

A Discrete Event Simulation Analysis of the Bullwhip Effect in a Multi-Product and Multi-Echelon Supply Chain of Fast Moving Consumer Goods



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Abstract

Timely delivery is the major issue in Fast Moving Consumer Good (FMCG) since it depends on the lead time which is stochastic and long due to several reasons; e.g., delay in processing orders and transportation. Stochastic lead time can cause inventory inaccuracy where echelons have to keep high product stocks. Such performance inefficiency reflects the existence of the bullwhip effect (BWE), which is a common challenge in supply chain networks. Thus, this paper studies the impact of stochastic lead time on the BWE in a multi-product and multi-echelon supply chain of FMCG industries under two information-sharing strategies; i.e., decentralized and centralized. The impact was measured using a discrete event simulation approach, where a simulation model of a four-tier supply chain whose echelons adopt the same lead time distribution and continuous review inventory policy was developed and simulated. Different lead time cases under the information-sharing strategies were experimented and the BWE was measured using the standard deviation of demand ratios between echelons. The results show that the BWE cannot be eliminated but can be reduced under centralized information sharing. All the research analyses help the practitioners in FMCG industries get insight into the impact of sharing demand information on the performance of a supply chain when lead time is stochastic.

Key Words: Bullwhip effect; Discrete event simulation; Fast-moving consumer goods; Information sharing; Lead time; Supply chain management.

Mathematical Subject Classification: 81T80; 90B06

1. Introduction

Supply chain management (SCM) can be perceived as the assimilation of business procedures from end-users (customers) through final suppliers providing products or services which add value for customers (Brandenburg & Seuring, 2011). The suppliers are linked in a supply chain with physical and information flow. Physical flow involves the processes of manufacturing and logistics and the storage of finished materials and goods. Information flow meanwhile includes the coordination of echelons (tiers or members) of a supply chain in a short or long term and the control of a product or material flow in the upstream and downstream echelons. The cooperation of all the echelons determines the performance of the supply chain.

In the past decades, studies on SCM have gained significant attention among practitioners and academic researchers. There have been many success stories where the best practice of SCM enables companies to perform better in many

aspects of management (Tummala & Schoenher, 2008). SCM has been proved to help companies keep accurate inventory in hand, deal with supply and demand uncertainties, keep the cost at a minimum value and satisfy customer demand (Das & Islam, 2019; Mehrotra et al., 2013). However, efficiently managing a supply chain is a challenging task due to its complex nature in terms of its number of echelons. A complex supply chain can pose challenges mainly caused by the uncertainty in supply chain networks due to the fluctuations in the end customer's demand, elimination of manual business processes and decrease in operational visibility. Other challenges reported by wholesalers and distributors are the inability to control and track inventory in multiple facilities such as warehouses or stores, the absence of clarity in inventory management and the shortage of the product traceability. To overcome these challenges, companies require mechanisms to efficiently manage their supply chains and help them raise their profits, reduce costs and increase collaboration. From experience, these challenges could be mitigated through an integrated solution; i.e., by controlling inventory holding costs and improving manufacturing lead time (Duffie, Bendul, & Knollmann, 2017; Poles & Cheong, 2011; Seeanner, 2013; Öztürk 2018) especially in Fast Moving Consumer Goods (FMCG) industries.

FMCG refers to fast-moving items directly used by consumers. They can be classified as personal care, household care, branded and packaged food/beverages, spirits, and tobacco (Patil, 2016). Typically, the FMCG products quickly leave shelves, are likely to have high volumes in demand but low in their prices and do not involve much decision efforts while shopping. These products are non-durable and sold in packaged forms. Due to this reason, they are always bought by end-consumers in small quantities. Most of them are considered household products including laundry and cleaning products, food items, personal care goods, and medicines which can be sold without a prescription.

In today's business world, FMCG is essential to the market since they are a dominant part of consumers' demand and budget. According to the Daily Times report, Pakistan's 2018 retail market size is \$152 billion and has been forecasted to expand 8.2% a year until 2021. FMCG market thus requires a constant supply of products since these products are typically delivered to their customers at a high rate of turnover. Examples of top FMCG international companies are Coca-Cola, Johnson & Johnson, Unilever, Nestlé, Procter & Gamble, Body Shop International, Colgate-Palmolive, Fujifilm Electronic Imaging and L'Oréal (UK). FMCG can be characterized by two main perspectives; i.e., a consumer and a marketer. From the consumer's perspective, these goods are habitually purchased, have low involvement (i.e., the decision to buy requires little or no effort) and low price, short shelf life and rapid consumption. From the marketer's perspective, these goods are produced in high volumes with low-profit contribution margins, have extensive distribution networks and high stock turnover.

FMCG companies usually produce their products at several places in different countries. The raw materials of the products are often purchased from different parts of the world and supplied by many potential suppliers. Thus, the right suppliers should very carefully be selected in terms of their material quality and services and how fast the materials can be delivered to the companies to satisfy their demand in a minimum time. For this reason, FMCG companies typically sign long term contracts with the suppliers which have short lead time and are efficient in delivery, even though the availability and quality of the materials are not guaranteed. Any delay in delivery can cause a phenomenon called the bullwhip effect (BWE).

The BWE is a situation reflecting the occurrence of inadequacies of the demand management and usually causing bottlenecks in companies. The BWE is sometimes coined as demand amplification, variance amplification or the Forrester effect. The BWE is the uncertainty in the supply chain caused by an increase in demand variability and lead time (Jaipuria & Mahapatra, 2016). In FMCG industries, the lead time is a significant factor influencing the performance of SCM at every stage of its operations. It comprises the sum of setup time, waiting time and transportation time which can be long and stochastic and affect the inventory level. The lead time differs from supplier to supplier due to their geographical locations and the transportation modes used to deliver orders (Seeanner, 2013) and is usually more prolonged due to particular reasons; e.g., delays in processing orders, arranging payment, consolidation houses and delay at cross-docks or ports. These delays can result in inefficient inventory planning which can later cause the possibility of shortage or excess on-hand inventory levels (Duffie, Bendul, & Knollmann, 2017). There has been much literature showing that stochastic lead time significantly affects the inventory level of an echelon (e.g., Michna, Nielsen & Nielsen, 2018; Nielsen et al., 2017; Ye & Xu, 2010). Inappropriately managing such lead time can pose problems in the field of SCM; e.g., an inaccurate inventory level and lost customers.

