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Strategic Positioning of the Push-Pull Boundary within a Supply Chain: An Ordering Policy Co-ordination Perspective

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Abstract

The rapid advancement in IT communication enables the availability of demand data in a seamless manner. One manifestation of this technological advancement within the supply chain (SC) domain has been the emergence of a push-pull boundary (PPB). Push-pull boundary is a virtual demarcation point separating the portion of the SC under decentralized from that operating under centralized information sharing. However, the impact of key issues like adoption of inventory ordering policy characterized by the various echelons of a SC network structure while positioning the push-pull boundary need to be investigated comprehensively (Ahn and Kaminsky, 2005). This paper is concerned with the '*Average Fill Rate*' and '*Average Total Inventory Cost*' performance behaviour of a SC network structure. These performances typically results from different parameters that involves: (i) inventory ordering policy, (ii) push-pull boundary under the influence of information sharing, (iii) forecasting error, and (iv) lead time and their standard deviations. The study is accomplished via Taguchi experimental design framework and simulation analysis. The results suggest the effect of various factors on SC network system wide performance and identify the appropriate combinations of these factors for optimal performance concerned.

Keywords: *supply chain, push-pull boundary, information sharing, discrete event simulation, Taguchi experimental design, average fill rates, average inventory levels*

1. Introduction

The aim of supply chains is to create agile groups of independent but cooperating companies able to reduce costs and increase their competitiveness on the market (Chandra and Chilov, 2001). For a supply chain to be responsive, the coordinated management of all the participating elements is essential. Supply chain management (SCM), therefore, implies the organization of several industrial nodes, called to work in a collaborative environment, share common objectives, information and plans (Cachon and Fisher, 2000).

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Increasingly, customers' needs have become highly focused. In this endeavour, manufacturing organizations have universally acknowledged the pivotal role played by their supply chain networks (SCNs). Furthermore, there is a need to build-in flexibility within the SCN to ensure the reconfigurability – a primary requirement when developing '*leagile*' supply chain systems. In such systems, the *lean* and *agile* paradigms are combined within a total supply chain strategy (Naylor *et al.*, 1999) by appropriately positioning the '*push-pull boundary*' (PPB) so as to best suit the supply chain's need for responsiveness to the extant environmental dynamics. Yang and Burns (2003) stressed the need for an efficient positioning of the PPB in an SCN, given the significant role it plays in the context of information sharing within a supply chain. However, how far the upstream of a supply chain information should be shared, is an issue which is at best in a stage of adolescence (Van Hoek, 2000). Towards this end, in this paper we focus on the customer responsive aspect. More specifically, we use the '*average fill rates*' as a surrogate measure of responsiveness, whilst simultaneously acknowledging its relevance in the context of information sharing initiative based on the premise that the *higher* fill rates would be the natural result of the greater transparency afforded by information sharing schemes. However, the high fill rates come at a price: average inventory levels must go up in order to guarantee the lower stockouts needed to ensure the high levels of customer responsiveness. In view of this, we used another measure of performance: '*average total inventory cost*' that comprises *average procurement cost* and *average carrying cost*.

Further, the deployment of differing inventory monitoring policies has been the suggested measure by various researchers to enhance the performance (Beamon and Chen, 2001, Olhager and Persson 2006, Jammernegg and Reiner 2007). Keeping this in view, we consider *inventory ordering policy* as a factor to analyze. The other factors considered are "Push-Pull Boundary level", "Forecasting Error", "Lead Time and their Standard Deviation" and "Customer Demand". Importantly, it is noted here that several researchers have observed that a prime objective in pursuing an information sharing policy is to control the uncertainties arising from lead time and its standard deviations (Beamon and Chen, 2001; Hwarng *et al.*, 2005; Zanoni *et al.*, 2006; Aigbedo, 2007). Hence, we intentionally included lead times and their standard deviations as a factors in our experimental setup. Our motivation in conducting this research is to investigate the relative impact of different experimental factors on the *average fill rate* and *average total Inventory cost* performance measure over the complete supply chain (from the manufacturer end through to the retailer end) for assumed SC network configurations.

In the context of the push-pull boundary (PPB), researchers have oftentimes interwoven the words 'postponement' and 'mass customization'. PPB is used to increase the efficiency and effectiveness of the supply chain. It provides the ability of ensuring individually designed products and services to every customer, and is thus a prime enabler of mass customization. In business processes, PPB has also been used to offset uncertainty and improve supply chain integration. The recent past has witnessed a mushrooming growth in research articles on mass customization and postponement. In context of postponement, Lee and Billington (1993) posited that postponement promotes enterprise flexibility to satisfy the need of quick response. Ernst and Kamrad (2000) evaluated different supply chain structures (rigid, modularized, postponed and flexible) based upon different degrees of modularization and postponement. Dong (2001) states that process restructuring can be achieved by postponing an operation downstream. When postponement penetrates deeper into the value chain it improves SC strategic performance. Skipworth and Harrison (2006) studied the application of Form postponement in a manufacturer of industrial electric motors. Contrary to the basics of moving the PPB point closer to the end user, they suggest that it is better to locate the PPB further upstream in the manufacturing process. Aigbedo (2007) assessed the effect of mass customization strategies on the inventory level of a supplier in an endeavour to prevent stock-outs. The author suggested that as the level of mass customization increases, the supplier's inventory levels must commensurately increase in order to prevent stock-outs.

