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THE APIOBPCS DEZIEL AND EILON PARAMETER CONFIGURATION IN SUPPLY CHAIN UNDER PROGRESSIVE INFORMATION SHARING STRATEGIES

Salvatore Cannella
Elena Ciancimino

viale delle Scienze, Parco d'Orleans
Faculty of Engineering
University of Palermo
Palermo, 90128, ITALY

ABSTRACT

The aim of this paper is to investigate how different smoothing parameter levels of the Automatic Pipeline Inventory and Order Based Production Control System smoothing replenishment rule impact on the bullwhip dampening efficacy, under progressive information sharing strategies. The main results of this work are: (1) The smoothing parameter variations significantly impact on performance of the supply chains characterised by low information sharing level. (2) As smoothing parameters increase, the supply chain process performance improves and the customer service level worsens. This opposite trend noticeably decreases as information sharing level increases. (3) Amongst the bullwhip dampening techniques, deeper information sharing weights more than the value of smoothing parameters. The analysis is performed through continuous time differential equation modelling.

1 INTRODUCTION AND PROBLEM STATEMENT

In the last decade, while the existence of bullwhip phenomenon has been widely confirmed, the scientific debate in demand amplification studies has shifted from strategies aimed at preventing the bullwhip effect (Lee et al. 1997, Chen et al. 2000, Disney and Towill 2003a, 2003b, Chatfield et al. 2004, Geary et al. 2006) to collaboration in the supply chain through collaborative planning, information sharing and VMI and other strategies (Holweg and Disney 2005).

The Operation Management Community highlights that a way forward to systematically remove all avoidable causes of supply chain instability is to re-engineer the production/distribution channel, such as redesigning the decision process (Dejonckheere et al. 2004). In this field the use of smoothing replenishment rules permits to avoid the bullwhip effect by decreasing the tiers' lot size in presence of distortion of the marketplace demand information.

The smoothing order policies studied in this paper belong to the Automatic Pipeline Inventory and Order Based Production Control System (APIOBPCS) replenishment rules (John et al. 1994). This policy is a base-stock decision rule in which the review period is fixed, and the size of the order is such that the inventory position and the work in progress amount are raised up to a target level: a modification to the classical order-up-to. The rule can be expressed as "let the production targets be equal to the sum of a forecast of perceived demand, plus a fraction (1/Ty) of the inventory discrepancy between actual and target levels of finished goods, plus a fraction (1/Tw) of the discrepancy between target WIP and actual WIP" (Disney and Towill 2003a). The APIOBPCS archetype has been used to extend understanding of the dynamic behaviour of supply chains, and its analysis is not only theoretical but has been applied in industry (Wikner et al. 2007). It may be embedded within commercial software, although often it is developed and implemented on an ad hoc basis (Disney and Towill 2006).

A particular design of APIOBPCS has been investigated by Deziel and Eilon (1967), the so-called DE-APIOBPCS which refers to the case when smoothing inventory parameter is equal to the smoothing work in progress parameter, that is equalising the pipeline and inventory recovery times (Ty=Tw).

A further notorious amplification dampening approach is the redesign of the information patterns (Dejonckheere et al. 2004). Real-time point-of-sales information, sales forecasts, inventory order policies and inventory reports are shared between trading partners for establishing suitable operations and limiting the bullwhip effect.

The aim of this paper is to investigate how different Deziel and Eilon smoothing parameter levels impact on the bullwhip dampening efficacy under progressive information sharing strategies.

Continuous time differential equation methodology is used to model three different four-echelon base-stock policy supply chains: Traditional Linked structure, Sharing Customer Demand Information structure and Vendor Managed Inventory structure.

This article is organized as follows. Section 2 reports methodology, simulation tool, model nomenclature, and the three supply chain models. Performance metrics, experimental sets, data analysis and discussion are reported in section 3. Section 4 provides conclusions and suggestions for future research.

2 MODELLING THE SUPPLY CHAINS

2.1 Methodology, simulation tool and model nomenclature

The supply chains are modelled through continuous time differential equations. A generic nonlinear ordinary difference equation can be expressed as:

$$X_t = X_{t-\Delta t} + \Delta(X_{t-\Delta t,t}). \tag{1}$$

$$\Delta(X_{t-\Delta t,t}) = f(X_{t-\Delta t}, U_t, C). \tag{2}$$

X_t represents a state variable of the system, Δt is the finite time interval, $\Delta(X_{t-\Delta t,t})$ is the variation of the state variable in Δt, U_t is a generic exogenous variable, and C represents parameters or constants.

