STATISTICAL ANALYSIS OF THE BULLWHIP EFFECT IN A SPECIAL SUPPLY CHAIN STRUCTURE

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Abstract –

According to the bullwhip effect (BWE), demand variability increases as customer orders move upward the supply chain. A special two-stage supply chain with one manufacturer and one retailer is used to forecast, quantify, and measure the bullwhip effect. Based on ABC analysis, a single product is chosen to represent the highest annual consumption of class "A" items. For stock replenishment, the retailer adopts "order-up-to" inventory policy. Statistical analysis is employed to analyze and evaluate the impact of BWE. Moving average and exponential smoothing forecasting algorithms are used by retailers to forecast demand in advance. According to the findings, the extent of the increase in variability is dependent on the forecasting method used. In addition, information sharing and customer loyalty are thought to be important elements in decreasing the bullwhip effect.

Keywords - Supply Chain Management, Bullwhip Effect, Exponential Smoothing Forecast, Moving Average Forecast, ABC Analysis.

I. INTRODUCTION AND RELATED WORK

Supply chain management (SCM) is the coordination and linking of production plants, wholesalers, distribution centers, and retailers[1,2,3]. The advantage of having proper SCM is to reduce expenses, increase revenues, and reduce the effect on the bottom line of the company. Supply chain (SC) companies may contract more than one supplier to deliver orders requested by customers. If the forecasting is too high, it will cause losses to the company and accumulate none-sold products which will increase inventory cost. On the other hand, when the forecasting is very low, the company will not be able to fulfill all incoming orders. "Bullwhip effect" indicate that demand variability increases as customer orders move upstream throughout the supply chain [4]. The bullwhip effect is a main concerned factor for many suppliers, manufacturers, and retailers as the increased demand variability in the order process:(1) requires an increase of safety stock in order to maintain a given service level, (2) increased costs, and (3) lead to an inefficient use of resources, such as labor and transportation [4]. To reduce the impact of the "bullwhip effect" in a SC, its causes must be considered, understood, and mitigated. Causes include variations in demand forecasting, batch ordering, price differences, and lead time.

*Chen, F., et al. (1999),*show how the supply chain with a two-stage (maker and retailer) can use demand forecasting techniques like exponential smoothing and moving average forecast to calculate inventory levels and order quantities. The study quantifies the increase in SC variability at every stage [4]. A two-stage supply chain including demand forecasts and order lead times was explored *by Chen et al. (2000).* They explain how to reduce the bullwhip effect by centralizing demand data[5]. *Chen, F., J.K. Ryan, and D. SimchiLevi (2000)* quantified the bullwhip effect in a simple two-stage SC. A correlated and linear trend demand processes are utilized to analyze bullwhip effect caused by using retailer exponential smoothing method[5]. *Wright, D. and X. Yuan (2008)*focused on bullwhip effect which is explored under the Holt and Brown forecasting methods and ordering policies. In a four-stage supply chain, simulation modeling is developed to determine the impact of enhanced forecasting methods [6].*Sunil Agrawal et al. (2009)* investigated the bullwhip effect and on-hand inventories in a two tiers-SC (warehouse - retailer). The results demonstrate that reducing lead time is more useful than sharing knowledge in reducing the bullwhip effect[7]. *Ghaffari, M. and N. Javadian (2013)* proposed a new methodology based on demand forecasting technique and uses a simple moving average to reduce the bullwhip effect in a multi-echelon and multiple products supply chain with correlated market demands. The result showed the necessity of using a moving average forecast demand to smooth product market demand and retailers bullwhip effect in a multi-product SC[8]. *Michna, Z. and P. Nielsen (2013)* investigated a simple two-stage SC with one supplier and one retailer. The bullwhip effect is measured when demand and lead times are predictable. Under uncertainty conditions it is necessary to estimate the lead time for a SC member to place an order. The findings suggest that lead time forecasting is a key contributor to the bullwhip effect, and its impact on SC management cannot be overlooked.[9]. *Sadeghi, A.,(2015)* considered a supply chain with two-product (Demands of the products are correlated) and two-echelon in order to quantify the bullwhip effect. The bullwhip effect measure has been performed using two main forecasting methods, namely, exponential smoothing and moving average forecast. In addition,