The reduction in inventory levels curtails inventory carrying cost, but this is usually achieved at the expense of lowered fill rates. Effective replenishment policies ensure that service levels remain high but costs are kept low. Replenishment policies adopted by various researchers in their respective studies includes (Reddy and Rajendran, 2005; Olhager and Persson, 2006; Jammernegg and Reiner, 2007). Ahn and Kaminsky (2005) emphasize the need to develop approaches that manage the coordination of production and inventory policy systems under the prevalence of push-pull boundary.

Pawlak and Małyszek (2008) suggested that the companies should collaborate with other chain components in order to choose appropriate *inventory control policies*. Further they emphasize that companies which try to reduce their inventory costs independently must realize that policies used by other chain components can be changed and there is a high risk of failure when they select policies in isolation from others. Hidayat *et al.* (2011) proposed a mathematical model for optimal replenishment quantity under coordination with partner considering demand uncertainty, inventory costs versus lead time crashing cost in a multi-echelon supply chain system.

From the above discussion, it is apparent that information sharing in supply chains is often exploited to enhance the performance of SC systems. However, we find sparse evidence of research within which different inventory ordering policies addressing the penetration of push-pull boundary upstream under the premise of information sharing. In pursuance of the above, we adopt Taguchi's experimental design framework (Phadke, 1989) for conducting the simulation study. Taguchi's experimental design procedure provides a convenient framework for establishing both, the relative factor effects, as well as the significance of the assumed experimental factors. To use Taguchi's orthogonal experimentation procedure, additivity of experimental factor effects is assumed. In order to justify the validity of this assumption (*i.e.*, to disprove the presence of significant interaction affects), a verification experiment needs to be carried out with the optimal factor combination (which is the outcome of the orthogonal experiment).

More specifically, the objectives of the present paper are:

- To determine the significance of the impact of the parameters considered;
- To determine the relative impact of the parameters (in terms of their main factors effects) on the assumed performance measures;
- To determine appropriate combinations of parameter for optimal SC performance.

The paper is organized as follows. Section 2 describes the configuration details for the assumed SC network configuration. Section 3 details the inventory control procedure utilized in the study and also dwells on the information sharing mechanism adopted. Simulation experiment details appear in Section 4, while in Section 5 we present details for the matrix experiment conducted based on the Taguchi design framework. In Section 6 we present details for the matrix experiment conducted based on the Taguchi design framework of Section 5. Also discussed are the results for the *analysis of the means* and *analysis of variance* for each assumed performance measure. In Section 7 we present the additivity experiment details and results for each matrix experiment conducted. We discuss the insights of the results in Section 8. Finally, Section 9 concludes the paper.

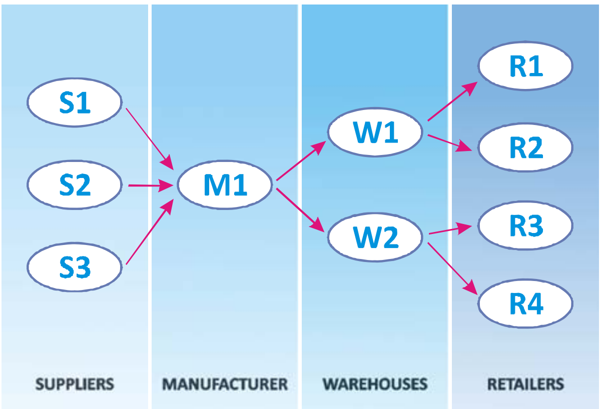
2. Hypothetical Supply Chain Network Description

Our study system is assumed to operate in a discrete manner, given that the activities within a typical supply chain system, including order fulfillment, inventory replenishment and product delivery, are either triggered by customers' orders or the arrival of the shipments from the suppliers at discrete instants in time. The operational performance of a hypothetical supply chain network structure shown in Figure 1 comprises of four partnering echelons.

We assume three suppliers that supply sub-assemblies to a downstream manufacturer with normally distributed supply lead times. The manufacturer in turn, assembles the finished product using the sub-assemblies received from the suppliers in a constant duration of time. Without loss of generality, it is assumed that the manufacturing operation is accomplished without breakdowns. The next echelon comprises of two warehouses to which the finished product is sent, again with normally distributed lead times.