Another critical factor for appropriate inventory management is timely and accurate information sharing among echelons in a supply chain (Feng, 2012). The echelons are typically located at different geographical locations. Without adequate information sharing, a profitable supply chain and cost minimization cannot be ensured. The

information which should be shared can vary across dimension (demand or inventory), nature (independent or correlated) and inventory policies (periodic or continuous) (Liu & Zhao, 2007). Both the availability and accuracy of information are thus significant for ensuring better performance of a supply chain and is regarded as one of the most effective remedies to minimize the BWE (Jeong & Hong, 2017).

Given all these challenges, there is a need to study the impact of lead time and information sharing on the performance of FMCG supply chains. Stochastic lead time and incomplete information sharing are two important factors causing the BWE. However, most of the previous studies have been conducted either under deterministic lead time, single product multi-echelon supply chains or multiple product single-stage supply chains (Merkuryev et al., 2004). In practice, the lead time is stochastic since it depends on several uncertain events at the suppliers' facilities. The suppliers should meanwhile deliver products on time so that FMCG retailers can manage their inventory efficiently to retain their customers. Therefore, this study investigates the effect of stochastic lead time on the BWE under two information-sharing strategies (i.e., decentralized and centralized) and in a multi-product and multi-echelon supply chain. By analysing the effect, the practitioners in FMCG industries can understand the importance of sharing demand information on the performance of a multi-product and multi-echelon supply chain.

The rest of this paper is organized as follows: Section 2 provides reviews of relevant literature on the impact of lead time on the BWE and how it could be measured and minimized. Section 3 discusses how to measure the BWE in a multi-echelon with a single product and multi-products under the two different information-sharing strategies using our developed DES models. How to develop the models based on a conceptual model and how they were validated are also discussed in this section. Section 4 analyses the demand variability occurring at each echelon and the overall BWE due to stochastic lead time under both information-sharing strategies. Finally, conclusions with a summary of our contributions are outlined in Section 5.

2. Literature Review

Many researchers have shown that stochastic lead time and the lack of coordination between members can significantly affect inventory policies and cause the BWE in a supply chain. To minimize the BWE, inventory has to be efficiently managed. The inventory level can be optimized by managing lead time (Vijayashree & Uthayakumar, 2016) to reduce inventory holding costs, increase inventory turnover and shorten the order delivery time (Nemtajela & Mbohwa, 2016; Zhou, Wang & Sun, 2015) and avoid the overall capital of a company to be scarce of resources (Ahmed & Sultana, 2014).

2.1. Lead Time and BWE

The impact of lead time on the BWE has been examined by many studies. For example, Jaggi and Arneja (2011) analysed how to minimize the BWE using a stochastic integrated vendor-buyer model with uncertain lead time. Lead time minimization was also studied by Gholami-Qadikolaei, Sobhanallahi and Mirzazadeh (2013) using storage space-restricted lot size reorder point inventory models with a controllable negative exponential backorder rate. In the meantime, managing lead time by formulating an integrated supply chain inventory model with imperfect-quality items and distribution-free demand was studied by Lin (2013). Duffie, Bendul and Knollmann (2017) meanwhile studied the impact of time delays and lead-time-related adjustments on the dynamic behaviour of a production system. However, most of the studies only focused on inventory models under deterministic lead time. In many situations, the lead time is stochastic and long which has been proved to make supply chain behaviour more complex and interrupt production processes and inventory planning (Ben Ammar et al., 2013).

The relationship between suppliers' lead time and retailers' order quantities has also been studied by many studies; e.g., by Michna and Nielsen (2013) and Wijaya (2013). Appropriate order quantities placed by retailers are generally determined based on the predicted data about their customers' demand and suppliers' lead time. How lead time affects the performance of a supply chain has been reported in the literature on SCM; e.g., by Hoque (2013) and Mohamed and Coutry (2015). Such literature shows that a supply chain with shorter lead time is to be more responsive and has higher confidence on-time deliveries, most satisfied customers and less cost of inventory. Shorter lead time not only improves supply chain performance but also reduces the BWE (Li & Liu, 2013).

The BWE could also be caused by an inaccurate inventory level which is a mismatch level between recorded inventory and physical inventory. How such an inaccurate level can primarily be caused by the uncertainty in lead time and demand and eventually determines the BWE behaviour has been analysed by some studies; e.g., Jaipuria and Mahapatra (2014). The uncertainty of demand is induced by poor coordination among all echelons in a supply chain where they have to estimate the demand without real information. The demand variability generally increases while moving up through a supply chain and causes the BWE (Kumar & Keswani, 2016; Mbhele & Phiri, 2014). The BWE, as revealed by many studies, exaggerates when real-time information rather than statistical data is obtained. As a fact, the information about the demand is an essential element and more critical for upstream echelons since lead time increases with the number of echelons in a supply chain (Kalpakam, Rajendran & Saha, 2014). Therefore, the lead time is typically used to measure the performance of companies in addition to their customer satisfaction and retention.

Information availability and accuracy determines the operations and management improvement of supply chains (Li, 2013). In traditional SCM, orders are used to be significant information that companies exchange. Now, information sharing can involve the share of inventory information, sales data, sales forecasted data, order status tracking information, product development information such as lead time and delay sharing (Feng, 2012). Many studies have argued that such complete information sharing is required for attaining a timely and accurate manner to meet customer's variable demand. For example, Liu, Zhao and Shen (2016) used system dynamics to study the relationship between demand information sharing and inventory levels on different modes of an agri-food supply chain in China to figure out which mode is efficient.

