Estimation of Bullwhip Effect in Supply Chain Management

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF

Master of Technology
in
Production Engineering

by
Priyanka Jena
210ME2240

Under the supervision of
Prof. S.K. Patel

NATIONAL INSTITUTE OF TECHNOLOGY
ROURKELA - 769008
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Dedicated to my parents

NATIONAL INSTITUTE OF TECHNOLOGY
ROURKELA

CERTIFICATE

This is to certify that thesis entitled, **“Estimation of Bullwhip Effect in Supply Chain Management”** submitted by **Priyanka Jena** in partial fulfillment of the requirement for the award of **Master of Technology** Degree in ***Mechanical Engineering*** with “**Production Engineering**” specialization during session 2011-2012 in the Department of Mechanical Engineering, National Institute of Technology, Rourkela.

It is an authentic work carried out by her under my supervision and guidance. To the best of my knowledge, the matter embodied in this thesis has not been submitted to any other university/ institute for award of any Degree or Diploma.

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PRIYANKA JENA

Abstract

A supply chain consists of all parties involved, directly or indirectly, in fulfilling a customer request or demand. The supply chain not only includes the manufacturers and suppliers, but also transporters, warehouses, retailers, and finally the end consumers themselves. The objective of every supply chain is to maximize the overall value generated. The value a supply chain generates is the difference between what the final product is worth to the customer and the effort the supply chain expends in filling the customer's request. An important phenomenon in Supply Chain Management is known as bullwhip effect (BWE), which suggests that the demand variability increases as one moves up a supply chain. Bullwhip effect is an undesirable phenomenon in the supply chain which exacerbates the supply chain performance. The impact of BWE is to increase manufacturing cost, inventory cost, replenishment lead time, transportation cost, labor cost for shipping and receiving, cost for building surplus capacity and holding surplus inventories, and to decrease level of product availability and relationship across the supply chain. Various factors can cause bullwhip effect, one of which is customer demand forecasting. In this study, impact of forecasting methods on the bullwhip effect and mean square error has been considered.

The preceding study highlights the effect of forecasting technique, order processing cost and demand pattern on BWE and mean square error (MSE). The BWE and MSE have been evaluated using MATLAB coding. The results were analyzed using ANOVA and Fuzzy Logic, and finally the optimal parameters for minimum values of BWE and MSE have been determined.

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Chapter-1

Introduction

1.1 Supply Chain Management and Its Basic Layout

Supply chain management (SCM) is a set of approaches utilized to efficiently integrate suppliers, manufactures, warehouses and stores so that merchandise is produced and distributed at the right quantities, to the right location and at the right time in order to minimize system wide cost while satisfying service level requirement. It can also be defined as the coordination of production, inventory, location and transportation among the participants in a supply chain to achieve the best mix of responsiveness and efficiency for the market being served.

Supply chain management arose in late 1980s and came into widespread use in 1990s. Earlier it was known as “Logistics” and “Operations Management”. There is a difference between the concept of supply chain management and traditional concept of logistic:-

- Logistics refers to activities that occur within the boundaries of a single organization whereas supply chain management refers to network of companies that work together and coordinate their action to deliver a product to market.
- Logistics focuses its attention on activities such as procurement, distribution, maintenance and inventory management whereas supply chain management acknowledges all the traditional logistics, and also include activities such as marketing, new product development, finance and customer service.

Effective supply chain management requires simultaneous improvement in both customer service level and the internal operating efficiencies of the companies in the supply chain. Customer service at its most basic level means consistently high order fill rates, high on-time delivery rates and very low rate of products returned by customers. Internal efficiency in an organization of a supply chain means that these organizations get an attractive rate of return on their investments in inventory and other assets, and also find ways to lower their operating and sales expenses.

A typical supply chain includes the following stages:

1. Customer
2. Retailer
3. Wholesaler/distributor
4. Manufacturer
5. Component/raw material supplier

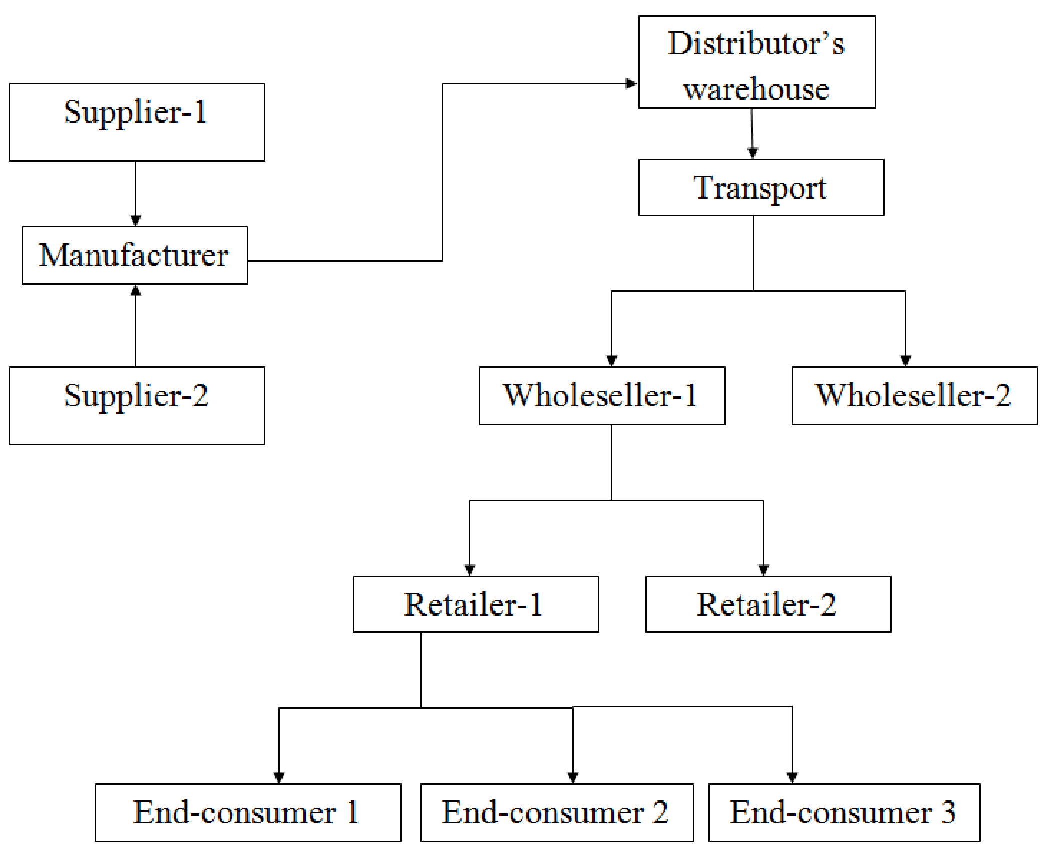

Figure 1: Basic layout of supply chain

1.2 Objectives of Supply Chain

The main objective of the supply chain is to add value to a product or in other words to increase the throughput while simultaneously reducing both inventory and operating expenses. Throughput refers to the rate at which sales to the end customer occur. Supply chain management is a tool to accomplish following strategic objectives:-

- Reducing working capital
- Taking assets of the balance sheet
- Accelerating cash to cash cycles
- Increasing inventory turns

For example, a customer purchasing a computer from Dell pays $5000, which shows the revenue the supply chain receives. Dell and other stages of the supply chain incur costs to convey information, produce components, stores them, transport them, and transfer funds, and so on. The difference between the $5000 that the customer paid and the sum of all costs incurred by the supply chain to produce and distribute the computer indicates the supply chain profitability. Supply chain profitability is the total profit to be shared across all supply chain stages. The higher the supply chain profitability, the more successful is the supply chain. Supply chain success should be evaluated in terms of supply chain profitability and not in terms of the profits at an individual stage.

The next logical step to look for the success of a supply chain in terms of supply chain profitability is revenue and cost. For any supply chain, there is only one source of revenue: the customer. At manufacturer, a customer purchasing an item is the only one providing cash flow for the supply chain. All other cash flow is simply fund exchanges that occur within supply chain given that different stages have different owners. When a manufacturer pays its supplier, it is taking a portion of the customer provides and passing that money on to supplier. All flow of information, products, or funds generate costs within the supply chain. Thus, the appropriate management of these flows is a key to supply chain success. Supply chain management involves the management of flows between stages in a supply chain to maximize total supply chain profitability.

1.3 Bullwhip Effect and the Origin of the Concept

The lack of supply chain coordination leads to a phenomenon known as bullwhip effect (BWE), in which fluctuation increases as we move up the supply chain from retailers to wholesalers to manufacturers to suppliers. The bullwhip effect distorts demand information within the supply chain, with each stage having a different estimate of what demand looks like. Common practical effects of this variance amplification were found in cases of companies Procter & Gamble (dealing with mainly diapers) and Hewlett-Packard (dealing with mainly computers and its components), and are presented to students worldwide through the business game "Beer Game" developed at MIT. Since then, worldwide researches have been carried out by various authors to study different aspects of SCM causing the bullwhip effect and suggested a number of methods to reduce its effect.

1.4 Lack of Coordination and its Effect on the Supply Chain Performance

Lack of coordination in a supply chain occurs if each stage optimizes only its local objectives, without considering the impact on the complete chain. The performance of the entire supply chain is impaired if each stage of the chain tries to optimize its local objectives.

Lack of coordination also results in information distortion within the supply chain. The performance measures which are directly affected by the lack of supply chain coordination are:-

- Manufacturing Cost
- Inventory Cost
- Replenishment Lead Time
- Transportation Cost
- Labor Cost for Shipping and Receiving
- Level of Product Availability
- Relationship Across the Supply Chain

The lack of coordination reduces the profitability of a supply chain by making it more expensive to provide a given level of product availability.

1.5 Hindrances due to Lack of Supply Chain Coordination

The hindrance to the coordination in the supply chain is any factor that leads to either local optimization by different stages of the supply chain, or an increase in information delay, variability and distortion within the supply chain. The major hindrances are divided into following categories:-

- Incentive obstacles
- Information processing obstacles
- Operational obstacles
- Pricing obstacles
- Behavioral obstacles

1.5.1 Incentive Obstacles

This occurs when incentives offered to supply chain members lead to action that increases demand variability. The major two reasons for its occurrence are explained below.

a) *Local maximization within functions or stages of supply chain:*

The decisions which are taken to maximize the profit at a single stage or in other words have a local impact of an action results in ordering policies that do not maximize supply chain profits.

b) *Sales force incentives:*

In many firms sales force incentives are proportional to quantity of sales during a period. But if the quantity of sales to distributors and retailers (i.e. Sale In) is more than that to final customers (Sale Through), then the firm may have a high jump in order at the beginning of next period.

1.5.2 Information Processing Obstacles

This occurs when demand information is distorted as it moves between different stages of the supply chain due to the following reasons.

a) *Forecasting Based On Orders and Not Customer Demand:*

Each stage of supply chain forecasts demand based on the stream of orders received from downstream stage which results in fluctuation of demand as we move up the supply chain from the retailer to the manufacturer. This results in bullwhip effect in the supply chain.

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b) Lack of Information Sharing Between Retailer and Manufacturer:

The lack of information sharing between the stages of the supply chain leads information distortion. If a retailer motivated by the periodic planned policy increases the size of the order then the manufacturer interpreting the large demand may place larger order with the supplier.

