Quantifying the impact of a supply chain's design parameters on the bullwhip effect using simulation and Taguchi design of experiments

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Abstract

Purpose – The purpose of this paper is to quantify the effect of design parameters on the bullwhip effect and dynamic responses produced by a multi-echelon supply chain with information sharing.

Design/methodology/approach – Taguchi design of experiments and system dynamics simulation are used to quantify the impact of a supply chain's design parameters, including degree of information sharing, on its dynamic performance, and the interactions that occur as the parameter values are varied.

Findings – Quantified relationships between supply chain design parameters and dynamic performance, including the bullwhip effect, are presented. Two parameters in particular, time to adjust inventory error and production lead time, are shown to have a particularly strong impact on the order variance compared to other parameters. However, there are several other significant findings.

Research limitations/implications – Batching and capacity constraints are common causes of the bullwhip effect, but they are not included here. Future work should quantify the impact of these.

Practical implications – This paper presents a systematic way for quantifying and understanding the impact of supply chain design parameters on the bullwhip effect and dynamic responses, and their interactions. The experimental results provide practical understanding for supply chain managers.

Originality/value – Previous studies have identified causes of the bullwhip effect but little attention has been given to quantifying their impact and interactions. This paper makes a contribution towards filling this gap, using system dynamics simulation and Taguchi design of experiments.

Keywords Supply chain dynamics, Taguchi, Bullwhip effect, Simulation, Supply chain management, Design, Taguchi methods

Paper type Research paper

1. Introduction

1.1 The bullwhip effect

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

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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 behaviours or misperceptions of feedback. Towill (1996) confirmed the findings of Forrester that reducing delays and collapsing all cycle times reduces the bullwhip effect. Lee *et al.* (1997) found that the bullwhip effect is caused by demand signal processing, order batching, 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. Hussain *et al.* (2012) has found that depending on the structure of the demand process, the appropriate selection of forecasting technique can reduce, or even eliminate the bullwhip effect.

To explain the bullwhip effect further, it can be described as the variance of the orders being larger than that of sales, with this distortion tending to increase as it moves upstream in the chain from retailer to manufacturer:

> 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 (Svensson, 2005).

Typical amplification ratios of 2:1 have been observed between two echelons (Towill, 1992), whilst amplification has been observed up to 20:1 between four echelons (Houlihan, 1987). Figure 1 shows a typical picture of demand amplification across four tiers of a supply chain.

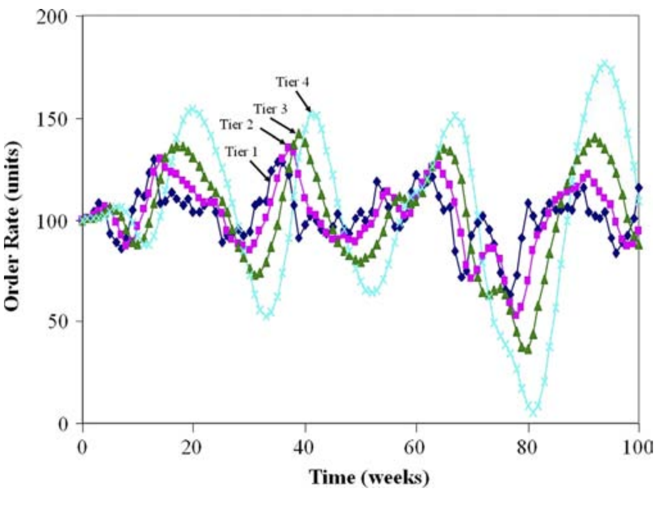

Figure 1.
Bullwhip effect in multi-echelon supply chain

The effects of demand amplification 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).

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; Moinzadeh, 2002; Kelepouris *et al.*, 2008; Agarwal *et al.*, 2009; Bottani *et al.*, 2010; Hussain and Drake, 2011). Whilst information sharing is frequently cited as being the key to reducing demand amplification, there has been little research to investigate the impact of information enrichment percentage on bullwhip effect. With full information enrichment a tier bases its order rate solely on end-customer demand, whilst with no information enrichment production is based solely on the incoming orders from the previous tier.

1.2 Review of APIOBPCS

Several supply chain models have been developed to study the causes of the bullwhip effect and their potential remedies and they continue to be the basis of much research; it is not feasible to conduct many experiments with a real supply chain. As these models grow in complexity due to increasing the detail at each tier and the number of tiers, there are a large number of parameters to be experimented with to understand their effects and interactions and to gain a sense of "best" values. One of the most commonly studied periodic review models in the supply chain literature is the "Beer Game". 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.

Towill (1982) introduced 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 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 work in progress (WIP) error.

This is the "Automatic Pipeline Inventory and Order Based Production Control System" (APIOBPCS) (John *et al.*, 1994), which is used in this paper to model the individual tiers of a supply chain.

In the model used here (APIOBPCS) there are five control or design parameters at each echelon. These five design parameters have been identified as the possible determinants of the bullwhip effect (Shang *et al.*, 2004; Paik and Bagchi, 2007) and this study quantifies their impact on bullwhip effect. Table I presents a brief definition of these parameters and a description of them is given in Section 4.1.