a cost analysis based on shortage and holding costs is carried out using various bullwhip effect measurements. The results reveal that in the SC, moving average forecasting produces less fluctuation than exponential smoothing. When setting the smoothing values and increase lead-time, the difference between bullwhip effects of two products increased. So, smaller measure of α and L is better for the stability of the bullwhip effect of both products, simultaneously [10].According to *Zarandi, at.el (2008)*, the bullwhip effect is decreased in multi-stage supply chains where lead time, demand, and orders are ambiguous. A modified Hong fuzzy time series is used to simulate the bullwhip effect, followed by defuzzification using a neural network. An agent-based system is developed to reduce the bullwhip effect and total cost. The proposed system outperforms the analytical system in terms of realizing the best available ordering policies[11].

Customer Relationship Management (CRM) is used to manage the interaction of the company with the potential and current customers. Data analysis is often used to identify and improve the relationship between the company and the customer [12].When CRM is integrated in supply chain, many benefits would be gained. It can be summarized as; "The right product will arrive at the right time, in the right amount, in the right quality, and at the right price for the right consumer"[13, 14]. As a result, inventory will be practically reduced, on-shelf availability will nearly double, the overall cost of the supply chain will be lowered, and the accuracy of demand forecasting and revenue growth will both increase. The bullwhip impact will, in fact, be reduced.

II. THE PROPOSED METHODOLOGY

A special product is considered based on ABC analysis -which is a technique for inventory categorization. Specifically, class "A" product has been selected because it has 80% of the annual demand consumption. Demand is forecasted using moving average and exponential smoothing forecasting techniques. Occasionally, when retailers submit orders to manufacturers, errors occur as demand increases. This will result in a cost increase, an increase in inventory, and a drop in profitability. So, reducing these errors is important in order to improve SC efficiency. Mean square error (MSE), mean absolute deviation (MAD), and mean absolute percentage error (MAPE) are used to quantify and measure the percentage of error in each forecasting method and determine the cases that has the lowest and highest predicting errors. Then, information sharing and customer loyalty are considered as a means for reducing the bullwhip effect. Figure (1) shows the flow chart of the proposed methodology.

The ABC analysis is used to identify different categories of stock that will require different controls and monitoring. The common classifications of ABC analysis include: 'A'Class – 10-20% of the items accounts for 70-80% of the annual consumption value of the items. 'B'Class – 30% of the items accounts for 15-25% of the annual consumption value of the items. 'C'Class – 50% of the items accounts for 5% of the annual consumption value of the items. Class "A" products have the fewest inventory items but the greatest demand values, necessitating greater controls and administration. These items are critical to an organization because they have the largest annual consumption, a corporation must select an acceptable order pattern to avoid the Bullwhip Effect (excess capacity). To this end, for bullwhip effect analysis, we will select the items with the largest yearly consumption, which appears first in "A" Class items.

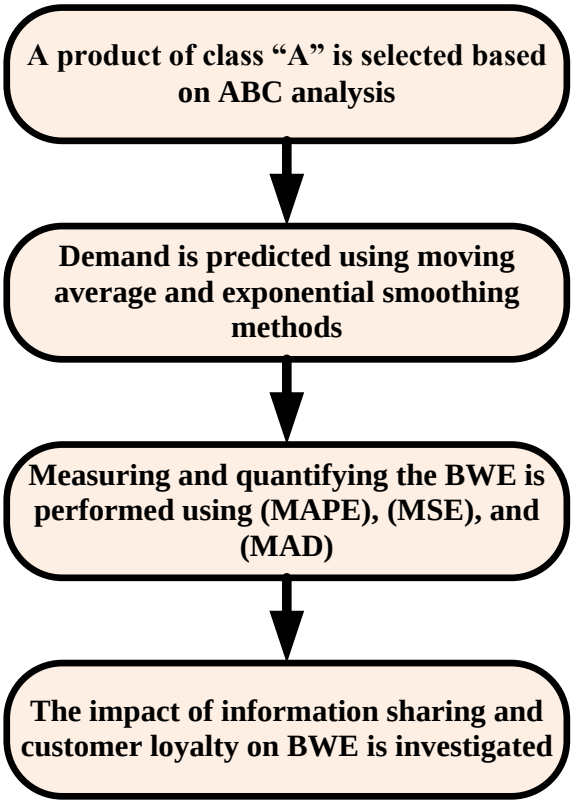


Fig.1. The proposed methodology.