1.5.3 Operational Obstacles

This occurs when actions taken in course of placing and filling orders lead to increase in variability. The causes for such obstacles are explained below.

a) Ordering in Large Lots:

Firms place order in lot size which are much larger than the lot size in which demand arises due to which variability of order is magnified up the supply chain. They order in large lots as there is a significant fixed cost associated with placing, receiving, or transporting an order and also if the supplier offers quantity discount based on lot size.

b) Large Replenishment Lead Times:

Variability in demand is magnified if the lead time between stages is long. For example, if the replenishment lead time is one month, then a retailer has to forecast much before one month whether demand will increase or not, and accordingly place an order before one month.

c) *Rationing and shortage gaming:*

Shortage gaming occurs in an environment of tight supply and when the manufacturer is expected to ration its products. The customers, wholesalers and retailers may order in large quantities with the expectation that they will receive a greater allocation of products that are in short supply. The impact on the supply chain is significant as the demand forecast is greatly, and unrealistically, increased with these inflated orders. Eventually orders disappear and cancellations pour in, making it impossible for the manufacturer to determine the real demand for its products.

1.5.4 Pricing Obstacles

This occurs when pricing policies for a product lead to increase in demand variability.

a) *Lots Size Based Quantity Discount:*

There is an increase in the lot size of orders placed within the supply chain when the there is a lot size-based quantity discount. These large lots magnify the bullwhip effect within the supply chain.

b) *Price Fluctuations:*

The wholesaler or retailer opt for forward buying that is they purchase large lots during the discounting period to cover demand during future period. The forward buying results in large orders during the promotion period followed by very small order after that. This results in variation in demand pattern.

1.5.5 Behavioral Obstacles

These types of obstacles are problems in learning within organization that contribute to information distortion.

a) Each stage of the supply chain views its action locally and is unable to see the impact of its action on other stages.

b) Different stages of the supply chain react to the current local situation rather than trying to identify the root causes.

c) Based on local analysis, different stages of the supply chain blame each other for the fluctuation, with successive stages in the supply chain becoming enemies rather than partner.

d) No stage of the supply chain learns from its actions over time because the most significant consequences of the actions any one stage takes occurs else where. The result is a vicious cycle where actions taken by a stage blames on other.

e) A lack of trust between the supply chain partners causes them to be opportunistic at the expense of overall supply chain performance. The lack of trust also results in significant duplication of efforts. More important information available at different stages is either not shared or is ignored because it is not trusted.

1.6 Objectives of the Project

The objectives of the present research work are as follows:

- Understanding the basic structure of supply chain network and the concept of BWE.
- Determination of BWE and MSE through demand generated using different demand patterns.
- Analysis of the results using statistical methods.
- Optimization of parameters for minimum BWE and MSE.

1.7 Outline of the Thesis

The remainder of this thesis is organized in five more chapters. Chapter 2 throws a brief light on the literature review to provide a summary of the base knowledge on the issue of interest. In chapter 3 a brief explanation of various methods and techniques used were given for analyzing bullwhip effect in supply chain systems. Chapter 4 gives a clear insight of how the simulation experiments are carried out and various other details regarding the experiment. Chapter 5 includes all the results of the experimental run. Finally, the conclusions are outlined in Chapter 6.

Chapter-2

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Literature Review

In this chapter, a basic review of literature on BWE, its causes and quantification, effect of various factors on BWE, and fuzzy logic approach to BWE.

2.1 Bullwhip Effect

The initial work on the bullwhip effect was carried out by Jay W. Forrester [1]. In his groundbreaking work he discovered existence of demand amplification or bullwhip effect while working on a four echelon supply chain. He predicted decision making process and time delay in each phase of Supply Chain Network (SCN) and the factory capabilities could be the main reason of the demand amplification. He also found that the advertising factor also influences the system by generating BWE. Burbidge [2] studied about production and inventory control along with demand amplification. He concluded that if demands are carried over a series of inventories using "stock control ordering" then an increase in demand variability would occur with every transfer of demand information.

Sterman [3-6] in his works focused on the existence and causes of BWE using an experimental four-stage SCN role-playing simulation which simulated the beer distribution in a simple SCN. This SCN simulation game successfully portrays the idea of system dynamics. The "Beer Distribution Game", is widely used for teaching the behavior, concept and structure of SCN. He also analyzed the decision methodology of the participants of the SCN and found out that the participants are not focusing on the system delays and nonlinearities. He concluded that anchoring and adjustment heuristics are inconsequent as these heuristics lack sensibility to delay.

Towill [7, 8] and Wikner et al. [9] used Forrester's model with additional quantitative measures, and analyzed the supply chain system applying the system dynamics model. Towill

[10, 11] defined System Dynamics as “A methodology for modeling a redesign of manufacturing, business and similar systems which are partly man and partly machine”. He concluded that time delay is one of the reasons behind demand amplification.

Wikner et al. [9] used Forrester’s three echelon systems as base and compared it with several methods of resolving dynamic performance of distribution system. They tried to gain improvement by eliminating echelon, altering decision rules for providing improvement, abating delay, arranging system ordering pattern, constructing a smooth information flow. They concluded that reduction in delay and better information flow has a dominant impact on BWE reduction.

2.2 Causes of BWE and its Quantification

Lee et al. [12, 13] made a very important analysis which made a way for many other studies. The study was basically related to the causes, quantification and handling tools of BWE. They stated the following four major causes for BWE:

i) demand signal processing (forecast updating)

ii) rationing game

iii) order batching

iv) price fluctuation

They also proposed methods to mitigate BWE. Research on quantification of BWE is a new area of research and the most preferred system for quantifying the BWE is computing the ratio of variance or standard deviation of demand of the two consequent stages of SCN. Metters [14] and Chen et al. [15] quantified the BWE from cost-profit perspective of quality management. Chen [16] also simulated a two staged SCN model which focused on demand variance, forecast error and demand seasonality, and analyzed it under several circumstances. In addition, he showed the effect of BWE on profitability and demonstrated that BWE reduction can achieve profitability.

Chen et al. [17] analyzed the effects of forecasting, lead time and information sharing on BWE and quantified it as ratio of demand variances of two consequent stages of simple SCN system. They showed that the order variance in the upstream echelon will be amplified if demand decision of upstream echelon is changed using the monitored values of the predecessor downstream echelon order periodically. In brief, they constructed a two stage SCN model which used moving average technique for analyzing the unknown demand pattern essential for the inventory system that is operated and developed a lower bound on order variances placed by retailer concerning customer demand and developed their findings to multistage models.

2.3 Effect of Forecasting Techniques and Other Factors on BWE

The authors later studied the effect of exponential smoothing forecasting technique on BWE for independently identically distributed and linear trend demand case. The study was same as the previous one. The conclusions of the study were:-

- The size of demand variability directly influenced from the forecasting technique used to predict future demand variances and from the type of the demand pattern.
- BWE occurs when retailer updates the order-up-to point according to the periodically computed forecast values.
- The longer the lead time, the greater the demand variability.
- Smoothing the demand forecast with more demand information will decrease BWE.

Gavirneni et al. [18] showed the importance of information sharing in inventory control using uniform and exponential demand patterns. Cachon et al. [19] examined a two staged SCN with stochastic stationary demand and compared the importance of information sharing between the case in which only demand information is available, and the case in which both demand and inventory information was available. The result showed that there is no remarkable difference between the analyzed cases. In his further study of US industrial level data in 2005, Cachon et al. [20] observed contrary to understanding of BWE that demand variability does not always increase as one moves up through the SCN stages due to manufacturer's production smoothing attitude which arises due to marginal cost and seasonality. Kimbrough et al. [21] studied SCN and BWE from a different perspective, analyzed effectiveness of artificial agents in a beer game simulation and investigated their ability of mitigating BWE through the system. The study showed that agents have the effective ability of playing beer game. The study brought to view that agents can find optimal policies or good policies that eliminates BWE. They found solution of the problem from point of computer aided decision models such as artificial intelligence and neuro-fuzzy system.

Towill et al. [22], Dejonkheere et al. [23-25] and Disney et al. [26-29] made important studies on bullwhip effect from control theory approach. Aviv [30], Alwan et al. [31], So et al. [32], Zhang [33], and Liu et al. [34] studied the phenomenon of BWE using stationary demand modeling and the process as an ARMA type. Aviv [30] made the study using adaptive replenishment policy. Alwan et al. [31], Zhang [33] and Liu et al. [34] analyzed the forecasting procedure and displayed the effect of moving average (MA), exponential weighted moving average (EWMA) and minimum mean squared error (MMSE) forecasting model. So et al. [32] used lead time as a main factor and analyzed a simple two phased model. Zhang [33] showed that delayed demand information reduces BWE by using a model of first order autoregressive customer demand and MMSE forecasting model.

Machuca et al. [35] studied the effects of information sharing on BWE by focusing on the usage of electronic data interchange (EDI) in SCN systems. The American Standards Institute defines EDI as "the transmission, in a standard syntax, of unambiguous information of business or strategic significance between computers of independent organizations". EDI provides rapid inter-organization coordination standardizing electronic communication, lead time reduction reducing the clerical process and reduction in the inventory costs due to the improvement of trading partner relationship, expedited supply cycle and enhanced inter-organizational relationship. They concluded that BWE can be minimized by using EDI. Wu et al. [36] also studied on the effects of information sharing on BWE. They used beer game to analyze BWE from information sharing together with organizational learning point of view. The concluded that demand variability can be reduced if there is organizational training and learning combined with coordinated thought data sharing and communication.

Makui et al. [37] used Lyapunov exponent in their study of BWE and quantified it in terms of this exponent for centralized and decentralized information cases in a two echelon SCN model and illustrated it with simple numerical example. They also stated that the Lyapunov exponent used for quantification of the irregularities of non-linear system dynamics may also be used for quantifying BWE if LPE is sensed as a factor for expanding an error term of a system.
Hwarng et.al [38] quantified the system chaos in SCNs and discovered "chaos-amplification" using Lyapunov exponent. They showed that exogenous factors such as demand together with related endogenous factors such as lead times and information flow may also generate chaotic behavior in SCN system. They concluded that for effective management in chaotic SCN systems, the interactions between exogenous and endogenous factors have to be understood as well as the

effects of various SCN factors on the system behavior for reducing system chaos and inventory variability.

Sohn et al. [39] used Monte Carlo simulation which simulates various conditions of market environment of SCN for suggesting appropriate information sharing policy along with appropriate forecasting method for multi-generation products of high-tech industry through which customer satisfaction and net profit was maximized considering seasonality, supplier's capacity and price sensitivity of multi-generation products as factors. The study throws light on forecasting methods which are appropriate for specific information policies in SCNs for cases such as the environmental factors like seasonality and price sensitivity exists.

Wright et al. [40] extended Sterman's model and studied BWE under different ordering policies and forecasting methods (Hold's and Brown's methods) separately and in combination. They concluded that there is a decrease in BWE if the forecast is made in conjunction with appropriate ordering policy and showed that Holt's or Brown's forecasting method may provide stability in SCN if they are combined with slow adjustment of stock levels and rapid adjustment of supply line levels.

Saeed [41] constructed a SCN model in which, a classical control mechanism was implemented and it used the forecast of stock of inventory to demonstrate the use of trend forecasting as a policy tool in SCN. He proposed that if trend forecasting was applied to SCN systems as in derivative control, remarkable performance improvements in stability could be achieved.

Sucky [42] studied BWE taking into account the network structure of SCNs and the risk of pooling effect. He used a simple three staged SCN and revealed that BWE may be overestimated by assuming a reasonable SCN and risk pooling effect and concluded that order-up-to systems generally generate BWE, depending on the statistical correlation of the demand data.