One of the approaches to studying the performance of a multi-echelon supply chain model is the control theoretic approach as reviewed by Ortega and Lin (2004) and for an example see Disney and Towill (2002). However, Riddalls *et al.* (2000) pointed out that differential equations produce a smooth output that is not suitable for the modeling of all supply chains. Even if the control theorists are able to write differential equations on the dynamic behaviour of the model, in many cases these differential equations cannot be integrated. Instead the control theorists resort to a numerical approach, usually with the help of computer simulation (Pidd, 2004). Furthermore, direct mathematical and control theoretic approaches can require an academically advanced understanding of mathematics that most supply chain operations managers do not have (Agaran *et al.*, 2007). In contrast, the use of simulation methods involving simple equations can help practitioners to understand the basic phenomena and to analyse the effects of supply chain design parameters and the interactions that occur between them, and then to search for good combinations of parameter values. Shukla *et al.* (2009) also present an argument for using a simulation rather than a control theoretic approach. Therefore, system dynamics simulation has been applied in this research to study the bullwhip effect.

1.3 Rationale of the research

Paik and Bagchi (2007) mention that literature has identified several causes of the bullwhip effect but little attention has been given to measuring quantitatively the impact of these causes on the bullwhip effect. Further, supply chains consisting of many interacting factors are difficult to optimize (Holweg and Disney, 2005) and little research has been carried out to identify "optimal" or "good practice" values and relationships among the different design parameters of supply chains. This papers addresses this gap using a multi-echelon supply chain simulation model. It explores the impact of design parameters, particularly the degree of information sharing, on the dynamic response of the supply chain.

Some studies changed the value of one supply chain design parameter at a time and measured its effect on demand amplification. This "one-at-a time" methodology reveals the effect of one factor with one specific set of values for the other factors, but does not

Table I.
Description of parameters

Parameters	Abbreviation
Information enrichment percentage	IEP
Production or transportation delay	Tp
Time to average sales (smoothing constant)	Ta
Time to adjust inventory	Ti
Time to adjust WIP	Tw

provide the information for calculating or understanding the effect of the factor across a range of values for the other factors, i.e. the effect in general. A more appropriate methodology is to use experiments designed using "Taguchi's Orthogonal Arrays" in which levels of each factor are systematically varied across a range of values and all possible combinations of factor levels (parameter values) are considered, but without having to test every combination. Furthermore, this methodology can be used to measure quantitatively the effects of the design parameters on demand amplification, explore the interactions among the parameters and identify the "best" or at least "good" combinations of parameter values for mitigating the impact of demand amplification. Authors such as Dellino *et al.* (2010), Shukla *et al.* (2010) and Tiwari *et al.* (2010) have also applied Taguchi design of experiments successfully in the optimization of supply chains.

The structure of this paper is as follows. Section 2 introduces the methodology. Section 3 discusses the supply chain simulation model. An initial analysis of the impact of the design parameters on the dynamics of the inventory levels and order rates is presented in Section 4. Section 5 introduces the orthogonal arrays (OA) technique to explore the impact of various levels of the design parameters and the interactions between them on a measure of the bullwhip effect. Section 6 offers some concluding remarks.

2. 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 (Shukla *et al.*, 2009). 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. 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 – see Figure 2.

The use of other systems dynamics modeling and simulation packages has been reported in the literature, for example Wangphanich *et al.* (2010) used Vensim® recently.

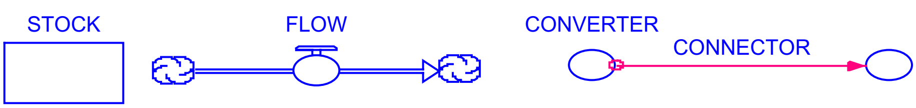

Figure 2.
Building blocks of *iThink* software

Discrete event simulation packages such as Arena® (Shang *et al.*, 2004) and Simul8® (Bottani and Montanari, 2010) have also been used recently. This paper makes no comment on the commercially sensitive issue of the relative merits of individual software packages. However, it should be possible to replicate the experiments presented here in most of these environments.

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). As the dynamics of the inventory and order rate at the fourth echelon present the "worst-case" scenario, the bullwhip effect experienced at this echelon is studied here. Taguchi design of experiments and analysis of variance (ANOVA) techniques are used to analyse quantitatively this effect with respect to the supply chain's design parameters. As the APIOBPCS design parameter values are varied, the same values are applied at all echelons in the supply chain as in previous studies (Mason-Jones and Towill, 1997; Coppini *et al.*, 2010).

3. Multi-echelon supply chain model

Figure 3 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 (from the direction of the market). 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 work-in-progress, 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, like Disney and Towill (2003), $DINV^n$ is kept constant and equal to original demand. The work-in-progress (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 ($IEP = 100$ 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)% 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 (Mason-Jones and Towill, 1997; Coppini *et al.*, 2010; Shukla *et al.*, 2009). In *iThink*® the built-in function *SMTH1*

