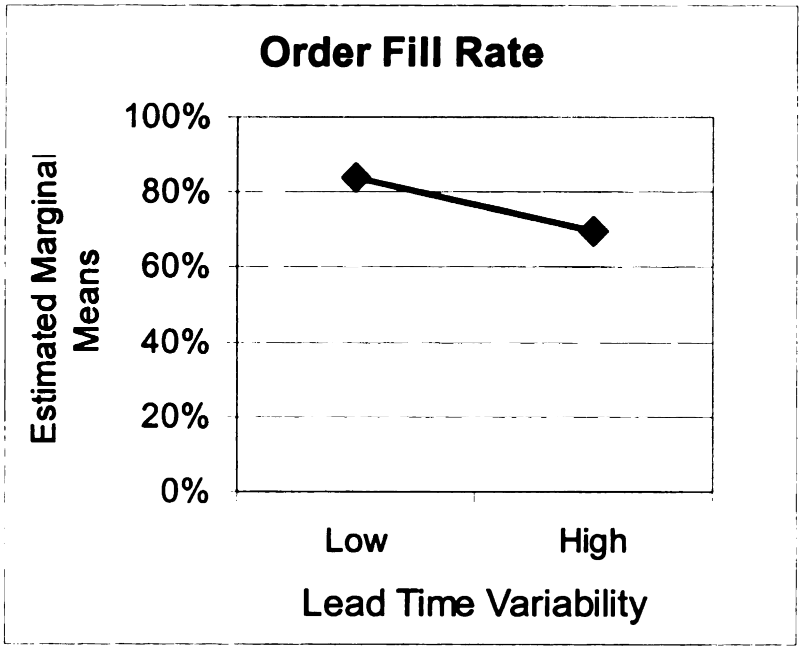


Figure 23 – Effect of Lead Time Variability on Order Fill Rate

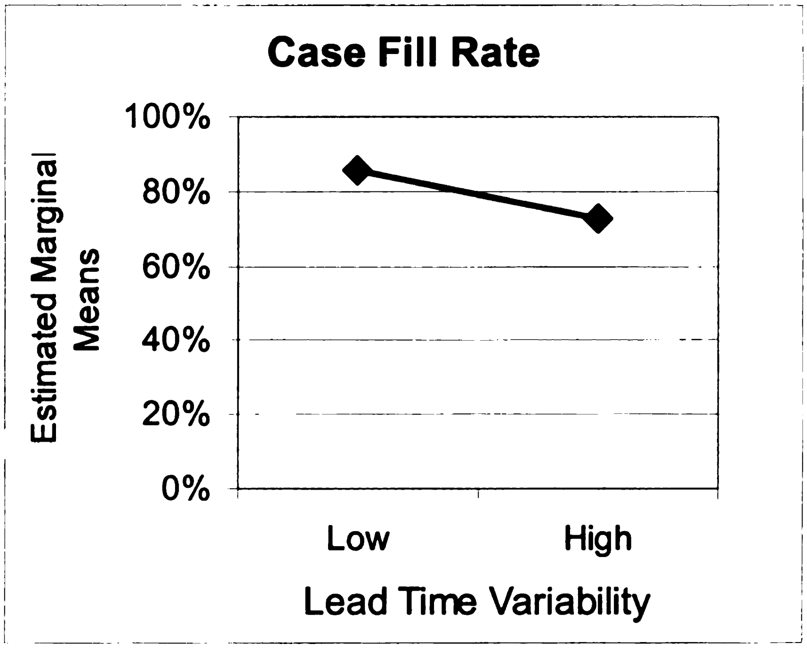


Figure 24 - Effect of Lead Time Variability on Case Fill Rate

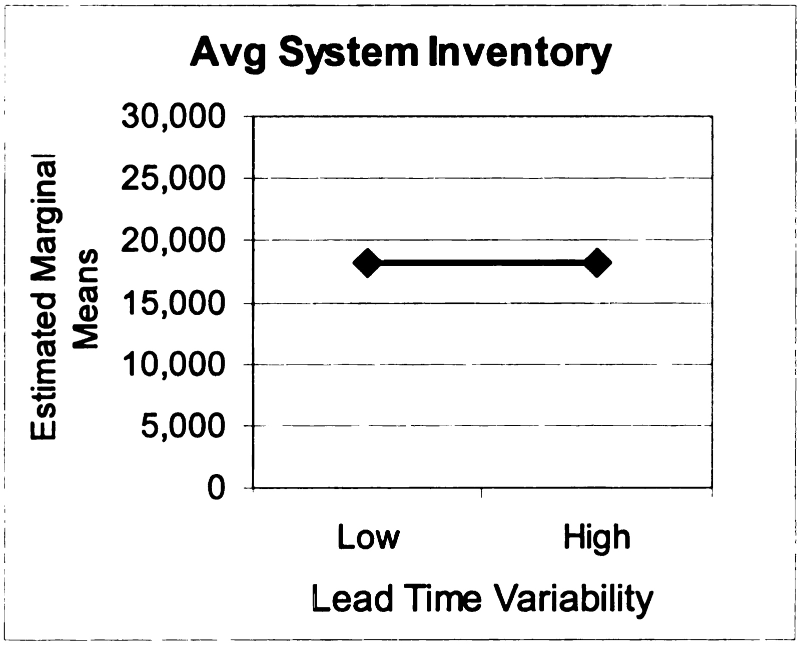


Figure 25 - Effect of Lead Time Variability on Avg System Inventory

As variability on transit lead time increases, Order Fill Rate decreases from 83.7% to 69.6%, Case Fill Rate decreases from 85.7% to 72.9% and Average System Inventory increases from 18,137 to 18,214. Lead Time

Variability, thus, substantially affects service variables and slightly affects inventory. Estimated marginal means are all statistically significant at the $p=0.05$ level.

The third factor is key to this dissertation: Forecast Bias. According to Table 20, Forecast Bias is statistically significant at $p<0.001$ for all dependent variables. In addition to statistical significance, this factor has a very large impact on all dependent variables. Forecast Bias partially accounts for 97.5% of variation on Order Fill Rate, 96.6% of variation on Case Fill Rate, and 99.7% of variation on Average System Inventory. Therefore, Forecast Bias is the primary factor affecting both service and inventory in this dissertation.

Interesting relationships can be observed on the graphical displays of estimated marginal means. Figure 26 presents the effect of Forecast Bias on Order Fill Rate. When Forecast Bias is equal to -40%, forecasts are systematically higher then actual demand. In this case, biased forecasts result in higher levels of inventory and ultimately service. As Forecast Bias moves to +40%, when forecasts are systematically lower than actual demand, service decreases as a result of decreased inventory levels.