We assume that Warehouse 1 (W1) fulfills the demands of Retailers 1 and 2 (R1 & R2), while Warehouse 2 (W2) caters to the demands of Retailers 3 and 4 (R3 & R4), respectively. Further, each of the four distinct retailers experience different demand

Figure 1: Hypothetical Supply Chain Network Structure



patterns, each of which are exponentially distributed with differing parameters. Importantly, the retailers comprise the only echelon that experience external demand; accordingly, all customer orders are placed at these retail outlets alone and must be satisfied at the said location only.

3. Inventory Control Procedure and Information Sharing Mechanism

The procedure for the order fulfillment process in the assumed SC model is considered as a factor to be analyzed. We adopt a conventional (*s, S*) inventory control procedure operating in a *periodic review* mode in which we consider three situations of ordering; (i) after the review period, the order is placed irrespective of inventory in-hand, (ii) after the review period, the order is placed only if the inventory in-hand is below the re-order point, (iii) after the review period if the inventory in-hand is less then re-order point, the order placed is equal to safety stock plus economic order quantity and (iv) we consider the scenario of continuous review working under (*r, Q*) control procedure. The order fulfillment process is in consistent with the relation used by Olhager and Persson (2006). After receipt of a demand order, each retailer checks his product storage inventory, and if there is adequate inventory in store, demand is fulfilled completely. Else, the demand ordered is partially fulfilled from the inventory in stock, and the remaining amount is backordered. The backordered quantity is then replenished in a first-in, first-out (FIFO) manner immediately on receipt of stock.

We assume the presence of a suitable mechanism, for example an electronic data interchange (EDI) system, for enabling demand information sharing seamlessly upwards from the retailer-end through to the echelon in question. For instance, if we mention information sharing between the retailers and Warehouses, then the warehouse has access to the real-time demand experienced at the retailer end. Such a situation is referred to as a "*Pull with information sharing*" setup in the literature (Simchi-Levi *et al.*, 2008). In contrast, a "*Push*" setup implies the absence of any information sharing between echelon members; in this latter situation, each echelon member forecasts its demand for estimating safety stock and order-up-to levels on the size of the order placed to its immediate upstream echelon. For our purposes then, "Push" and "Pull" mechanism in a peace-meal approach wherein the decentralized (push) and centralized (pull) information sharing is adopted in tandem as the levels of push-pull boundary factor across the partnering echelons.

4. Simulation Experiment Details

Simulation models of the assumed four-echelon supply chain network structure(s) were developed in the Arena® simulation language (Kelton *et al.*, 2004). External Visual C++ code was linked into the Arena models to capture the inventory control logic utilized in the simulation models. The simulation model was run for 1825 simulation days (5 years) with 5 replications were found adequate for comparison purposes. The performance measure of interest in this paper was *average fill rates* and *average total inventory cost*. The *average fill rate* is the percentage of total orders been fulfilled directly from the inventory storage at each echelon (averaged over all echelons) while *average total inventory cost* comprise of summation of average procurement cost and average carrying cost.

5. Taguchi's Experimental Design Framework

The Taguchi experimental design paradigm is based upon the technique of *matrix experiments* (Phadke, 1989). A matrix experiment consists of a set of experiments where the settings of process parameters under study are changed from one experiment to another. Experimental data generated is subsequently analyzed to determine the effects of various process parameters. In the statistical literature, matrix experiments are called *designed experiments* and the individual experiments in a matrix experiment are called treatments. Settings are also referred to as levels and parameters as *factors* (Phadke, 1989).

Taguchi suggests using a summary 'η' called *Signal-To-Noise* (*S/N*) *Ratio*, as the objective function for matrix experiments. Phadke (1989) discusses the rationale for using η as the objective function. Taguchi classifies objective functions into one of three categories: (i) *smaller-the-better* type; (ii) *larger-the-better* type; and (iii) *nominal-the-best* type. He then suggests appropriate S/N ratios for each category (see (Phadke, 1989)). S/N ratios are measured in decibel units.

An important goal in conducting a matrix experiment is to determine optimum factor levels. The optimum level for a factor is the level that results in the highest value of η in the experimental region. The effect of a factor level (also called the main effect) is defined as the deviation it causes from the overall mean. The process of estimating the main effects of each factor is called *analysis of means* (*ANOM*). Taguchi makes a fundamental assumption in the method suggested for determining the optimal factor combination (based upon the optimal level for each factor) for a defined objective function. He assumed that the variation of η as a function of the factor levels is additive in nature, *i.e.*, cross product terms involving two or more factors are not allowed. The assumption of additivity essentially implies the absence of significant interaction between factors. Taguchi suggests that a *verification experiment* (with factors at their optimum levels) be run to validate the additivity assumption.

After running a verification experiment, Phadke (Phadke, 1989) points out " …. If the predicted and observed η are close to each other, then we may conclude that the additive model is adequate for describing the dependence of η on the various parameters. … On the contrary, if the observation is drastically different from the prediction. Then we say the additive model is inadequate ….. This is evident of a strong interaction among the parameters". In fact, *Taguchi considers the ability to detect the presence of interactions to be the primary reason for using orthogonal arrays to conduct matrix experiments*.