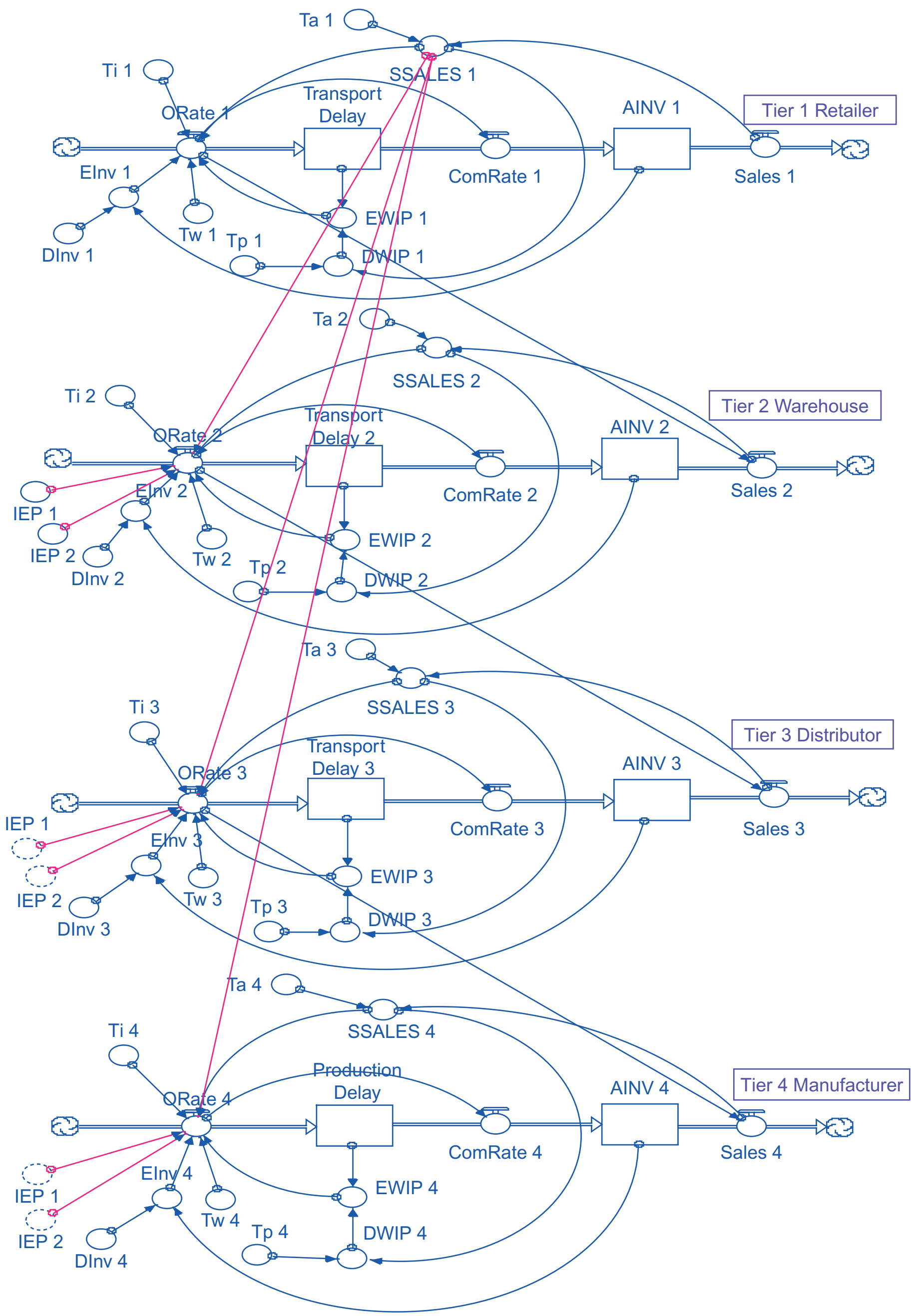

Figure 3.
iThink model of information enriched multi-echelon supply chain

calculates the first-order exponentially-smoothed value, with the smoothing constant (Ta) representing the time to average sales and the average age of data in the forecast. The value of Ta determines the degree of smoothing applied to the demand. Decreasing Ta produces "lighter" smoothing, so that the higher-frequency or "noise" components of the demand signal are allowed through, and vice versa.

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

In summary, at echelon n:

$$\text{for } \mathrm{n}=1: SALES_t^1 = \text{the actual end-customer demand data} \tag{1}$$

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

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

$$\begin{aligned}\text{for } \mathrm{n}>1: ORATE_t^n = {} & IEP^n \times SSALES_t^1 + (100\% - IEP^n) \times SSALES_t^n \\ & + EINV_t^n/Ti^n + EWIP_t^n/Tw^n\end{aligned} \tag{4}$$

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

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

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

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

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

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

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

4. Initial analysis of effects of parameters

4.1 The design parameters

In the model used here there are five control or design parameters at each echelon:

(1) Information enrichment percentage (*IEP*).

(2) Time to adjust inventory (Ti).

(3) Time to adjust WIP (Tw).

(4) Production (or pipeline) delay (Tp).

(5) Time to average sales (Ta) (exponential smoothing constant).

In the initial simulations $Tp = 6$ units of time, as in the work of Riddalls and Bennett (2002) and Hussain and Drake (2011) and levels around this value are chosen in the Taguchi design of experiments.