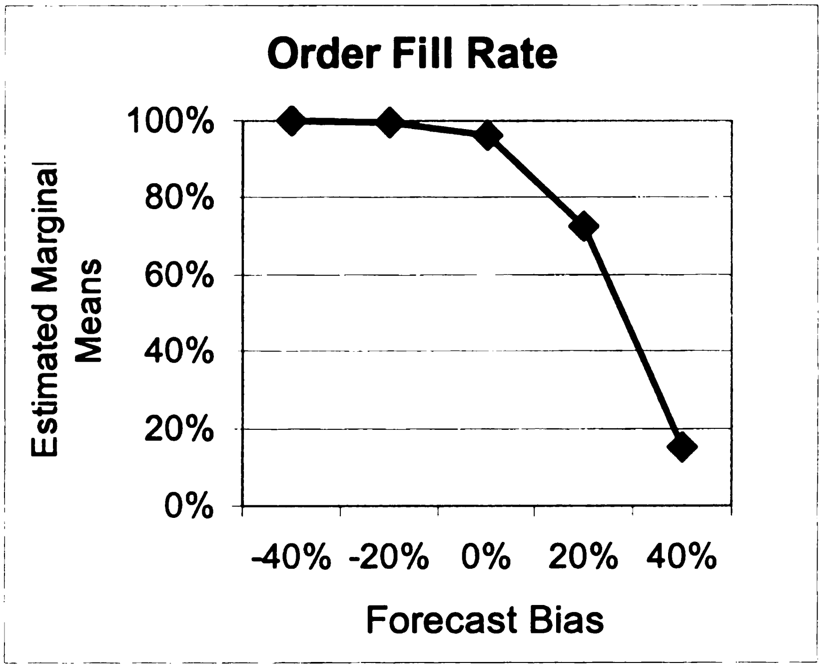


Figure 26 - Effect of Forecast Bias on Order Fill Rate

As Forecast Bias moves from -40% to +40%, Order Fill Rate dramatically decreases from 99.8% to 15.3%. The interesting information on Figure 26 is that this relationship is non-linear. Estimated marginal means are all statistically different at the p=0.05 level, except for the difference between the -40% and the –20% Forecast Bias levels.

Figure 27 presents the effect of Forecast Bias on Case Fill Rate. Results are similar to the Order Fill Rate case. Forecast Bias affects Case Fill Rate in a non-linear way. As Forecast Bias moves from -40% to +40%, Case Fill Rate dramatically decreases from 99.9% to 20.7%. Means for Case Fill Rate are all statistically different at the p=0.05 level, except for the difference between the -40% and the -20% Forecast Bias levels.

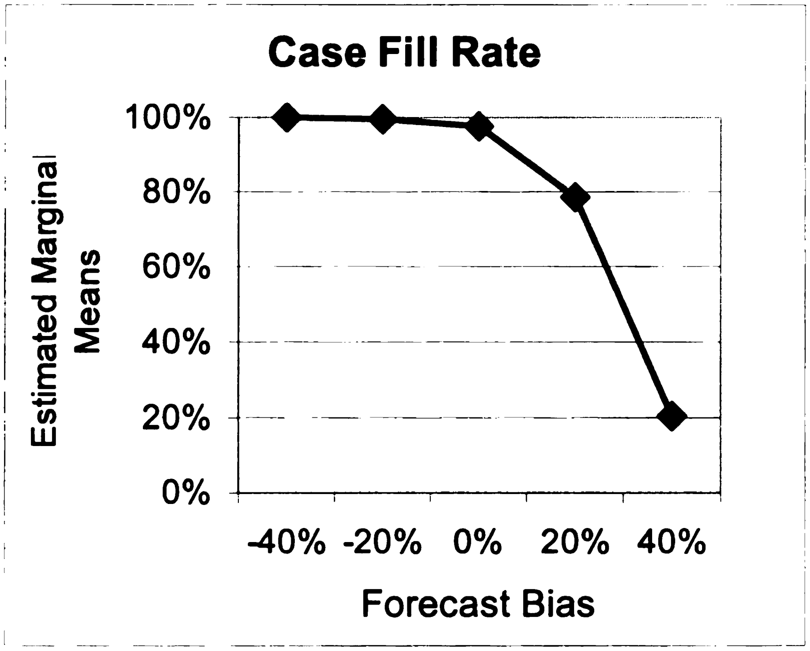


Figure 27 - Effect of Forecast Bias on Case Fill Rate

The effect of Forecast Bias on Average System Inventory is presented in Figure 28. Forecast Bias affects inventory in a linear way. As Forecast Bias moves from -40% to +40%, Average System Inventory decreases from 26,026 to 10,467. This occurs because, in this study, replenishments occur in an anticipatory way. Forecasts are used to build target levels of inventory to be maintained. When forecasts are systematically higher than actual demand, excess inventory is built in the system. The opposite occurs when forecasts are systematically lower than actual demand. Estimated marginal means of Average System Inventory are all statistically different at the p=0.005 level.

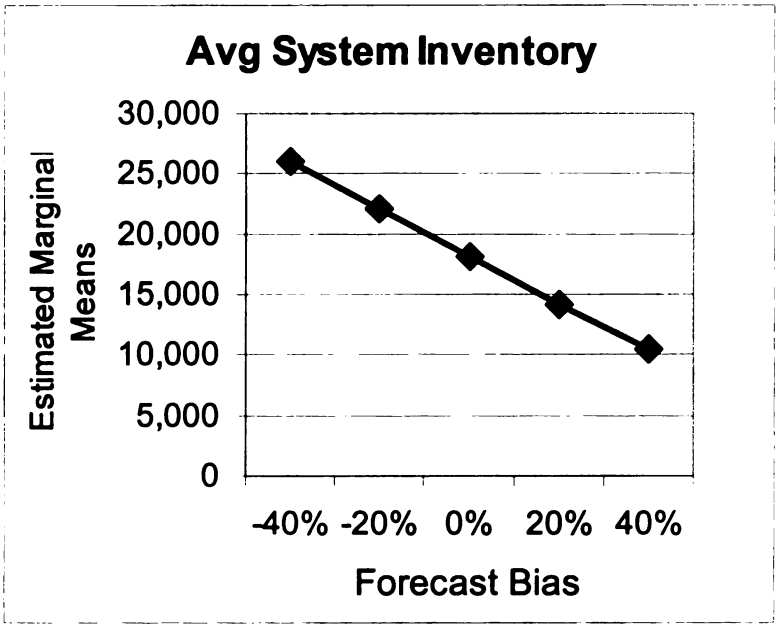


Figure 28 - Effect of Forecast Bias on Avg System Inventory

The relationships presented in Figure 26 and Figure 28 suggest that there are trade-offs involving the level of Forecast Bias. When Forecast Bias assumes extreme negative values, higher service is obtained with higher inventory commitments. When Forecast Bias assumes extreme positive values, lower service results from lower inventory commitments.