Taguchi has tabulated 18 basic orthogonal arrays called standard orthogonal arrays. The real benefit in using matrix experiments is the economy they afford in terms of the number of experiments to be conducted. In the present study, we consider L_{16} orthogonal array in case of comparing *average inventory levels* performance for five different factors with four levels each for experimentation. A full factorial experiment for L_{16} would have required 4^5 = 1024 experiments. In contrast, having found that L_{16} orthogonal array to be suitable for our purposes require only 16 experiments to be conducted.

6. Matrix Experiment Details

To study the impact of the assumed factors within the hypothetical supply chain network structures considered, standard orthogonal experiments are performed. We considered Taguchi's standard L_{16} orthogonal array, found suitable for experimentation purposes for the assumed performance measure. This enables the simultaneous consideration of five factors each at four levels.

As mentioned in Section 1, the average fill rate performance is studied based on five factors: (i) *Push-Pull Boundary level*, (ii) *Ordering Policy*, (iii) *Forecasting Error*, (iv) *Lead time and Lead time Standard Deviation*,

Table 1: Standard $L_{16}(4^5)$ Orthogonal Array

Exp. No.	Factors				
	1	2	3	4	5
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	4	4	4	4
5	2	1	2	3	4
6	2	2	1	4	3
7	2	3	4	1	2
8	2	4	3	2	1
9	3	1	3	4	2
10	3	2	4	3	1
11	3	3	1	2	4
12	3	4	2	1	3
13	4	1	4	2	3
14	4	2	3	1	4
15	4	3	2	4	1
16	4	4	1	3	2

Table 2: Factor Level Details Used in Average Fill Rates Performance in Decentralized Experiment of the Two-Warehouse Case

Factor Name	Factor Level	Factor Level Details (Name or Values)				
PUSH-PULL BOUNDRYLEVEL (PPB)	1	PPB1 (Demand sharing between echelons not present)				
	2	PPB2 (W1 & W2 Shares Demand Information)				
	3	PPB3 (Manufacturer Shares Demand Information)				
	4	PPB4 (Demand sharing between echelons not present)				
ORDERING POLICY (OP) (Days)	1	After review period, Order = Order upto level – (In-hand Inventory + Order in process)				
	2	After review period, if storage inventory <=ROP, Order = Order upto level – (In-hand Inventory + Order in process)				
	3	Inventory is reviewed continuously, if storage inventory <=ROP, Order = Order upto level – (In-hand Inventory + Order in process)				
	4	After review period if storage inventory <=ROP, Order = EOQ				
FORECAST ERROR (FER)(%)	1	FER1 (5%)				
	2	FER2 (10%)				
	3	FER3 (15%)				
	4	FER4 (20%)				
LEAD TIME & STANDARD DEVIATION (LTSD) (Days)	1	LTSD1 (3.0, 0.2)				
	2	LTSD2 (3.5, 0.4)				
	3	LTSD3 (4.0, 0.6)				
	4	LTSD4 (4.5, 0.8)				
DEMAND(D) (Nos. / day			***Retailer1***	***Retailer2***	***Retailer3***	***Retailer4***
	1	D1	13	08	15	11
	2	D2	17	12	19	15
	3	D3	21	16	23	19
	4	D4	25	20	27	23

and (v) *Demand*. Similar factors are studied for average total inventory cost performance. However, for both these cases we adopted the L_{16} orthogonal array for experiment purposes. The L_{16} orthogonal array is shown in Table 1.

The factor levels for this experiment are detailed below in Table 2. As alluded to in Section 2, drawing motivation from the previous work of various researchers in context of ordering policies, specifically the work of Pawlak and Małyszek (2008), it was decided deployment of different inventory ordering policies across the partnering echelons. In Table 2, we have repeated the fourth level of '*Push-Pull Boundary*' as '*Demand sharing between echelons not present*'. Phadke (1989) suggests that a level can be repeated, called as dummy level (fourth level in this case) without losing the orthogonality of an array, provided that dummy level remain consistent throughout the experiment. Phadke further suggests that the choice of repetition of level depends upon about which we want more precise information. Literature suggests that supply chain operating under decentralized information system results in high safety stock which ultimately results high fill rates (Chopra and Meindl, 2004), we repeat the first level, *i.e.*, '*Demand sharing between echelons not present*' at the fourth level of the factor '*Push-Pull Boundary*'.

