Analysis of the bullwhip effect with order batching in multi-echelon supply chains

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Abstract

Purpose – The purpose of this paper is to analyze the effect of batching on bullwhip effect in a model of multi-echelon supply chain with information sharing.

Design/methodology/approach – The model uses the system dynamics and control theoretic concepts of variables, flows, and feedback processes and is implemented using *iThink*® software.

Findings – It has been seen that the relationship between batch size and demand amplification is non-monotonic. Large batch sizes, when combined in integer multiples, can produce order rates that are close to the actual demand and produce little demand amplification, i.e. it is the size of the remainder of the quotient that is the determinant. It is further noted that the value of information sharing is greatest for smaller batch sizes, for which there is a much greater improvement in the amplification ratio.

Research limitations/implications – Batching is associated with the inventory holding and backlog cost. Therefore, future work should investigate the cost implications of order batching in multi-echelon supply chains.

Practical implications – This is a contribution to the continuing research into the bullwhip effect, giving supply chain operations managers and designers a practical way into controlling the bullwhip produced by batching across multi-echelon supply chains. Economies of scale processes usually favor large batch sizes. Reducing batch size in order to reduce the demand amplification is not a good solution.

Originality/value – Previous similar studies have used control theoretic techniques and it has been pointed out that control theorists are unable to solve the lot sizing problem. Therefore, system dynamic simulation is then applied to investigate the impact of various batch sizes on bullwhip effect.

Keywords Bullwhip effect, Batching, Information sharing, Multi-echelon supply chain, Simulation, Supply chain management, Inventory management

Paper type Research paper

1. Introduction

A potentially devastating phenomenon seen in supply chains is the bullwhip effect, i.e. the amplification of demand variability as it progresses up a supply chain. It was first observed in industry by Forrester (1961), who named the effect "demand amplification", and there has since been much research published by many authors who have studied it. Forrester pointed out that demand amplification is due to system dynamics and can be tackled by reducing delays in the supply chain. Sterman (1989) through the Beer Game interprets the phenomenon as a consequence of players' irrational behaviors or misperceptions of feedback. Towill (1996) confirmed the findings of Forrester that reducing delays and collapsing all cycle times reduce the bullwhip effect. Lee *et al.* (1997) found that the bullwhip effect is caused by demand signal processing, order batching,

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price variations, and rationing and gaming, and can be reduced through information sharing. Slack and Lewis (2002) give a textbook introduction to these causes with some remedies. Wangphanich *et al.* (2010) also mention late deliveries and incomplete shipments, i.e. poor and unreliable service, as causes. In general, they characterize factors that contribute to uncertainty in demand as causes. However, they remind us that some industries with reliable demand patterns can still experience the bullwhip effect due to a lack of synchronization in ordering up the supply chain:

> The bullwhip effect indicates that the stocking level variability in supply chains tends to be higher upstream than downstream, e.g. it is caused by factors such as deficient information sharing, insufficient market data, deficient forecasts or other uncertainties (Sevenson, 2005).

Its effects include inaccurate forecasting leading to periods of low capacity utilization alternating with periods of having not enough capacity, i.e. periods of excessive inventory caused by over production alternating with periods of stock-out caused by under production, leading to inadequate customer service and high inventory costs. Since the bullwhip effect is very costly to upstream echelons of the supply chain, there is a real and substantial cost benefit associated with its reduction. Recently, some sophisticated techniques have been applied to this reduction, such as genetic algorithms to determine optimal ordering at each echelon (O'Donnell *et al.*, 2006), fuzzy inventory controllers (Xiong and Helo, 2006), and distributed intelligence (De La Fuente and Lozano, 2007). Although many remedies to the bullwhip effect have been published, it is still a concern in the real world, so research into understanding and controlling it continues (Wangphanich *et al.*, 2010).

It is generally advocated that batch size should be reduced as much as possible (Burbridge, 1981), but there has been limited detailed investigation into the impact of batch size on demand amplification, which raises the question, "Does findings of Burbridge (1981) hold totally true in respect of minimizing demand amplification?" This paper addresses this gap in the research by introducing batching into the four-tier supply chain model and then conducting simulation experiments to understand: the impact of batch sizes on the bullwhip effect under deterministic and stochastic demand processes and the impact of information sharing across wide ranges of batch sizes.

The remainder of this paper is organized as follows. Section 2 provides brief survey of the related literature. In Section 3, the methodology is introduced and then the supply chain simulation model is presented in Section 4. After that, the impact of the batching on bullwhip effect under step and stochastic demand process has been explored, and value of information sharing with respect to batch size has been discussed in Section 5. Sensitivity analysis has been carried out in Section 6. Section 7 concludes.

2. Batching and bullwhip effect

Order batching is one of the key causes of the bullwhip effect identified by Lee *et al.* (1997) and Riddalls and Bennett (2001). It refers to the phenomenon of placing orders to upstream echelons in batches. Finding the optimal solution to batching is not easy since it is directly related to inventory holding and backlog costs. In many production-distribution systems materials move from one echelon to another in fixed lot sizes. For example, a retailer might order a full truck or container load from the wholesaler to qualify for a quantity discount and to optimize transport costs by fully utilizing the fixed-cost truck or container. For a manufacturer, significant economies of scale can be achieved by producing in large batches, but the resultant large inventories will increase the stock holding costs. The inventory manager, however, always favors policies that meet the forecasted demand with minimal inventory. The rapprochement of these conflicting objectives is a fundamental aim of inventory management theory.