Now, industries are also conducting researches to study the benefits of information sharing in a multi-stage supply chain with non-zero replenishment lead time. In real life, factual and complete information is however unrealistic due to many issues; e.g., economic and social reasons. In addition to information sharing, managing inventory has also been found to minimize the BWE and improve the overall supply chain performance (Sabitha et al., 2016). In the meantime, how to properly measure the BWE using relevant methods have also been proposed.

2.2. Methods to Measure the BWE

Various quantitative methods have been developed to minimize the BWE. Prevalent methods proposed so far include statistical analysis, optimization and simulation.

2.2.1. Statistical Analysis

Many researchers have adopted statistical methods to measure the BWE. As defined, the BWE is the amplification of order volatility in a supply chain. This volatility can be measured by the coefficient of variation, variance or standard deviation. From mathematical investigation, the BWE can conveniently be measured by comparing the variance between demand and order as done by Wang and Disney (2016). The BWE can also be measured by comparing the difference between order variance and demand variance (Li, Disney & Gaalman, 2014). To minimize the BWE, some advanced methods have also been implemented. Babai et al. (2016), for example, reduced the BWE between echelons through an autoregressive parameter and showed that inventory reduction could be achieved by sharing information. Similarly, Dai, Peng and Li (2017) minimized the BWE and raised profits by reducing the number of echelons of a supply chain and linearized information by utilizing an advanced information management system. Cao, Xiao and Sun (2017) built a supply and demand driven supply chain, implemented the minimum mean squared error forecasting to predict lead time demand and used statistical analysis to measure the BWE. To minimize the BWE, they suggested that a supplier be in an active position and lead time be in the optimal interval. Bray and Mendelson (2015) meanwhile used a smoothing technique for measuring the BWE and suggested that the BWE can be minimized by shortening production lead time or improving demand forecasts.

2.2.2. Optimization

Optimization technique is deployed to minimize the overall costs in a supply chain including the inventory holding cost, manufacturing cost and shortage cost using operational research techniques; e.g., linear programming, integer programming, queuing theory and Markov chain. For example, Cohen and Lee (1988) used mixed integer programming to develop the optimization model for supply chain processes. Meanwhile, Devika et al. (2016) used an evolutionary multi-objective metaheuristics approach to minimize the BWE impacted by the demand signal processing, order batching, rationing and shortage gaming and lead time. The results showed that the BWE could be decreased if order batching in a wholesaler was kept at its lowest value.

2.2.3. Simulation

Simulation approaches have been proposed by many studies to realistically analyse the BWE. For example, a spreadsheet simulation for effective inventory policy and BWE minimization was utilized by Buchmeister, Friscic and Palcic (2014). Similarly, Jaipuria and Mahapatra (2016) used a simulation model to measure the impact of uncertainty in demand, lead time, and the target inventory and the total cost. They concluded that through proper decision making regarding the target inventory, the BWE can be minimized. Similarly, Lin et al. (2014) used a system dynamics model to show that the BWE can be minimized by minimizing order processing time to respond to demand variability.

Another simulation approach is known as discrete event simulation (DES). It has been used to investigate the performance of various systems including transportation (Zulkepli, Khalid, Nawawi & Hamid; 2018) and traffic flow (Khalid, Baten, Nawawi & Ishak, 2016). In a supply chain, it can be used to simulate the strength of the BWE at every stage, study the behaviour and performance of the supply chain and make relevant decisions to minimize the BWE and other uncertainties. For example, DES has been utilized to simulate a supply chain of a single product with a four-stage multi-period inventory system to determine the demand variability at every stage of the supply chain (Costantino et al., 2014; Merkurjev, Petuhova & Buikis, 2004). Similarly, a study by Pacheco et al. (2017) used a DES approach to introduce a new reorder point in an ordering policy and modify lot size according to the demand variation under lead time and demand absorption to minimize the BWE. This paper also utilises a DES approach to analyse a multi-product and multi-echelon supply chain inventory system to measure the BWE.

3. Research Design

To achieve the objective, the research was designed into three phases. The first phase dealt with the development of a conceptual model and how it was translated to a DES model to study the effect of lead time on the BWE in a multi-echelon with a single product under different information-sharing strategies. The second phase dealt with the validation of the DES model and its extension to support multiple products at a retailer stage and different lead time scenarios under the information-sharing strategies. In the last phase, the BWE was measured in all echelons using a standard deviation ratio of demand. The results were then discussed with an appropriate recommendation for minimizing the BWE.

3.1. Phase 1: DES Model Development

3.1.1. Conceptual Model of a Single Product and Four Stage Inventory System

A four-stage FMCG supply chain consisting of four echelons; i.e., a retailer, a distributor, a manufacturer and a supplier was considered as illustrated in Figure 1. In Figure 1, the retailer considers the end customer demand of a single product and places an order to the respective distributor. The order from the distributor is then received by the manufacturer. The order from the manufacturer is later received by the supplier. After a certain lead time, the order is accomplished and returned to the previous echelon.

Two types of information sharing were modelled; i.e., decentralized and centralized information. In the supply chain with decentralized information sharing, each echelon forecasts its demand based on the order received from the previous echelon and manages its inventory. Only the retailer has access to the end customer's demand. Thus, other echelons only rely on the information shared by the lower echelon in the form of orders since they do not have access to the end customer's demand data. In the supply chain with centralized information sharing, the first echelon; i.e., the retailer observes the demand from the end customer. It shares the complete information about its size with other upstream echelons. These echelons then use this information to manage their inventories and forecast the demand. All echelons are assumed to use the same forecasting technique during the considered periods; i.e., a moving average of demand.