The underlying reasons for considering various design factors and their levels for analysis shown in Table 2 are:

(1) As mentioned in Section 1, the spiraling customer demand in modern business necessitates supply chains to be highly responsive. Further, one of the manifestations of IT technology in the supply chain domain is the emergence of Push-pull boundary to counter the uncertainty of customer demand. Picking on this lead we consider 'push-pull boundary' as one of the parameters under study operating at different levels (*i.e.*, levels 1 through 4). For instance, if we mention W1 and W2 share

demand information (level 2), then these warehouses have access to the real-time demand experienced at the retailer end. This corresponds to the situation of PPB at warehouse echelon. Subsequently, if information sharing is assumed between the retailers through to the manufacturer end (level 3), then each partnering echelon accesses real-time demand experienced at the retailers. This corresponds to the situation of PPB at Manufacturer echelon.

(1) (2) As mentioned in Section 1, we use the 'average fill rates' as a surrogate measure of responsiveness. However, average fill rates has a trade off with 'average inventory levels', that is, the inventory levels must go up in order to ensure high level of fill rates. As stated in Section 1, researchers studied various replenishment policies and suggested coordination with the partners of supply chain on the basis of replenishment policies (Pawlak and Małyszek, 2008; Hidayat *et. al.*, 2011) such that it ensures high service level and low cost. This motivates analyzing various '*ordering policies*' as the second factor under study in this paper. Various replenishment or ordering policies at different levels in design of experimentation connote to conventional (*s*, *S*) policy in levels 1 through 3 and (*r*, *Q*) policy in level 4 which are consistent to ordering policies suggested in literature (Chopra and Meindl, 2004; Olhager and Persson, 2006). We would like to mention here that each echelon adopts same ordering policy while experiment is carried out at specific level of ordering policy factor. For instance, if the simulation experiment is conducted at level 2 of ordering policy factor, each echelon would order according to the rule; After review period if the storage inventory is less than or equal to re-order point (ROP), Order = Order upto level – (In-hand Inventory + Order in process).

(3) The echelon which is under decentralized mode (*i.e.*, push mode), forecasts its demand for computing its order quantity. This motivates us to introduce another factor to analyze, 'forecasting error'. The percentage of error implies the amplification of demand at upstream level (under push mode) in comparison to demand at immediate downstream level due to which the upstream echelon orders more. This is consistent to (Masuchun *et al.*, 2004).

(4) Finally, as mentioned in Section 1, pursuing a centralized information policy is to control the uncertainties arising from: (i) lead time and its standard deviation, and (ii) demand. Therefore, we consider them as fourth and fifth factor respectively at different designed values as levels of the factors.

The results obtained for the *average fill rate* performance are detailed in Table 3. The ANOM plots for the *average fill rates* averaged over the entire supply chain for this experiment is shown in Figure 2. Using the simulation results data summarized in Table 4, the resulting ANOM and ANOVA are presented below.

6.1 Analysis of ANOM and ANOVA for Average Fill Rate Performance

The ANOM plots for *average fill rates* over the total supply chain for this experiment is shown in Figure 2. The ANOM plots shown in Figure 2 reveals the relative magnitude of factor effects on the *average fill rates*: while '*Push-Pull Boundary*' is seen to affect average fill rates the most, the effect of '*Ordering policy*' factor is also seen significant. The other factors are seen to be relatively less pronounced. It may be noted that the factor level combination that should optimize (*i.e.*, maximize) the *average fill rate* performance measure is: (PPB1, OP1, FER4, LTSD3 and D1) which is interpreted to mean: demand information sharing among all echelons is not

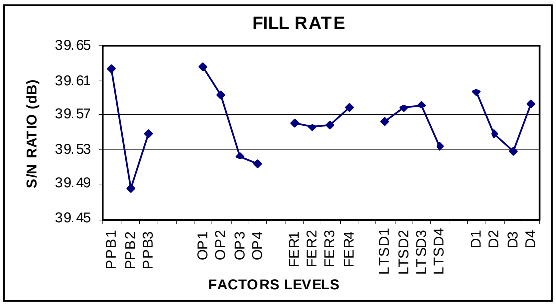
Table 3: Simulation Results of Average Fill Rate Performance

Expt. #	Observed Fill Rates (%)	Observed Fill Rates (η)(dB)
1	96.7588	39.7138
2	95.9784	39.6434
3	95.0611	39.5600
4	95.2684	39.5789
5	95.2499	39.5773
6	93.8355	39.4473
7	93.8039	39.4444
8	94.1586	39.4772
9	95.0477	39.5588
10	95.9638	39.6421
11	94.8135	39.5374
12	93.9029	39.4535
13	96.0875	39.6533
14	95.9313	39.6392
15	94.9524	39.5501
16	94.9295	39.5480

Table 4: Factor Main Effects of Simulation Experiment Results of Average Fill Rate Performance