III. THE CASE STUDY

The research is based on a data set that represents information about Power-Driven Hand Tools (supply chain # 24). The data set, which can be downloaded online, reveals how practitioners using an inventory optimization tool mimic supply networks in the actual world. These chains show how real-world supply networks have been modeled by actual users. The results of applying ABC analysis to the Power-Driven Hand Tools data set are shown in Table 1 and Fig. 2,respectively.

Based on ABC Analysis, item # 58 is selected because it has the highest annual consumption compared to the other items. Item # 58 comes first in

class "A" items and considered suitable for bullwhip effect analysis in this research.

Category	% of items	% of usage
Class A Items	23.81	78.77
Class B Items	28.57	13.61
Class C Items	47.62	7.62

Item #	Class	Item #	Class	Item #	Class
Item_58	A	Item_76	B	Item_63	C
Item_43	A	Item_65	B	Item_64	C
Item_38	A	Item_61	B	Item_55	C
Item_54	A	Item_74	B	Item_75	C
Item_59	A	Item_66	B	Item_41	C
Item_60	A	Item_51	B	Item_67	C
Item_39	A	Item_42	B	Item_48	C
Item_36	A	Item_77	B	Item_50	C
Item_45	A	Item_68	B	Item_69	C
Item_44	A	Item_46	B	Item_49	C

Table 1
ABC classes for the Data.

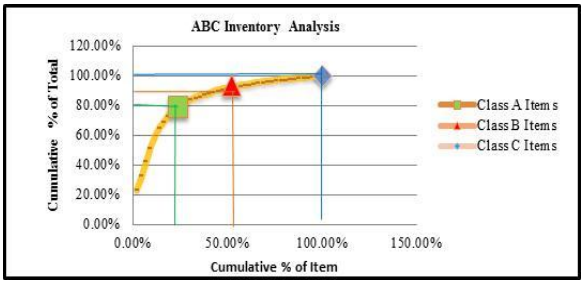


Fig.2. Classifications of the data.

IV. RESULTS AND DISCUSSION

4.1 Predicting the Bullwhip Effect

The impact of demand forecasting on the "bullwhip" effect for the two-stage SC under investigation will be predicted using exponential smoothing forecast and a moving average to estimate the mean and variance of demand. The retailer uses these estimates to form a simple "order-up-to" inventory policy [5].

Exponential Smoothing Forecasting: We assume that the retailer follows a simple "order-up-to" inventory policy Y_t requires each stage of the supply chain to increase its inventory level up to a given target level in each period.

$$Y_t = \hat{D}^L{}_t + z\hat{\sigma}^L{}_{et} \qquad (1)$$

D^L: is an estimate of the mean demand over L periods, σ^L: is an estimate of the standard deviation of the L period forecast error, ***z:*** is a constant chosen to meet a desired service level (safety factor).If the retailer uses a simple exponential smoothing forecast with smoothing parameter (α); $0 < \alpha < 1$, then the variance of the orders, q^{EX}, placed by the retailer to the manufacturer, satisfies:

$$\frac{Var\,(qEX)}{Var\,(D)} \geq 1 + (2L\,\alpha + \frac{2L^2\alpha^2}{2-\alpha})(\frac{1-\rho}{1-\rho\beta}) \qquad (2)$$

Lead Time (L)	BWE	Smoothing parameter (α)	BWE	Correlation parameter (ρ)	BWE
1	1.2468	0.2	1.5432	-1	2.0864
2	1.5432	0.4	2.4976	-0.8	1.6161
3	1.8889	0.6	4.1153	-0.4	1.5433
				0	1.5432
4	2.2839	0.8	6.6657	0.4	1.5430
5	2.7288	1	10.600	0.8	1.4703
				1	1.0000

Table 2
The impact of Exponential Smoothing Forecasting on BWE

Table 2 shows the influence of lead time, smoothing parameter, and correlation on BWE when using exponential smoothing forecasting. From Table 2, we can conclude that as a result of using exponential smoothing forecasting, BWE increases as lead time and smoothing parameter increase.