Equation (1) is solved through Euler integration by software packages like Vensim. The tool evaluates the system state every constant time interval (Δt), then the new system state is recorded and statistics collected (Ventana Systems Inc. 2006).

Table 1 reports the operations management variables and parameters used in this study.

Table 1: Model Nomenclature

Material variables	
Wip_t^i	work in progress (includes incoming transit units) at echelon *i* at time *t*
Inv_t^i	inventory of finished materials at echelon *i* at time *t*
S_t^i	units/orders finally shipped from echelon *i* at time *t*
F_t^i	throughput at echelon *i* at time *t*
Information variables	
$\hat{d}_t^i$	demand forecast at echelon *i* at time *t*
$\hat{d}_t^{cust}$	customer demand forecast at time *t*
d_t^{cust}	customer demand at time *t*
R_t^i	replenishment order quantity at echelon *i* at time *t*
B_{t-1}^i	existing backlog of orders at echelon *i* at time *t*
$TInv_t^i$	target inventory at echelon *i* at time *t*
$TWip_t^i$	target work in progress at echelon *i* at time *t*
$VirtInv_t^i$	virtual inventory at echelon *i* at time *t*
$VirtWip_t^i$	virtual work in progress at echelon *i* at time *t*
$TVirtInv_t^i$	target virtual inventory at echelon *i* at time *t*
$TVirtWip_t^i$	target virtual work in progress at echelon *i* at time *t*
$\sigma^2_{R^i}$	variance of order quantity rate at echelon *i*
σ^2_d	variance of customer demand.
$\sigma^2_{Inv^i}$	variance of inventory at echelon *i*
μ_{R^i}	mean value of order quantity at echelon *i.*
μ_d	mean value of market demand.
Parameters	
α	forecast smoothing factor
T_p^i	physical production/distribution lead time at echelon *i* (incoming transit time from supplier plus the production lead time)
T_c^i	cover time for the inventory control at echelon *i*
T_y^i	smoothing inventory parameter at echelon *i*
T_w^i	smoothing work in progress parameter at echelon *i*

2.2 Model 1: Traditional Linked

The Traditional Linked (TL) model is a serially-linked four-echelon supply chain, in which trading partners use a smoothing replenishment rule. Each echelon only receives information on local stock, local work in progress levels, and local sales. The retailer forecasts customer demand on the basis of market time series, and the remaining echelons only take into account for their replenishment downstream incoming orders.

Equations (3), (4) and (5) represent the state variables of the model.

$$Wip_t^i = Wip_{t-1}^i + S_t^{i-1} - F_t^i . \quad (3)$$

$$Inv_t^i = Inv_{t-1}^i + F_t^i - S_t^i . \quad (4)$$

Work in progress (3) and Inventory (4) describe the physical flow of items in downstream direction. Note that at every echelon the shipments sent by the supplier S_t^{i-1} immediately become work in progress.

$$B_t^i = B_{t-1}^i + R_t^{i+1} - S_t^i . \quad (5)$$

Backlog (5) is representative of service level for each tier. Backlogging is allowed as a consequence of stockholding; in each echelon the backlog will be fulfilled as soon as on-hand inventory becomes available.

$$S_t^i = \min(R_t^{i+1} + B_{t-1}^i ; Inv_{t-1}^i + F_t^i) . \quad (6)$$

Equation (6) expresses the dynamic of delivered orders.

$$F_t^i = S_{t-T_p}^{i-1} . \quad (7)$$

Equation (7) models the production/delivery lead time delay, represented by the parameter T_p.

$$\hat{d}_t^i = \alpha R_{t-1}^{i+1} + (1-\alpha)\hat{d}_{t-1}^i ; 0 < \alpha \le 1, \forall i \ne 4 . \quad (8)$$

$$\hat{d}_t^{cust} = \alpha d_{t-1}^{cust} + (1-\alpha)\hat{d}_{t-1}^{cust} ; \; 0 < \alpha \le 1 . \quad (9)$$

$$\hat{d}_t^{\,i} = \hat{d}_t^{\,cust} \quad \forall i = 4 . \quad (10)$$

Equation (8) and (9) represent the exponential smoothing formulae to forecast demand (Makridakis et al. 1978). The forecast smoothing factor α represents the weighting factor of the exponential smoothing rule. The value of α is between 0 and 1. The higher the value of α, the greater is the weight placed on the more recent demand levels. The lower the α value the greater is the weight given to demand history in forecasting future demand. Two equations are adopted to take into account the forecast on customer orders $\hat{d}_t^{cust}$ and the forecast on orders placed by tiers $\hat{d}_t^i$. Equation (10) shows that only the tier next to the customer carries out a forecast based on market demand, while at the upstream stages the input demand data is given by equation (9).

