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A COMPARATIVE STUDY OF SIMULATION AND TIME SERIES MODEL IN QUANTIFYING BULLWHIP EFFECT IN SUPPLY CHAIN

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Abstract

Bullwhip (or whiplash) effect is an observed phenomenon in forecast driven distribution channel and careful management of these effects is of great importance to managers of supply chain. Bullwhip effect refers to situations where orders to the suppliers tend to have larger variance than sales to the buyer (demand distortion) and the distortion increases as we move up the supply chain. Due to the fact that demand of customer for product is unstable, business managers must forecast in order to properly position inventory and other resources. Forecasts are statistically based and in most cases, are not very accurate. The existence of forecast errors made it necessary for organizations to often carry an inventory buffer called “safety stock”. Moving up the supply chain from the end users customers to raw materials supplier there is a lot of variation in demand that can be observed, which call for greater need for safety stock.
This study compares the efficacy of simulation and Time Series model in quantifying the bullwhip effects in supply chain management.

Keywords: Comparison; efficacy; simulation and time series model; quantifying; bullwhip effect,; supply chain.

1. INTRODUCTION

Supply chain exists due to the fact that it is difficult for any company to provide all that is required from raw materials to final products and at the same time getting the products to the end users. To have a successful SCM an organization requires a change from managing individual function to integrating activities into key supply chain process. With the recent development in the market place, organizations must consider the issues of increased competition, rising customer expectations, and the demand for

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product variety. Simultaneously, organizations are being forced to decrease profit margins and cope with changing government regulations on taxes, tariffs and the protection of the environment, to remain competitive. To cope with these pressures, organizations must consider the impact of operational decisions on not only their own firm but also all members of their supply chain. Thus, developing close long-term relationships with both customers and suppliers will be a potentially valuable way of securing competitive advantage.

The frequency in the changes experienced by inventory may arise as a result of order smoothing which can later translate into poor customer service. This is often due to inaccurate information within the supply chain, leading to bullwhip effect. Instability in supply chain do result to holding excessive inventories, poor customer service, and unnecessary capital investment.

1.1. Statement of the problem

Understanding customer demand is a key to any manufacturer to make and keep sufficient inventory so that customer's orders can be effectively and correctly met. Accurate and timely demand plans are important component of a good supply chain, while inaccurate demand forecasts would result in imbalances in supply. Bullwhip effect is a situation where orders to suppliers have larger variance than sales to buyer, leading to demand distortion. This distortion increases as one move up the supply chain, hence because the demand of customer for product is unstable, manufacturing organizations must forecast in order to properly position inventory and other resources. Existence of forecast errors leads to variance in demand and supply.

There are many factors that contribute to bullwhip effect, hence, the need to understand a manufacturing company's supply chain management to be able to assess the level of effect the factors (forecast errors, lead time variability, batch ordering, price fluctuations, product promotions and orders variability) have on its supply chain.

1.2. Research objective

Organizations practice the concept of supply chain to achieve efficiency in system operations. This is done by sharing information rather than responding to unknown and highly variable demand, thereby bringing down the variability in demand significantly. However, the assumption that sharing information and forming strategic alliances among supply chain partners will enhance a new level of efficiency is wrong.

According to Simchi-Levi, Kaminsky and Simchi-Levi (2000), one of the ways by which the magnitude of the bullwhip effect could be brought down is to ensure that information about customers demand is available to every stage of the supply chain. However, this might only reduce the impact but not eliminate the bullwhip effect. To avoid holding excessive inventory, insufficient capacities and high transportation costs, it is important to know the magnitude of this effect. Thus, for a better understanding and control of the bullwhip effect, it is necessary to quantify it. The objective of this study is to compare the efficacy of simulation and time-series model in quantifying bullwhip effect in supply chain.