Batching is a clustering of items for purchasing, transportation, or manufacturing processes and is also known as "lot sizing". It is a mechanism that induces time-phased production that is usually non-synchronized with the actual demand. In this way, batching results in excessive inventory or backorders. The reasons for batch ordering include the economic order quantity (EOQ), periodic inventory review, and transportation economies. Batching is also related to economic batch quantity where it is beneficial economically for a company to produce large batches since it can reduce the number of facility set-ups and improve manufacturing efficiency. Companies prefer to order in batches to gain economies of scale. Long process set-up times are a major cause of large production batches within factories with the corollary being that rapid changeovers are required to reduce batch sizes. These large batch sizes can lead to large fluctuations in inventory levels as first a large batch is produced, far in excess of current demand, so that the inventory levels rise to high levels only to be reduced until they reach a reorder point, at which point a new large batch enters the inventory.

Furthermore, batching amplifies the demand as it passes up a supply chain as the real demand is rounded up to whole batch sizes for production processes and ordering from suppliers, and this rounding-up stacks up along the supply chain when different batch sizes are used. For example, demand for a product may be ten units, the production batch size may be 100, and an outsourced component used in the product (one component per product) may have an order batch size of 40. The initial demand of ten is amplified to 100 in the factory, which results in a further amplified order for $3 \times 40 = 120$ components, assuming there are no components in stock already. This amplification can continue unabated up the supply chain. For example, if the component supplier ordered sub-components in batches of 50, the demand signal would jump to 150.

There is a clear and crucial need to fully understand the impact of varying the batch size on demand amplification across multi-echelon supply chains in order to enable operations managers to make better decisions around batching. Burbridge (1981) emphasized the need to reduce the batch size as much as possible. Technical or economical problems may not allow the implementation of smaller batch sizes. Cachon (1999) has studied the impact of order batching in a two-level supply chain with a single supplier and many retailers. The study suggests that the bullwhip effect at the supplier's level can be reduced by balancing the orders of the retailers, a longer order interval time, and smaller batch sizes. Riddalls and Bennett (2001) studied the impact of batch production cost on the bullwhip effect. They proposed measuring the magnitude of the bullwhip effect in a two-tier supply chain by observing the peak order rate of the upper level (the supplier). They found that the relationship between batch size and demand amplification is non-linear and depends on the remainder of the quotient of average demand and batch size. The limitation of their findings is that there is always an initial increase (overshoot) in the order rate after a step change in demand. Hence, such assessment of the peak of the order rate as a measure of the bullwhip effect is not an accurate, qualitative measure of demand amplification.

Holland and Sodhi (2004) studied a two-tier supply chain model in which the retailer is bound to order in integer multiples of the batch size (e.g. for order quantity of 50 units, batch size should be either 1, 2, 5, 10, 25, or 50). Both retailer and manufacturer follow a periodic review and order-up-to-level replenishment policy. Simulation was run for five different batch sizes and statistical analysis was carried out to quantitatively measure the impact on the bullwhip effect of batch size across each echelon. They found that the bullwhip effect across each echelon of the supply chain was proportional to the square of the batch size. Hejazi and Himolla (2006) argue that lot-sizing decisions of an upstream member may also cause order batching at the downstream level of the supply chain, and thus be a major source of the bullwhip effect. Therefore, the members of the supply chain seem not only to be locally opportunistic, but also their decisions are based on variables identified in the supply chain level, and most often decisions are made knowing the abilities of upstream manufacturing. Mehra *et al.* (2006) used a simulation, based on an actual process industry, to investigate the results of two lot size (or batch size) reductions within continuous processing firm. Results of the study indicate that lot size reduction can be a valid performance improvement method for actual firms utilizing a continuous flow system.

Potter and Disney (2007) continued the work of Holland and Sodhi by considering the impact of a full range of batch sizes on demand amplification in a single echelon of Automatic Pipeline Inventory and Order-Based Production Control System (APIOBPCS). They found that the bullwhip effect from batching can be reduced if the average demand is an integer multiple of the batch size.

It has been recognized generally that the bullwhip effect can be minimized by reducing the batch size as much as possible, but there has been little study of the impact of batch size across a multi-echelon supply chain. Riddalls and Bennett (2001) pointed out that control theorists are unable to solve the lot sizing problem. Potter and Disney (2007) mentioned that the impact of order batching on bullwhip has not been clearly explored. They pointed out that studying the impact of batch size on the APIOBPCS, under a stochastic demand process, using the transform techniques of control theory is extremely challenging. System dynamics simulation then seems an appropriate methodology to investigate the impact of varying batch size on the bullwhip effect with a stochastic demand process. The value of information sharing as a remedy to reduce the bullwhip effect has been widely recognized. However, whilst some studies have analyzed the value of information sharing in capacity constraint supply chains, there has been little research into the value of information sharing when there is order batching; this paper addresses these gaps.

2.1 Review of APIOBPCS

One of the most commonly studied periodic review models in the supply chain literature is the Beer Game mentioned above. This is a simplified but still realistic representation of a multi-echelon supply chain (Larsen *et al.*, 1999), consisting of a retailer, a wholesaler, a distributor, and a brewer (factory). The model was developed at Massachusetts Institute of Technology in the 1960s, with the earliest description of the game dating back to Forrester's (1961) work in industrial dynamics. Coming from a control theory background, Towill (1982) introduced a greater level of detail into this model by using the Inventory and Order-Based Production Control System (IOBPCS) to model each echelon in more detail, applying a basic periodic review algorithm for issuing orders into the supply pipeline, based on current inventory deficit and incoming demand from customers. As its name implies, IOBPCS combines make-to-stock and make-to-order production control as seen in much industrial practice. Edghill and Towill (1989) extended the model by incorporating variable desired inventory as a function of the demand. Later, a work-in-progress (WIP) feedback loop was added to the IOBPCS:

> Let the production targets be equal to the sum of an exponentially smoothed demand (over Ta units of time) plus a fraction (1/Ti) of the inventory error, plus a fraction (1/Tw) of the WIP error.