Initially, the effect of the parameters is examined by observing the response of the order rate and inventory to a step change in demand from 100 to 120 per unit of time, with the initial conditions corresponding to a steady state of 100. Figures 4 and 5 show the effect on the response at the fourth tier of varying Ta with $Ti = Tw = 6$ and $IEP = 100$ percent. Figure 5 shows that when Ta decreases the response (recovery) is quicker; displaying a reduced peak deficit, rise time and settling time. However, decreasing Ta produces "lighter" smoothing, so that the higher-frequency or "noisy"

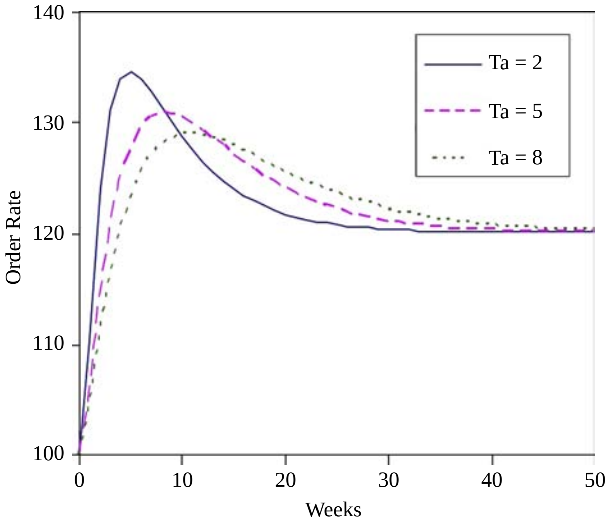

Figure 4.
Impact of Ta on order rate

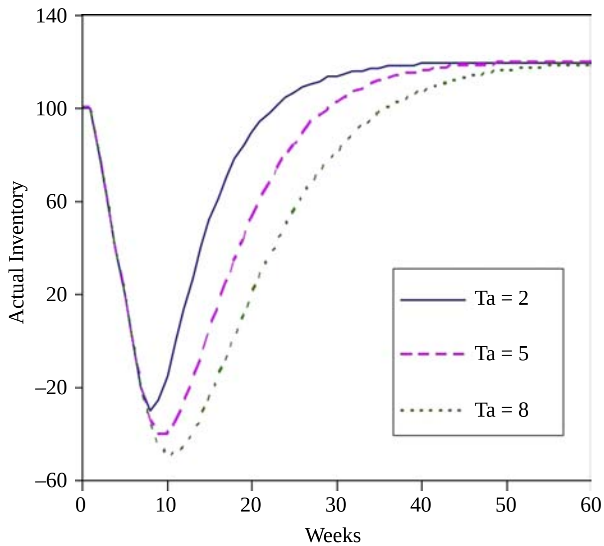

Figure 5.
Impact of Ta on inventory

components of the demand signal are allowed through. Figure 4 shows that when Ta increases, the rise time and the settling time of the order rate increase, but the magnitude of the overshoot or peak-value decreases. This illustrates the general system dynamics compromise between speed of response and the size of overshoots or over-reactions; a fundamental, control compromise that production managers should be aware of.

Five different levels of *IEP* (0, 25, 50, 75, and 100 percent) have been simulated. The simulation results in Figures 6 and 7 show information sharing damps the peaks in the responses, whilst effectively matching settling times. The effect on $ORATE_t^n$ would be most beneficial to a manufacturing business, as the very large fluctuations in $ORATE_t^n$ seen without information sharing would be highly destructive and costly to satisfy. The cost of improving $ORATE_t^n$ is the damping of the inventory response. Whilst the large reduction in the peak inventory deficit is a good thing, there is a much

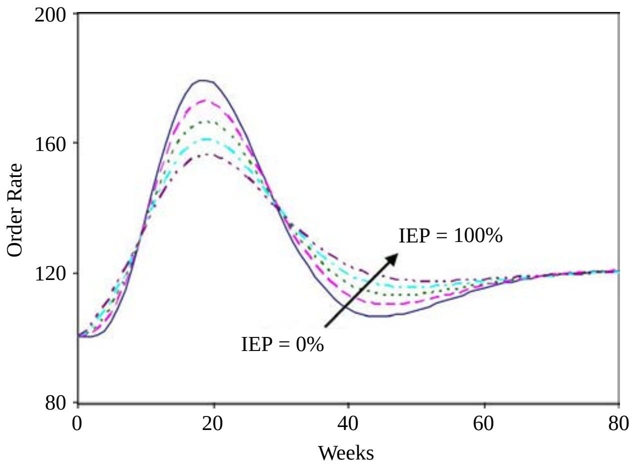

Figure 6.
Impact of information sharing on order rate

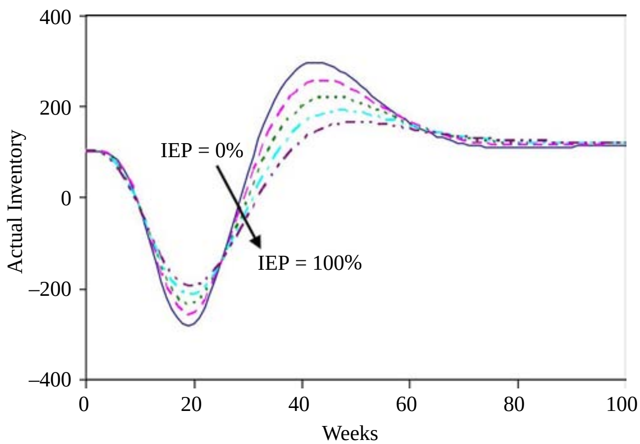

Figure 7.
Impact of information sharing on inventory

longer time to replenish the inventory up to the desired level, causing a much greater period during which there is a risk of stock-out if any other surges in demand or other supply problems occur.