Moving Average Forecasting: Moving average forecasting method is used in "up-to-order" inventory policy to estimate standard deviation and mean of customer demand by retailer. In every period the retailer estimates the mean lead time demand as $\hat{\mu}_t^L = L\,\hat{\mu}_t$. Where $\hat{\mu}_t$ is the average of demand observations (p).

$$\hat{\mu}_t = \frac{\sum_{i=1}^{p}(Dt-i)}{p} \qquad (3)$$

If "order-up-to" inventory policy is used, and simple moving average method is used by retailer, then the variance of the order q^{MA} placed by the retailer to the manufacturer satisfies:

$$\frac{Var\,(qM\,A)}{Var\,(D)} \geq [1 + (\frac{2L}{p} + \frac{2L2}{p2})(1-\rho^p)] \qquad (4)$$

Where $Var(D)$ is the variance of customer demand. The bound is tight when $z = 0$.

More than one observation can be noted from Equation (4). First of all, the amplification of variability from the retailer to the manufacturer is a function in terms of three parameters, (1) p, the number of observations, (2) L, the lead time from the retailer to the manufacturer, and (3) ρ, the correlation parameter. As number of observation (p) decrease and lead time increase (L), the variability increase. The three parameters of moving average forecasting method (ρ, L, p) are analyzed to understand their effect on bullwhip effect as shown in Table 3.

Lead Time (L)	BWE	Smoothing Parameter (α)	BWE	Correlation Parameter(ρ)	BWE
1	1.37	0.2	1.81	-1	2.63
2	1.81	0.4	3.00	-0.8	2.52
3	2.33	0.6	4.71	-0.4	2.27
				0	1.98
4	2.93	0.8	7.22	0.4	1.64
5	3.59	1	11.00	0.8	1.23
				1	1.00

Table 3
The impact of Exponential Smoothing Forecasting on BWE

Table 3 shows the influence of lead time, smoothing parameter, and correlation on BWE when using moving average forecasting technique. From Table 3

we can conclude that as a result of using moving average forecasting technique, BWE decreases as the correlation parameter increase and increase as lead time and smoothing parameter increases.

4.2. Quantifying and Measuring the BWE

The level of the increase in variability is determined by the forecasting method used. Demand forecasting can generate the bullwhip effect. Furthermore, the extent of the increase in unpredictability is clearly dependent on the forecasting approach. This result is driven by comparing the extent of variability increase for the two forecasting systems (moving average and exponential smoothing),for i.i.d demands and $z = 0$ [4].So, we choose the parameters $P($number of observations$)$ and α (smoothing parameter), such that both forecasts have the same variance of the forecast errors when designing the forecasts[4].

When equating the standard deviation of moving average and exponential smoothing method, the result is shown in following equation:

$$\frac{Var\,(qEX)}{\sigma^2} = 1 + \frac{4L}{p+1} + \frac{4L^2}{P(P+1)} = 1 + \frac{2P}{P+1}\left(\frac{2L}{P} + \frac{2L^2}{P^2}\right) \quad (5)$$

As a result, the variability of exponential smoothing is greater than moving average by a factor. The bullwhip effect is greater for a retailer using an exponential smoothing forecast than for a retailer using a moving average forecast [4].

4.3Accuracy of Forecasting Methods

In this section, we will compare the previously discussed forecasting methods: exponential smoothing and moving average. However, in order to select the most accurate forecasting approach, several factors must be considered: Mean Square Error (MSE), Mean Absolute Deviation (MAD), and Mean Absolute Percent Error (MAPE). Values of (MSE, MAD and MAPE) are computed and compared to select the best forecasting method which gives accurate demand forecasting for the product.By the following relationship, different values of (α) and (p) are obtained in different trials to forecast the demand with exponential smoothing and moving average methods. It is applied to a supply chain data that represents "Power-Driven Hand tools information". Table 4 demonstrates different values of (α) and (p)obtained using equation 6 in different trials to forecast the demand with exponential smoothing and moving average methods.