The adopted periodic review/smoothing order-up-to/base-stock replenishment rule is represented by equation (11).

$$R_t^i = \hat{d}_t^{\,i} + \frac{1}{T_w^i}(TWip_t^i - Wip_t^i) + \frac{1}{T_y^i}(TInv_t^i - Inv_t^i) . \quad (11)$$

Equation (12) models the non-negativity condition for the replenishment order quantity.

$$R_t^i \ge 0, \forall i . \quad (12)$$

Target inventory (13) is updated every period according to the covering time and the new demand forecast.

$$TInv_t^i = \hat{d}_t^{\,i} T_c . \quad (13)$$

Target orders are placed in the pipeline on the basis of the demand forecast and production/delivery lead time (14).

$$TWip_t^i = \hat{d}_t^{\,i} T_p . \quad (14)$$

2.3 Model 2: Sharing Customer Demand Information

The Sharing Customer Demand Information (SCDI) model is a point-of-sales decentralised base-stock supply chain. All echelons base their replenishment on local stock and work in progress levels, local sales, downstream incoming orders and the actual marketplace demand. This structure is modelled through equations (3), (4), (5), (6), (7), (8), (9), (10), (12), (13), (14). The order decision rule implemented in the Sharing Customer Demand Information supply chain (15) takes into account the conjoint use of the market demand forecast (9), based on the end consumer order rate, and the demand forecast at echelon *i* (8), based on the orders placed by the subsequent stage. The customer demand forecast is directly included into the replenishment rule, while the forecast on the order incoming by echelon *i+1* is used to compute Target Work in Progress (14) and Target Inventory (13), as in the Traditional Linked model.

$$R_t^i = \hat{d}_t^{\,cust} + \frac{1}{T_w^i}(TWip_t^i - Wip_t^i) + \frac{1}{T_y^i}(TInv_t^i - Inv_t^i) . \quad (15)$$

2.4 Model 3: Vendor Managed Inventory

The Vendor Managed Inventory (VMI) model represent a centralised base-stock supply chain. Each echelon bases its replenishment on local stock and work in progress level, local sales, downstream incoming orders, actual marketplace demand, inventory information and work in progress data incoming from downstream nodes. The model is described by equations (3), (4), (5), (6), (7), (9), (12). Equation (16) represents the periodic review order quantity for the centralised base-stock supply chain.

$$R_t^i = \hat{d}_t^{\,cust} + \frac{1}{T_w^i}(TVirtWip_t^i - VirtWip_t^i) + \frac{1}{T_y^i}(TVirtInv_t^i - VirtInv_t^i) . \quad (16)$$

The variable Virtual Inventory for an individual echelon *i* is the sum of the local Inventory plus all Inventories of subsequent echelons (17).

$$VirtInv_t^i = \sum_{j=i}^{4} Inv_t^j . \quad (17)$$

The variable Virtual Work In Progress for echelon *i* is given by orders-in-the-pipeline at stage *i* plus the sum of work in progress of all downstream echelons (18).

$$VirtWip_t^i = \sum_{j=i}^{4} Wip_t^j \; . \tag{18}$$

Target Virtual Inventory (19) in echelon *i* depends from the forecasted marketplace demand and from the sum of the local and subsequent tiers' cover times for the inventory control.

$$TVirtInv_t^i = \hat{d}_t^{\,cust} \sum_{j=i}^{4} T_c^j \; . \tag{19}$$

Target Virtual Wip (20) in echelon *i* depends from the forecasted marketplace demand and from the sum of the local and subsequent stages' physical production/distribution lead time.