Figures 6 and 7 suggest that a compromise may be the best solution. In particular, when $IEP = 75$ percent, the inventory response is much faster, whilst retaining the benefit of a greatly reduced peak deficit and only a small overshoot beyond the desired level. Finding $IEP = 75$ percent preferable agrees with the results of Mason-Jones and Towill (1997). So in the Taguchi design of experiments presented below, the *IEP* levels are chosen around 75 percent. The second value chosen is 100 percent, to test basing production on end-customer sales alone. The third value chosen is 50 percent, to keep a constant difference between the levels, i.e. a linear increase, to simplify the statistical analysis.

To verify the *iThink*® model, the difference equations (1)-(11) were also implemented in a spreadsheet model. This produced results that agreed with the *iThink*® results.

4.2 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):

$$\text{Bullwhip} = (\sigma_{ORATE^2}/\mu_{ORATE})/(\sigma_{SALES^2}/\mu_{SALES}) \tag{12}$$

σ_{ORATE^2} and μ_{ORATE} are the unconditional variance and mean, respectively, of *ORATE* at the tier of the supply chain being measured; the example presented in this paper being the fourth tier. σ_{SALES^2} 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):

$$\text{Bullwhip} = \sigma_{ORATE^2}/\sigma_{SALES^2} \tag{13}$$

5. Taguchi design of experiments

5.1 Introduction

The Taguchi approach is used to identify the effects of different levels of the design parameters on the measure of the bullwhip effect, the interactions that occur and ultimately the best values. Taguchi recommended a three stage process: system design, parameter design, and tolerance design. In this paper, Taguchi's parameter design technique is applied. Taguchi argues that parameter design increases system robustness, reduces experimental cost and improves quality. Parameter design creates fractional factorial designs using OA of parameter value levels. Changing only one factor at a time cannot detect interaction effects (Anderson and Whitcomb, 2004), whereas fractional factorial design enables the experimenter to investigate the effect of each parameter (main effect), to determine whether parameters interact, and to evolve a robust design (Khumwan and Pichitlamken, 2007). The aim of the robust design technique is to minimize the variance of the response. OA of parameter levels determine the simulation experiments run to evaluate the relative effects of parameter values on supply chains with the minimum number of experiments. Figure 8 outlines the Taguchi method applied here.

The first step in the parameter design technique is to select parameters and their suitable levels. The second step is to choose the *OA* to be used in the design of experiments. The choice of OA size depends on the total degrees of freedom (*DoF*) required for the parameters. In this study, the DoF for five control factors with three levels is $5 \times (3-1)+1=11$. The $\mathbf{L}_{18}$ (3^5) OA in Table III, which can be used for one two-level factor and up-to seven three-level factors, is appropriate for this study. In this array, the columns are mutually orthogonal. That is, for any pair of columns, all combinations of parameter levels occur an equal number of times. The benefit of three level experiments is that they decompose the main effect into linear and quadratic effects, which allows non-linear effects caused by the design parameters to be taken into consideration (Roy, 2001). The factor levels used in the experiments reported here are given in Table II.

The third step is the selection of quality characteristics of which there are three types in Taguchi methods; "smaller-the-better, larger-the-better," and "nominal-the-best" (Roy, 2001). As the aim is to minimize demand amplification by exploring the best parameter levels, the "smaller-the-better" quality characteristic is used here.

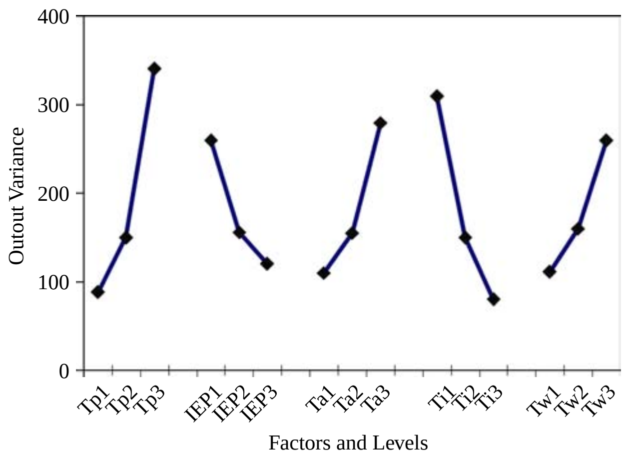

Figure 8.
Outline of Taguchi method applied

Table II.
Factors and level

Factor	Level 1	Level 2	Level 3
Production (pipeline) delay (Tp)	4	8	12
Information enrichment percentage (IEP) (percent)	50	75	100
Time to average sales (Ta)	2	5	8
Time to adjust inventory (Ti)	4	8	12
Time to adjust WIP (Tw)	4	8	12

The fourth step is to run simulation experiments according to the combination of design parameters given in Table III. To analyze the results of experiments designed with OA many approaches have been used (Tsai, 2002). One commonly used approach involves graphing the effects and the interactions among the parameters and visually identifying the significant factors and interactions (Vlachogiannis *et al.*, 2005). This technique involves the average values and is used in this study. To discover which effects are statistically significant, ANOVA is performed to quantify the contribution of each parameter to the total variation in the experimental data. The analysis of the results obtained with the $\mathbf{L}_{18}$ arrays is given in the following sections. The final step in the Taguchi approach applied in this study is to run the confirmatory test.