This trade-off between service and inventory can be further explored by analyzing the graphical display of the transformed variable, obtained by the division of Order Fill Rate by Average System Inventory. This variable gives us information regarding the unit of service that is obtained from every unit of inventory. Estimated marginal means for the different levels of Forecast Bias are presented on Figure 29. All means are statistically different at the p=0.05 level.

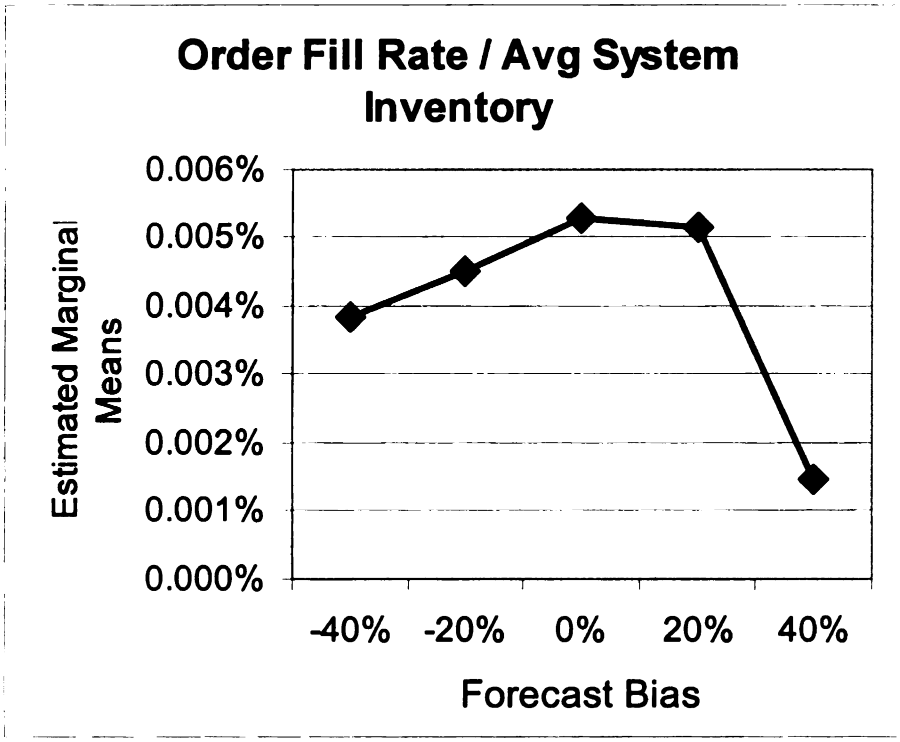


Figure 29 - Effect of Forecast Bias on Order Fill Rate / Avg System Inventory

The relationship presented in Figure 29 supports the concept that bias in forecasts should be avoided. When Forecast Bias is equal to 0%, the highest service is achieved with lowest inventory commitment. In practice, though, the optimal point for this relationship depends on the cost structure of the company. Specifically, it directly depends on the relationship between inventory holding costs and stockout costs. Further discussion about this issue is presented when managerial guidelines are developed.

The fourth and last experimental factor is Forecast Skewness, also a key factor in this dissertation. According to Table 20, Forecast Skewness is statistically significant at $p<0.001$ for all dependent variables. This factor has a relatively small impact on service variables. It partially accounts for 2.0% of variation on Order Fill Rate and 1.4% of variation on Case Fill Rate.

Figure 30 displays the impact of Forecast Skewness on Order Fill Rate. As Forecast Skewness moves from –1.3693 to +1.3693, Order Fill Rate decreases from 77.7% to 75.5%. Statistical differences in estimated marginal means only occur between the –1.3693 and the 0 levels, and between the 0 and the +0.6838 levels.

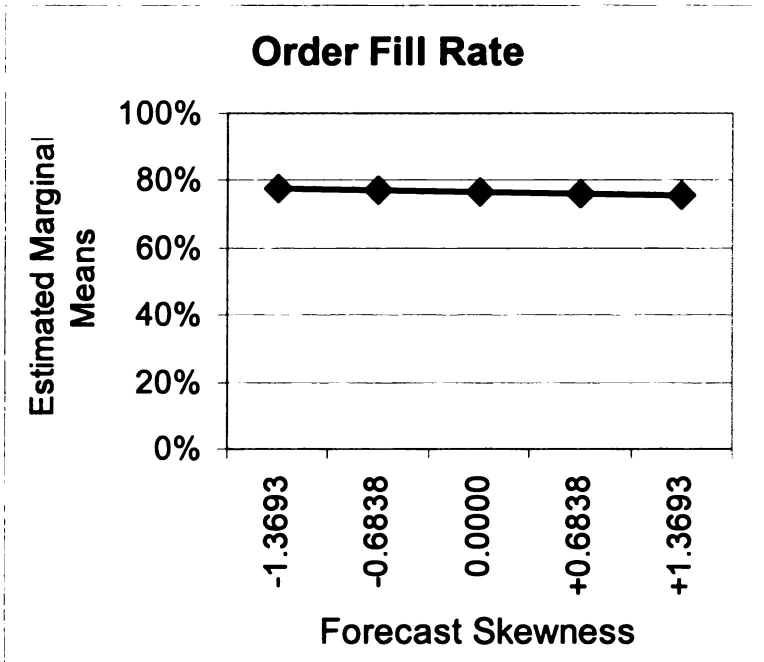


Figure 30 - Effect of Forecast Skewness on Order Fill Rate

Figure 31 shows the impact of Forecast Skewness on Case Fill Rate. As it moves from –1.3693 to +1.3693, Case Fill Rate decreases from 80.3% to 78.3%. For this dependent variable, there is no statistical significance in mean differences between any adjacent levels of skewness.