$$\alpha = \frac{2}{P+1} \quad (6)$$

Trial	Number of observations (P)	Smoothing parameter (α)
#1	7	0.25
#2	5	0.33
#3	3	0.5

Table 4
Different experimental trials

Exponential Smoothing Forecasting Method:

In this method value of forecast can be obtained by the following equation:

$$F_{t+1} = \alpha\,(Actual\ demand) + (1-\alpha)\,(Forecasted\ demand) \quad (7)$$

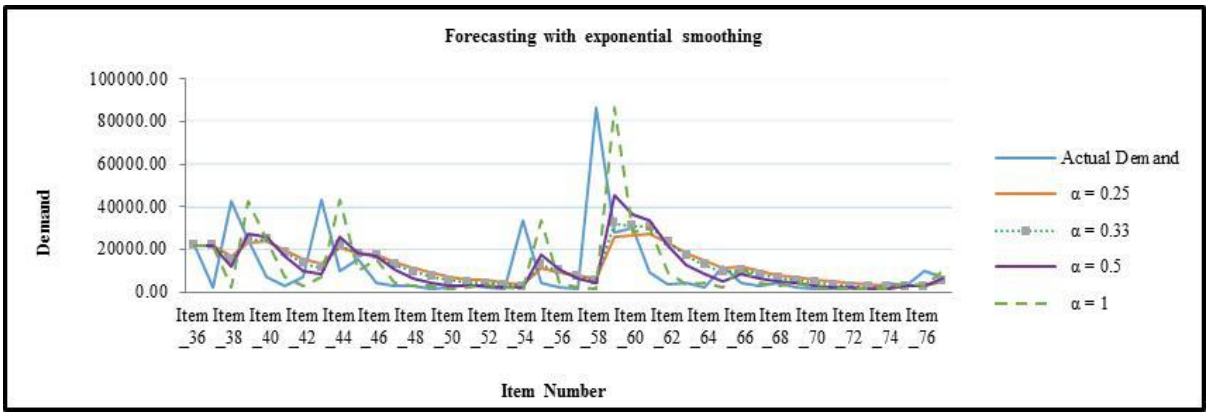


Fig. 3.Forecasting using exponential smoothing method

Moving average forecasting method:

In this method value of forecast can be obtained by the following equation:

$$\hat{Y}_{t+1} = (Y_t + Y_{t-1} + \ldots + Y_{t-m+1}) / (m) \quad (8)$$

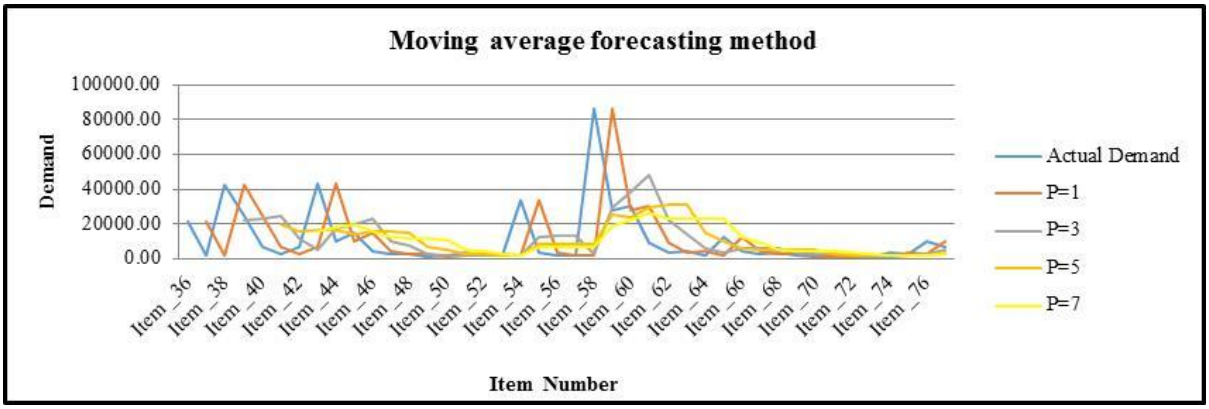


Fig.4. Forecasting with moving average method

As shown in Fig.3. the exponential smoothing method, trial #4 is the most accurate because the anticipated demand is close to the actual demand when compared to the other trials. It also provides predictability in demand estimates. On the other hand as shown in Fig.4.,the moving average approach, trial #1 is likewise the most accurate because the anticipated demand is close to the actual demand when compared to other trials. Moving average smoothing is generally more accurate than exponential smoothing. This is plainly demonstrated in Table (5), where the moving average has the lowest number of errors.