This is the "APIOBPCS" (John *et al.*, 1994), which is used in this paper to model the individual tiers of a supply chain.

Riddalls and Bennett (2002) analyzed the impact of a pure time delay to represent the production lead-time and explored the stability boundaries of the APIOBPCS. Disney extended the model into the vendor-managed inventory scenario. Dejonckheere *et al.* (2004) studied the order-up-to-level inventory control model and its variants as an important subset of the APIOBPCS. Adjusting the gain of the inventory error (Ti) and the pipeline feedback (Tw) allows the APIOBPCS to mimic a range of make-to-stock and make-to-order production control strategies.

3. Methodology

System dynamics is an approach to understanding complex systems, using modeling and simulation techniques capable of modeling feedback loops explicitly and evaluating the dynamics of complex processes and systems. If difference equations are used to model a system, as in the model presented here, then the model can be implemented in a spreadsheet to simulate the system in operation, for example (Shukla *et al.*, 2009). One of the most commonly applied methodologies to study the various aspects of the multi-echelon supply chain model is the control theoretic approach. The problem now a days that faces control theorists is that, although they are often able to write differential equations on the dynamic behavior of the model, in many cases these differential equations cannot be integrated. Instead the control theorists resort to numerical approach, usually with the help of computer simulation (Pidd, 2004). Further, mathematical and control theoretic approaches can demand an academically advanced understanding of mathematics that most supply chain operations managers do not have (Agaran *et al.*, 2007). In contrast, the use of system dynamic simulation methods can help practitioners to better understand the basic phenomenon and to examine the effects of parameters.

The particular system dynamics software used in this research is *iThink*®. This requires a reasonably good knowledge of spreadsheet modeling as well as difference equations. It is also very time consuming and prone to errors as the spreadsheet can soon become quite intricate and ultimately unwieldy. Proprietary software packages have been developed to be more user-friendly and functionally powerful for the task of systems dynamics modeling and simulation, especially in their user-interface. One package that is used commonly for system dynamics modeling is MATLAB® (Coppini *et al.*, 2010), which has its origins in the traditional control engineering community. The particular system dynamics software used in this research is *iThink*®. This has been developed more for the business community rather than for control engineers, so it should be suitable for supply chain managers and designers.

iThink® is a useful tool that can help management to gain insight in the dynamic complexity of business systems (Ashayeri *et al.*, 1998). However, limitation of system dynamics and *iThink*® software is that system dynamics simulation is a modeling tool. For optimization, system dynamics must be coupled with an optimization tool.

Models are built in *iThink*® using flows (e.g. of products from a factory to an inventory), stocks to model simple inventories or process delays such as a factory between flows, connectors to provide information flows (e.g. feedback of actual inventory levels for comparison with desired levels) and converters to apply gain factors or other formulae to variables (Figure 1).

4. Multi-echelon supply chain model

Figure 2 shows the simulation model of the four-echelon supply chain produced in *iThink*®. At the material flow level, each echelon consists of one inventory and one time delay, i.e. factory or other facility. Each echelon operates independently based on demand from downstream (towards the end-customer). At echelon-n, the input to the factory or other facility at time period t is the order rate ($ORATE_t^n$), which is determined by feeding forward the exponentially smoothed sales ($SSALES_t^n$), i.e. the demand forecast, and the actual end-customer demand, i.e. the smoothed sales from the retailer ($SSALES_t^1$), and feeding back the error in the inventory and the WIP, with the aim of keeping the inventory at the desired level. The error in the inventory ($EINV_t^n$) is the difference between the desired inventory level ($DINV^n$) and the actual inventory level ($AINV_t^n$). Here, $DINV^n$ is fixed and equal to original demand. The WIP (WIP_t^n) is the accumulation of orders that have been placed on the echelon but not yet completed and the desired WIP is $DWIP_t^n$. The error in the WIP ($EWIP_t^n$) is the difference between the desired $DWIP_t^n$ and the actual WIP_t^n. Ti is a divisor applied to the inventory deficit to control the rate of recovery and Tw similarly controls the WIP replenishment rate.

The retailer shares its end-customer demand with the other tiers, which then base their production rates ($ORATE_t^n$) on the weighted sum of this end-customer demand and incoming orders from their previous tier, i.e. their immediate customer in the supply chain. With full information enrichment (information enrichment percentage (IEP) = 100 percent) a tier bases its $ORATE_t^n$ solely on end-customer demand, whilst with no information enrichment ($IEP = 0$ percent) production is based solely on the incoming orders from the previous tier. $ORATE_t^n$ can be based on a combination using IEP of end-customer demand plus ($100 - IEP$) percent of the incoming orders from the previous tier; in the *iThink*® model these percentages are referred to as IEP1 and IEP2, respectively.