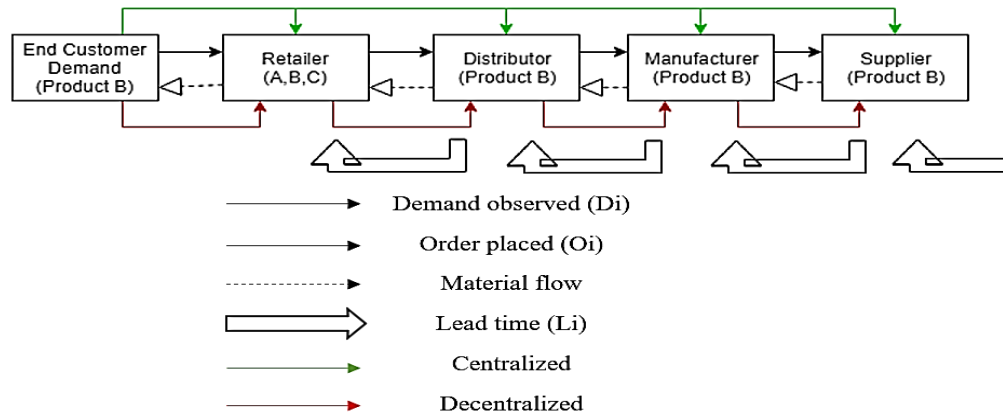


Figure 1: A Conceptual Model with a Single Product

3.1.2. Continuous Review Inventory Policy

To manage the inventory, each echelon is assumed to adopt a continuous review (Q, R) inventory control policy since there is a safety stock level maintained in this policy to avoid stock-outs. Replenishment quantity, Q and reorder level, R are the two parameters to be decided under the policy. Replenishment quantity, Q is ordered from the next upstream echelon whenever the on-hand inventory level crosses level, R . If the upper echelon has sufficient inventory on hand to fulfil the demand, the order lead time will be minimal since it only involves transportation time. Otherwise, there will be more delay since the lead time involves the processing time of the order and the transportation time. If the demand is not satisfied due to stock-outs, sales are considered lost. The supply chain is subjected to the following assumptions:

- The retailer observes the demand from the end customer and places orders to the upper echelon using the (Q, R) inventory policy.
- All unsatisfied demand is considered as lost sales.
- The lead time between each echelon is considered constant and the same.
- The demand received is variable in size and follows a respective distribution.
- All orders in each echelon are treated based on the first come first served (FCFS) basis.
- The probability of not losing sales is 97.5%, i.e., a service level where each echelon is expected not to hit the stock-out situation.

3.1.3. Calculation of Q and R

When lead time is constant, the reorder point (ROP) is calculated as the sum of demand during the lead time and safety stock using equation (1) (Merkuryev & Petuhova, 2002).

$$ROP = \bar{d} \times LT + \sigma_d \times \sqrt{LT} \times z \quad (1)$$

where

$\bar{d}$ – average demand

LT – lead time between replenishment

σ_d – standard deviation of demand

z – safety stock factor based on probability during lead time

The safety stock (SS) under constant lead time depends on the deviation of demand during the lead time and the service level. Therefore, the safety stock is calculated using equation (2).

$$SS = z \times \sigma_d \times \sqrt{LT} \quad (2)$$

When the inventory level is equal to or less than ROP , the quantity Q of the product is placed according to equation (3) (Do et al., 2016).

$$Q = \text{desired upto level} - \text{relative inventory level} \quad (3)$$

As described earlier, inventory policy order placement highly depends on replenishment lead time and variance of demand since an FMCG industry with regular inventory balance should cover the demand during lead time. However, considering the stochastic nature of demand, the frequency of order placement depends on the demand variance. The smaller the variance of demand, the more stable an order placement process will be.

The behaviour of the system described above can be captured using DES. The DES models were developed using Arena 15.10 where each echelon was modelled separately. The models assumed that end-customer demand arrives with fixed time intervals in a variable size following a normal distribution, the lead time between all echelons is constant and no capacity constraint is applied to the last stage of the supply chain.

3.1.4. DES Models

Figure 2 and Figure 3 respectively illustrate the DES models for the retailer handling a single type of demand under decentralized and centralized strategies. Each model generates the incoming demands, handles demand fulfilment and places the order to the distributor. Models with the same logic were developed for the distributor, the manufacturer and the supplier.