Forecast Error	α =1 & P=1		α =0.5 & P=3		α =0.33 & P=5		α =0.25 & P=7	
	E.S	M.A	E.S	M.A	E.S	M.A	M.A	E.S
MAD	11519.8	11519.8	10375.3	10028.3	10224.5	9811.2	10546.3	10512.2
MSE	451534308.2	451534308.2	321692757.4	340404924.3	299403601.5	298443840.7	292686386.1	307269944.1
MAPE	1.24%	1.24%	1.62%	1.61%	1.93%	1.92%	2.17%	2.05%

Table 5
Summary of forecasting methods' accuracy

4.4 Reduction of BWE

We have illustrated that the bullwhip effect may increase when the demand forecast is not accurate also when lead time is high. In fact, most of the errors that cause the increase in BWE are done by humans, whether they were customers or retailers in the supply chain structure. Retailer might fail in forecasting customers demand by using inaccurate forecasting methods. On the other hand, customers' lack of sincerity and loyalty could cause distortion in demand which lead to high variance between actual demands and orders. Information sharing is one of the used methods to reduce bullwhip effect and increase efficiency of the supply chain with reduced costs. Information sharing has many types like inventory, sales, demand forecast, order status, and production schedule information[15]. The two basic types of information exchange that will be explored are inventory and sales.

Inventory information: we presume that the retailer and the manufacturer handle their stocks separately and do not share inventory status information. They might end up with stock outs or excess in safety stock. In fact, inventory information can be shared in different ways. In typical CRP form (Continuous Replenishment Programs) the buyers share with the seller their inventory status and request him to manage their inventory. [15]. Sales information: assume that the retailer uses exponential smoothing or moving average method to estimate and forecast market trend, The retailer may experience a larger sale, pushing him to adjust his schedule upward, resulting in orders being magnified upstream in the supply chain. To avoid this distortion in demand (double or triple forecasting), actual sales data should be shared from retail stores.

4.5 Impact of Customer Loyalty in Mitigating the BWE

Customer loyalty has a good effect if being consistent and honest with customers, It makes customers happy and satisfied, and raises the perceived value of the product or service [16]. Bullwhip effect has an impact on customer satisfaction and supply chain costs. As a result of this effect, company competition will become more challenging. Obtaining consumer attention to become loyal customers is a critical competitive tactic for organizations in CRM. Hence, cost of retaining customers is less than wining new one [17]. There are two types of customer loyalty: behavior loyalty and attitude loyalty. The first denotes a pattern of continuous purchase and recommendation activity. The second refers to costs tolerance. This can be broken down into three categories: 1) willing to repurchase and recommend. 2) Price adjustment tolerance. 3) The frequency of consumption. Demand will be reasonably stable if the corporation succeeds in haunting and retaining the

customer. In other words, When the consumer will not be impacted by other competitors, demand fluctuation will be reduced. The bullwhip impact will be reduced.

V. CONCLUSION AND FUTURE WORK

In this paper, the bullwhip effect is predicted and quantified using a particular two-stage supply chain comprising one manufacturer and one retailer. The ABC analysis is utilized to select the suitable product. The study assumes that the store is unaware of the exact distribution of demand. The mean and variance of demand are estimated using moving average and exponential smoothing forecasting methods. The bullwhip effect ratio metrics were used for evaluation and comparisons. Moreover, the impact of the number of observations, smoothing constant, and lead-time on the bullwhip effect values has been studied. The results indicate that a retailer employing an exponential smoothing prediction have greater bullwhip effect than a retailer using a moving average forecast. Furthermore, knowledge sharing and customer loyalty are viewed as two means of mitigating the bullwhip impact. Other forecasting methodologies, such as time series analysis, could be used to extend this research and predict demand lead-time.

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