Demand needs to be forecast at each tier before applying it in scheduling and there are potentially many methods to do this. Simple exponential smoothing is used in the APIOBPCS model used here. This is justified as it is the basis of much industrial practice and the approach used in other published models, e.g. in Mason-Jones *et al.* (1997), Coppini *et al.* (2010), and Shukla *et al.* (2009). In *iThink*® the built-in function SMTH1 calculates the first-order exponentially smoothed value, with the smoothing constant (Ta) representing the time to average sales and the average age of data

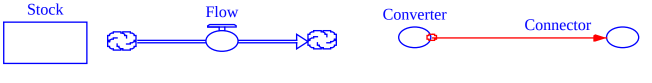

Figure 1.
Building blocks of *iThink* software

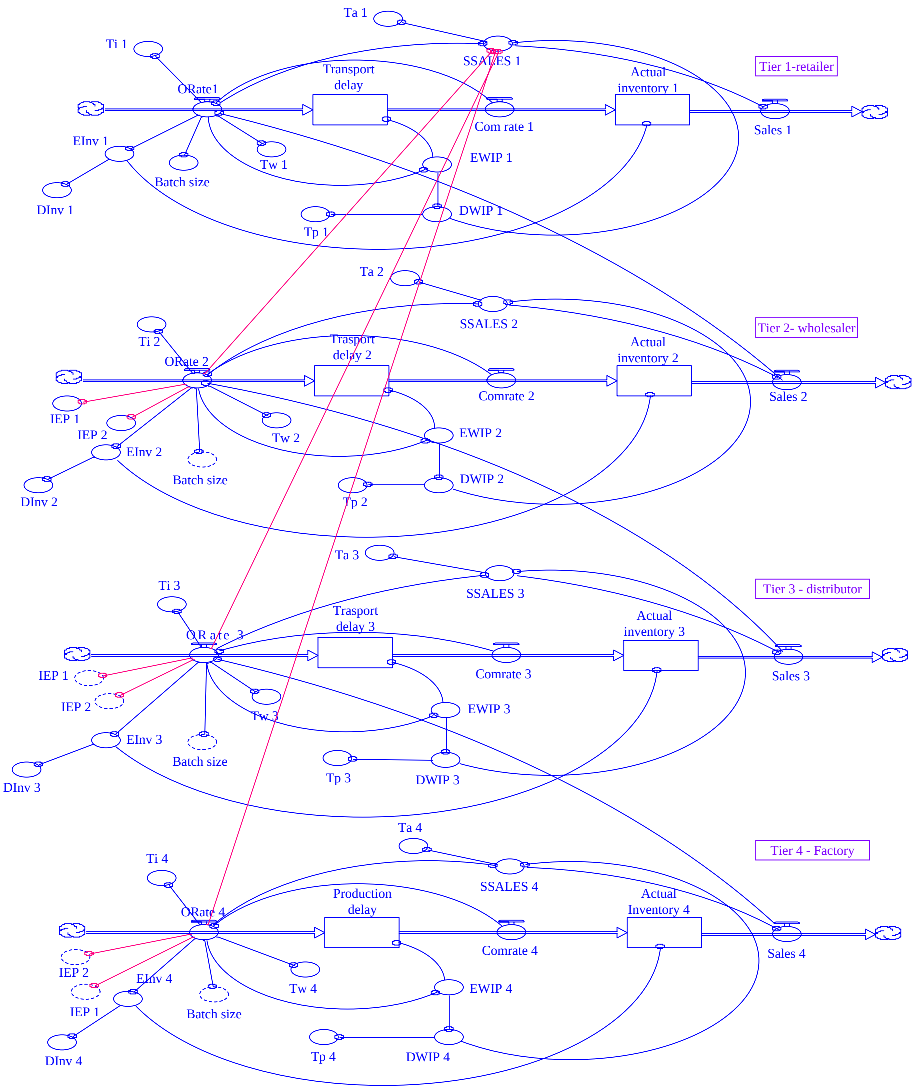

Figure 2.
iThink model of multi-echelon supply chain with information sharing and batching

in the forecast. The value of Ta determines the degree of smoothing applied to the demand and is subject to $0 \leq 1/Ta \leq 1$.

$COMRATE_t^n$ is the completion (output) rate of the factory or facility at echelon-n. As a simple time delay (Tp) is used to model the lead-time, $COMRATE_t^n$ is simply equal to $ORATE_{t-\mathrm{Tp}}^n$. The actual inventory $AINV_t^n$ is the accumulation of stock determined by $COMRATE_t^n - SALES_t^n$.

In summary, at echelon-n:

$$\text{for } n = 1 : SALES_t^1 = \text{the actual end} - \text{customer demand data} \qquad (1)$$

$$\text{for } n > 1 : SALES_t^n = ORATE_t^{n-1} \tag{2}$$

$$SSALES_t^n = SSALES_{t-1}^n + \frac{(SALES_t^n - SSALES_{t-1}^n)}{Ta^n} \tag{3}$$

$$\text{for } n > 1 : ORATE_t^n$$

$$= IEP^n \times SSALES_t^1 + (100\% - IEP^n) \times SSALES_t^n + \frac{EINV_t^n}{Ti^n} + \frac{EWIP_t^n}{Tw^n} \tag{4}$$

$$\text{for } n = 1 : ORATE_t^1 = SSALES_t^1 + \frac{EINV_t^1}{Ti^1} + \frac{EWIP_t^1}{Tw^1} \tag{5}$$