$$TVirtWip_t^i = \hat{d}_t^{\,cust} \sum_{j=i}^{4} T_p^j \tag{20}$$

3 PERFORMANCE METRICS, EXPERIMENTAL SETS, DATA ANALYSIS AND DISCUSSION

3.1 Supply chain performance metrics

The *Order Rate Variance* (ORVr) *Ratio* metric (Chen et al. 2000) is a smart and concise quantification of the bullwhip effect. In equation (21) $\sigma^2_{R^i}$ and μ_{R^i} are respectively the variance and the order quantity rate mean value at echelon *i*, $\sigma^2_{d^{cust}}$ and $\mu_{d^{cust}}$ stand for the variance and the mean value of market demand. The higher the value of Order Rate Variance Ratio, the greater is the magnitude of demand amplification phenomenon

$$ORVrRatio^i = \frac{\sigma^2_{R^i} / \mu_{R^i}}{\sigma^2_{d^{cust}} / \mu_{d^{cust}}} \, . \tag{21}$$

The *Inventory Variance* (InvVr) *Ratio* is a supplementary measure of multi-echelon system instability obtained by comparing the inventory variance magnitude to the variance of the market demand. Equation (22) permits to investigate the effect of order policies on inventory levels. The higher the value of Inventory Variance Ratio, the greater is the inventory instability.

$$InvVrRatio^i = \frac{\sigma^2_{Inv^i} / \mu_{Inv^i}}{\sigma^2_{d^{cust}} / \mu_{d^{cust}}} \, . \tag{22}$$

A complementary measure of supply chain inventory performance is the *Average Inventory* (23), computed as the mean value of Inventory levels at echelon *i* over the simulation time span T.

$$AverageInventory^i = \frac{1}{T} \sum_{t=0}^{T} Inv_t^i \, . \tag{23}$$

A concise measure of multi-echelons system performance related to stock levels is the *Global Average Inventory*, computed as the sum of Average Inventory values over the four tiers.

For fixed cycled inventory policies, the circumstance associated to a null argument in a replenishment order quantity is herein defined *Zero-Replenishment* (ZR) phenomenon. The Zero-Replenishment (24) is quantified as the number of times in which tier *i* does not place any order, while market demand has reached a stable value. ZR is a measure of timely and ponderated reactivity of a tier's operations towards changes in demand. It provides an assessment supply chain scalability: the ability of business manufacturing, or technology process, to support sudden increases in demand. A high value of ZR is indicative of an excessive dimensioning of the order lot size.

$$ZR^i = \sum_{t=0}^{T} x_t^i ; \quad x_t^i = \begin{cases} 1 & R_t^i = 0 \\ 0 & R_t^i \neq 0 \end{cases} . \tag{24}$$

The ZR phenomenon can also be evaluated at system level referring to a *Global Zero-Replenishment* (GZR), computed as the sum of the ZR^i of the single echelons in a given supply chain.

Note that ZR shall be analysed conjointly with a customer service level assessment: to affirm that a system is reacting timely and ponderately, a good service level has to be associated to a low value of ZR. The ZR alone cannot be viewed as a stand-alone supply chain performance metric. Apparently a low value of ZR is indicative of optimal operations and lot sizing: this is true only when at the same time the system assures a high customer service level. Otherwise, a poor customer service level associated to a low ZR reflects the exact contrary: poor system reactivity.

As customer service level measure, the *Fill Rate* is defined as the percentage of orders delivered 'on time', that is, no later than the delivery day requested by the customer. Equation (25) is calculated as the fraction of demand immediately filled from the stock on hand (Kleijnen and Smiths, 2003).

$$FillRate_t = \frac{S_t^4}{d_t} * 100 \, . \tag{25}$$

The Fill Rate is evaluated every single Δt and the time series reproduce the supply chain customer service level history. To associate to each supply chain a customer service level indicator and concisely compare different scenarios, an additional measure is used: the *Average Fill Rate*. The Average Fill Rate is the mean of a censored set of Fill Rate values computed over a restricted time interval. This interval is selected by considering, among all simulations, the longest time span with Fill Rate values lower than 100%. Once selected, the same restricted interval is used to compute the Average Fill Rate of all simulations. Note that the censored data is used to analyse the multi-echelon system during stock-holding and to compare the magnitude of backlog in the supply chain configurations.