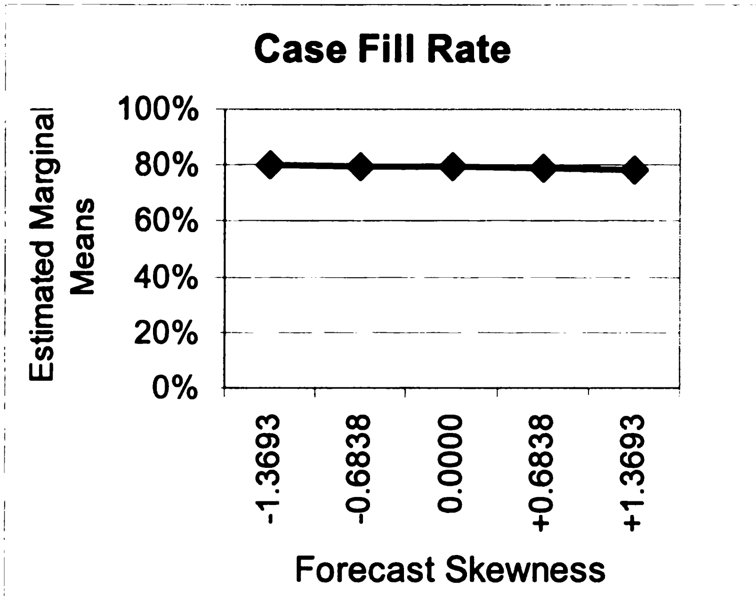


Figure 31 - Effect of Forecast Skewness on Case Fill Rate

Finally, the impact of Forecast Skewness on Average System Inventory is exhibited on Figure 32. The impact is medium. This main effect partially accounts for 24.3% of the variance on Average System Inventory (Table 20). As Forecast Skewness moves from –1.3693 to +1.3693, Average System Inventory decreases from 18,431 to 17,960. Estimated marginal means are all statistically different at the p=0.05 level.

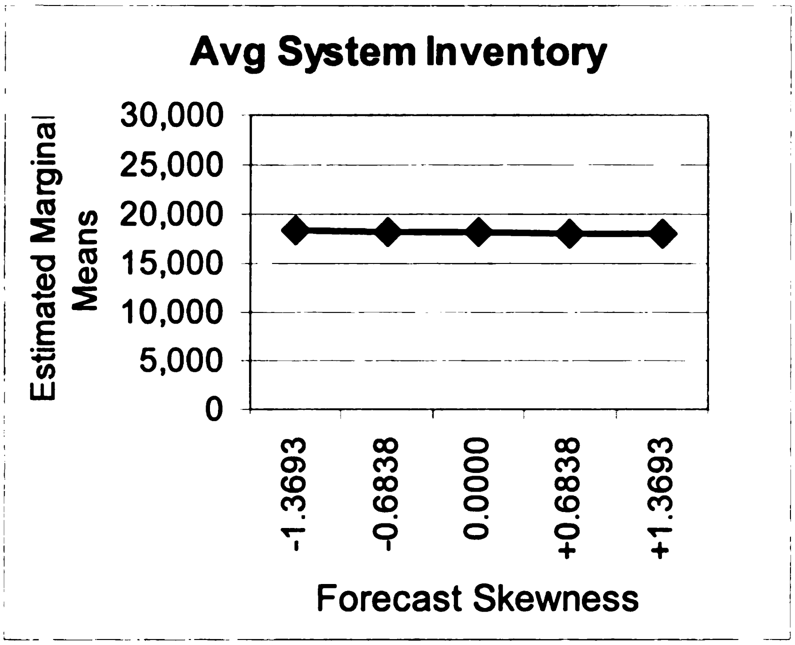


Figure 32 - Effect of Forecast Skewness on Average System Inventory

A summary of the relative impact of main effects on dependent variables is presented on Table 21. The shaded cells represent primary findings. Lead Time Variability has a substantial impact on service variables. Forecast Bias is the primary factor, responsible for a very large impact in all performance variables. Forecast Skewness has medium impact on Average System Inventory. There is a large impact of the interaction between Forecast Bias and Lead Time Variability on both Order Fill Rate and Case Fill Rate.

Source	Order Fill Rate	Case Fill Rate	Average System Inventory	Comment
Demand Variability	- p-value < 0.001 - Partial Eta Squared = 0.008	- p-value < 0.001 - Partial Eta Squared = 0.006	- p-value = 0.899 - Power = 0.066	Statistically significant for service variables, but main effect has small impact.
Lead Time Variability	- p-value < 0.001 - Partial Eta Squared = 0.655	- p-value < 0.001 - Partial Eta Squared = 0.557	- p-value < 0.001 - Partial Eta Squared = 0.018	Substantial impact on service variables. Small impact on inventory.
Forecast Bias	- p-value < 0.001 - Partial Eta Squared = 0.975	- p-value < 0.001 - Partial Eta Squared = 0.966	- p-value < 0.001 - Partial Eta Squared = 0.997	Very Large impact on all performance variables.
Forecast Skewness	- p-value < 0.001 - Partial Eta Squared = 0.020	- p-value < 0.001 - Partial Eta Squared = 0.014	- p-value < 0.001 - Partial Eta Squared = 0.243	Medium impact on inventory. Small impact on service variables.
Demand Variability x Forecast Bias	- p-value < 0.001 - Partial Eta Squared = 0.011	- p-value = 0.005 - Partial Eta Squared = 0.005	- p-value = 0.989 - Power = 0.117	Statistically significant, but interaction has small impact.
Lead Time Variability x Forecast Bias	- p-value < 0.001 - Partial Eta Squared = 0.708	- p-value < 0.001 - Partial Eta Squared = 0.612	- p-value < 0.001 - Partial Eta Squared = 0.053	Large impact on Service Variables. Small impact on Inventory.
Forecast Bias x Forecast Skewness	- p-value < 0.001 - Partial Eta Squared = 0.016	- p-value < 0.001 - Partial Eta Squared = 0.012	- p-value < 0.001 - Partial Eta Squared = 0.010	Statistically significant, but interaction has small impact.
Lead Time Variability x Forecast Bias x Forecast Skewness	- p-value = 0.050 - Power = 0.928	- p-value = 0.643 - Power = 0.597	- p-value = 1.000 - Power = 0.118	Non-significant.
Demand Variability x Lead Time Variability x Forecast Bias	- p-value = 0.005 - Partial Eta Squared = 0.005	- p-value = 0.113 - Power = 0.725	- p-value = 0.998 - Power = 0.088	Statistically significant for Order Fill, but interaction has small impact
Demand Variability x Lead Time Variability	- p-value = 0.683 - Power = 0.112	- p-value = 0.413 - Power = 0.204	- p-value = 0.837 - Power = 0.078	Non-significant.
Demand Variability x Forecast Skewness	- p-value = 1.000 - Power = 0.054	- p-value = 1.000 - Power = 0.053	- p-value = 1.000 - Power = 0.058	Non-significant.
Lead Time Variability x Forecast Skewness	- p-value = 0.903 - Power = 0.108	- p-value = 0.786 - Power = 0.153	- p-value = 0.998 - Power = 0.056	Non-significant.
Demand Variability x Forecast Bias x Forecast Skewness	- p-value = 1.000 - Power = 0.063	- p-value = 1.000 - Power = 0.056	- p-value = 1.000 - Power = 0.064	Non-significant.