2.4 Fuzzy Logic Approach on BWE

Carlsson and Fuller [43-46] were the first to apply fuzzy logic approach to BWE topic. In their study they built a decision support system describing the four BWE driving factors of Lee et al. [12]:-

i) Demand signal processing
ii) Rationing game
iii) Order batching
iv) Price variation

They showed that using an ordering policy with imprecise orders, BWE can be significantly reduced with centralized demand information and fuzzy estimates on future sales.

Wang et al. [47-48] used fuzzy set theory to model SC uncertainties and fuzzy SC model to evaluate SC performance. They developed a fuzzy decision methodology for handling SC uncertainties and determining appropriate strategies for SC inventories. The study is not directly related to BWE, but the proposed inventory policy and cost reduction can be used to reduce demand variability indirectly.

Zarandi et al. [49] designed a fuzzy agent-based model for reduction of BWE using demand data, lead time and ordering quantities as fuzzy and simulated and analyzed BWE in fuzzy environment. A genetic algorithm module added fuzzy time series forecasting model was used to estimate the future demand and a back propagation neural network was used for defuzzification of the output. The result showed that the BWE still exist in fuzzy domain and genetic algorithm module added time series model performs successfully. Kahraman [50] in his study provided both neural networks and adaptive nuero-fuzzy inference system (ANFIS) for demand forecasting for retailer level with a real-world case study. The study showed that hybrid forecasting models perform successfully for demand forecasting in SCNs.

Balan et al. [51] used soft computing approach to deal with BWE. They measured BWE with a discrete time series single input single output model (SISO) and reduced it using soft computing. The study also showed that the application of fuzzy logic and artificial neural network in SCN successfully reduced BWE.

Chapter-3

Methodology

In this chapter, various factors, techniques and statistical tools that are used to analyze the two echelon supply chain network are precisely explained.

3.1 Demand Forecasting in a Supply Chain

Forecasting of future demand is essential for taking decisions related to supply chain. Demand forecasting is the activity of estimating the quantity of a product or service that consumers will purchase in future. It involves techniques including both informal and quantitative methods. Informal methods include educated guess, prediction, intuition etc whereas quantitative methods are based on the use of past sales data or current data from test markets. It may be used in making pricing decisions, in assessing future capacity requirements, or in making decisions on whether to enter a new market not.

3.1.1 Characteristics of Forecast

These are the characteristics of forecast which supply chain managers should be aware of:-

- ❖ Forecasts are always inaccurate and should thus include both the expected values of forecast and measure of forecast error.
- ❖ Long-term forecast is usually less accurate than short-term forecast as it has a larger standard deviation of error relative to that in short-term forecast.
- ❖ Aggregate forecasts are usually more accurate than disaggregate forecasts, as they tend to have smaller standard deviation of error.
- ❖ As we move up the supply chain away from the end consumer, the companies suffer greater information distortion. But collaborative forecasting based on sales to end customer helps

upstream enterprise reduce forecast error. Collaborative forecasting is the process of setting up a continual line of communication between distributors and those customers with the ability to predict the future needs of the products they buy from the distributors.

3.1.2 Components of a Forecast and Forecasting Methods

A company should identify the factors that influence the future demand and should ascertain the relationship between these factors and future demand. Some of these factors are:-

- Past demand
- Lead time of product replenishment
- Planned advertising or marketing efforts
- State of the economy
- Planned price discounts
- Actions that competitors have taken

The companies should understand the factors first and then select an appropriate forecasting methodology.

3.1.3 Basic Categories of Forecasting Method

Forecasting methods can be divided into the following four main categories:-

- Qualitative or judgmental methods
- Extrapolative or time series methods
- Causal or explanatory methods
- Simulation

3.1.3(i) *Judgmental or qualitative methods* rely on expert's opinion in making a prediction for the future. They are most appropriate when little historical data is available or when experts have market intelligence that may affect the forecast.

3.1.3(ii) *Extrapolative or time series methods* use the past history of demand in making a forecast for the future. The objective of these methods is to identify the pattern in historic data and extrapolate this pattern for the future. They are based on the assumption that the past demand history is a good indicator of future demand.

3.1.3(iii) *Causal methods* of forecasting assume that the demand for an item depends on one or more independent factors (like price, advertising, competitor's price etc.). These methods seek to establish a relationship between the variable to be forecasted and independent variables. Once this relationship is established, future values can be forecasted by simply plugging in the appropriate values for the independent variables.

3.1.3(iv) *Simulation* forecasting method imitates the consumer choices that give rise to demand to arrive at a forecast. Using simulation, a firm can combine time-series and causal methods to answer questions like: What will be the impact of a price promotion? What will be the impact of a competitor opening a store nearby?

The observed demand always consists of two components that is a systematic component and random component. It is represented as:

Observed demand (O) = Systematic component(S) + Random component(R)

Systematic component measures the expected value of demand and consists of:-

- ❖ Base or current deseasonalized demand
- ❖ Trend or rate of growth or decline in demand for the next period

- ❖ Seasonality or the predictable seasonal fluctuation in demand

The random component is that part of the forecast that deviates from the systematic part.

3.1.4 Time-Series Forecasting Methods

The goal of any forecasting method is to predict the systematic component of demand and estimate the random component. In its most general form, the systematic component of demand contains a level, a trend, and a seasonal factor. The equation for calculating the systematic component may take form as shown below:-

Multiplicative: Systematic component = level $\times$ trend $\times$ seasonal factor

Additive: Systematic component = level + trend + seasonal factor

Mixed: Systematic component = (level + trend) $\times$ seasonal factor

3.1.4.(i) Moving Average

The moving average method is used when demand has no observable trend or seasonality. In this case,

Systematic component of demand = level

In this method, the level in period t is estimated as average demand over the most recent N period. This represents an N-period moving average and is evaluated as follows :

$$L_t = (D_t + D_{t-1} + \dots\dots\dots\dots ..D_{t-N+1}) / N$$

The current forecast for all future periods is the same and is based on the current estimate of level. The forecast is stated as:

$$F_{t+1} = L_t \text{ and } F_{t+n} = L_t$$

$$L_{t+1} = (D_{t+1} + D_t + \dots\dots\dots + D_{t-N+2}) / N,$$

After observing the demand for period $t+1$. We revise the estimates as follows:

$$F_{t+2} = L_{t+1}$$

To compute the new moving average, the latest observation is added and the oldest one is dropped. The revised moving average serves as the next forecast. The moving average corresponds to giving the last N periods of data equal weight when forecasting and ignoring all data older than this new moving average. As N is increased, the moving average becomes less responsive to the most recently observed demand.

3.1.4.(ii) Simple Exponential Smoothing

The simple exponential smoothing method is appropriate when demand has no observable trend or seasonality. In this case,

Systematic component of demand = level

The initial estimate of level, L0, is taken to be to be the average of all historical data because demand has been assumed to have no observable trend or seasonality. Given demand data for periods 1 through n, we have following:

$$L_0 = \frac{1}{n}\sum_{i=1}^{n} D_i$$

The current forecast for all future periods is equal to the estimate of level and is given as:

$$F_{t+1} = L_t \qquad \text{and} \qquad F_{t+n} = L_t$$

After observing the demand, D_{t+1}, for period $t+1$, the estimate of the level is revised:

$$L_{t+1} = \alpha D_{t+1} + (1-\alpha)L_t$$

Where α is a smoothing constant for the level, 0<α<1. The revised value of the level is weighted average of the observed value of the level (D_{t+1}) in period $t+1$ and the old estimate of the level (L_t) in period t. The above equation for level can also be expressed as a function of current demand and the level in the previous period. The equation can be written as:

$$L_{t+1} = \sum_{n=0}^{t-1} \alpha(1-\alpha)^n D_{t+1-n} + (1-\alpha)^t D_1$$

The current estimate of the level is a weighted average of all of the past observations of demand, with recent observations weighted higher than older observations. A higher value of α corresponds to a forecast that is more responsive to recent observations, whereas a lower value of α represents a more stable forecast that is more responsive to recent observations.

3.1.4.(iii) Trend-Corrected Exponential Smoothing (Holt's Model)

The trend-corrected exponential smoothing (Holt's model) method is appropriate when demand is assumed to have level and a trend in the systematic component but no seasonality. In this case, we have

Systematic component of demand = level + trend

An initial estimate of level and trend is obtained by running a linear regression between demand D_t and time period t of the form

$$D_t = at + b$$

In this case, running a linear regression between demand and time periods is appropriate because, it is assumed that demand has a trend but no seasonality. The underlying relationship between demand and time is thus linear. The constant b measures the estimate of demand at period $t=0$ and is our initial estimate of the trend T_0. In period t, given estimates of level L_t and trend T_t, the forecast for future periods is expressed as

$$F_{t+1} = L_t + T_t \quad \text{and} \quad F_{t+n} = L_T + nT_t$$

The estimates for level and trend are revised after observing demands for period t.

$$L_{t+1} = \alpha D_{t+1} + (1-\alpha)(L_t + T_t)$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)T_t$$

where α is a smoothing constant for the level in the range 0<α<1, and β is a smoothing constant for the trend in the range 0<β<1. It is seen that in each of the two updates, the revised estimate (of level or trend) is a weighted average of the observed value and the old estimate**.**

3.1.4.(iv) Trend-and Seasonality-Corrected Exponential Smoothing (Winter's Model)

This method is appropriate when the systematic component of demand has a level, a trend, and a seasonal factor. In this case, we have

Systematic Component of demand= (level + trend) ×seasonal factor

Assuming the periodicity of demand to be *p* and taking initial estimates of level (L_0), trend (T_0), and seasonal factors ($S_1, \ldots\ldots, S_p$). In period *t*, given estimates of level, L_t, trend T_t, and seasonal factors, $S_t, \ldots\ldots S_{t+p-1}$, the forecast for future periods is given by

$$F_{t+1} = (L_t + T_t)S_{t+1} \quad , \quad F_{t+l} = (L_t + lT_t)S_{t+l}$$

Observing the demands for period t+1, the estimates for level, trend and seasonal factors are revised as follows:

$$L_{t+1} = \alpha\left({}^{D_{t+1}}\!/\!_{S_{t+1}}\right) + (1-\alpha)(L_t + T_t)$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)T_t$$

$$S_{t+p+1} = \gamma\left({}^{D_{t+1}}\!/\!_{L_{t+1}}\right) + (1-\gamma)S_{t+1}$$

where α is a smoothing constant for the level in the range $0<\alpha<1$, and β is a smoothing constant for the trend in the range $0<\beta<1$, and γ is a smoothing constant for seasonal factor in the range $0<\gamma<1$. It is seen that in each of the updates (level, trend, or seasonal factors), the revised estimate is a weighted average of the observed value and the old estimate.

3.2 Analysis of Variance

Minitab R14 software was used for experimental analysis. The process parameters that significantly affect the performance characteristic were identified using a statistical analysis of variance (ANOVA). ANOVA test can also be used for estimating the percentage contribution (%P) of various process parameters on the selected performance characteristic. In addition, significance of factors can also be determined by comparing calculated F-value with standard F-value at a particular level of confidence (95% in this study). Thus, information about the effect of each controlled parameter on the quality characteristic of interest can be obtained.

Two performance measures- bullwhip effect and mean square error are considered with an aim to minimize all these simultaneously at the single factor setting. Fuzzy logic unit can combine the entire considered performance characteristic (objectives) into a single value that can be used as single characteristic in optimization problems. In the present study, to consider the two different responses in ANOVA method, the bullwhip effect values and mean square error values are normalized and then processed by fuzzy logic unit.