5.2 Calculation of main effects

A normally distributed, stochastic demand pattern with a known mean of 100 and standard deviation of 20 per unit of time is considered. Simulation is run for 500 units of time for each condition. Following Reddy and Rajendran (2005), replication is carried out for 50 simulation runs and averages of the results are taken. The effect of a design parameter on the measured response when the parameter's value is changed from one level to another is known as a "main effect" and is calculated for a particular level of a factor by examining the OA, the factor assignment, and the experimental results (Roy, 2001). For example, to calculate the average effect of information sharing at Level 1 ($IEP = 50$ percent), all the results for *IEP* at Level 1 are averaged.

Figure 9 shows the sensitivity of the bullwhip effect measurement to changes in the parameter values across the experimental values in Table III. It is most sensitive to *Ti*, and *Tp* is the next most significant factor. Smaller values of *Ti* produce over-reaction and oscillatory behaviour that results in higher production costs, higher inventory costs and poorer customer service. Forrester (1961) also proposed not to recover the "error of inventory position" in one time period. Instead, recovery should be spread

Experimental run	Tp	IEP	Ta	Ti	Tw
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	2	1	1	2	2
5	2	2	2	3	3
6	2	3	3	1	1
7	3	1	2	1	3
8	3	2	3	2	1
9	3	3	1	3	2
10	1	1	3	3	2
11	1	2	1	1	3
12	1	3	2	2	1
13	2	1	2	3	1
14	2	2	3	1	2
15	2	3	1	2	3
16	3	1	3	2	3
17	3	2	1	3	1
18	3	3	2	1	2

Table III.
Inner arrays (*L*18)

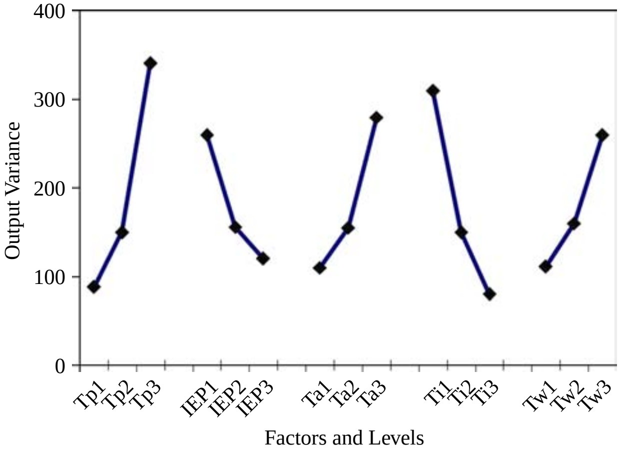

Figure 9.
The plot of main effect response

over time by ordering only a fraction of the inventory deficit. Suitable values of *Ti* not only ensure stability but also determine the capacity requirements; with larger values of *Ti* less capacity is effectively required to satisfy an increase in demand. It is observed that reducing *Tp* minimizes the bullwhip effect and this result verifies the time compression paradigm and the importance of compressing *Tp* to reduce demand amplification as highlighted by Forrester and, for example, Towill (1996).

The third highest level of sensitivity is seen with *IEP*. A notable finding is that increasing the information enrichment percentage to 100 percent reduces the bullwhip measure used here; there is no optimum around 75 percent as intimated earlier and in the work of Mason-Jones and Towill (1997).

Smaller *Ta* values are highly responsive to recent changes in underlying demand pattern, amplifying the demand, whilst larger values produce smoother ordering. Increasing *Ta* increases the damping effect of the exponential smoother, so it is not totally surprising that it also reduces the bullwhip effect. The least sensitivity is seen with *Tw*. Larger values of *Tw* increase the peak overshoot of the order rate but decrease the recovery time. On the other hand, smaller values of *Tw* dampen the peaks in the response of the order rate, but increase the settling time. However, smaller *Tw* values provide an opportunity to reduce the demand amplification.

5.3 Calculation of interaction effects

Interaction here refers to the effect of a particular parameter value changing as the values of the other parameters change. The number of two factor interactions possible among k factors is $k(k-1)/2$ (Roy, 2001). In this experiment of five factors, the number of possible interactions is $5(5-1)/2 = 10$. Simple but powerful "interaction graphs" (Figures 10-13) are used to determine the severity of the interactions between control parameters. If the lines in the graph are parallel there is no interaction between the parameters, whilst non-parallel lines indicate interaction with intersecting lines indicating strong interaction (Antony, 2001).

"Interaction plots" are obtained by graphing the combined effects of the pairs of the factors studied. So, to test for the presence of interaction between *IEP* and *Ta*, the average effects of *IEP1* with *Ta1*, *IEP1* with *Ta2*, *IEP1* with *Ta3*, *IEP2* with *Ta1*, *IEP2*