Table 21 – Summary of Impact of Main Effects and Interactions on Dependent Variables

The main effects and interactions obtained from the experimental design have been described and discussed. In the following sections, hypotheses are restated and statistical support is discussed.

4.3.4 Hypothesis H1a

Hypothesis H1a states that Forecast Bias has a significant impact on Supply Chain Performance.

Multivariate results in Table 16 show that the effect of Forecast Bias is statistically significant at $p<0.001$. In addition, univariate results in Table 20 show that Forecast Bias is statistically significant at $p<0.001$ for Order Fill Rate, Case Fill Rate and Average System Inventory. In addition to statistical significance, the impact of Forecast Bias on performance variables is very large.

Therefore, Hypothesis H1a is strongly supported.

4.3.5 Hypothesis H1b

Hypothesis H1b states that Forecast Skewness has a significant impact on Supply Chain Performance.

Multivariate results in Table 16 show that the effect of Forecast Skewness is statistically significant at $p<0.001$. Univariate results in Table 20 show that Forecast Skewness is statistically significant at $p<0.001$ for Order Fill Rate, Case Fill Rate and Average System Inventory. The impact of this factor is small for Order Fill Rate and Case Fill Rate, but medium for Average System Inventory.

Therefore, results support Hypothesis H1b.

4.3.6 Hypothesis H1c

Hypothesis H1c affirms that there is a significant interaction effect between Forecast Bias and Forecast Skewness.

Multivariate results on Table 16 show that this interaction effect is statistically significant at $p<0.001$. Univariate results on Table 19 show that the interaction is statistically significant at $p<0.001$ for Order Fill Rate, Case Fill Rate, and Average System Inventory. The impact of this interaction is small for all dependent variables.

This dissertation's results, thus, support Hypothesis H1c.

4.3.7 Hypothesis H1d

Hypothesis H1d asserts that Forecast Bias has a relatively greater impact than Forecast Skewness on Supply Chain Performance.

The individual effects of Forecast Bias and Forecast Skewness on performance variables are statistically significant.

Univariate results on Table 20 show that Forecast Bias partially accounts for 97.5% of variation on Order Fill Rate, 96.6% of variation on Case Fill Rate and 99.7% of variation on Average System Inventory. The impact of Forecast Bias is very large on performance variables.

Forecast Skewness, on the other hand, partially accounts for only 2% of the variation on Order Fill Rate, 1.4% of variation on Case Fill Rate and for 24.3% of variation on Average System Inventory.

Therefore, there is support that Forecast Bias has a relatively greater impact than Forecast Skewness on all performance variables. Hypothesis H1d is then supported.

4.3.8 Hypothesis H2a

Hypothesis H2a affirms that there is a significant interaction effect between Forecast Bias and Demand Variability.

According to Table 16, this interaction effect is statistically significant at $p<0.001$. Univariate results on Table 19 show that the interaction is statistically significant at $p<0.001$ only for Order Fill Rate and Case Fill Rate. The impact of this interaction for Average System Inventory is not statistically significant. The low power of the test suggests that the manipulation of Demand Variability levels may not be enough to capture sufficient power.

Hypothesis H2a is partially supported. The interaction impact is significant only for service variables.

4.3.9 Hypothesis H2b

Hypothesis H2b states that there is a significant interaction effect between Forecast Bias and Lead Time Variability.

This interaction effect is statistically significant at $p<0.001$ (Table 16). Univariate results (Table 19) shows that the interaction is statistically significant at $p<0.001$ for all dependent variables. The impact is large for service variables, where the interaction partially accounts for 70.8% of variation on Order Fill Rate and 61.2% of variation on Case Fill Rate. The impact is small for Average

System Inventory, where the interaction partially accounts for only 5.3% of the variation. There is strong support for Hypothesis H2b.

4.3.10 Hypothesis H3a

Hypothesis H3a asserts that there is a significant interaction effect between Forecast Skewness and Demand Variability.

Multivariate results support that this interaction effect is not statistically significant (Table 16). Hypothesis H3a is, therefore, not supported. One explanation is that Forecast Skewness per se is not a primary factor. Although it affects Average System Inventory, and interacts with Forecast Bias, its relative impact is relatively small when compared to other factors. Other explanation is suggested by the low power of the test. The discussion is analogous to Hypothesis H2a.

4.3.11 Hypothesis H3b

Hypothesis H3b states that there is a significant interaction effect between Forecast Skewness and Lead Time Variability. Multivariate results on Table 16 provide no support for statistical significance of this interaction effect. Hypothesis H3b is thus not supported. The explanation for this lack of support is analogous to Hypothesis H3a.

Table 22 summarizes results obtained from hypotheses testing.

Hypothesis	Test Result
Hypothesis 1a: Forecast Bias has a significant impact on Supply Chain Performance.	**Supported.**
Hypothesis 1b: Forecast Skewness has a significant impact on Supply Chain Performance.	**Supported.**
Hypothesis 1c: There is a significant interaction effect between Forecast Bias and Forecast Skewness.	**Supported.**
Hypothesis 1d: Forecast Bias has a relatively greater impact than Forecast Skewness on Supply Chain Performance.	**Supported.**
Hypothesis 2a: There is a significant interaction effect between Forecast Bias and Demand Variability.	**Partially Supported.** The impact is significant only for service variables.
Hypothesis 2b: There is a significant interaction effect between Forecast Bias and Lead Time Variability.	**Supported.**
Hypothesis 3a: There is a significant interaction effect between Forecast Skewness and Demand Variability.	**Not supported.**
Hypothesis 3b: There is a significant interaction effect between Forecast Skewness and Lead Time Variability.	**Not supported.**

Table 22 – Summary of Hypotheses Testing

The next chapter develops conclusions from research findings. A summary of key findings is presented, followed by implications to academic researchers. Managerial implications are discussed, including a cost trade-off analysis. As a result, managerial guidelines are presented to help decision makers manage Forecast Bias. Finally, research limitations are discussed and potential paths for future research are presented.