$$COMRATE_t^n = ORATE_{t-Tp}^n \tag{6}$$

$$AINV_t^n = AINV_{t-1}^n + COMRATE_t^n - SALES_t^n \tag{7}$$

$$DINV^n = SALES_0^n \tag{8}$$

$$EINV_t^n = DINV^n - AINV_t^n \tag{9}$$

$$DWIP_t^n = Tp^n \times SSALES_t^n \tag{10}$$

$$EWIP_t^n = DWIP_t^n - WIP_t^n \tag{11}$$

The supply chain model used in this paper is extended by introducing batch ordering across each APIOBPCS echelon. Batching is introduced by the ROUND function in the *iThink*® software package. The round function rounds values up to the next integer value. So to convert an ORATE to batches of size (BS), the following formula is used:

$$Number\ \ of\ \ batches = ROUND\left(\frac{ORATE_t^n}{BS_t^n}\right) \tag{12}$$

and the new ORATE is then:

$$Batched\ \ ORATE = Number\ \ of\ \ batches \times BS_t^n \tag{13}$$

Unless stated otherwise, the APIOBPCS parameter values applied in this paper are Ti = Tw = Tp = 6, and Ta = 2Tp = 12, i.e. a "good" set of values in accord with the findings of the Mason-Jones *et al.* (1997) and also used by Wilson (2007). When the four-echelon supply chain is simulated, it is the fourth echelon that experiences the greatest demand amplification as it is farthest from the end-customer (Coppini *et al.*, 2010), the bullwhip effect experienced at this echelon is studied here. To verify the *iThink*® model, the difference equations (1)-(13) were also implemented in a spreadsheet model. This produced results that agreed with the *iThink*® results.

4.1 Measuring the bullwhip effect

Several approaches can be applied to measure the bullwhip effect. A commonly used approach based on the variance-to-mean ratio is given in equation (12) (Chen *et al.*, 2000; Wangphanich *et al.*, 2010), and there is a similar approach based on the standard deviation-to-mean ratio (Fransoo and Wouters, 2000; Xiong and Helo, 2006):

$$\text{Bullwhip} = \left(\frac{\sigma^2_{ORATE} / \mu_{ORATE}}{\sigma^2_{SALES} / \mu_{SALES}} \right) \tag{14}$$

σ^2_{ORATE} and μ_{ORATE} are the unconditional variance and mean, respectively, of *ORATE* at the tier of the supply chain being measured. σ^2_{SALES} and μ_{SALES} are the unconditional variance and mean of *SALES* at the first tier, i.e. the end-customer demand. It is normally assumed that the two unconditional means are identical so that they cancel in equation (12), i.e. average orders = average end-customer demand, to give the simpler bullwhip measure in equation (13), which is used here and by others (Muramatsu *et al.*, 1985; Disney and Towill, 2003; Bottani and Montanari, 2010):

$$\text{Bullwhip} = \left(\frac{\sigma^2_{ORATE}}{\sigma^2_{SALES}} \right) \tag{15}$$

5. Impact of batching and information sharing on bullwhip effect

5.1 Step change in demand

Figure 3 shows the impact of the various batch sizes on the bullwhip effect at the retailer level, with Tw = Tp = 6, Ta = 2Tp = 12, and IEP = 0 percent, under a step change in demand;, i.e. demand is changed from 2,000 to 2,400 and simulation is run for 500 weeks. Similar results are observed for upstream echelons. Note, in this graph some of the plotted output variances give the appearance of being zero. However, they are not actually zero but relatively very small values that are difficult to depict on a scale that is large enough to accommodate the other much larger values. This is also true of the other output variance graphs that appear later. It can be seen that the relationship between batch size and demand amplification is non-monotonic. In general, demand amplification cannot be reduced by reducing the batch size as found by Riddalls and Bennett (2001).

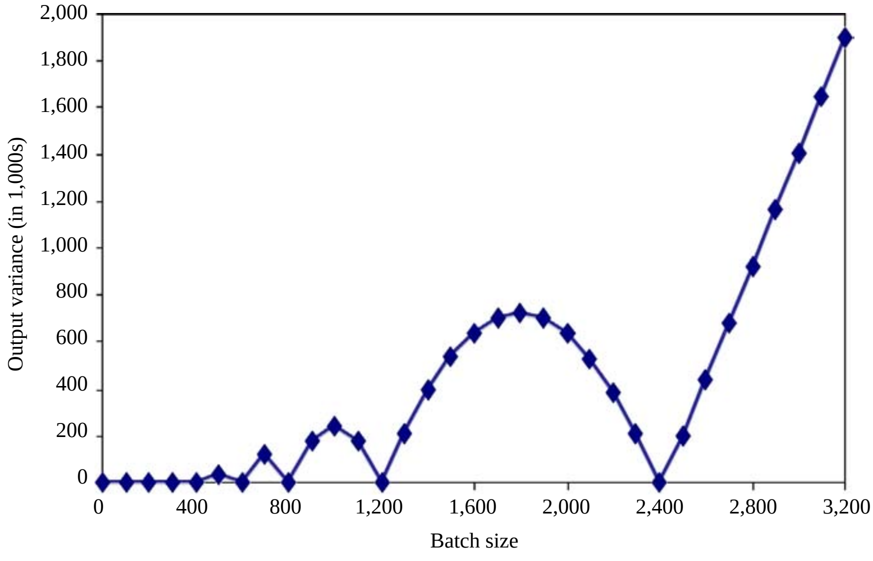

Figure 3. Impact of batch size on bullwhip effect for step demand

Burbridge (1981) emphasized reducing the batch size as much as possible. However, when the quotient of the average demand and batch size (average demand/batch size) is integer, demand amplification does not grow with the increase of batch size in APIOBPCS as pointed out by Potter and Disney (2007). In other words, large batch sizes, when combined in integer multiples, can produce order rates that are close to the actual demand, produce little effect on the demand amplification, i.e. it is the size of the remainder of average demand divided by batch size that is the determinant here. Hence, unless the batch is made very small (in this case < 400) demand amplification is not suppressed simply by reducing the batch size as pointed out by Burbidge, rather it can be controlled by a judicious mix of decreases in batch size and adjusting the batch size so that the average demand is an integer multiple of it, i.e. the remainder of demand/batch size is zero or close to zero. However, it is noted that use of a large batch size placed at one of the local minima amplification points has the danger that changes in average demand can lead to large increases in amplification unless the batch size is adaptive, i.e. there is high sensitivity.