3.3 Fuzzy Logic Unit

The structure of the two-input-one-output fuzzy logic unit is shown in Figure 3.1. A fuzzy logic unit comprises of a fuzzifier, knowledge base (membership functions and fuzzy rule base), an inference engine, and a defuzzifier. These components are described below:

- *Fuzzifier*: It is used to apply real input to the fuzzy system. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. It converts the precise quantity to the form of imprecise quantity like 'small', 'medium', 'large' etc. with a degree of membership to it. Typically, the value ranges from 0 to 1.

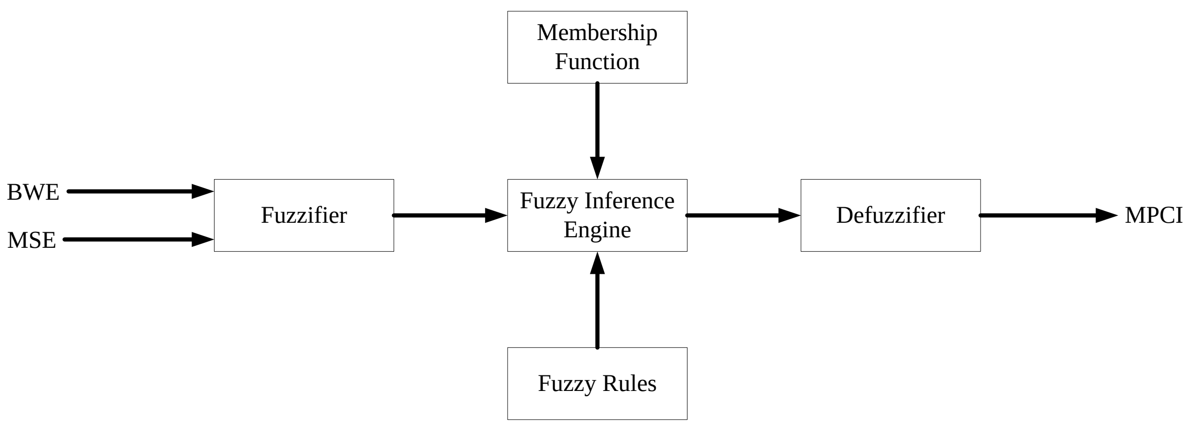

Figure 3.1: Structure of the two-input-one-output fuzzy logic unit

As shown in Figure 3.1 crisp inputs are BWE and MSE, and crisp output is MPCI.

- *Knowledge base:* It is the most important part of the fuzzy system. In this both rule base and database are jointly referred. Membership functions of the fuzzy sets used in fuzzy rules are defined by the database. Rule base contains a number of fuzzy if-then rules.

- *Inference engine:* The inference operations on the rules are performed by the fuzzy inference engine or inference system or decision-making unit. It handles the way in which the rules are combined.
- *Defuzzifier:* Inference block always generate output that is fuzzy in nature. The work of the defuzzifier is to receive the fuzzy input and convert it to real output.

3.3.1 Development of Mamdani Fuzzy Model

In the analysis, fuzzy system (Mamdani model) is used to estimate the multi-performance characteristic index. The set of output data is evaluated through the given input condition in the model. The proposed Mamdani fuzzy model for evaluation of multi performance characteristic index is presented in Figure 3.2. The given model has a multiple input and single output

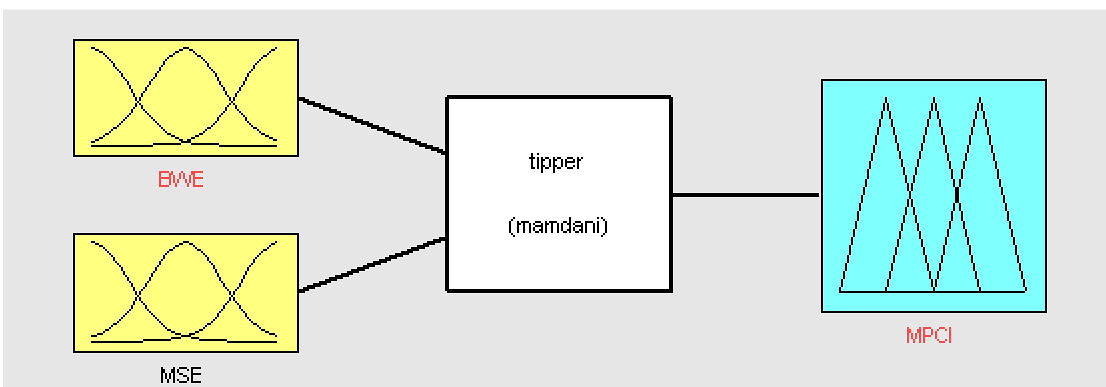

Figure 3.2: Structure of Mamdani fuzzy rule based system for evaluating Multi Performance Characteristic Index (MPCI)

3.3.2 Steps in the Fuzzy Model

Steps to be followed in a fuzzy model is shown as a flowchart in Figure 3.3

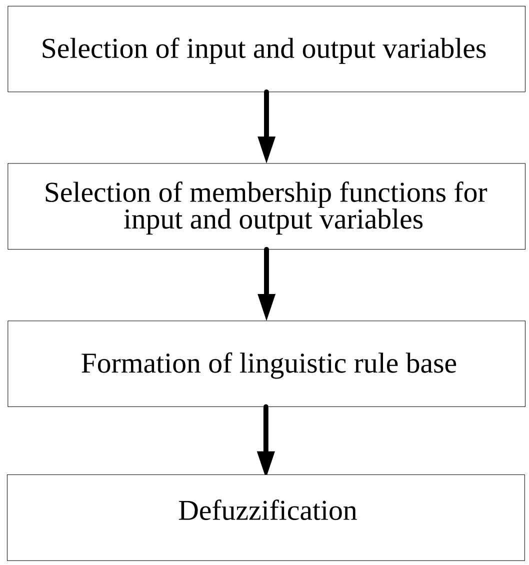

Figure 3.3: Steps in the fuzzy model

❖ *Selection of input and output variables*

In the initial step of system modeling the input and output variables called the system variables are identified. The input variables are identified as bullwhip effect and mean square error and the output variable is multi-performance characteristic index. Linguistic format is used for taking inputs and output which displays an important role in the application of fuzzy logic. Linguistic variables are those variables whose values are words in a natural or artificial language and meaning remains same but form varies.

❖ *Selection of membership functions for input and output variables*

The membership function of a fuzzy set is a generalization of the indicator function in classical sets. In fuzzy logic, it represents the degree of truth as an extension of valuation. In general, triangular and trapezoidal membership functions are because of their simplicity and computational efficiency. Triangular membership function are used for defining the input and output variables. The input variables, Bullwhip effect and mean square error is varied in three different levels that is {low, medium, high} and output variable, Multi-performance characteristic index (MPCI) into five different levels such as very low, low , medium, high and very high as shown in Figures 3.4-3.6.

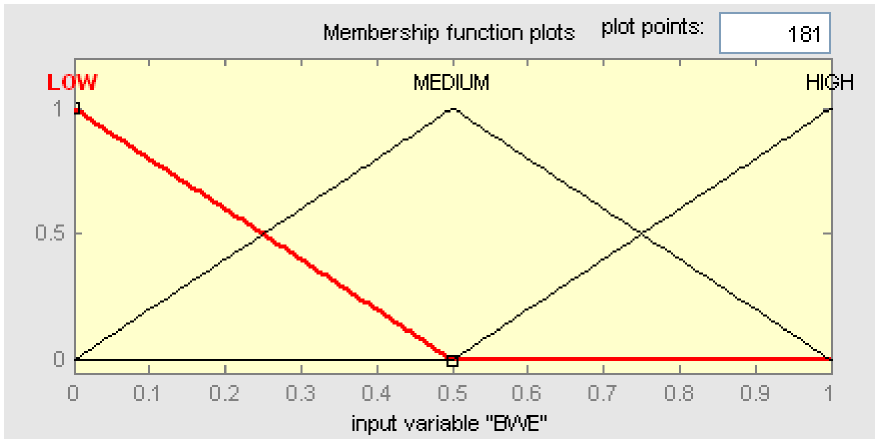

Figure 3.4: Membership Function for BWE

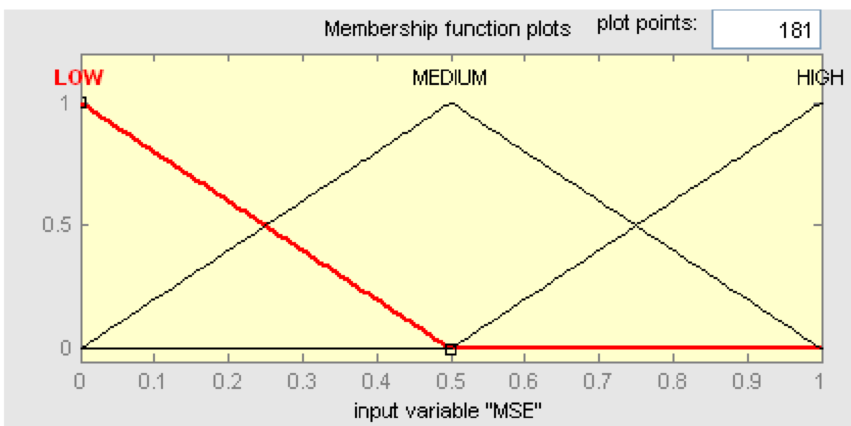

Figure 3.5: Membership Function for MSE

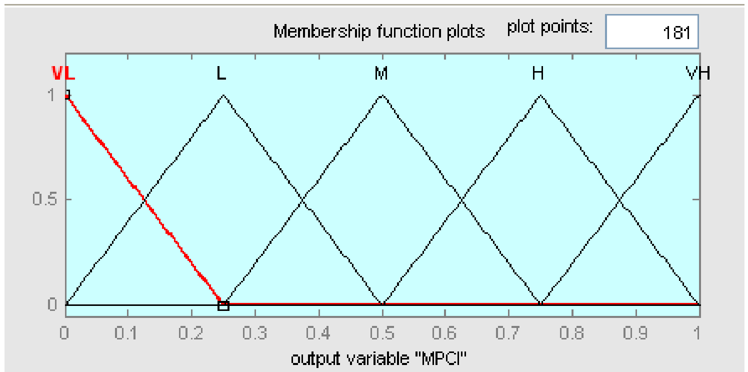

Figure 3.6: Membership Function for MPCI

❖ *Formation of linguistic rule-base*

The input and the output relationship were represented in the form of if-then rules. According to the fuzzy system, the inputs BWE and MSE have three membership functions each, hence 9 (3^2) rules can be obtained. In the Mamdani fuzzy system, output MPCI has been generated using the following rules:

Rule 1: if BWE is *low*, MSE is *low*, then MPCI is *very low* else

Rule 2: if BWE is *low*, MSE is *medium*, then MPCI is *low* else

Rule 3: if BWE is *low*, MSE is *high*, then MPCI is *medium* else

Rule 4: if BWE is *medium*, MSE is *low*, then MPCI is *low* else

Rule 5: if BWE is *medium*, MSE is *medium*, then MPCI is *medium* else

Rule 6: if BWE is *medium*, MSE is *high*, then MPCI is *high* else

Rule 7: if BWE is *high*, MSE is *low*, then MPCI is *medium* else

Rule 8: if BWE is *high*, MSE is *medium*, then MPCI is *high* else

Rule 9: if BWE is *high*, MSE is *high*, then MPCI is *very high* else

❖ *Defuzzification:* Defuzzification is the process of linguistic values into crisp values.