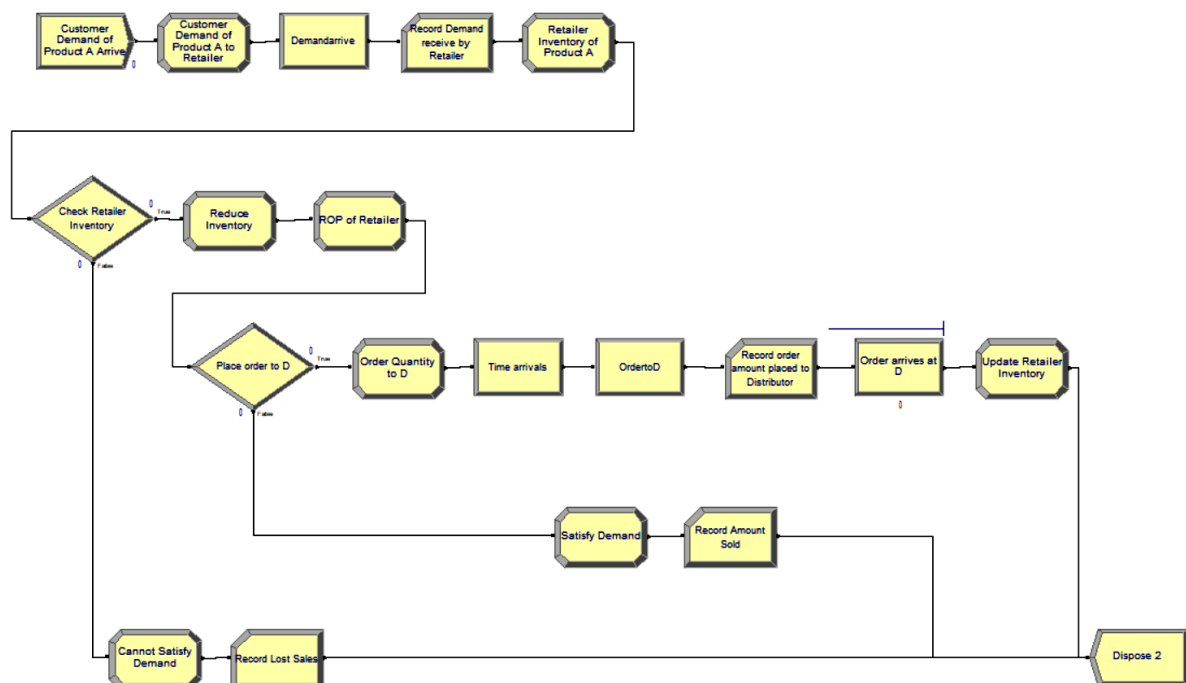


Figure 2: Inventory Management Model for the Retailer (Decentralized)

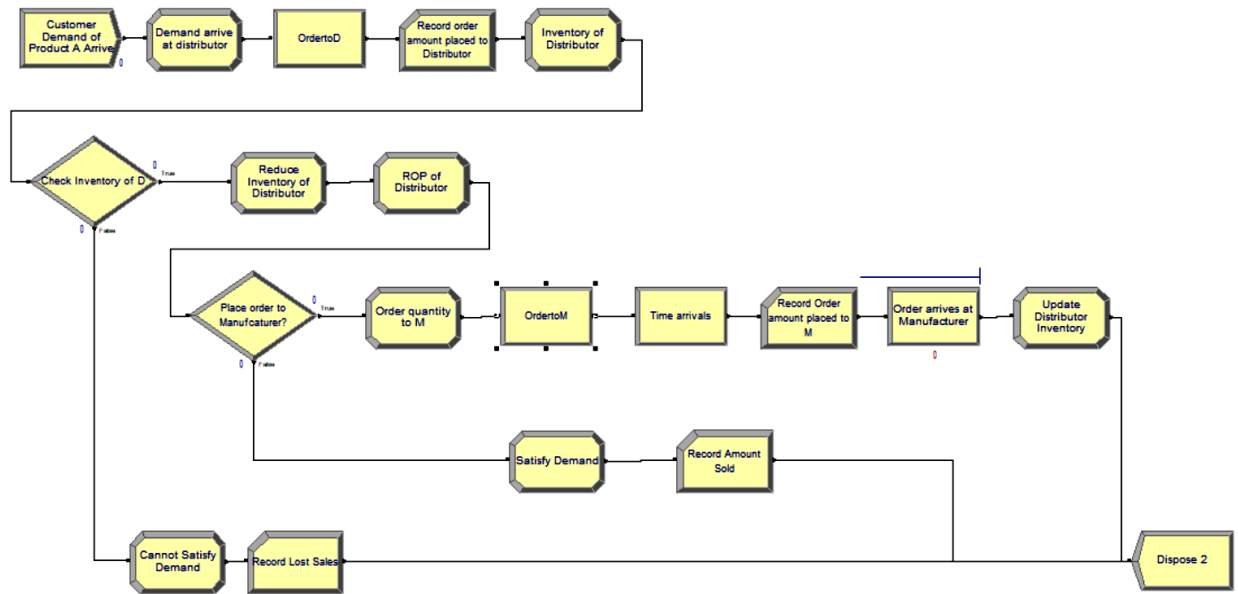


Figure 3: Inventory Management Model for the Retailer (Centralized)

In brief, a daily single demand arrives at the retailer through a *Create Arena* module. On arrival, the demand is attached to the demand quantity forecasted by the retailer, the total number of demand arrivals is updated and the product inventory is initialized using an *Assign* module. The demand quantity is recorded using a *Record* module and is also saved into a file using a *ReadWrite* module to analyse the deviation of the demand. Next, the model checks if the demand quantity can be satisfied based on the retailer's current amount of inventory using a *Decide* module. The decision has two possible outcomes. First, if the inventory is larger than or equal to the demand quantity, the demand quantity is then deducted from the inventory. Otherwise, the demand quantity is considered lost, recorded and then disposed.

The *ROP* of the retailer is calculated according to equation (1). After satisfying the demand, the inventory is tracked to check if its level is smaller than or equal to the reorder point. If true, the order quantity is placed to the distributor using equation (3). When the order is placed, the time arrivals of the order are recorded to calculate the time between arrivals which then becomes the input for the distributor. The received order quantity is also recorded to measure the deviation of the order placed and the demand received to measure the BWE ratio. The standard deviation ratio of an order placed to the demand received results in the BWE measurement. The amount of the quantity placed is recorded and passed through a *Process* module to model the transportation delay from the distributor to the retailer which is considered as the lead time of the distributor. The model then updates the retailer inventory and the demand is disposed using a *Dispose* module.

The model logic was validated using the data published in Merkurjev, Petuhova and Buikis (2004). The initial parameters of the model are shown in Table 1.

Table 1: Initial Input Parameters	
Parameter	Values
Demand	NORM(100,30)
Lead time	2 days

The model was run for 30 replications with the replication length of 365 days. The standard deviation of demand at each echelon was then calculated. The standard deviation of demand ratios between echelons can then be used to calculate the BWE between echelons. By taking the average of all BWE between echelons, the overall BWE could be obtained. The results under the two information-sharing strategies are shown in Table 2 and Table 3. The BWE between echelons is meanwhile shown in Table 4 and Table 5. The model is then validated by comparing its outputs with the benchmark model outputs. The results of the validation are shown in Table 6.