Factor Levelmain Effects	Applicable Formula	Main Effect Value Fill Rates
m_{PPB1}	$(\eta_1 + \eta_2 + \eta_3 + \eta_4)/4$	**39.6240**
m_{PPB2}	$(\eta_5 + \eta_6 + \eta_7 + \eta_8)/4$	39.4865
m_{PPB3}	$(\eta_9 + \eta_{10} + \eta_{11} + \eta_{12})/4$	39.5480
m_{PPB4}	$(\eta_{13} + \eta_{14} + \eta_{15} + \eta_{16})/4$	39.6240
m_{OP1}	$(\eta_1 + \eta_5 + \eta_9 + \eta_{13})/4$	**39.6258**
m_{OP2}	$(\eta_2 + \eta_6 + \eta_{10} + \eta_{14})/4$	39.5930
m_{OP3}	$(\eta_3 + \eta_7 + \eta_{11} + \eta_{15})/4$	39.5230
m_{OP4}	$(\eta_4 + \eta_8 + \eta_{12} + \eta_{16})/4$	39.5144
m_{FER1}	$(\eta_1 + \eta_6 + \eta_{11} + \eta_{16})/4$	39.5616
m_{FER2}	$(\eta_2 + \eta_5 + \eta_{12} + \eta_{15})/4$	39.5561
m_{FER3}	$(\eta_3 + \eta_8 + \eta_9 + \eta_{14})/4$	39.5588
m_{FER4}	$(\eta_4 + \eta_7 + \eta_{10} + \eta_{13})/4$	**39.5797**
m_{LTSD1}	$(\eta_1 + \eta_7 + \eta_{12} + \eta_{14})/4$	39.5627
m_{LTSD2}	$(\eta_2 + \eta_8 + \eta_{11} + \eta_{13})/4$	39.5778
m_{LTSD3}	$(\eta_3 + \eta_5 + \eta_{10} + \eta_{16})/4$	**39.5818**
m_{LTSD4}	$(\eta_4 + \eta_6 + \eta_9 + \eta_{15})/4$	39.5338
m_{D1}	$(\eta_1 + \eta_8 + \eta_{10} + \eta_{15})/4$	**39.5958**
m_{D2}	$(\eta_2 + \eta_7 + \eta_9 + \eta_{16})/4$	39.5486
m_{D3}	$(\eta_3 + \eta_6 + \eta_{12} + \eta_{13})/4$	39.5285
m_{D4}	$(\eta_4 + \eta_5 + \eta_{11} + \eta_{14})/4$	39.5832

Figure 2: ANOM Plots for Average Fill Rate Performance



present, ordering is done after each review period irrespective of re-order point quantity, forecast error is 20%, Lead time and their standard deviation is (4, 0.6) days, while the demand is respectively 13, 8, 15, 11 units per day at R1, R2, R3 and R4.

It is interesting that the predicted best settings (*i.e.*, 1 1 4 3 1) as mentioned above do not correspond to any of the rows in the matrix experiment shown

Table 5: ANOVA for Average Fill Rate Performance

Factors	DOF*	Sum of Sq.	Mean Sq.	F$
Push-Pull Boundary	3	0.043983	0.014661	**12.4551**
Ordering Policy	3	0.035206	0.011735	**9.9694**
Forecasting Error	3	0.001366#	0.000455	0.3868
Lead Time and their Standard Deviation	3	0.005697#	0.001899	1.6131
Demand	3	0.011484	0.003828	3.2520
Error	0	0		
Total	15	0.097736		
(Error)	(6)	(0.007063)	(0.001177)	

* Degree of freedom
\# Indicates sum of squares added together to estimate the pooled error sum of squares indicated by parentheses. The F ratio is calculated using the pooled error mean square.
$ Indicates critical F ratio (at $\alpha = 0.05$, *i.e.*, $F_{0.05,3,6}) = 4.76$.

in Table 1. Further, a better feel of relative effects is obtained by conducting the *analysis of variance*. Table 5 shows the resulting ANOVA tableau for average fill rate performance measure. From Tables 5, the error variance is calculated to be $(\sigma_e^2)_{\text{fill rates}} = 0.001177$ $(\text{dB})^2$. Based upon the calculated F ratios shown in Table 5, the factors: *Push-Pull Boundary* (F = 12.4551) and *Ordering Policy* (F = 9.9694**)** are the only significant factors in terms of its effect on the *average fill rate* measure in this experiment.

Table 6: Simulation Results of Average Total Cost

Expt. #	Observed Total Cost	Observed Total Cost (η)(dB)
1	35147.18	-90.9178
2	27696.16	-88.8484
3	26413.47	-88.4365
4	26715.88	-88.5354
5	34421.70	-90.7366
6	31388.37	-89.9354
7	21369.75	-86.5960
8	17561.03	-84.8910
9	34694.82	-90.8053
10	26178.46	-88.3589
11	28573.12	-89.1192
12	23349.11	-87.3654
13	35354.06	-90.9688
14	32617.20	-90.2689
15	19675.09	-85.8783
16	20962.62	-86.4289

Table 7: Factor Main Effects of Simulation Experiment Results of Average Total Cost