5.2 Stochastic demand process

Potter and Disney (2007) reported that studying the impact of batch size under a stochastic demand process in APIOBPCS is extremely difficult using a control theoretic approach of Laplace and Z-transforms. APIOBPCS is a periodic review system for issuing orders based on incoming demand signals and feedback loops of inventory and pipeline deficit. These feed-forward and feedback loops are in turn affected by control parameters and it is hard to understand the nature of the transformation involved. Hence, control theorists have been unable to study the impact of batch size under a stochastic demand process, so the system dynamics simulation approach seems an appropriate methodology for the investigation.

To simulate a stochastic customer demand, SALES follows a normally distributed, stationary stochastic I.I.D. process with a known mean, μ, and variance σ^2. It is assumed that σ is significantly smaller than μ, so that the probability of negative demand is negligible (Lee *et al.*, 1997). A normally distributed stochastic demand pattern with a known mean of 2,000/week and standard deviation of 400 is simulated. Following Reddy and Rajendran (2005), replication is carried out for 50 simulation runs, each for 500 weeks, and averages of the results are taken.

It can be seen from Figure 3 that the pattern, rather than the amplitude, of the impact of batch size on the demand amplification is the same as seen in Figure 4 for the stochastic change in SALES. Again it is found that the output variance (bullwhip effect) decreases to a local minimum as the quotient of average demand and batch size approaches an integer value. Clearly, reducing demand amplification due to batching is not just about getting as close as possible to a batch size of one, it is also about how close demand is to an integer multiple of the batch size.

Figures 3 and 4 show that when the quotient of batch size and average demand is not integer, increasing the batch size increases the gap between the minimum variance points and the magnitude of the peak demand amplification between these points. Consequently, fairly small changes in large batch sizes can cause big changes in demand amplification. If operations managers with large batch sizes monitor trends in average demand, it may be possible to monitor and anticipate movement up the curve of the output variance, i.e. to forecast high amplification, and subsequently plan

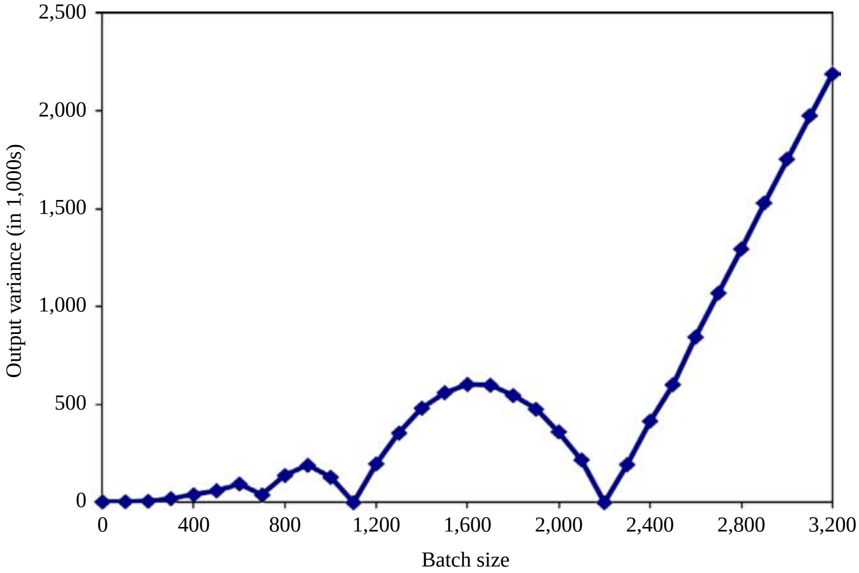

Figure 4.
Impact of batch size on bullwhip effect for random demand

to change the batch size to reduce this. If the batch size is changed so that there is an integer multiple of it that matches demand, the bullwhip effect is minimized. If the batch size is increased beyond the average demand, then the output variance, i.e. the bullwhip effect, increases rapidly and linearly. A corollary to this is that if the demand starts to decrease below the batch size, then the bullwhip effect will grow rapidly. Again, the operations manager should monitor for this condition.

Managerial implications of our work are followings; relationship between batch sizes and the bullwhip effect is not linear. It cannot be guaranteed that smaller bath size will effectively reduce the demand amplification. Economies of scale processes usually favor large batch sizes. Reducing batch size in order to reduce the demand amplification is not a good solution. It depends how close average demand is to an integer multiple of the correct batch size. There are certain ranges in batch size, like when quotient of average demand and batch size is approaching to integer value, a modest increase in batch sizes can lead to substantial reduction in bullwhip effect. By monitoring this trend, production manager can forecast high amplification in advance and can better plan to change the batch size to reduce this amplification. This is quite logical that as batch size increases, the marginal cost of the production reduces, so it is convenient to take advantage of this temporary low production cost and a small increase in production can be accommodated by increasing the batch size to integer multiple of average demand without needing the whole new batch. By looking at the graph of the demand amplification due to batch size, operations manager can substantially reduce the inventory holding and backlog cost by carefully choosing the batch size without complex mathematical calculations. When the upstream echelons of the supply chain are not working with batching constraints in their order rates, changing the batch size of the only retailers does not have any impact on the demand amplification of the factory.