Table 2: Standard Deviation of Demand at Each Echelon under the Decentralized Strategy

	End Customer	Echelon 1	Echelon 2	Echelon 3	Echelon 4
Merkuryev et al. (2004)	30	47	103	182	333
Our DES model	30	49	124	247	393

Table 3: Standard Deviation of Demand at Each Echelon under the Centralized Strategy

	End Customer	Echelon 1	Echelon 2	Echelon 3	Echelon 4
Merkuryev et al. (2004)	30	47	74	97	112
Our DES model	30	50	74	99	103

Table 4: Bullwhip Effect between Echelons under the Decentralized Strategy

	BE1	BE2	BE3	BE4	BEa
Merkuryev et al. (2004)	1.55	2.20	1.77	1.83	1.84
Our DES model	1.63	2.53	1.99	1.59	1.94

Table 5: Bullwhip Effect between Echelons under the Centralized Strategy

	BE1	BE2	BE3	BE4	BEa
Merkuryev et al. (2004)	1.55	1.59	1.31	1.16	1.40
Our DES model	1.67	2.48	1.34	1.04	1.38

Table 6: Validation Results

Decentralized	5.43%
Centralized	-1.34%

3.2. Phase 2: Model Extension

3.2.1. Conceptual Model of a Multiple-products and Four-stages Inventory System

Since the objective of this paper is to develop a model where the FMCG retailer manages multiple products with stochastic lead time, the DES models were extended to the arrivals of demand for three different products. For this, a multi-echelon supply chain with a retailer, a distributor, a manufacturer and a supplier was considered. All echelons were assumed to adopt the same inventory policy (Q, R). The structure of the supply chain with multiple products is shown in Figure 4.

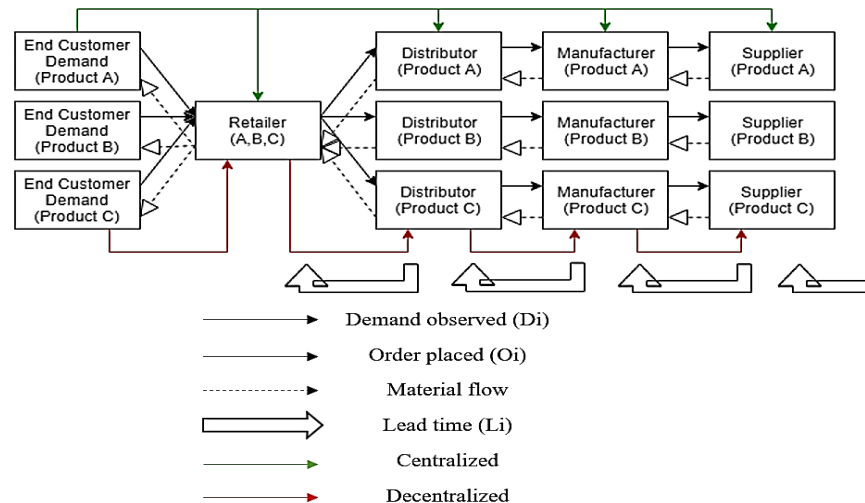


Figure 4: A Conceptual Model with Multiple Products

Figure 4 shows that the retailer observes the demand of three products (Product A, Product B and Product C) denoted by D_i ($i = 1, \dots, n$). Each product has its respective supply chain. Based on the demand of product type, the retailer places order O_i to its distributor, and so on. L_i represents the lead time of i th echelon. When lead time is stochastic, the reorder point is calculated as the sum of demand during the lead time and the safety stock level as in equation (4). If the inventory level is equal to or falls below the reorder point, the order is placed to the respective supply chain of the products.

$$ROP = \bar{d} \times \bar{LT} + z \times \sqrt{\bar{LT} \sigma_d^2 + \bar{d}^2 \sigma_{LT}^2} \quad (4)$$

where

$\bar{d}$ – average demand

$\bar{LT}$ – average lead time between replenishment

σ_d – standard deviation of demand

σ_{LT} – standard deviation of lead time

z – safety stock factor based on probability during replenishment lead time

Due to stochastic lead time, safety stock is calculated based on the service level, standard deviation of demand and lead time according to equation (5). The order quantity is placed using equation (3).

$$SS = z \times \sqrt{\bar{LT} \sigma_d^2 + \bar{d}^2 \sigma_{LT}^2} \quad (5)$$

The extended models were also developed under two information-sharing strategies. Under the decentralized information sharing, the end customer's demand for multiple products is observed by the retailer and is forecasted. The rest of the supply chain relies on the order placed from the previous echelon. In contrast, under the centralized information-sharing strategy, all echelons in the supply chain can completely access the end customer's demand information and forecast the demand based on the information. Experimentation was performed to analyse the BWE of multiple products when lead time is stochastic.

3.2.2. Data Collection

The data on multiple products were gathered from the research conducted by Tanweer et al. (2014). The end customer's demand and the forecasted demand for the three products were considered for modelling. The forecasted demand for each product was performed using the exponential smoothing method.

3.2.3. DES Models

The extended DES model for each echelon was developed separately. The DES model of the retailer management segment is shown in Figure 5. The replication length for the simulation was set to 365 days. Monthly customer demand arrives in variable size. The lead time was considered stochastic between all echelons. The initial input parameters of the model are shown in Table 7.