3.2 Experimental sets

For each supply chain model three levels of Deziel and Eilon smoothing parameters are explored:

$$T_y = T_w = T_p + 1 . \qquad (26)$$

$$T_y = T_w = T_p . \qquad (27)$$

$$T_y = T_w = 2T_p . \qquad (28)$$

The first level is chosen on the basis of the empirical formula (26), which has been tested into several simulations and analytical environments and it lies well within the stable regime with extremely well behaved dynamic response (Disney and Towill 2006). Equations (27) and (28) are two further empirical formulae tested in this work
The experiments share the followings:

- The simulation runs are for a total of 52 time units, with constant time interval equal to Δt=0.25 time units.
- Marketplace demand is assumed to be 4 units per time unit, until there is a pulse at t=5, increasing the demand value up to 8 units per time unit.
- The values of the parameter vector [α; Tp; Tc; Ty; Tw] elements are: forecast smoothing factor α=0.5; physical production/distribution lead time Tp=2; cover time for the inventory control Tc=3.
- The state value vector at t=0 [Wip_0^i; Inv_0^i; B_0^i] is as Sterman's configuration (1989).
- For echelon 1 (manufacturer) no replenishment lead time is considered.

The next sub-sections report data analysis for the experimental sets.

3.3 Data analysis

The Order Rate Variance Ratio and Inventory Variance Ratio measures are reported by echelon; the curves in Figure 1 result from plotting the values of the metrics for a single echelon in the same supply chain structure for variations of the Deziel and Eilon smoothing parameters. The x axis is constituted by the values of $T_y = T_w$. The adopted graphic representation enables to emphasise the effect of the smoothing parameters for a single echelon in a given supply chain. The curve trends in Figure 1 represent the extent of the demand amplification variations as smoothing parameters change. An analogous graphical representation is adopted for Inventory Variance Ratio: the curve trends in Figure 2 represent the extent of inventory instability variation as smoothing parameters increase.

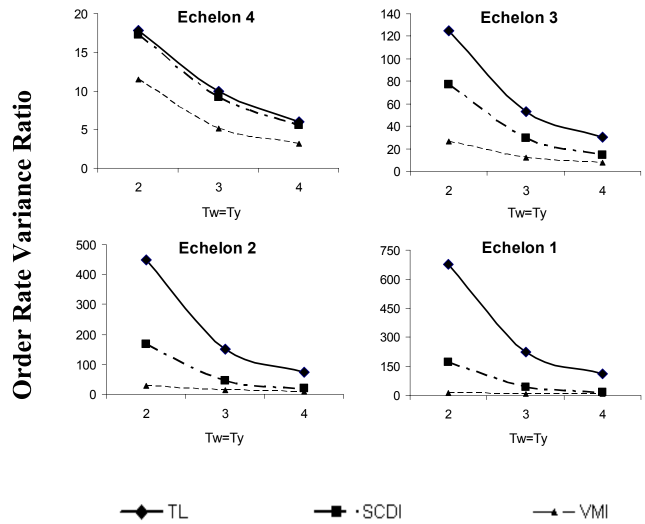

Figure 1: Order Rate Variance Ratio for variable smoothing parameters experimental set.

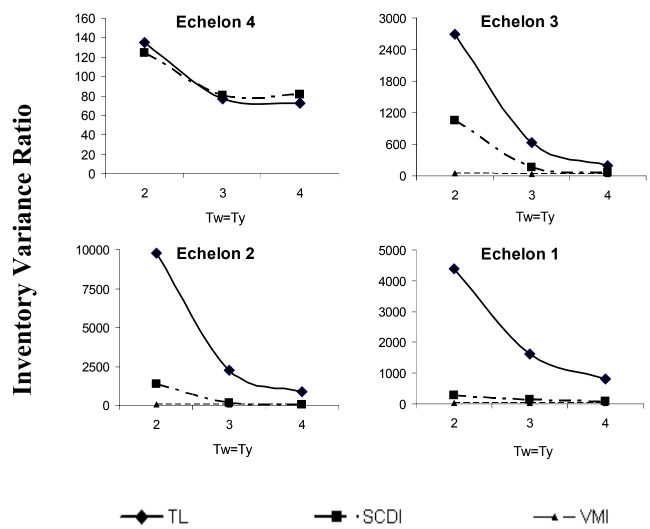

Figure 2: Inventory Variance Ratio for variable smoothing parameters experimental set.

The following statistics on the metrics are reported: the slope for Order Rate Variance Ratio and Inventory Variance Ratio, the Global Zero Replenishment, the Global Average Inventory, and the Average Fill Rate.
In order to quantify with a single value the effect of the smoothing parameters on an individual echelon in a given supply chain, the value of the slope of the interpolated curves is computed. The value of the slope quantifies how the variation of T_w and T_y is correlated to the performance of a single echelon of a given supply chain structure: the extent of the variation of bullwhip propagation for the Order Rate Variance Ratio (Table 2) and the extent of the

variation of inventory instability for Inventory Variance Ratio (Table 3). These values are indicative of the echelon's sensitivity to variations in smoothing parameters within a given range.