5.3 Impact of information sharing with respect to batch size

The impact of information sharing on the bullwhip effect has been discussed by many authors and they have revealed the value of information sharing (Lee *et al.*, 2000, 2004; Moinzadeh, 2002; Roman, 2009). Whilst information sharing is frequently cited as being the key to reducing demand amplification, there has been little research to investigate the value of information sharing in a batched model although batching is acknowledged as a major cause of amplification.

The phenomenon of demand amplification across multi-echelon supply chain can be seen clearly in Figure 5, which shows the output variance of the step response of 20 percent for Tier 1 and Tier 4 with 0 and 100 percent IEP. Figure 5 shows that in percentage terms the increase in demand amplification between Tiers 1 and 4 is greatest with the smaller batch sizes, i.e. a large batch size may cause a large output variance at Tier 1, but then this output variance does not increase so much in percentage terms, as it passes up the supply chain. So whilst the drive in manufacturing might be to reduce batch sizes, this will lead to greater demand amplification in percentage terms at upstream of supply chain. It is further noted that the value of information sharing is greatest for the smaller batch sizes, as there is a much greater improvement in the amplification ratio when IEP is changed from 0 to 100 percent, where amplification ratio is the ratio of the output variances of Tiers 4 and 1.

In the literature, a typical amplification ratio observed between two echelons is 2:1 (Towill, 1992) and between four echelons is 20:1 (Houlihan, 1987). In Figure 5, for batch sizes less than 400, an amplification ratio of the order of 20:1 is indeed seen between Tier 4 with IEP = 0 percent (no information sharing) and Tier 1. However, this ratio is far less for the larger batch sizes. The amplification ratio can be reduced to the order of 8:1 for the smaller batch sizes through full information sharing, i.e. IEP = 100 percent and this agrees with the findings of Chen *et al.* (2000) and Chatfield *et al.* (2004). For the larger batch sizes, whilst the amplification ratio is less, making demand amplification arguably a less significant problem, the use of information sharing can almost eliminate any significant demand amplification. There is a dilemma here because

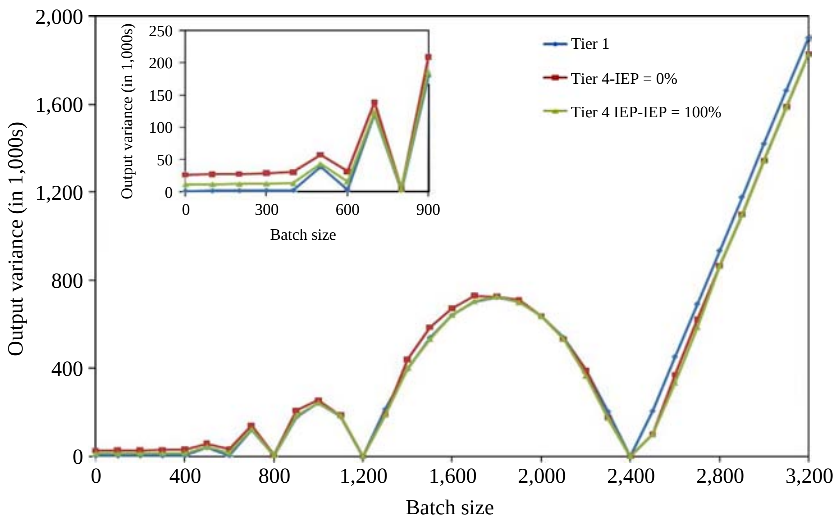

Figure 5.
Impact of information sharing on batch size

information sharing will have a cost associated with its implementation, and whilst it may deal with the problem of demand amplification very well, the problem is primarily caused at Tier 1 with very large batch sizes for the supply chain studied here. In contrast, information sharing is clearly of great value when the batch size is smaller. So, with the increasing drive to reduce batch sizes, there is an increasing justification for adopting and investing in information sharing.

When batch size is larger than average demand, the bullwhip effect does not exist, or the variance of the order quantity is smaller than the variance of demand resulting in an anti-bullwhip or de-whip effect. From the managerial point of view, a de-whip effect means that the production planning phase at the manufacturer level becomes easier and more stable. The manufacturer prefers to smooth production, thus he prefers a smooth ordering pattern from the retailer. Bullwhip effect increases the variances in orders and destabilizes the production planning phase at the manufacturer level. When the variance of the order quantity is smaller than the variance of the demand (de-whip effect), the production manager can stabilize the production schedule and minimize the production cost.

6. Sensitivity analysis

System dynamics approaches typically involve four stages: model identification, verification, model testing, and policy design (Sterman, 2000). The purpose of model testing is to increase confidence in the model, leading to the acceptance of underlying dynamic results. Among the various model testing procedures, one commonly applied technique in system dynamics simulation is sensitivity analysis, which investigates the robustness of the model and determines the stability boundaries of the system. The above simulation results are based on a specific set of design parameters, i.e. $Ti = Tp = Tw = 6$, $Ta = 2Tp = 12$. There is the possibility that these results are particular to this combination of design parameters. Therefore, sensitivity analysis is carried out by changing the values of design parameters associated with the model in order to validate the above findings and to explore the stability and critical stability boundaries of the system.