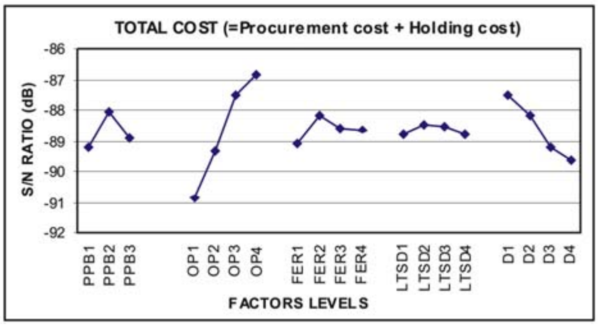
Factor Levelmain Effects	Applicable Formula	Main Effect Value Fill Rates
m_{PPB1}	$(\eta_1 + \eta_2 + \eta_3 + \eta_4)/4$	-89.1845
m_{PPB2}	$(\eta_5 + \eta_6 + \eta_7 + \eta_8)/4$	**-88.0398**
m_{PPB3}	$(\eta_9 + \eta_{10} + \eta_{11} + \eta_{12})/4$	-88.9122
m_{PPB4}	$(\eta_{13} + \eta_{14} + \eta_{15} + \eta_{16})/4$	-89.1845
m_{OP1}	$(\eta_1 + \eta_5 + \eta_9 + \eta_{13})/4$	-90.8571
m_{OP2}	$(\eta_2 + \eta_6 + \eta_{10} + \eta_{14})/4$	-89.3529
m_{OP3}	$(\eta_3 + \eta_7 + \eta_{11} + \eta_{15})/4$	-87.5075
m_{OP4}	$(\eta_4 + \eta_8 + \eta_{12} + \eta_{16})/4$	**-86.8052**
m_{FER1}	$(\eta_1 + \eta_6 + \eta_{11} + \eta_{16})/4$	-89.1003
m_{FER2}	$(\eta_2 + \eta_5 + \eta_{12} + \eta_{15})/4$	**-88.2072**
m_{FER3}	$(\eta_3 + \eta_8 + \eta_9 + \eta_{14})/4$	-88.6004
m_{FER4}	$(\eta_4 + \eta_7 + \eta_{10} + \eta_{13})/4$	-88.6148
m_{LTSD1}	$(\eta_1 + \eta_7 + \eta_{12} + \eta_{14})/4$	-88.7870
m_{LTSD2}	$(\eta_2 + \eta_8 + \eta_{11} + \eta_{13})/4$	**-88.4568**
m_{LTSD3}	$(\eta_3 + \eta_5 + \eta_{10} + \eta_{16})/4$	-88.4902
m_{LTSD4}	$(\eta_4 + \eta_6 + \eta_9 + \eta_{15})/4$	-88.7886
m_{D1}	$(\eta_1 + \eta_8 + \eta_{10} + \eta_{15})/4$	**-87.5115**
m_{D2}	$(\eta_2 + \eta_7 + \eta_9 + \eta_{16})/4$	-88.1696
m_{D3}	$(\eta_3 + \eta_6 + \eta_{12} + \eta_{13})/4$	-89.1765
m_{D4}	$(\eta_4 + \eta_5 + \eta_{11} + \eta_{14})/4$	-89.6650

The results obtained for the *average Total cost* (average procurement cost + average holding cost) are detailed in Table 6. The ANOM plots for the *average total cost* averaged over the entire supply chain for this experiment is shown in Figure 3. Using the simulation results data summarized in Table 7, the resulting ANOM and ANOVA are presented below

6.2 Analysis of ANOM and ANOVA for Average Total Cost

The ANOM plots for *average total cost* over the total supply chain for this experiment is shown in Figure 2. The ANOM plots shown in Figure 3 reveals the relative magnitude of factor effects on the *average total cost*: while '*Ordering Policy*' is seen to affect average total cost the most, the effect of '*Demand*' factor is also seen significant. The other factors are seen to be relatively less pronounced. It may be noted that the factor level combination that should optimize (*i.e.*, minimize) the *average total cost* is: (PPB2, OP4, FER2, LTSD2 and D1) which is interpreted to mean: demand information sharing among both the warehouses, ordering is done if after each review period inventory in-hand is less than or equal to re-order point and the order is equal to economic order quantity above safety stock, forecast error is 10%, Lead time and their standard deviation is (3.5, 0.4) days, while the demand is respectively 13, 8, 15, 11 units per day at RI, R2, R3 and R4.

Figure 3: ANOM Plots for Average Total Cost



Again the predicted best settings (2 4 2 2 1) do not correspond to any of the rows in the matrix experiment shown in Table 1. Further, a better feel of relative effects is obtained by conducting the *analysis of variance*. Table 8 shows the resulting ANOVA tableau for average total cost. From Tables 8, the error variance is calculated to be $(ó_e{}^2)_{\text{fill rates}}$ = 0.33359 (dB)^2. Based upon the calculated F ratios shown in Table 8, the factors: *Ordering Policy* (F = 40.2590) and *Demand* (F = 11.3227**)** are the only significant factors in terms of its effect on the *average total cost* in this experiment.