5 Conclusions

This chapter relates the research findings to the general body of knowledge in forecast research. The first section addresses results of hypotheses tests in relation to the research questions. The second section proposes managerial guidelines after a cost trade-off analysis is conducted. Next, research limitations are noted. Finally, suggestions for future research are presented.

5.1 Implication of Research Findings

The first research finding is that Forecast Bias is the primary factor affecting the performance of an anticipatory supply chain system. Results from this dissertation indicate a very large impact on both service and inventory variables. No other factor in this study had the same type of effect. The implication is that any study of an anticipatory inventory system should consider bias in forecasts.

The second finding is that Forecast Skewness has relatively less impact on performance than does Forecast Bias. The implication is that researchers and managers should focus their attention on Forecast Bias, although Forecast Skewness should not be totally ignored. It has a moderate influence on inventory in this study. This impact may be larger at higher levels of skewness not tested in this dissertation. Further research is needed to explore this relationship.

A third finding is that the impact of Forecast Bias on performance is amplified at higher levels of demand and transit lead time variability. According to the results of this dissertation, the combined effect of Forecast Bias and Lead Time Variability is large for service variables. This implies that the higher the supply chain instability, the greater is the impact of Forecast Bias on performance. One implication is that researchers and practitioners should be especially concerned with Forecast Bias when supply chain instability is considerable.

A fourth finding is that Lead Time Variability has a relatively larger impact on performance than does Demand Variability. This finding is also supported by Wagenheim (1974)'s dissertation results. In anticipatory supply chains, forecasts are used to build inventory in advance of demand. If there is high variability in transit lead times, then it is difficult for the system to build inventory in a timely manner. The results support that transit lead time variability significantly influences performance. In addition, the results indicate that lead time variability is more critical when compared to demand variability. One implication for practitioners is that if resources are limited, the focus should be on investments to reduce variability in transit lead times rather than daily demand requirements.

The fifth finding is the interesting relationship of Forecast Bias to Order Fill Rate and to Average System Inventory. The results support the view that Forecast Bias affects Order Fill Rate in a non-linear way (Figure 26), while it affects Average System Inventory in a linear way (Figure 28). These relationships suggest a trade-off effect of Forecast Bias on service and inventory. One implication is that, conceptually, managers should aim to eliminate any source of bias in their forecasts. In this dissertation, when Forecast Bias is equal to 0% the system achieves the highest level of service at the lower level of inventory commitment (Figure 29). The word "conceptually" should be emphasized; in practice the optimal balance point of this trade-off depends on the relationship between inventory holding costs and stockout costs. In other words, the ultimate financial impact of Forecast Bias depends on the loss function associated with forecast errors. This issue is investigated in the next section.

The research conclusion is that Forecast Bias is indeed the primary factor affecting supply chain performance. The effect is amplified as demand and transit lead time variability increase. Forecast Bias directly increases (or decreases) inventory in a linear way, but directly increases (or decreases) service in a non-linear way. This combined effect implies a trade-off relationship between inventory and service.

5.2 Managerial Guidelines

This section develops managerial guidelines. The objective is to identify acceptable levels of Forecast Bias and the actions to minimize its effects. As previously noted, managers should attempt to eliminate bias in their forecasts, but accuracy improvements have associated costs. For example, processes must be redesigned and workers need to be trained in forecasting methods and software use. Increased information needs require investments in data collection, automation, and information systems.

Even if such investments are made, it is possible to reach a point at which no additional improvements in forecast accuracy can be obtained. If the source of error is Demand Variability, for example, and if there are no feasible actions to influence demand patterns, then a certain amount of error must be tolerated. This is commonly referred to as acceptable forecast error (Jain 1990).

In theory managers should aim to eliminate bias in their forecasts, but in practice improvements should be sought only when the impact of Forecast Bias is detrimental to the company. Actions should be chosen carefully because resources and capital are limited. The acceptable level of Forecast Bias depends on how forecast errors ultimately translate into cost.

Kahn (2003) presents a framework to help understand the financial impact of forecast errors. If forecasts are systematically higher than demand, Forecast Bias is negative. In this case, the company incurs excess inventory costs, increased inventory holding costs, possibly transshipment costs, obsolescence costs, and reduced profit margin if products must be sold at a discount in order to reduce inventory. If forecasts are systematically lower than demand, Forecast Bias is positive. In this situation, there may be order expediting costs and higher production costs, if the company needs to shorten lead times to satisfy demand. If demand cannot be satisfied, there is potential loss in profit due to lost sales. Also, customer satisfaction may be reduced.

A basic implication of over forecasting (negative Forecast Bias) is that financial resources are tied up in excess inventory (inventory cost), and a basic implication of under forecasting (positive Forecast Bias) is the potential loss of profit margin (stockout cost). Managers should not blindly aim at eliminating bias in forecasts. Rather, they should seek to determine the acceptable region. Depending on the relationship between these two types of cost, there is a particular region of bias in which the company can operate without substantially increasing costs.

Toward that end, an analysis was conducted to evaluate how operational results from the simulation experiments translate to total cost. Two variables obtained from the simulation results are used in this analysis: Case Fill Rate and Average System Inventory.

The Case Fill Rate refers to the percentage of units in customer orders that are fulfilled. The remaining percentage represents units that were demanded but were not shipped to customers. For example, if the rate is 98%, then 2% of demand is stocked out. Because average demand is known in the simulation environment, it is possible to record how many units of product were not sold to customers (stockouts). Average System Inventory provides information on how many product units were held in stock during the simulation period.

If unit costs are defined, it is possible to calculate the total cost of a particular simulation experiment. The two basic components of cost considered in this analysis are inventory cost and stockout cost. Both are defined as a percentage of product value, to minimize the arbitrary choice of values.

Figure 33 is an example of how simulation results can be translated to total cost. For simplification, variability in customer demand and transit lead time are combined. In the low variability case, variation in both transit lead time and daily demand is low. In the high variability situation, variation in both lead time and demand is high. In Figure 33 it is assumed that the cost to hold inventory is lower than the cost of lost sales. Inventory cost represents 5% of product value, and stockout cost represents 100% of product value.