Table 7: Initial Input Parameters

Parameters	Distribution	Value
Lead time	Normal	NORM(2,1)
Product A Demand	Exponential	769 + EXPO(63.3)
Product B Demand	Beta	679 + 177 * BETA(0.438, 0.333)
Product C Demand	Triangular	TRIA(728, 742, 884)

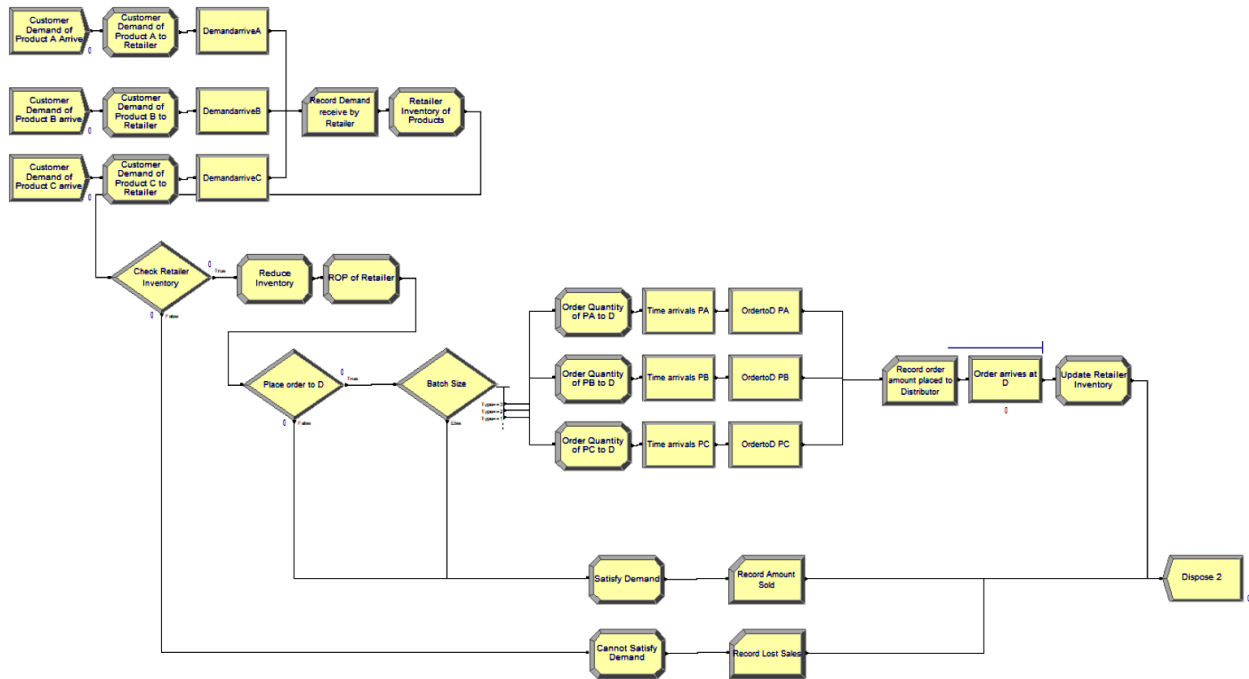


Figure 5: Inventory Management Model for the Retailer for Multiple Products

3.3. Phase 3: BWE Measurement

The developed DES models were then used to quantify the BWE; i.e., the increase in demand variability occurring at all echelons in the supply chain and the stability of the entire supply chain. To measure the BWE occurrence at each echelon, the standard deviation of the demand faced by each echelon was calculated using ratio BE_i :

$$BE_i = STD(Q_i) / STD(Q_{i-1}) \quad (6)$$

where

$STD(Q_i)$ – standard deviation of orders placed by stage i to its supplier

$STD(Q_{i-1})$ – standard deviation of demand received by supply chain stage i

If $BE_i > 1$, then the BWE exists. Else, the BWE does not exist.

The overall BWE of the entire supply chain was measured by taking the arithmetical mean of all observed BE_i ratio (Merkuryev, Petuhova & Buikis, 2004) using equation (7):

$$\overline{BE}_a = \sum_{i=1}^n BE_i / n \quad (7)$$

where

n – number of supply chain stages

BE_i – BWE of i stage

4. Experimental Results

The objective of the experimental study is to analyse the demand variability occurring at each echelon due to stochastic lead time under both information sharing strategies. The variability in the supply chain can be measured by taking into account the demand of the previous echelon and order placed to the next echelon. Since the demand is variable and changes at every period, the mean and the standard deviation can be calculated. The lead time scenarios with variable demand are shown in Table 8.

Table 8: Scenarios of Lead Time when Demand is Variable for Each Product

Strategies	Lead time (Stochastic)	Lead time (Constant)
Decentralized	N(2,1)	C = 2
Centralized	N(2,1)	C = 2

To imitate the dynamic behaviour of the system, the model was replicated for 30 replications. Based on the resulting performance measure, the standard deviation of demand at each echelon was calculated for each product as shown in Table 9 and Table 10. The overall BWE of each product supply chain is plotted in Figure 6 and Figure 7.

Table 9: Standard Deviation of Demand when Lead Time Follows N(2,1)

Echelon	Product A		Product B		Product C	
	Dctl	Ctl	Dctl	Ctl	Dctl	Ctl
End Customer	254	254	145	145	175	175
Retailer	67	67	60	60	36	36
Distributor	433	298	491	433	400	214
Manufacturer	1066	578	91	55	91	110
Supplier	1738	578	181	55	182	55

Dctl = Decentralized, Ctl = Centralized

Table 10: Standard Deviation of Demand when Lead Time Follows C=2

Echelon	Product A		Product B		Product C	
	Dctl	Ctl	Dctl	Ctl	Dctl	Ctl
End Customer	254	254	145	145	175	175
Retailer	67	67	60	60	36	36
Distributor	334	237	410	256	219	54
Manufacturer	731	78	1060	458	796	60
Supplier	1462	79	181	325	1593	46