Chapter-4

Experimental Details

Bullwhip effect is a wasteful phenomenon that occurs due to lack of information across the supply chain. This phenomenon is one of the current challenges that a supply chain faces. This makes it essential to understand the performance of supply chain on the basis of bullwhip effect and mean square error (MSE) with the variation of process parameters. In this study bullwhip effect and mean square error are considered as measures of supply chain performance. To achieve this, the present chapter describes process parameters used for analyzing the two staged supply chain and also presents detailed methodology related to design of experiment technique based on ANOVA method.

4.1 Model Analysis

In the analysis a two staged real supply chain consisting of one supplier and four retailers was considered and simulated. In this study various conditions including various demand patterns, and various ordering costs were investigated in retailer's level. Ordering cost for each retailer was different from another retailer and also customer demand received by each retailer is independent from the other retailer because of the different geographical market of retailers. The simulation is done using MATLAB programming.

In this project work, the following assumptions are made:

- The supplier can produce any required amount of the ordered products.
- Shipment was made from the supplier to the retailer by truck and it is assumed that the truck capacity is large enough, so that the ordered quantity in each period can be shipped

by one truck. Transportation costs per truck from supplier to the retailer are taken as $225, $331, $450, $553 respectively for each retailer [52].

- The manufacturing lead time is equal to one period of time.
- The retailers use Economic Order Quantity (EOQ) model to make ordering decision.
- Order processing cost of $30 per order is incurred when a retailer places an order to the supplier. So, the total order processing costs for four retailers are $285, $361, $480, $583 respectively.
- Unit inventory holding cost per period for the retailer is $4.

4.2 Demand Generation

There are four components of demand which are explained below:

- *Base or Horizontal component* of demand exists when the demand fluctuates about an average demand. The average demand remains constant and does not consistently increase or decrease.

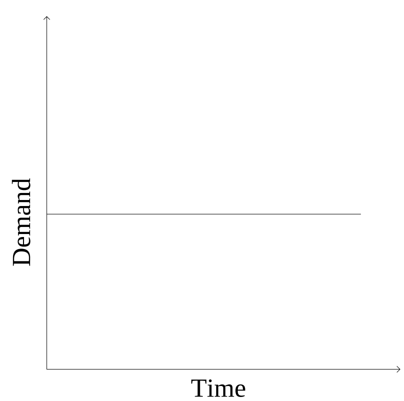

Figure 4.1: Horizontal component of demand

For example- The sales of a product in the mature stage of the product life cycle shows horizontal demand pattern.

- *Trend component* of demand refers to sustained increase or decrease in demand from one period to the next.

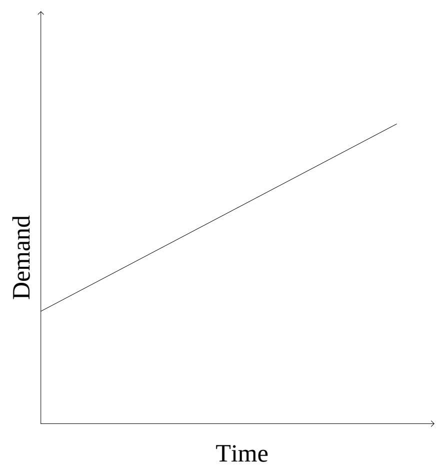

Figure 4.2: Increasing trend

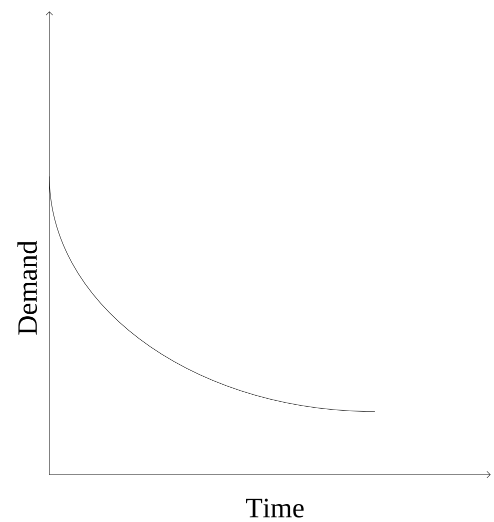

Figure 4.3: Decreasing trend

For example- The sales of the product in the growth stage of the product life cycle tend to show upward trend, whereas those in decline tend to show a downward trend.

- *Seasonality component* of demand pertains to the influence of seasonal factors that impact demand positively or negatively.

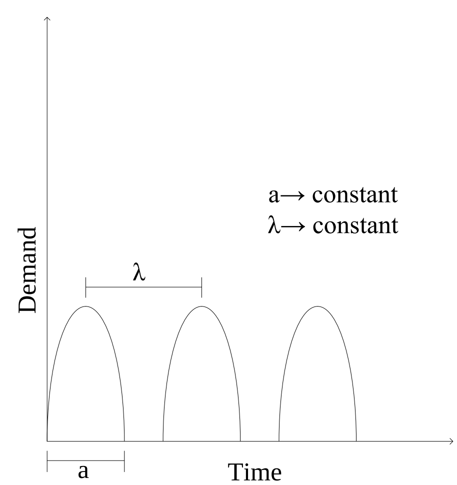

Figure 4.4: Seasonality component

For example- The sales of an air cooler will be higher in summer months and lower in winter months every year, indicating a seasonal component in the demand of air cooler.

- *Cyclic component* of demand is similar to the seasonal component except that seasonality occurs at regular intervals and is of constant length whereas the cyclic component varies in both time and duration of occurrence.

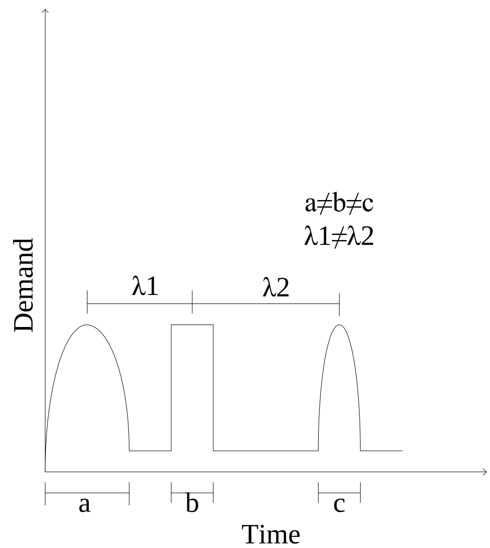

Figure 4.5: Cyclic component

For example- The impact of a recession on the demand for a product will be reflected by the cyclic component. Recession occurs at irregular intervals and the length of time a recession lasts varies.

The formula to be used for generation of demand through simulation is:-

$$Demand_t = Base + Slope \times t + Season \times \sin\left(\frac{2\pi}{Seasoncycle} \times t\right) + noise \times snormal()$$

where $Demand_t$ = demand in period t

snormal() = standard normal random number generator season cycle = 7 (in this study)

The other parameters (base, slope, season, and noise) are characteristic parameters of each demand patterns. Four Demand Patterns (DP) representing different combinations of trends and seasonality, as shown in Table 1, are used in this study.

DP1: demand pattern with neither seasonality nor trend

DP2: demand pattern with seasonality but without trends

DP3: demand pattern with seasonality and an increasing trend

DP4: demand pattern with seasonality and a decreasing trend

Table 1: Characteristics of Demand Pattern

Demand Pattern	Base	Slope	Season	Noise
DP1	1000	0	0	100
DP2	1000	0	200	100
DP3	551	2	200	100
DP4	1449	-2	200	100

4.3 Retailers Ordering Decisions

In the first step, forecast for the next period is determined using a forecasting method and demand is generated using MATLAB Simulation. In the second step, order quantity is determined using EOQ policy. The forecasting methods used are:

- Moving average
- Exponential smooth

The study tests the effect of forecasting method on bullwhip effect and accuracy of forecasting method is also an essential characteristic of appropriate forecasting method.

- *Moving Average Method:*

The general form of this method is as follows:

$$\boxed{F_{t+1} = \frac{1}{n} \sum_{i=t-n+1}^{t} X_i}$$

where F_{t+1} is the forecast for the next period,

t is the current time, and

X_i is the real demand for the period i and n.

In the analysis, n is taken as 50, 100, 200 and 300.

- *Exponential Smoothing*

The forecasting method is defined as the following:

$$\boxed{F_{t+1} = \sum_{i=t-n}^{t-1} \alpha(1-\alpha)^i X_{t-i} + (1-\alpha)^t F_l}$$

where α is the correlation parameter in the range of [0, 1] and F_l is average of some previous real demand.

In the analysis, α is taken as 0.25, 0.5 and 0.75.

4.4 Experimental Design

In conventional experiments, effect of only one factor is investigated independently at a time keeping all other factors at fixed levels. Therefore, visualization of impact of various factors in an interacting environment really becomes difficult. Thus, more experimental runs are required for the precision in effect estimation, general conclusions cannot be drawn and the optimal factor settings are difficult to obtain. To overcome this problem, design of experiment (DOE) approach is used to effectively plan and perform experiments, using statistics and is commonly used to improve the quality of products or processes. Design of experiments is a robust analysis tool for modeling and analyzing the influence of control factors on performance output.

Bullwhip effect in supply chain is controlled by number of parameters which collectively determine the performance output. Hence, in the present work ANOVA's parameter design can be adopted to optimize the process parameters leading to reduction of bullwhip effect and mean square error. The most important stage in the DOE lies in the selection of the control parameters and their level. In the experimental design three factors that are holding cost (Cp), method and demand pattern (Pp) with four, ten and four levels are considered respectively. The levels of the factors are represented as shown in Tables 2-4.

Table 2: Representation of levels for the factor Cp

Level	Representation
$285	285
$361	361
$480	480
$583	583

Table 3: Representation of levels for the factor method

Level		Representation
Moving Average	n=50	1
	n=100	2
	n=200	3
	n=300	4
Exponential Smoothing	n=7, α=0.25	5
	n=7, α=0.5	6
	n=7, α=0.75	7
	n=15, α=0.25	8
	n=15, α=0.5	9
	n=15, α=0.75	10

Table 4: Representation of levels for the factor Pp

Level	Representation
DP1	1
DP2	2
DP3	3
DP4	4

There are 3 factors such as order processing cost, method and demand pattern with different levels of values i.e., 4, 10 and 4 resepectively as shown in Table 5. Thus, in a classical full factorial design of experiment (DOE) the total number of experiments required will be 160 (i.e. 4 x 10 x 4) which are shown in Table 6. After design of experiment is completed, the experiment or in other words the MATLAB codes are run in that order to generate the results. In the analysis the MATLAB codes are run to get experimental results. The responses are bullwhip effect and mean square error. The supply chain was simulated to run at each of the above 160 different combinations of the three factor settings and the corresponding output responses are measured.