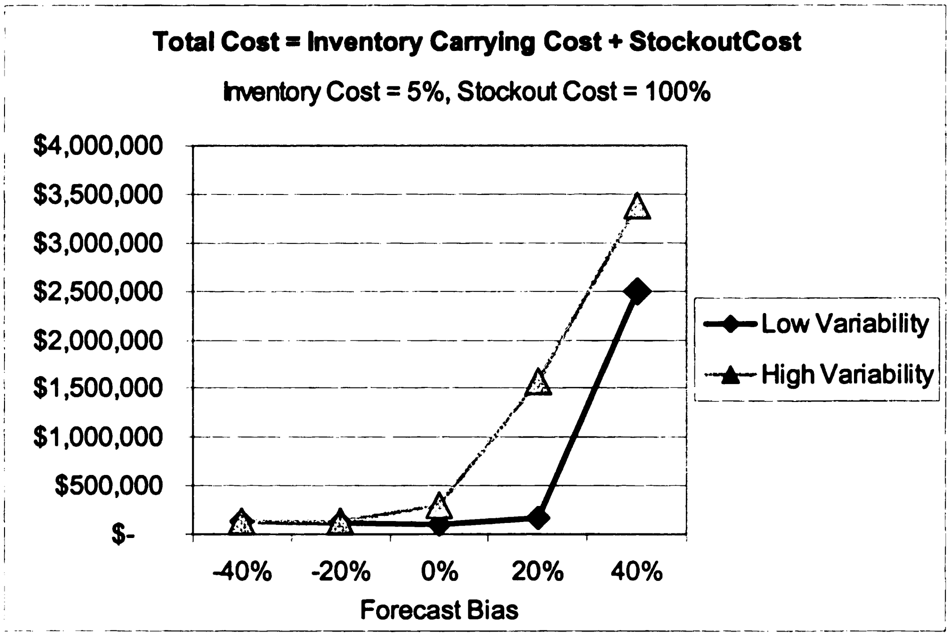


Figure 33 – Example of Cost Analysis: Inventory Cost = 5%, Stockout Cost = 100%

In the low variability situation presented in Figure 33, the total cost impact is relatively low when Forecast Bias ranges from -40% to -20%. For practical purposes, cases will be considered acceptable in a range of plus or minus 20% of difference from the minimum total cost. When variability is high, the acceptable range of Forecast Bias is between -40% and -20%. The acceptable range depends on the level of variability and on the profile of costs. Forecasts that are higher than demand are acceptable in this case because the cost of excess inventory is low compared to the cost of lost sales.

Figure 34 displays another example: inventory cost is higher than stockout cost. In this case, at the low variability level, a Forecast Bias of 20% results in minimum cost. This occurs because the cost to hold stock is higher than the cost of lost sales. At the high variability level, the acceptable range stays between -20% and 0%.

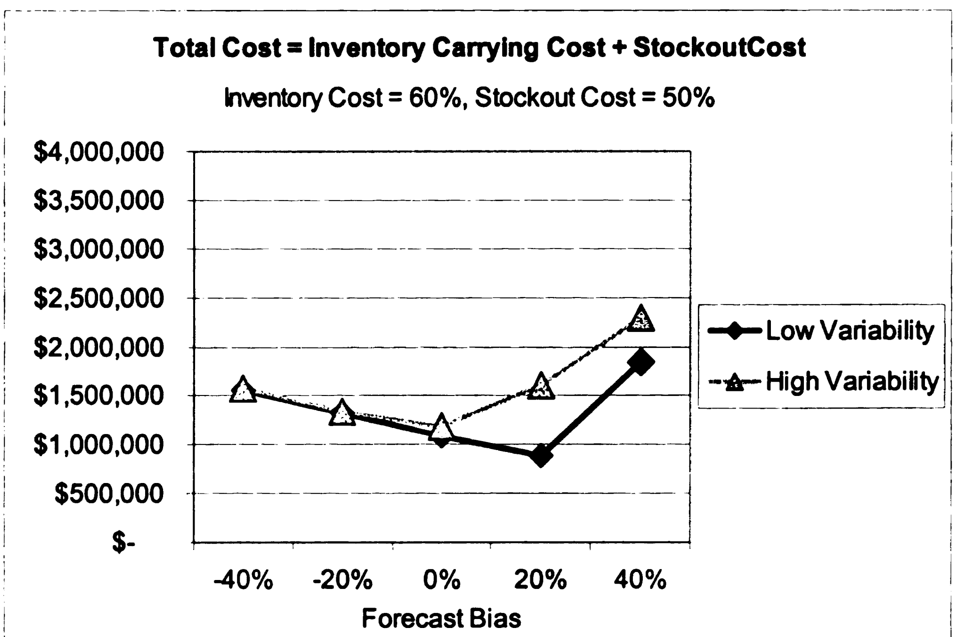


Figure 34 - Example of Cost Analysis: Inventory Cost = 60%, Stockout Cost = 50%

Generalization of these two examples is obtained if different combinations of cost profiles are used to evaluate the total cost performance of the simulated system. Inventory cost was manipulated at six levels: 5%, 10%, 20%, 40%, 60%, and 80%. Stockout cost also was manipulated at six levels: 5%, 10%, 30%, 50%, 80%, and 100%. All possible combinations were then analyzed, and acceptable ranges were obtained. The results are presented in Table 23. The hashed bar represents low variation in transit lead times and daily demand requirements. The solid bar represents high variability situations. These results were obtained by combining different levels of inventory and stockout cost and by observing total cost at each level of Forecast Bias. The acceptable range allows values of total cost that are within 20% of the minimum cost.

Cost Profile		Forecast BIAS				
Inventory Cost	Stockout Cost	-40%	-20%	0%	+20%	+40%
5%	5%					
5%	10%					
5%	30%					
5%	50%					
5%	80%					
5%	100%					
10%	5%					
10%	10%					
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80%	30%					
80%	50%					
80%	80%					
80%	100%					

Table 23 – Acceptable Ranges of Forecast Bias

Three conclusions can be drawn from Table 23. First, when variability is high, the acceptable range of Forecast Bias tends to be greater. This occurs because of more uncertainty in the system. Second, when stockout cost exceeds inventory cost, the bias range moves to negative values. Third, when the opposite occurs, the acceptable range moves to the positive side.