2. RELATED STUDIES

Most of the intellectuals that have carried out researches on the bullwhip effect concentrated their focus on its existence, identifying its possible causes, and providing suggestions on how to reduce its impact. Lee, Padmanabhan & Whang (1997) identified the main causes of bullwhip effect. Chen et al. (2000) examined the impact of the demand forecasting on the bullwhip effect. It was not assumed that the customers' demands were known to the retailers, but employed the use of a standard forecasting technique to estimate certain parameters of the demand process. The forecast of future demand lays the foundation for all strategic and planning decision in supply chain. When demand forecast is well made, it gives room for better decision in supply chain management. Chen et al. explained the increase in demand variability by the necessity for each supply chain stage to make orders based on the forecasted demand of the previous stage.

Disney & Towill (2002) developed an analytical expression for quantifying the bullwhip effect from the control theory point of view using a Z-transform model. Kelhe & Milne (1999) suggested using approximations of the asymptotie renewal theory to evaluate a variance of placed orders in inventory systems that implement S-s inventory control policy. Petuhova & Merkuryev (2007) proposed a statistics-based analytical approach for evaluating the bullwhip effect in inventory system with a focus on the supply chain from the inventory management. They developed an analytical model for quantification of the demand fluctuations magnification as orders move up in the supply chain in the case of stochastic demand. Fawcett & Magnan (2001) examined the reasons why organizations pursue supply chain management strategies, the barriers, and bridges to effective supply chain management. A number of their findings demonstrated the importance of information sharing to supply chain management.

This article compared the efficacy of simulation and Holt-Winters model as forecasting tools in supply chain management. In particular, the research sought to know which of the two methods can better quantify the bullwhip effects in supply chain.

2.1. Theoretical framework

One of the most successful forecasting methods is the exponential smoothing techniques. Moreover, it can be modified and use effectively for time series with seasonal patterns. Tong (1995) opine that it is easy to adjust for past errors, easy to prepare follow-on forecasts, ideal for situations where many forecasts must be prepared and several different forms are used depending on the presence of trend or cyclical variation. However, it has been noticed that smoothing techniques are well suited for one-period ahead forecast. If a series is non-seasonal but display trend, then we need to estimate both the current level and the current trend. The Holt's Linear Exponential Smoothing Technique is used to handle such a series by the introduction of two smoothing parameters α and β. In addition to Holt parameters, suppose that the series exhibits multiplicative seasonality and let S_t be the multiplicative seasonal factor at time t. According to Yar and Chatfield (1990), if there are S periods in a year (S = 4 for quarterly data; S = 12 for monthly data);S_{t-s}

is the seasonal factor in the same period in the lst year. However, in some time series, seasonal variation is so strong that it obscures any trends or cycles, which are very important for the understanding of the process being observed. Winters' smoothing method can remove seasonality and makes long term fluctuations in the series stand out more clearly.

Doganis, Aggrelogiannaki & Sarimveis (2006) make use of Auto-Regressive Integrated Moving Average (ARIMA) model, and Holt-Winter's methodology which is an exponential smoothing methodology to quantifying the bullwhip effect in the supply chain management. The general form of ARIMA (p, d. q) model is

$$\left[1-\sum_{i=1}^{p}\varphi_i L_i\right][1-L]^d x_t = \\ = \left[1+\sum_{i=1}^{q}\theta_i L^i\right]\varepsilon_t \qquad (1)$$

where L is the lag operator, φ_i are the parameters of the autoregressive part of the model, Q_i are the parameters of the moving average part; p is the order of auto-regressive, d is the order of differencing, q is the order of the moving average process and ε_t are error terms. Depending on the values of the parameters in the general form depicted above, there are many types of ARIMA models, like the Autoregressive (AR) model, which is an ARIMA (p, o, o) model where only past values of the function are used to produce a forecast. A model which depends only on the previous outputs of the system is called an autoregressive model (AR), while a model that depends only on the inputs to the system is called a moving average model (MA), and of course, a model based on both inputs and outputs is an autoregressive-moving-average model (ARMA). According to Ho, Xie and Goh (2002), deriving the autoregressive model (AR) involves estimating the coefficient of the model using the method of least squared error.