Table 8: ANOVA for Average Total Cost

Factors	DOF*	Sum of Sq.	Mean Sq.	$F^{\$}$
Push-Pull Boundary	3	3.17973	1.05991	3.1772269
Ordering Policy	3	40.29078	13.43026	**40.259069**
Forecasting Error	3	1.604247#	0.534749	1.6029842
Lead Time and their Standard Deviation	3	0.397329#	0.132443	0.3970158
Demand	3	11.33169	3.777231	**11.322774**
Error	0	0		
Total	15	56.80378		
(Error)	(6)	(2.001575)	(0.333596)	

7. Testing for Additivity

In order to validate the assumption of additivity, a verification experiment needs to be conducted with the optimal factor settings (Phadke, 1989). The result of the verification experiment is then compared with a predicted optimal value, resulting in a prediction error. If the prediction error happens to fall within two-standard-deviation confidence limits of the variance of prediction error, the additivity assumption can be assumed to be justified (Phadke, 1989). Validation of the additivity assumption essentially implies the absence of significant interaction effects between factors.

As mentioned above, testing for additivity requires that a verification experiment be carried out. Accordingly, the verification experiments carried out for the various matrix experiments conducted are detailed in Table 9.

Since, in the experiments the prediction error (column 4 of Table 9) happens to be within the calculated 2-standard deviation confidence limits (column 6 of Table 9), the additivity assumption is justified.

8. Discussion of results

We have suggested and used the Taguchi experimental design paradigm in order to gain a quick understanding into the behavior of the assumed parameters considered. We now discuss the results obtained so as to underline some of the insights made. This indeed is the value of the procedure suggested.

Based on the ANOM plots shown in Figure 2 wherein the optimal levels of significant factors for the high fill rates are PPB1 and OP1, reveals that:

(i) In a case when each echelon operates under decentralized fashion (corresponding to level 1 of PPB factor), there would be an amplification in order quantity as we move up the stream, which is a well established result in literature (Lee *et al.*, 1997). This would increase the inventory levels over the total supply chain. However, it ensures the availability of inventory every time when the order arrives and thereby results in high fill rates.

(ii) In a case when ordering is done after every review period, immaterial of the condition that inventory is equal to or less than re-order point (corresponding to level 1 of OP factor), interprets that the chances of availability of inventory on the arrival of orders would be more and thus result in high fill rates.

The result shown in Figure 2 also highlights the relevance and importance of synchronizing the decentralized scenario with the ordering policy in order to optimize average fill rates.

Further, based on ANOM plots shown in Figure 3 wherein the optimal levels of significant factors for total inventory cost are OP4 and D1, reveals that:

(i) The result corresponds to the situation when each echelon operates under ordering policy in which an order of quantity equal to EOQ is placed to the upstream echelon every time when the inventory level is less than or equal to re-order point at immediate downstream echelon (level 4 of factor OP). The result makes an intuitive sense in a way that, EOQ is a function of demand and the optimal level of demand (D1), shown in Figure 3 is seen to be at low level. This would result low EOQ quantity thereby resulting in low total inventory cost.

The result shown in Figure 3 also highlights the relevance and importance of synchronization between ordering policy and demand in order to optimize the average total inventory cost.

Table 9: Results of Additivity test for assumed performance measures

Performance Measure	η (Observed optimal)	η (Predicted optimal)	Predicted Error	Variance of Predicted error $\sigma^2_{e\ pred}$	2-Std. Deviation confidence limit $\pm 2\times\sqrt{\sigma^2_{e\ pred}}$
Average Fill Rate	39.66581	39.6858	-0.0200	0.0007504	±0.0547
Average Total Inventory cost	-84.8986	-85.6860	0.7874	0.21266	± 0.9223

9. Conclusions

In this paper we propose a methodology based on the Taguchi experimental design procedure which can be used by decision makers/managers in gaining rapid insights into the behavior of assumed design parameters within supply chain network structure. On the basis of studies conducted in this paper, we can say that the penetration of push-pull boundary up the stream is largely effected by inventory control policy adopted and thereby has impact on system wide average fill rates and average total inventory cost. From the managerial implications view point the paper suggest that the companies which try to reduce their inventory costs must realize that they should select ordering policies in coordination with other echelons of supply chain. Therefore, under the given set of operational units, the benefit of push-pull boundary in the premise of demand information sharing can be realized on successful selection of inventory control policies in coordination. We do point out however, the results obtained in this paper are context specific and deserve more detailed analysis in terms of parameterization and SC network structures in order for generalization. In the proposed research here the average total inventory cost borne due to procurement and holding costs. In reality the inventory costs measurement is a difficult process and therefore other measures of inventory control evaluation can be applied, for example, order execution time (time delay) can be another option for further research.

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