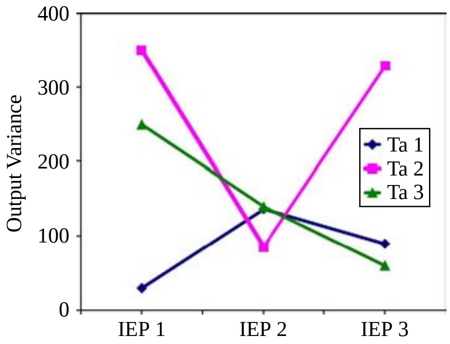

Figure 10.
Interaction between IEP and Ta

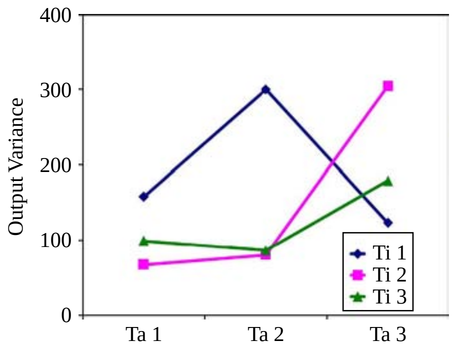

Figure 11.
Interaction between Ta and Ti

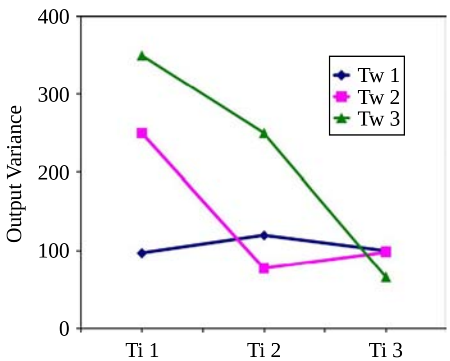

Figure 12.
Interaction between Ti and Tw

with *Ta2*, *IEP2* with *Ta3*, *IEP3* with *Ta1*, *IEP3* with *Ta2* and *IEP3* with *Ta3* need to be calculated. For example, the average effect of *IEP1* with *Ta1* is obtained by averaging the results of experimental runs that contain both *IEP1* and *Ta1*. Four important interactions are observed in this analysis. Figure 10 shows the strong interaction between *IEP* and *Ta*; the value of information sharing is affected significantly by the forecasting error generated due to inaccurate forecasts. Without information sharing the demand amplification increases considerably as *Ta* is reduced,

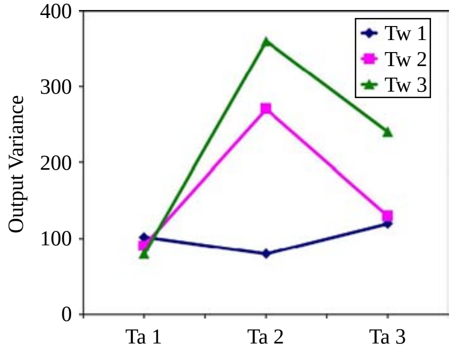

Figure 13.
Interaction between Ta and Tw

and then the smaller *Ta* (with the much higher amplification to start with) benefits most from information sharing, indeed it benefits considerably. The next most significant interaction occurs between *Ti* and *Ta* as shown in Figure 11. Smaller values of both *Ti* and *Ta* are highly responsive to changes in underlying demand while larger values yield much smoother ordering. A third important interaction is observed between *Ti* and *Tw* as shown in Figure 12. Smaller values of *Ti* yield quicker responses but poor filtering properties and smaller values of *Tw* result in larger settling times. Figure 13 shows the small interaction between *Ta* and *Tw*.

5.4 Analysis of variance

To discover which effects are statistically significant, ANOVA is performed to quantify the contribution of each parameter to the total variation in the measure of the bullwhip effect. The ANOVA results in Table IV show that all the factors involved in this study are statistically significant at the 95 percent confidence level. However, *Ti* clearly makes the largest contribution to the variation, with a contribution of 37 percent and next is *Tp* at 27 percent, so that these two parameters account for 64 percent of the total variance. This means that demand amplification at the farthest upstream echelon can be reduced greatly by fine-tuning the gain of the inventory error (*Ti*) and reducing delays (*Tp*). The percentage contribution of the remaining three parameters is much smaller. The *F*-ratios can also be used to see the relative significance of the parameters.

Table IV.
Results of ANOVA

Factors	DOF	Sum of squares	Variance	*F*-ratios	Pure sum	(%)
Production delay (Tp)	2	187,016	93,508	117	185,412	27
Information enrichment percentage (IEP)	2	103,297	51,649	64	101,694	14
Time to average sales (Ta)	2	83,875	41,937	52	82,271	12
Time to adjust inventory (Ti)	2	256,454	28,227	160	254,850	37
Time to adjust WIP (Tw)	2	69,063	34,532	43	67,460	9
Error	7	5,612	802			1
Total	17	705,317				100

5.5 Determining the best parameter values

It should be noted that *Tp*, the production lead time, is not strictly speaking a control system design parameter to be optimized at will. It is instead a parameter of the system under control, although a company could choose to reduce *Tp* through investment in resources and improved operations management. Nevertheless, *Tp* is included in this analysis so that its effect can be understood along with the interactions it has with the control parameters.

The "best" parameter levels within the range of values considered here are given in Table V; this is in the context of minimizing the stated measure of the bullwhip effect. It is seen that *Tp* should be made as small as possible, which verifies the value of the time compression paradigm for reducing bullwhip as seen in the literature. According to the bullwhip measure, 100 percent information enrichment is preferred. This is contrary to the initial analysis of the step response and the results of Mason-Jones and Towill (1997). This suggests that further study of how the bullwhip effect should be measured is required. The result supports the use of a small *Ta* and *Tw*, which will give faster responses to change, whilst the largest *Ti* should be used to control excessively large fluctuations in $ORATE_t^n$ by damping the reaction to errors in the inventory.

However, it should be noted that the "best" set of parameters with respect to demand amplification, as measured by the output variance, is not necessarily the best set of parameters overall. There are compromises to be made between conflicting characteristics of the dynamic responses. So, the set of parameter values presented here is not being portrayed as definitively the best, but rather a demonstration of what might be done in a specific application using Taguchi design of experiments. The work presented can also serve as a summary guide to how demand amplification can be controlled by varying parameter settings.