Another very successful forecasting technique is simulation which permits the evaluation of operating performance prior to the implementation of a system. It enables firms to perform powerful 'what-if-analyses' thus leading to better planning decisions, as well as permit the comparison of various operational alternatives without interrupting the real system. It also permits time compression so that timely policy decisions could be made. Chang and Makatsoris (2002) gave the benefits of supply chain simulation as helping to understand the overall supply chain processes and characteristics by graphics/animation through capturing of system dynamics by using probability distribution, user can model unexpected events in certain areas and understand the impact of these events on the supply chain, and this could dramatically minimize the risk of changes in planning process since by what-if simulation, user can test various alternatives before changing plan. Simple simulations of supply chains are even possible to conduct using spreadsheet based models (Mahamani and Rao, 2010), based on a previously defined theoretical framework (Kushwaha and Barman, 2010).

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3. METHODOLOGY

We next discuss the methodologies employed in developing the time-series model and the simulation method used in this study as follows:

3.1. Developing the Time-Series model

3.1.1. Assumption

For even distribution of data, we base our model on 4-week period per month, thus, having 48-weeks per year.

3.1.2. Notations

The following notations are adopted in the model:

t - present time period

t–i - is the previous time period (i = 1, 2, ... , 48), with each time period representing a weekly planning horizon.

3.1.3. Parameters

Y_t – the actual observation (demand/sales) at time t.

T_t – the smoothed trend at time t.

I_t – the smoothed seasonality at time t.

S_t – the smoothed value at time t.

α– the smoothing parameter

γ – the trend coefficient

β – the seasonality coefficient

with α, β, γ taking values between 0 and 1, exclusive of the boundaries.

3.1.4. Definition of variables

X_{t+m} is the forecast for the mth period ahead of the present time t.

3.1.5. The Time Series model

The multiplicative Holt-Winters prediction function adapted (McGraw-Hill and De Lurgio, 2004) in this study is

$$X_{t+m} = [St + mT_t]\ I_{t+m-i} \qquad (2)$$

$$S_t = (1 – \alpha)\ [S_{t-i} + T_{t-i}] + \alpha(Y_t/1_{t-i})$$

$$T_t = (1 - \gamma)\ T_{t-i} + \alpha\ (S_t - S_{t-i})$$

$$I_t = (1 – \beta)\ I_{t-i} + \beta(Y_t/S_t)$$

where I is as stated earlier in subsection 3.1.2.

3.2. Developing the Simulation model

The theoretical framework employed for the simulation model is as follows:

3.2.1. Assumptions

It is assumed that the following conditions are satisfied:

- the actual values of observations are probabilistic;
- there are random numbers assigned (which are either given or generated from a scientifically proved source called random table or via the use of computer based soft-wares), each representing the anticipated future periods observations.

3.2.2. Notations

The notations used are as follows:

Mc: the Monte Carlo values

Vbeg: value of observation at the beginning

Vend: value of observation at the end

Vrg : the value range

ABS : the absolute squared

CumP: the cumulative probability

NSAmp: the amplification of the inventory variance

CumPvbeg: the cumulative probability value (beginning)

CumPvend : the cumulative probability value (ending)

McVRg : the Monte Carlo value range

3.2.3. Procedures for obtaining Monte Carlo values

The Monte Carlo values are obtained by two procedures as

McVRg = CumPvbeg – 1 to CumPvend or McVRg = CumPvbeg to CumPvend – 1

3.2.4. Cumulative probability value

Given the probability P(i) of event i(i = 1,…,n), we express the cumulative probability, P_r. of event i, (E_i), as:

$$CumPr(E_i) = Pr(E_i) + CumP_r(E_i - 1) \quad (3)$$
$$\text{with } CumP_r(E_i) = 1$$

It follows from equation (3) that

$$CumP_r(E_i+1) = P_r(E_i+1) + CumP_r(E_i) \quad (4)$$

and

$$CumP_r(E_n) = P_r(E_n) + CumP_r(E_n-1) \quad (5)$$

There are three types of performance measures of the simulation analysis, namely:

- the variance amplification ratios ‘bullwhip effect’ or ‘net stock amplification’;
- the customer service measures ‘customer service level’ or ‘fill rate’;
- the average inventory and switching costs per period.