Acceptable Range of Forecast Bias
(measured as Percentage Error)

Inventory Cost	Stockout Cost: Low	Stockout Cost: High
High	• Low Variability: +20% to +40% • High Variability: 0% to +20%	• Low Variability: 0% to +20% • High Variability: -20% to 0%
Low	• Low Variability: 0% to +20% • High Variability: -20% to 0%	• Low Variability: -20% to 0% • High Variability: -40% to -20%

Figure 35 – Acceptable Range of Forecast Bias

Information from Table 23 is condensed and summarized in Figure 35, a matrix built from the cost analysis. It can help managers identify the acceptable range of Forecast Bias for their business. For example, in the lower left corner both stockout cost and inventory cost are low, measured as a percentage of product value. In this case, when there is low variability in lead times and demand, a Forecast Bias between 0% and +20% is acceptable. If variability is high, the minimum cost is obtained in a region of Forecast Bias between -20% and 0%. The rationale is analogous for the other three quadrants of the matrix.

The matrix has two interesting characteristics. The first is that the acceptable range of Forecast Bias is the same when stockout cost and inventory cost are either both low or both high. The second is that the acceptable range for low inventory cost and high stockout cost is a mirror image of the acceptable range for high inventory cost and low stockout cost. This symmetry reflects the fact that the acceptable bias range moves from the positive side to the negative side as the relative comparison between inventory and stockout cost changes.

Six guidelines to help decision makers manage Forecast Bias are presented below.

First, Forecast Bias is an important factor that substantially affects supply chain service and inventory therefore, managers should not rely on a single measure of forecast accuracy. For example, the Mean Average Percentage Error (MAPE), the most used measure, evaluates forecasting performance in absolute terms. If forecasts have a bias, MAPE will not capture it. The first guideline is that multiple measures of forecast accuracy are advised.

Second, managers should track the current level of Forecast Bias by keeping historical data on estimated and actual sales. Alternative measures of forecast accuracy should be computed, and histograms should be plotted.

Third, there are trade-offs in terms of service and inventory that are influenced by Forecast Bias. There is no single optimum level of bias. It varies with each business. The optimum level depends on the extent of variability in transit lead times and in daily demand requirements and the relative profile of inventory cost and stockout cost.

Fourth, managers should use the matrix provided in Figure 35 to help identify the acceptable level of Forecast Bias for their company.

Fifth, once the acceptable Forecast Bias level is identified, managers should compare it with the level of bias for their current forecasting process. They can then decide whether resources should be invested in improvements to reach the desirable Forecast Bias region.

Sixth, managers need to understand that initiatives to improve forecast accuracy can be both internal and external, that is, within the company and across supply chain partners. Examples of internal initiatives are the collection of more reliable and relevant data, the use of more complex and adaptive forecasting techniques, and an increase in cross-functional integration across departments involved in the forecasting process. External efforts may include a reduction in transit lead time variability through partnerships with service providers and a reduction of demand variability through incentives to customers, such as promotions or discounts.

5.3 Research Contributions

One contribution of this dissertation is that it investigates the impact of Forecast Bias in a supply chain context. Previous studies focused on a single facility, which restricts generalization to the broader supply chain. This difficulty arises because complex dynamics occur when facilities in a network exchange information and product flows. Therefore, this dissertation broadens current research.

A second important contribution is the comprehensive approach to model forecast errors used here. In this study, the histogram of forecast errors follows statistical distributions. One limitation of previous work is the use of a single aggregate measure of forecast accuracy. A measure such as MAPE or MAD cannot capture as much information as a histogram.

A third contribution of this study is a new approach to model forecast errors. Previous research considered stochastic errors and assumed that patterns followed a Normal distribution. As previously discussed, that imposes two limitations. First, undesirable extreme values of error can occur, because the Normal distribution is unbounded in its limits. Second, the Normal distribution assumes that errors are symmetrically distributed around the mean. This dissertation assumes that the histogram of forecast errors follows a generalized form of the Beta distribution. This new approach overcomes the two limitations of the Normal distribution. The Beta distribution is bounded on its limits, so the researcher can better control forecast error. In addition, asymmetric errors can be considered, which allows for more general patterns to be investigated.

The fourth contribution is a more in-depth understanding regarding of how Forecast Bias affects Supply Chain Performance. This impact is researched under different environmental contexts in terms of transit lead time and daily demand variability. The topic has not been explored in the literature.

The fifth contribution of this research is guidelines to help managers understand and control the impact of Forecast Bias on performance.

5.4 Research Limitations

Simulation studies are constrained to the extent that the simulation model accurately replicates the real world system. The present research is not free of that constraint. However, the model has been subjected to extensive validation tests and has been judged to be valid.

In addition, limitations of the conceptual model restrict the application of the research findings to similar distribution channel systems. Also, the findings are restricted to the experimental factors levels manipulated in this study. Results that were not statistically significant could be found otherwise if different experimental levels were tested.

Nevertheless, insights from this research provide useful general information in terms of the parameter relationships that could be further investigated.

5.5 Future Research

This research supports the conclusion that Forecast Bias has a substantial impact on supply chain performance. The study is essentially exploratory, but there is promising potential for future work in this area.

First, there is potential to better investigate the impacts of Forecast Bias on performance at different product type scenarios. This research considered a single product characteristic: the variability in daily demand. Future studies can examine such dimensions as product value, demand volume (different means of daily demand), and life cycles (perishable items). Forecast Bias should be evaluated for different combinations of product characteristics beyond demand variability.

Second, this research used a single inventory strategy technique (order-up policy). Future work can investigate the impact of Forecast Bias under different anticipatory replenishment strategies. In addition, the target levels of inventory were defined as fixed factors in the current research. This impact can be analyzed for different inventory parameters.

A third potential line of inquiry is Forecast Bias within different types of physical supply chain networks. This research used a single network with three tiers. It is important to investigate different network structures (convergent versus divergent) to determine whether inventory centralization (or decentralization) amplifies the effects of Forecast Bias.

Yet another path for future study is to include different levels of information sharing across the supply chain. It is important to evaluate the effects of Forecast

Bias in cooperative and non-cooperative chains. The negative influence should be greater when there is a low level of information sharing.

Finally, research that considers alternative patterns of forecast errors must be done. In this dissertation, forecast errors are assumed to be asymmetric and stationary. It is relevant to consider correlation of forecast errors across time periods. This assumes that decision makers improve the forecasting process as errors are monitored. In addition, the forecast planning horizon was set constant in this research. Future studies can consider it as an experimental factor.

Although the current study examined the role of Forecast Bias in supply chain performance, the relationships among Forecast Bias, Forecast Skewness, Demand Variability, and Transit Lead Time Variability cannot be fully explained through the data collected. Further investigation of these interactions, including additional factors, will be needed to obtain a full understanding of how Forecast Bias affects the supply chain.

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