6. Discussion and conclusion

This paper has demonstrated the use of simulation combined with Taguchi design of experiments to quantify the effects of design parameters and information sharing in controlling the bullwhip effect. Previous studies have paid little attention to measuring the impact of supply chain design parameters on the bullwhip effect. This paper has contributed towards addressing this gap by quantifying the effects of the design parameters, and their interactions, in the APIOBPCS supply chain model.

It has been seen that as the percentage of information enrichment increases, the amplification and response time of the order rate decreases, and in terms of reducing the bullwhip effect, 100 percent enrichment is preferred. In contrast, Mason-Jones and Towill (1997) found that $IEP = 75$ percent provides the best compromise between reducing bullwhip and improving speed of dynamic response. Their findings are based

Factors	Level	Level description
Production (pipeline) delay (Tp)	4	1
Information enrichment percentage (IEP)	100 percent	3
Time to average sales (Ta)	2	1
Time to adjust inventory (Ti)	12	3
Time to adjust WIP (Tw)	4	1

Table V. Factors at optimal condition on a supply chain model with no capacity constraints. However, in reality production and distribution will be constrained, so it might not be possible to increase activity levels sufficiently to cope with peak demand; even if it is possible the cost could be prohibitively high. The overshoot of the order rate determines the capacity requirements – the greater the overshoot the more capacity is needed. So when capacity is constrained, increasing the percentage of information enrichment ($IEP = 100$ percent) to further dampen the magnitude of the order rate overshoot makes sense.

In the Beer Game model studied here, the objectives are to minimize the backlog and the holding cost of the inventory (Sterman, 1989). Backlog typically costs twice as much as the holding cost and sometimes as much as ten times. The peak of the deficit and the recovery time determines the backlog cost and the maximum deficit of the inventory determines the safety stock requirements (Disney *et al.*, 2006). A bigger deficit requires more safety stock to maintain the desired customer service level. It has been seen that 100 percent information enrichment reduces the peak deficit of the inventory and makes recovery quicker. Hence, in terms of safety stock reduction and the minimization of the backlog cost, 100 percent enrichment is preferred. Information enrichment reduces the surplus inventory level by damping the peaks of the overshoot of the inventory. As surplus inventory adds to the holding cost, 100 percent enrichment is recommended to reduce the holding cost.

The downside of information sharing is that it increases the rise time of the inventory. Rise time determines the stock-out period and affects the customer service level. Whilst a large reduction in the peak inventory deficit is a good thing, there is a longer rise time to replenish the inventory up to the desired level, causing a longer period during which there is a risk of stock-out if there are any other increases in demand or other supply problems. In general, the 75 percent enriched model performs best for the rise time of the inventory as found by Mason-Jones and Towill (1997), but this is not a strict rule that can be applied in every supply chain, because in some situations the damping of the undershoot and overshoot levels and quicker recovery are more important than the rise time.

This paper has demonstrated the use of simulation combined with Taguchi design of experiments to quantify the effects of design parameters and information sharing in controlling the bullwhip effect in supply chains. A systematic approach to gaining an understanding of the relative contributions of the supply chain's design parameters and the interactions between them has been presented as an aid to supply chain designers and managers. The sensitivity of the bullwhip effect to parameters of the APIOBPCS has been analyzed with significant sensitivity being found in all cases, but to varying degrees. It has been found that Ti and Tp contribute nearly two-thirds (64 percent) of the total variance, suggesting supply chain managers can greatly reduce demand amplification at the higher upstream echelons by fine-tuning the gain of the inventory error (Ti) and reducing delays (Tp). It is observed that reducing Tp minimizes the bullwhip effect and this result verifies the "Time Compression Paradigm." If exponential smoothing is used, 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 cause bullwhip.

The interactions between parameters in respect of their effect on demand amplification have been analyzed. The strongest interaction is seen in the beneficial impact of information sharing on demand amplification being dependent upon the forecasting parameter (*Ta*). The value of information sharing is affected significantly by the forecasting error generated due to inaccurate forecasts. This is quite logical. Hussain *et al.* (2012) found that "depending on the structure of the demand process, the appropriate selection of forecasting technique can reduce, or even eliminate the bullwhip effect". Selection of inaccurate forecasting methods by managers will increase forecasting error and reduce the beneficial impact of information sharing on controlling the bullwhip effect.

The next most significant interaction occurs between *Ti* and *Ta*. Smaller values of both *Ti* and *Ta* are highly responsive to changes in underlying demand while larger values yield much smoother ordering. A third important interaction is observed between *Ti* and *Tw* and a fourth between *Ta* and *Tw*.

Multi-echelon supply chains consist of many interacting parameters at each echelon, such as forecasting constants, lead time, and times to adjust errors in the inventory and WIP. The design parameters have strong interactions; changing the value of one parameter will lead to changes in the effects of another. This implies that managers need to have a clear understanding of these interactions and to consider them when changing parameter values and otherwise making decisions.

This study paves the way for more detailed studies into controlling the bullwhip effect and to extending the supply chain model to incorporate capacity constraints and order batching, as these are known to be further causes of demand amplification. As Taguchi's OA are not efficient for analyzing the interactions among parameters (Montgomery, 2001), the "Response Surface Methodology" will be used in future work to explore these interactions.

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