However, the present study is aimed at determining which method, between Time-Series analysis and Simulation, is better for quantifying bullwhip effect in supply chain.

3.2.5. The bullwhip effect

We define the bullwhip (BW) effect as:

Bullwhip = Variance of order/Variance of demand (6)

Thus, when BW = 1, it implies that there is no variance amplification; when it is less than 1, it is known as “smoothing” scenario; while when greater than 1, it indicates that the bullwhip (amplification)effect is present. The amplification of the inventory variance is given by

NSAmp = Variance of net stock/Variance of demand (7)

Computer based software was employed in obtaining the required results. The Winter’s Three Parameter Exponential Smoothing software was used for the Time-Series model, while the Simulation model bullwhip explorer by Bonte and Lambrecht (2007) was used for the simulation model since it allows for duplicity of task and multiplicity of periods.

To allow for a comparison of the two models in the quantification of bullwhip effect, we considered a case study using one of the leading manufacturing firms in Nigeria.

3.3. Case study

Vitafoam Nigeria Plc is a leading manufacturer of foam and allied products in Nigeria. The company has a very good distribution network which makes its products readily available at the market. The company has also extended the market for its products to the West African sub-region.

With its corporate head office located at Ikeja- Lagos, the company has its factories geographically spread across the country, specifically at Ikeja, Aba and Jos, with distributors in all the major towns and cities in Nigeria, as well as West African countries. The spread of the operations of this giant in the foam industry would, no doubt, make a study on the bullwhip effect on its supply chain management necessary for consideration as a case study using the two models earlier proposed.

4. RESULTS AND DISCUSSION

4.1. Source of data

This study employed secondary data due to the peculiarity of the subject (comparison of the efficacy of Simulation and Time-Series in quantifying bullwhip effect in supply chain) being investigated. The required information was obtained from past production records, annual reports of the company, as well as sales and marketing departments.

4.2. Initialization of parameters

For the simulation model, we obtained a mean demand of 773700 foams per period from the company's entire distribution network and the demand pattern employed is Auto-Regressive AR(1). Safety stock and factor were calculated with the aid of excel spreadsheet. The simulation explored mean demand, exponential smoothing, moving average, demand signal processing and minimum expected mean squared error forecasting methods in tracking the bullwhip effect.

For the Time-Series model, the parameters S_t, T_t, and I_t were estimated by simple decomposition using the seasonal indices and trend line of the moving average. To obtain the starting values for sales, we took the mean of the first 18 observations which was 809813 foam mattresses and centered it on week 24.5. The trend was estimated by taking the differences between the 1st week and the 48th week of year one and year five, respectively, and this was divided by the total number of observations (240) in that period. The constant S was then estimated using the mean and the trend calculated with seasonal index. The initial value of the constant was 837897 foam mattresses. Thus, using the forecasting model in equation (2), our initial forecast model was

$$X_{t\ -i} = [837897 + 24.5]\ I_{t-i+1} \tag{8}$$

The seasonal index I_{t-i+1} was calculated by using $X_t/S_t + T_{t-1}$ and was adjusted with each observation. The excel feature 'solver' was used to optimize the values of the three smoothing parameters.

4.3. Analysis of results

Table 1 presents the bullwhip and net-stock amplification of the simulation and the Holt-Winter's models. First, we compared the analytical and simulation results of the bullwhip and then the net-stock amplification obtained from the various methods in order to select the best two results for comparison with the time series results.