The simulation results of the sensitivity analysis are shown in Figures 6-9. Increasing the values of Ti and Ta slows down the response of the APIOBPCS and decreases the bullwhip effect as pointed out by Disney and Towill (2003). With the small values of Ti, the feedback of the error in the inventory has a greater effect as $EINVt = (DINVt - AINVt)/Ti$ is larger, i.e. there is an increased gain in the loop

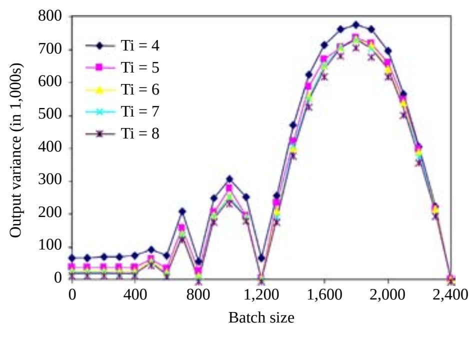

Figure 6.
Impact of Ti on bullwhip effect

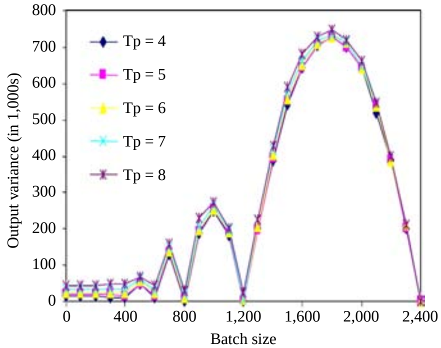

Figure 7.
Impact of Tp on bullwhip effect

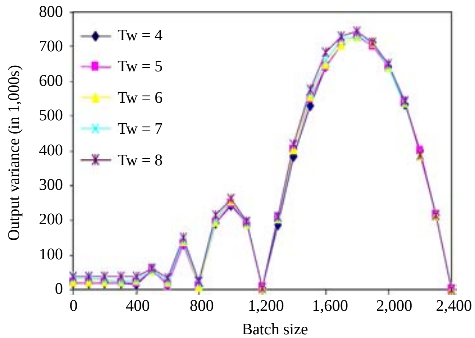

Figure 8.
Impact of Tw on bullwhip effect

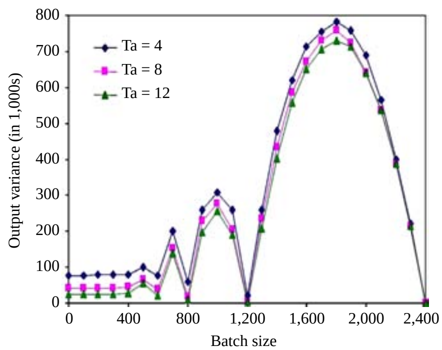

Figure 9.
Impact of Ta on bullwhip effect

and this provides an explanation for the over-reaction and bullwhip effect. If one considers the exponential smoothing, the noise or high-frequency component of demand is increasingly filtered out by increasing Ta but the smoother will be slower. If the smoother is made to respond faster by decreasing Ta, then the noise will not be so heavily smoothed and will result in bullwhip effect. This is quite logical because the noise and spikes in demand signals are smoothed into the order calculation and hence the output variance of the order rate decreases.

It is observed that reducing Tp minimizes the bullwhip effect and this result verifies the Time Compression Paradigm. However, when $Tp \leq 2$ the output of the farthest echelons starts decreasing. A possible explanation for this is that the system touches the stability boundaries. There is little effect of the Tw. Smaller values of Tw damp the peaks in the response of the ORATE providing an opportunity to reduce the demand amplification although the settling time is increased.

7. Summary

Batching is a clustering of items for purchasing, packaging, transportation, or manufacturing processes. The reasons for batch ordering include the EOQ, periodic inventory review, and transportation economies. Batch ordering often results in bullwhip effect, which has serious implications for whole supply chain. Burbridge (1981) emphasized reducing the batch size; the results presented here show that relationship between batch size and demand amplification is non-linear. When the quotient of the average demand and batch size is integer, demand amplification does not grow with increases in batch size. It has been proposed that if operations managers with large batch sizes monitor trends in average demand, they could anticipate movements up the curve of the output variance, i.e. high amplification, and subsequently plan to adjust the batch size to reduce this. If the batch size is increased beyond the average demand, then the output variance, i.e. the bullwhip effect, increases rapidly and linearly. A corollary to this is that if the demand starts to decrease below the batch size, then the bullwhip effect will grow rapidly. Again, operations managers could monitor for this condition.

It is further noted that the value of information sharing is greatest for smaller batch sizes, for which there is a much greater improvement in the amplification ratio when IEP changes from 0 to 100 percent. Whilst the amplification ratio beyond Tier 1 is much less for large batch sizes, making it a less significant problem, information sharing can almost eliminate any significant demand amplification. There is a dilemma here because information sharing will have a cost associated with its implementation, and whilst it may deal with the problem of demand amplification very well, the problem is primarily caused at Tier 1 with very large batch sizes. In contrast, information sharing is clearly of great value when the batch size is smaller. So, with the increasing drive to reduce batch sizes, there is an increasing justification for adopting and investing in information sharing. Batching is associated with the inventory holding and backlog cost. Therefore, future work should investigate the cost implications of order batching in multi-echelon supply chains.

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