Table 5: Factors and their levels

Sl. No.	Factor	Level
1	Order Processing Cost (Cp)	4
2	Method	10
3	Demand Pattern (Pp)	4

Table 6: Full factorial experimental design

Sl. No.	Factors				Sl. No.	Factors				Sl. No.	Factors				Sl. No.	Factors		
	Cp	Method	DP			Cp	Method	DP			Cp	Method	DP			Cp	Method	DP
1	583	5	4		21	361	4	3		41	361	5	2		61	361	1	3
2	583	1	1		22	285	5	1		42	583	9	4		62	583	6	3
3	285	9	1		23	361	5	3		43	583	4	1		63	480	1	4
4	361	10	2		24	480	5	4		44	480	8	1		64	285	1	3
5	583	5	1		25	285	6	2		45	361	9	4		65	583	8	3
6	361	7	1		26	583	2	3		46	480	2	2		66	480	1	2
7	583	3	1		27	480	8	2		47	361	6	3		67	285	9	4
8	285	5	4		28	285	8	4		48	480	2	1		68	361	6	1
9	480	10	1		29	583	2	4		49	361	7	2		69	361	3	4
10	480	9	3		30	285	3	3		50	480	3	3		70	583	5	3
11	285	6	1		31	480	4	3		51	285	7	2		71	583	5	2
12	285	1	2		32	583	4	3		52	285	5	3		72	285	4	1
13	480	9	4		33	480	2	4		53	361	1	4		73	285	9	3
14	480	1	3		34	361	3	3		54	361	8	4		74	285	2	3
15	583	10	4		35	583	6	1		55	583	4	2		75	361	9	3
16	583	1	2		36	583	3	4		56	361	10	4		76	361	2	1
17	361	4	2		37	480	3	1		57	361	7	3		77	285	7	4
18	583	8	2		38	285	1	4		58	285	3	4		78	480	7	2
19	361	9	1		39	583	10	1		59	583	1	3		79	480	4	4
20	583	3	2		40	285	5	2		60	361	8	2		80	480	1	1

Sl. No.	Factors				Sl. No.	Factors				Sl. No.	Factors				Sl. No.	Factors		
	Cp	Method	DP			Cp	Method	DP			Cp	Method	DP			Cp	Method	DP
81	583	2	1		101	480	8	4		121	285	9	2		141	480	3	4
82	480	6	2		102	361	5	1		122	361	3	2		142	285	7	1
83	285	10	1		103	480	5	1		123	285	3	1		143	480	7	1
84	480	6	4		104	583	9	1		124	480	6	1		144	480	9	1
85	480	9	2		105	285	8	1		125	361	10	1		145	480	3	2
86	361	2	4		106	583	7	3		126	285	4	3		146	285	2	2
87	361	1	2		107	361	2	3		127	480	8	3		147	285	10	4
88	285	8	3		108	285	6	3		128	285	4	4		148	285	2	1
89	480	10	2		109	583	9	3		129	583	1	4		149	480	2	3
90	361	9	2		110	361	7	4		130	480	7	4		150	480	4	2
91	480	5	2		111	583	10	2		131	361	6	2		151	285	10	3
92	480	5	3		112	285	8	2		132	583	7	4		152	285	6	4
93	285	10	2		113	480	10	4		133	361	6	4		153	583	4	4
94	583	7	1		114	285	2	4		134	285	4	2		154	583	7	2
95	361	10	3		115	480	10	3		135	480	7	3		155	361	8	3
96	583	9	2		116	583	3	3		136	361	4	4		156	480	4	1
97	583	8	1		117	285	3	2		137	361	3	1		157	285	7	3
98	361	5	4		118	583	6	2		138	285	1	1		158	583	10	3
99	480	6	3		119	361	8	1		139	361	2	2		159	583	2	2
100	583	6	4		120	361	4	1		140	361	1	1		160	583	8	4

4.5 MATLAB Codes

MATLAB is a numerical computing environment and a fourth-generation programming language developed by Math Works. This programming language allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages like C, C++, Java and FORTRAN. Using MATLAB, we can solve technical computing problems faster than with traditional programming languages, such as C, C++, and FORTRAN.

MATLAB codes were first written to generate demand for different conditions and then forecasting was done using the two previously mentioned methods and finally their respective bullwhip effect and mean square error were calculated.

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The experimental design was created using ANOVA and then the MATLAB codes were run in that order to generate their respective bullwhip effect and mean square error which is shown in Table 6. When the responses were analyzed, it was observed that there is a large variation amongst them, so it was necessary to normalize the responses. Depending upon the characteristics of the data sequence various methods have been used for data analysis of data preprocessing i.e. normalization. The normalization is taken by the following equations.

(1) Lower-the-better (LB):

$$\hat{x}_i(k) = \frac{\max_k x_i(k) - x_i(k)}{[\max_k x_i(k)] - \min_k x_i(k)}$$

(2) Higher-the-better (HB):

$$\hat{x}_i(k) = \frac{x_i - \min_k x_i(k)}{[\max_k x_i(k)] - \min_k x_i(k)}$$

Lower the better criterion has been selected for the normalization of bullwhip effect (BWE) and mean square error (MSE). Experimental data in Table 6 have been normalized using the lower the better criterion. The normalized data have been shown in Table 7.

ANOVA is applicable for single objective criteria, so multi-objective criteria is converted to single objective criteria using Fuzzy Inference System to generate Multi performance characteristic index (MPCI). The MPCI values are shown in Table 7.

The MPCI values are then analyzed and then the main effect plot for it is drawn in Minitab software. The main effect plots for MPCI of two responses as shown in Figures 5.1-5.2 give the optimum factor level. The significant factors are identified and analyzed using ANOVA.

Table 7: The observed values of BWE and MSE of each experimental run

Sl. No.	Responses			Sl. No.	Responses			Sl. No.	Responses			Sl. No.	Responses	
	BWE	MSE			BWE	MSE			BWE	MSE			BWE	MSE
1	0.1296	0.1684		21	2.3136	12.8301		41	0.3289	0.0903		61	0.3928	20.0764
2	0.509	18.2945		22	0.1046	1.1896		42	0.1486	0		62	0.3941	0.0402
3	0.1109	0		23	0.3923	0.086		43	0.1956	28.3577		63	0.1211	22.5869
4	0.5414	0		24	0.1169	0.1252		44	0.0234	0		64	0.644	14.7199
5	0.0446	0.2313		25	0.6676	0.0922		45	0.2119	0		65	0.1902	0
6	0.1063	0.0104		26	0.3368	22.4595		46	0.2677	29.1909		66	0.1943	21.3983
7	0.1209	26.0307		27	0.1752	0		47	0.6322	0.0432		67	0.1893	0
8	0.2262	0.1684		28	0.2529	0		48	0.0976	24.9277		68	0.1724	0.2655
9	0.1393	0		29	0.2056	29.538		49	0.5625	0.0098		69	0.8255	48.6484
10	0.2752	0		30	1.6504	16.3935		50	1.0196	19.1914		70	0.2358	0.0896
11	0.21	0.0876		31	1.7682	13.2703		51	1.0782	0.023		71	0.1372	31.5779
12	0.2224	24.1858		32	1.3962	13.0719		52	0.6367	0.1628		72	0.4164	28.9279
13	0.2014	0		33	0.2196	28.0224		53	0.1432	23.8526		73	0.5259	0
14	0.2581	19.1649		34	1.2637	18.1141		54	0.1529	0		74	0.7996	21.4335
15	0.158	0		35	0.0799	0.0664		55	0.5855	31.5779		75	0.4612	0
16	0.1611	23.6115		36	0.5073	47.9046		56	0.4203	0		76	0.1522	29.4007
17	0.9891	31.5229		37	0.1667	27.8624		57	1.1834	0.0341		77	0.5481	0.0016
18	0.1377	0		38	0.2083	24.5823		58	1.1085	46.0635		78	0.4122	0.159
19	0.1117	0		39	0.1206	0		59	0.2839	12.5504		79	1.263	63.0715
20	0.4115	26.1085		40	0.1898	0.1619		60	0.2245	0		80	0.0532	22.0875

Sl. No.	Responses			Sl. No.	Responses			Sl. No.	Responses			Sl. No.	Responses	
	BWE	MSE			BWE	MSE			BWE	MSE			BWE	MSE
81	0.0618	29.2464		101	0.137	0		121	0.3302	0		141	0.6985	38.8934
82	0.3392	0.017		102	0.0451	0.217		122	0.6724	32.2195		142	0.2024	0.0282
83	0.1489	0		103	0.033	0.2716		123	0.2796	29.0917		143	0.1025	0.0464
84	0.1875	0.0302		104	0.0597	0		124	0.0594	0.0876		144	0.0889	0
85	0.2462	0		105	0.1109	0		125	0.1556	0		145	0.4743	33.1291
86	0.3162	39.8289		106	0.3246	0.0117		126	2.9435	13.1172		146	0.46476	32.3566
87	0.2653	24.1224		107	0.6439	18.8508		127	0.2696	0		147	0.2614	0
88	0.5558	0		108	0.8656	0.0569		128	2.3707	91.6344		148	0.1579	24.675
89	0.5093	0		109	0.3386	0		129	0.1045	25.0139		149	0.4669	19.4359
90	0.3269	0		110	0.5083	0.0076		130	0.3147	0.0037		150	0.6657	27.7763
91	0.1536	0.2085		111	0.3752	0		131	0.5518	0.0399		151	0.976	0
92	0.31	0.1743		112	0.4483	0		132	0.2148	0.0073		152	0.293	0.0383
93	0.4959	0		113	0.1975	0		133	0.1844	0.036		153	1.1113	50.8351
94	0.0799	0.0127		114	0.4243	30.5566		134	1.2564	23.9599		154	0.2516	0.004
95	0.6291	0		115	0.5525	0		135	0.546	0.0145		155	0.3662	0
96	0.162	0		116	0.8279	20.9302		136	1.8589	64.5195		156	0.204	24.0227
97	0.0439	0		117	0.9651	42.5371		137	0.2078	28.1341		157	1.8237	0.0071
98	0.1645	0.2074		118	0.1636	0.0397		138	0.1436	21.3951		158	0.518	0
99	0.3587	0.0425		119	0.0601	0		139	0.4611	29.4007		159	0.2835	23.5904
100	0.19	0.0418		120	0.3643	23.3757		140	0.1522	26.0049		160	0.1148	0

Table 8: Normalized values of BWE and MSE for each experimental run

Sl. No.	N-bwe	N-mse		Sl. No.	N-bwe	N-mse		Sl. No.	N-bwe	N-mse		Sl. No.	N-bwe	N-mse
1	0.03637	0.00184		21	0.78429	0.14001		41	0.10462	0.00099		61	0.1265	0.21909
2	0.1663	0.19965		22	0.02781	0.01298		42	0.04288	0		62	0.12695	0.00044
3	0.02997	0		23	0.12633	0.00094		43	0.05897	0.30947		63	0.03346	0.24649
4	0.17739	0		24	0.03202	0.00137		44	0	0		64	0.21253	0.16064
5	0.00726	0.00252		25	0.22061	0.00101		45	0.06455	0		65	0.05712	0
6	0.02839	0.00011		26	0.10733	0.2451		46	0.08366	0.31856		66	0.05853	0.23352
7	0.03339	0.28407		27	0.05199	0		47	0.20849	0.00047		67	0.05681	0
8	0.06945	0.00184		28	0.07859	0		48	0.02541	0.27203		68	0.05103	0.0029
9	0.03969	0		29	0.0624	0.32235		49	0.18462	0.00011		69	0.27468	0.5309
10	0.08623	0		30	0.55717	0.1789		50	0.34115	0.20943		70	0.07274	0.00098
11	0.0639	0.00096		31	0.59751	0.14482		51	0.36122	0.00025		71	0.03897	0.34461
12	0.06815	0.26394		32	0.47012	0.14265		52	0.21003	0.00178		72	0.13458	0.31569
13	0.06096	0		33	0.06719	0.30581		53	0.04103	0.2603		73	0.17208	0
14	0.08037	0.20915		34	0.42475	0.19768		54	0.04435	0		74	0.26581	0.2339
15	0.04609	0		35	0.01935	0.00073		55	0.19249	0.34461		75	0.14993	0
16	0.04716	0.25767		36	0.16571	0.52278		56	0.13592	0		76	0.04411	0.32085
17	0.33071	0.34401		37	0.04907	0.30406		57	0.39725	0.00037		77	0.17969	1.75E-05
18	0.03914	0		38	0.06332	0.26827		58	0.3716	0.50269		78	0.13315	0.00174
19	0.03024	0		39	0.03329	0		59	0.08921	0.13696		79	0.42451	0.6883
20	0.13291	0.28492		40	0.05698	0.00177		60	0.06887	0		80	0.01021	0.24104