From the simulation results, mean demand forecasting with autoregressive coefficients of 0.2 and 0.75 gave the best result for the bullwhip at 1.00 both analytically and simulation-wise. This was closely followed by the minimum expected mean squared error approach with autoregressive coefficient 0.2 which gave an

Table 1. Bullwhip and net-stock amplification

Forecasting Method Employed	Auto-reg Coefficient	Bullwhip		Net-Stock amplification	
		Analytical	Simulation	Analytical	Simulation
Mean demand forecasting	0.2	1.00	1.00	8.38	7.48
	0.75	1.00	1.00	22.27	23.45
Exponential Smoothing	0.2	4.81	4.90	13.18	11.13
Moving average	0.2	6.28	5.80	17.53	17.57
	0.75	5.03	5.12	28.26	31.77
Demand signal processing	0.2		4.37		8.38
	0.75		2.02		18.01
Minimum expected mean squared error	0.2	1.50	1.53	8.31	7.71
	0.75	5.27	5.16	16.19	15.99
Holt-Winter's Model		Actual	Forecast	Actual	Forecast
		1.060996	0.231032	1.901071	0.540923

analytical bullwhip of 1.50 as against simulation bullwhip of 1.53. These two approaches also provided the best results for the net-stock amplification with the mean demand forecasting approach given 8.38 as the analytical net-stock amplification as against the simulation result of 7.48. Similarly, the minimum expected mean squared error approach provided an analytic net-stock amplification of 8.31 compared with the simulation result of 7.71. It does appeared that the two approaches provided better net-stock amplification results for the simulation compared with the analytic results.

We observed from table 1 that the Holt-Winter's model results for both the bullwhip and the net-stock amplification appeared better than the actual results. The forecast for the bullwhip was 0.231032 as against the actual bullwhip of 1.060996; while the forecast for the net-stock amplification was 0.540923 as against the actual net-stock amplification of 1.901071.

Next, we compare the results offered by these two approaches with the Holt-Winter's model results. From the above analysis, one could easily observe that the deviation between the actual bullwhip and the forecast value is more for the Holt-Winter's model than the simulation system. In other words, both the mean demand forecasting and minimum expected mean squared error approaches when simulated with an autoregressive coefficient of 0.2 provided a better reliable estimate of the bullwhip than the Holt-Winter model does. However, the Holt-Winter's model performed better in the quantification of the net-stock amplification as the magnitudes of the results for both the actual and the forecast are low compared with the analytic and simulated results. As can be deduced from equation (7), a high value of net-stock amplification implied that the variance of net stock is far greater than the variance of demand. This, no doubt, has a cost implication for the organization.

5. CONCLUSION

From the foregone analysis, it could be seen that a manufacturing organization may sometime have to employ various quantitative means of planning ahead of time to competitive advantage of servicing its customers better. While simulation has proved to be effective in quantifying bullwhip; time series model appeared to be better in quantifying net-stock amplification. It thus appear that reduction of cost could be easily achieved by manufacturing firms through the use of a combination of these techniques.

КОМПАРАТИВНА СТУДЕЈА СИМУЛАЦИЈЕ И МОДЕЛА ВРЕМЕНСКИХ НИЗОВА КОД КВАНТИФИКАЦИЈЕ “BULLWHIP” ЕФЕКТА ЛАНАЦА СНАБДЕВАЊА

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Извод

Ефекат “Bullwhip” је један од феномена уочених код дистрибуционих канала чији се рад заснива на предвиђању. Пажљиво управљање таквих ефеката је од великог значаја за менаџере ланаца снабдевања.Овај ефекат се односи на ситуацију када поруџбине од снабдевача имају веће варијансе од продаје крајњим корисницима (дисторзија потреба). Сама дисторзија расте померањем дуж ланца снабдевања. Захваљујући чињеници да је потреба купаца за производима нестабилна, пословни менаџери морају предвиђати како би правилно позиционирали залихе и друге ресурсе. Предвиђања се заснивају на статистици и у већини случајева нису најтачнија. Постојање грешке предвиђања доводи до тога да је најчешће неопходно да организације поседују “сигурносне залихе”. Померање дуж ланца снабдевања од крајњих корисника до снабдевача сировим материјалом, постоји много варијација у захтевима , које се могу уочити. Ово доводи до великих потреба за сигурносним залихама. У овом раду дато је поређење ефикасности симулације и модела временских низова за квантификовање “bullwhip” ефекта у менаџменту ланаца снабдевања..

Кључне речи: Поређење, ефикасност, симулациони и модел временских серија, квантификовање, “bullwhip” ефекат, ланци снабдевања.

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