Dctl = Decentralized, Ctl = Centralized

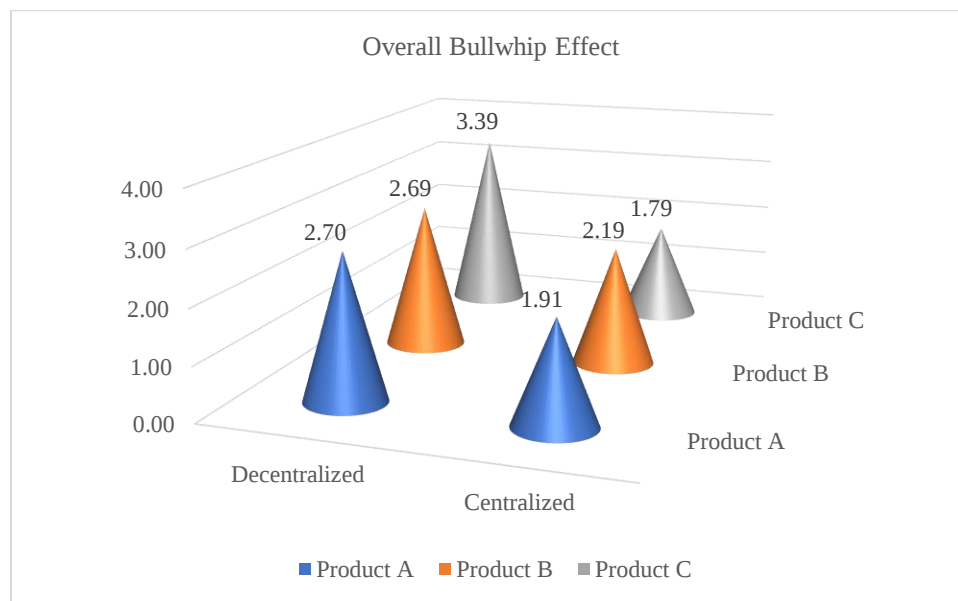


Figure 6: Overall BWE under Stochastic Lead Time

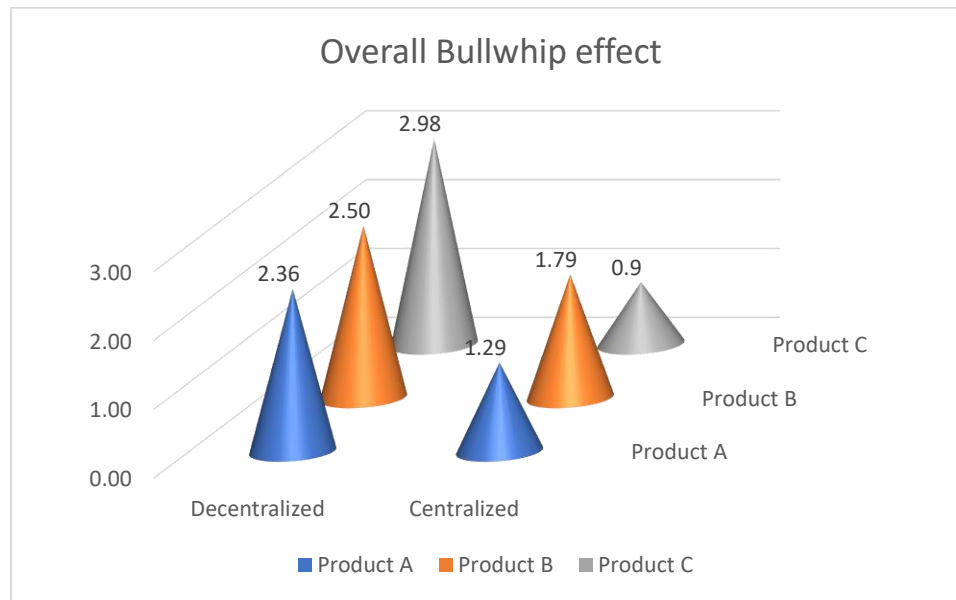


Figure 7: Overall BWE under Constant Lead Time

Under stochastic lead time, the experimental results show that the BWE exists in a multi-product and multi-echelon supply chain similar to the results obtained by Merkurjev et al. (2004). This reflects that the BWE generally cannot be eliminated in a supply chain. However, it can be reduced by sharing complete information of the end customer's demand. Under constant lead time with the centralized information sharing strategy, the results show that the BWE is small. Additionally, the BWE is not present for product C since its overall BWE is less than one and there is no BWE for the three products at the first echelon; i.e., the retailer.

It can also be observed that the retailer faces higher BWE when simultaneously managing the inventory levels of multiple products with its own supply chain stages. The BWE increases while moving up the supply chain due to the increase in demand variability caused by the lead time. The results of the model used for validation depicts the same nature. Generally, the BWE increases with the increase of the number of echelons since lead time will also increase. Such stochastic lead time increases the variability between demand received and orders placed in an inventory system. Analysing the order variability in all scenarios shows that even a small variation of the mean demand can cause an increase in variability of the placed order due to the stochastic lead time. This reflects that the variability of order significantly depends on lead time (Kumar & Keswani, 2016; Mbhele & Phiri, 2014). If lead time is stochastic, the reorder point needs to be set higher which later requires the change of order quantity at each echelon.

5. Conclusion

This paper investigates two main causes of the BWE; i.e., lead time and information sharing in an FMCG supply chain. The impact of lead time on the BWE in a multi-product and multi-echelon FMCG supply chain under decentralized and centralized information sharing strategies was investigated using a discrete event simulation approach. The results of the simulation models show that lead time causes the BWE whose value increases with the increasing number of echelons. To reduce the BWE, the reduction of demand variance is crucial and can in turn be achieved through sharing complete information on the end customer's demand. This is the main reason why the performance of a centralized supply chain is better than the performance of a decentralized supply chain especially under stochastic lead time. Without complete information sharing, a retailer typically sets a high reorder point to avoid any losing sales. This high reorder point demands a high inventory level to store the ordered products which will incur high holding inventory cost.

To reduce the demand variance, a supply chain manager should thus implement a centralized information sharing strategy. Under whatever information sharing strategies, the behaviour of demands should however be investigated in

detail and this requires more studies examining lead time under various distributions and inventory policies. Moreover, the developed simulation models have some limitations; e.g., sold quantities and lost quantities are not measured against the BWE. Thus, it is recommended that future research can analyse the effect of lead time with different demand distributions and inventory policies on the BWE for a multi-product and in multi-echelon supply chain. Furthermore, the cost involved in transportation and inventory storing can also be considered.

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