Sl. No.	N-bwe	N-mse		Sl. No.	N-bwe	N-mse		Sl. No.	N-bwe	N-mse		Sl. No.	N-bwe	N-mse
81	0.01315	0.31916		101	0.0389	0		121	0.10507	0		141	0.23119	0.42444
82	0.10815	0.00019		102	0.00743	0.00237		122	0.22225	0.35161		142	0.0613	0.00031
83	0.04298	0		103	0.00329	0.00296		123	0.08774	0.31748		143	0.02709	0.00051
84	0.0562	0.00033		104	0.01243	0		124	0.01233	0.00096		144	0.02243	0
85	0.0763	0		105	0.02997	0		125	0.04527	0		145	0.15441	0.36154
86	0.10027	0.43465		106	0.10315	0.00013		126	1	0.14315		146	0.15115	0.35311
87	0.08284	0.26325		107	0.21249	0.20572		127	0.08431	0		147	0.0815	0
88	0.18232	0		108	0.28842	0.00062		128	0.80384	1		148	0.04606	0.26928
89	0.1664	0		109	0.10794	0		129	0.02777	0.27298		149	0.15188	0.2121
90	0.10394	0		110	0.16606	8.29E-05		130	0.09976	4.04E-05		150	0.21996	0.30312
91	0.04459	0.00228		111	0.12048	0		131	0.18095	0.00044		151	0.32622	0
92	0.09815	0.0019		112	0.14551	0		132	0.06555	7.97E-05		152	0.09233	0.00042
93	0.16181	0		113	0.05962	0		133	0.05514	0.00039		153	0.37256	0.55476
94	0.01935	0.00014		114	0.13729	0.33346		134	0.42225	0.26147		154	0.07815	4.37E-05
95	0.20742	0		115	0.18119	0		135	0.17897	0.00016		155	0.11739	0
96	0.04746	0		116	0.2755	0.22841		136	0.62857	0.7041		156	0.06185	0.26216
97	0.00702	0		117	0.32249	0.4642		137	0.06315	0.30703		157	0.61652	7.75E-05
98	0.04832	0.00226		118	0.04801	0.00043		138	0.04116	0.23348		158	0.16938	0
99	0.11483	0.00046		119	0.01257	0		139	0.14989	0.32085		159	0.08907	0.25744
100	0.05705	0.00046		120	0.11674	0.2551		140	0.04411	0.28379		160	0.0313	0

Table 9: Multi-Performance Characteristic Index (MPCI) values

Sl. No.	MPCI	Sl. No.	MPCI	Sl. No.	MPCI	Sl. No.	MPCI	Sl. No.	MPCI	Sl. No.	MPCI	Sl. No.	MPCI	Sl. No.	MPCI
1	0.119	21	0.472	41	0.164	61	0.297	81	0.243	101	0.118	121	0.163	141	0.363
2	0.312	22	0.13	42	0.121	62	0.174	82	0.165	102	0.0928	122	0.351	142	0.136
3	0.11	23	0.175	43	0.273	63	0.245	83	0.121	103	0.0896	123	0.291	143	0.109
4	0.195	24	0.114	44	0.08	64	0.311	84	0.132	104	0.0934	124	0.0951	144	0.103
5	0.093	25	0.211	45	0.138	65	0.132	85	0.146	105	0.11	125	0.123	145	0.325
6	0.109	26	0.291	46	0.289	66	0.26	86	0.308	106	0.162	126	0.581	146	0.322
7	0.252	27	0.128	47	0.206	67	0.132	87	0.281	107	0.327	127	0.151	147	0.149
8	0.144	28	0.147	48	0.244	68	0.132	88	0.197	108	0.227	128	0.798	148	0.259
9	0.119	29	0.277	49	0.198	69	0.408	89	0.191	109	0.164	129	0.246	149	0.307
10	0.152	30	0.39	50	0.344	70	0.145	90	0.162	110	0.191	130	0.16	150	0.342
11	0.139	31	0.404	51	0.24	71	0.265	91	0.126	111	0.171	131	0.197	151	0.234
12	0.272	32	0.33	52	0.208	72	0.312	92	0.161	112	0.182	132	0.138	152	0.156
13	0.135	33	0.278	53	0.253	73	0.193	93	0.189	113	0.134	133	0.131	153	0.463
14	0.27	34	0.35	54	0.122	74	0.34	94	0.101	114	0.315	134	0.375	154	0.147
15	0.124	35	0.102	55	0.338	75	0.184	95	0.205	115	0.197	135	0.196	155	0.169
16	0.257	36	0.359	56	0.178	76	0.266	96	0.125	116	0.339	136	0.618	156	0.268
17	0.391	37	0.266	57	0.244	77	0.196	97	0.0877	117	0.403	137	0.276	157	0.318
18	0.118	38	0.27	58	0.428	78	0.179	98	0.129	118	0.126	138	0.248	158	0.192
19	0.11	39	0.113	59	0.26	79	0.55	99	0.168	119	0.0935	139	0.319	159	0.283
20	0.308	40	0.135	60	0.141	80	0.225	100	0.133	120	0.297	140	0.26	160	0.111

Statistical analysis has been performed treating MPCI as an equivalent response instead of BWE and MSE. Table 9 shows that order processing cost, method, demand pattern and interaction of order processing cost and method, demand pattern and order processing cost, method and demand pattern have significant effect on MPCI and the coefficient of determination R^2 has been found to be 97.34% .

Table 10: Mean Response Table

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Cp	3	0.062703	0.062703	0.020901	31.24	0.000
Method	9	1.497719	1.497719	0.166413	248.73	0.000
DP	3	0.153478	0.153478	0.051159	76.47	0.000
Cp* Method	27	0.047300	0.047300	0.001752	2.62	0.000
Cp* DP	9	0.012465	0.012465	0.001385	2.07	0.042
Method* DP	27	0.012465	0.210875	0.007810	11.67	0.000
Error	81	0.054192	0.054192	0.000669		
Total	159	2.038732				

Figure 5.1 shows the residual plot for MPCI where MPCI values are very close to the straight line and the histogram appears to be bell-shaped. This indicates that the MPCI values are normally distributed.

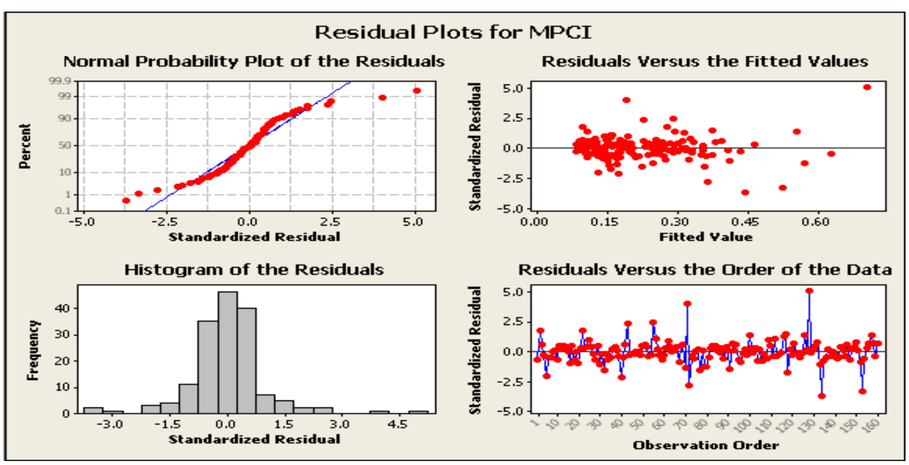

Figure 5.1: Residual plots for MPCI

In Figure 5.2 the main effect plot for MPCI has been shown which depicts the mean of the data of the multiple factors involved. The points in the plot are the means of the response variable at the various levels of each factor, with a reference line drawn at the grand mean of the response data. The main effects plot shows the magnitudes of main effects and the level of the factors which satisfy the higher the better criterion. From the main effect plot it has been observed that the MPCI is optimum at order processing cost Cp = \$285, Method = 4 (i.e., moving average method for n = 300), and Pp = Pp3 (i.e., demand pattern with seasonality and increasing trend).

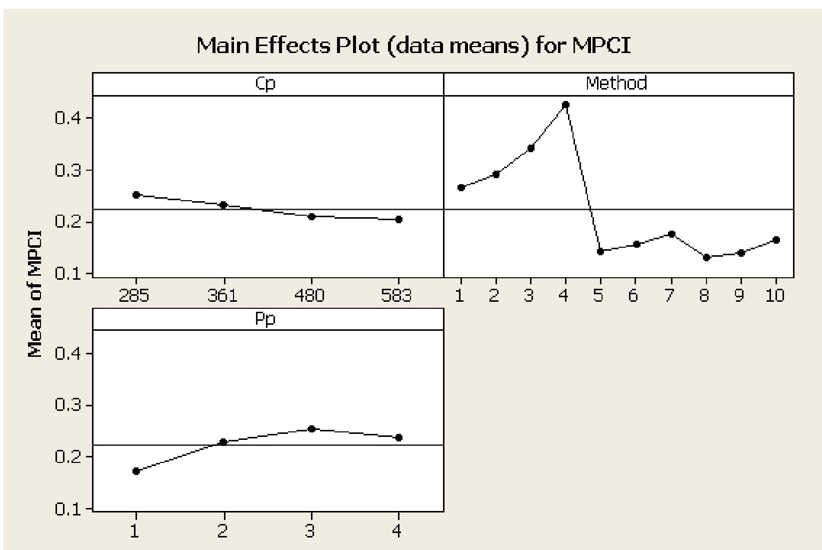

Figure 5.2: Main Effect Plot for MPCI

Chapter-6

Conclusion

It is observed from the above study that forecasting based demand variability is a major factor negatively influencing stability of supply chain network. In the present study, application of fuzzy logic reasoning using the ANOVA method for improvement of supply chain performance by reducing BWE and MSE has been studied. The optimization of the process parameters for minimum BWE and MSE were performed individually. Different forecasting methods have been compared from bullwhip effect and mean square error points of view by using simulation program written in MATLAB code, and then subsequently analyzed by fuzzy coupled with ANOVA for determining the optimal factors.

The study uses ANOVA and a fuzzy-rule based inference system, which forms a robust and practical methodology in tackling multiple response optimization problems. It has been demonstrated that a multiple response optimization problem can be effectively tackled by using fuzzy reasoning to generate a single MPCI as a performance indicator. Statistical analysis is then carried out on the MPCI to identify the key factors, which affect process performance and then determine the optimal factor settings to optimize process performance.

It was ascertained from the experimentation and analysis that minimum BWE and MSE have been obtained at order processing cost of $285 with moving average forecasting method taking 300 past demand data, and when demand pattern is with seasonality and increasing trend.

Bibliography

1. Forrester, J.W., *Industrial dynamics: a major breakthrough for decision makers,* Harvard Business Review, 1958, **36**(4), pp. 37-66.
2. Burbidge, J.L., *The new approach to production,* Production Engineer, 1961, **40**(12), pp. 769-784.
3. Sterman, J.D., *Instructions for running the beer distribution game,* System Dynamics Group Working Paper D-3679, MIT, Sloan School of Management, Cambridge, MA, 1984.
4. Sterman, J.D., *Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experimen,* Management Science, 1989, **35**(3), pp. 321-339.
5. Sterman, J.D., *Deterministic chaos in an experimental economic system,* Journal of Economic Behavior & Organization, 1989, **12**(1), pp. 1-28.
6. Sterman, J.D., *Misperceptions of feedback in dynamic decision making,* Organizational behavior and human decision processes, 1989, **43**(3), pp. 301-335.
7. Towill, D.R., *Supply chain dynamics,* International Journal of Computer Integrated Manufacturing, 1991, **4**(4), pp. 197-208.
8. Towill, D.R., *Supply chain dynamics—the change engineering challenge of the mid 1990s.* ARCHIVE: Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 1989-1996 (vols 203-210), 1992, **206**(42): pp. 233-245.
9. Wikner, J., Towill, D.R. and Naim, M., *Smoothing supply chain dynamics,* International Journal of Production Economics, 1991, **22**(3), pp. 231-248.

10. Towill, D.R., *System dynamics-background, methodology and applications. 1. Background and methodology,* Computing & Control Engineering Journal, 1993, **4**(5), pp. 201-208.

11. Towill, D.R., *System dynamics—background, methodology, and applications. Part 2: Applications,* Computing & Control Engineering Journal, 1993, **45**(5), pp. 261-268.

12. Lee, H.L., Padmanabhan, V. and Whang, S. , *The Bullwhip Effect In Supply Chains1.* Sloan Management Review, 1997, **38**(3), pp. 93-102.

13. Lee, H.L., Padmanabhan, V. and Whang, S., *Information distortion in a supply chain: the bullwhip effect*, Management Science, 1997, **43**(4), pp. 546-558.

14. Metters, R., *Quantifying the bullwhip effect in supply chains,* Journal of Operations Management, 1997, **15**(2), pp. 89-100.

15. Chen, F., Drezner, Z., Ryan, J. K. and Simchi-Levi, D., *Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information,* Management Science, 2000, **46**(3), pp. 436-443.

16. Chen, F., *Decentralized supply chains subject to information delays,* Management Science, 1999, **45**(8), pp. 1076-1090.

17. Chen, F., Ryan, J.K. and Simchi-Levi, D., *The impact of exponential smoothing forecasts on the bullwhip effect,* Naval Research Logistics, 2000, **47**(4), pp. 269-286.

18. Gavirneni, S., Kapuscinski, R. and Tayur, S., *Value of information in capacitated supply chains*, Management Science, 1999, **45**(1), pp. 16-24.

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

20. Cachon, G.P., Randall, T. and Schmidt, G.M., *In search of the bullwhip effect.*, Manufacturing & Service Operations Management, 2007, **9**(4), pp. 457-479.

21. Kimbrough, S.O., Wu, D. and Zhong, F., *Computers play the beer game: can artificial agents manage supply chains?,* Decision Support Systems, 2002, **33**(3), pp. 323-333.

22. Towill, D.R., Lambrecht, M.R., Disney, S.M. and Dejonckheere, J., *Explicit filters and supply chain design,* Journal of Purchasing and Supply Management, 2003, **9**(2), pp. 73-81.

23. Dejonckheere, J., Towill, D.R., Lambrecht, M.R. and Disney, S.M., *Transfer function analysis of forecasting induced bullwhip in supply chain,* International Journal of Production Economics, 2002, **78**(2), pp. 133-144.

24. Dejonckheere, J., Towill, D.R., Lambrecht, M.R. and Disney, S.M., *Measuring and avoiding the bullwhip effect: A control theoretic approach,* European Journal of Operational Research, 2003, **147**(3), pp. 567-590.

25. Dejonckheere, J., Towill, D.R., Lambrecht, M.R. and Disney, S.M., *The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective*, European Journal of Operational Research, 2004, **153**(3), pp. 727-750.

26. Disney, S.M. and Towill, D.R., *On the bullwhip and inventory variance produced by an ordering policy*, Omega, 2003, **31**(3), pp. 157-167.

27. Disney, S.M. and Towill, D.R., *The effect of vendor managed inventory (VMI) dynamics on the Bullwhip Effect in supply chain,.* International Journal of Production Economics, 2003, **85**(2), pp. 199-215.

28. Disney, S.M., Towill, D.R. and Velde, W. V., *Variance amplification and the golden ratio in production and inventory control,* International Journal of Production Economics, 2004, **90**(3), pp. 295-309.

29. Disney S. M., Farasyn I., Towill,.D.R., Lambrecht, M. and Velde, W. V., *Taming the bullwhip effect whilst watching customer service in a singular supply chain echelon,* European Journal of Operational Research, 2006, **173**(1), pp.151-172.

30. Aviv, Y., *A time-series framework for supply-chain inventory management*. Operations Research, 2003, **51**(2), pp. 210-227.

31. Layth, C.A., John, J. and Dong-Qing, Y., *Stochastic characterization of upstream demand processes in a supply chain,* IIE Transactions, 2003, **35**(3), pp. 207-219.

32. So, K.C. and Xiano, Z., *Impact of supplier's lead time and forecast demand updating on retailer's order quantity variability in a two echelon supply chain,* International Journal of Production Economics, 2003, **86(2),** pp.169-179.

33. Zhang, X., *The impact of forecasting methods on the bullwhip effect*. International journal of Production Pconomics, 2004, **88**(1), pp. 15-27.

34. Liu, H. and Wang, P., *Bullwhip effect analysis in supply chain for demand forecasting technology,* Systems Engineering-Theory & Practice, 2007, **27**(7), pp. 26-33.

35. Machuca, J.A.D. and Barajas, R.P., *The impact of electronic data interchange on reducing bullwhip effect and supply chain inventory costs,* Transportation Research Part E: Logistics and Transportation Review, 2004, **40**(3), pp. 209-228.

36. Wu, D.Y. and Katok, E., *Learning, communication, and the bullwhip effect,* Journal of Operations Management, 2006, **24**(6), pp. 839-850.

37. Makui, A. and Madadi, A., *The bullwhip effect and Lyapunov exponent*, Applied Mathematics and Computation, 2007, **189**(1), pp. 35-40.

38. Hwarng, H.B. and Xie, N., *Understanding supply chain dynamics: A chaos perspective*. European Journal of Operational Research, 2008, **184**(3), pp. 1163-1178.

39. Sohn, S.Y. and Lim, M., *The effect of forecasting and information sharing in SCM for multi-generation products,* European Journal of Operational Research, 2008, **186**(1), pp. 276-287.

40. Wright, D. and Yuan, X. *Mitigating the bullwhip effect by ordering policies and forecasting methods,* International Journal of Production Economics, 2008, **113**(2), pp. 587-597.

41. Saeed, K., *Trend forecasting for stability in supply chains,* Journal of Business Research, 2008, **61**(11), pp. 1113-1124.

42. Sucky, E., *The bullwhip effect in supply chains--An overestimated problem?*, International Journal of Production Economics, 2009, **118**(1), pp. 311-322.

43. Carlsson, C. and Fullér, R., *Soft computing and the bullwhip effect*, 1999, Åbo Akademi University.

44. Carlsson, C. and Fullér, R., *Reducing the bullwhip effect by means of intelligent, soft computing methods*. 2001, IEEE.

45. Carlsson, C. and Fullér, R., *A position paper on the agenda for soft decision analysis.* Fuzzy Sets and Systems, 2002, **131**(1), pp. 3-11.

46. Carlsson, C., Fedrizzi, M. and Fullér, R., *Fuzzy Logic in Management*, Springer, 2004, 66.

47. Wang, J. and Shu, Y.F., *Fuzzy decision modeling for supply chain management,* Fuzzy Sets and Systems, 2005, **150**(1), pp. 107-127.

48. Wang, J. and Shu, Y.F., *A possibilistic decision model for new product supply chain design,* European Journal of Operational Research, 2007, **177**(2), pp. 1044-1061.

49. Zarandi, M., Pourakbar, M. and Turksen, I., *A Fuzzy agent-based model for reduction of bullwhip effect in supply chain systems,* Expert Systems with Applications, 2008, **34**(3), pp. 1680-1691.

50. Kahraman, C., *Fuzzy Applications in Industrial Engineering (Studies in Fuzziness and Soft Computing)*, 2006, Springer-Verlag New York, Inc.

51. Balan S., Vrat, P. and Kumar P., *Information distortion in a supply chain and its mitigation using soft computing approaches,* International Journal of Management Science , 2009. **37(2),** pp.282-299.

52. Chaharsooghi, S.K., Faramarzi, H. and Heydari. J., *A simulation study on the impact of forecasting methods on the bullwhip effect in the supply chain*, IEEE Interntional Conference, 2008, pp.1875-1879.

APPENDIX

MATLAB Programs

Simple moving average

```
clc
base= [1000 1000 551 1449];
slope= [0 0 2 -2];
season= [0 200 200 200];
noise= [100 100 100 100];
choice= input('enter your choice')
switch choice
    case 1
        disp ('simple moving average')
        simpmovaverage(base,slope,season,noise);
    case 2
        disp('finish')
end


function simpmovaverage(base,slope,season,noise)
n=300;
p=n;
q=n;
m=n+10;
dd=demand_data(m,base(1),slope(1),season(1),noise(1))
x=1;
y=m-p;
z=0;
cp=583;
ch=4;
fc=[];
error1=[];
eoq=[];
for a=1:10
   for t=x:n
        z =z + dd(t);
   end
   fc(p+1)=z/n
   error1(p+1)=dd(p+1)-fc(p+1)
   ferror1(p+1)=error1(p+1)/dd(p+1)
   eoq(p+1) =sqrt((2*fc(p+1)*cp)/ch);
   p=p+1;
   x=x+1;
   n=n+1;
```

```
end
mse=meansqr_error(y,q,ferror1)
b=bwe(dd,eoq)
```

Exponential smoothing

```
clc
base= [1000 1000 551 1449];
slope= [0 0 2 -2];
season= [0 200 200 200];
noise= [100 100 100 100];
choice= input('enter your choice');
switch choice
    case 1
        disp ('exponential smoothning')
        exponentialsmoothning(base,slope,season,noise);
    case 2
        disp('finish')
end


function exponentialsmoothning(base,slope,season,noise)
n=15;
m=n+10;
p=n;
q=n;
y=m-p;
dd=demand_data(m,base(1),slope(1),season(1),noise(1))
a=0.75;
cp=583;
ch=4;
i=p-n;
s=0;
r=0;
q=0;
for b=1:10
    for j=1:p
            r=r+dd(j);
    end
         fl=r/p;
    for i=p-n:p-1
        s=s+ a*(1-a)^i*dd(p-i);
    end
    fc(p+1)=s+((1-a)^p)*fl;
    error1(p+1)=dd(p+1)-fc(p+1)
```

```
    ferror1(p+1)=error1(p+1)/dd(p+1)
    eoq(p+1)=sqrt((2*fc(p+1)*cp)/ch);
    p=p+1;
end
mse=meansqr_error(y,q,ferror1)
b=bwe(dd,eoq)
```

Data generation

```
function f=demand_data(m,base,slope,season,noise)
% generation of stochastic data
% syntax demand_data(n,base,slope,season,noise)
dd=[];
for t=1:m
    de =base + slope*t + season*sin((2*pi*t)/7) + noise*normrnd(0,1);
    dd=[dd;de];
end
f=dd;
```

Bullwhip effect calculation

```
function b= bwe(e,f)
% computes the variance and then bullwhip effect of the demand
% syntax bwe(m,dd,eoq)
O =var(e)
D =var(f)
b =O/D;
```

Mean square error calculation

```
function mse=meansqr_error(y,q,ferror1)
%calculates the mean square error
%syntax meansqr_error(Y,P,E)
s=0;
for i=1:y
    s=s+ferror1(q+i)^2;
end
mse=s/y;
```