Table 2: Order Variance Ratio slopes for variable smooting parameters.

ORVrRatio SLOPE

	Ech 4	Ech 3	Ech 2	Ech 1
TL	5.63	43.02	113.76	126.34
SCDI	5.58	28.46	64.17	64.87
VMI	3.92	8.86	8.01	2.31

Table 3: Inventory Variance Ratio slopes for variable smoothing parameters.

ORVrRatio SLOPE

	Ech 4	Ech 3	Ech 2	Ech 1
TL	8.76	123.13	143.5	64.6
SCDI	5.35	82.26	75.44	10.26
VMI	1.74	0.079	0.41	0.26

Average Inventory and Zero Replenishment values are reported in Table 4 and Table 5: data can be compared both by echelon and by supply chain structure, analysing the values by column or by row.

Table 4: Average Inventory for variable smoothing parameters experimental set.

AVERAGE INVENTORY

	Ty=Tw	Ech 4	Ech 3	Ech 2	Ech 1
TL	*2*	21	65	165	129
	3	19	32	68	77
	4	18	23	39	48
SCDI	*2*	21	41	59	41
	3	19	22	23	22
	4	18	18	18	17
VMI	*2*	20	19	18	18
	3	19	19	18	17
	4	18	18	18	17

Global Zero Replenishment, Global Average Inventory, and Average Fill Rate are the statistics used to compare the three supply chains for the different parameter vectors. These statistics are quantitative and concise representations of different dimensions of supply chain performance. To enable a quick comparison and to enhance the decision support function of the what-if analysis, a conjoint visualisation of the three statistics under different smoothing parameters for each supply chain is presented in Figure 3. The horizontal bar chart represents the Average Fill Rate; the histogram stands for the Global Average Inventory, and the column with a cylindrical shape represents the Global Zero Replenishment. The numerical value for each statistic is reported next to the corresponded diagram.

Table 5: Zero Replenishment for variable smoothing parameters.

ZERO REPLENISHMENT

	Ty=Tw	Ech 4	Ech 3	Ech 2	Ech 1
TL	*2*	6	25	35	33
	3	3	14	27	30
	4	0	9	17	21
SCDI	*2*	6	18	28	29
	3	1	9	12	12
	4	0	2	4	5
VMI	*2*	2	6	0	0
	3	0	0	0	0
	4	0	0	0	0

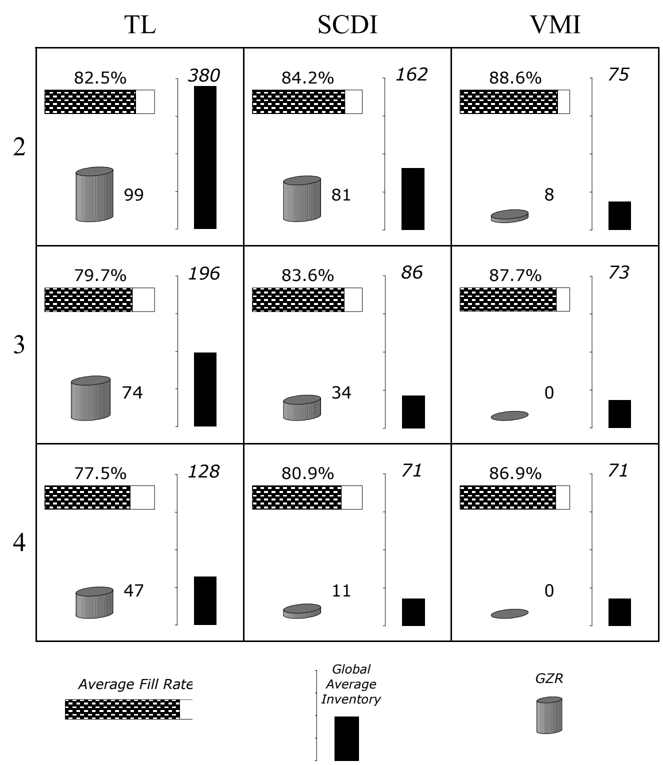

Figure 3: Average Fill Rate, Global Average Inventory and GZR for variable smoothing parameters.

3.4 Discussion

The first insight from this study is that *the smoothing parameter variations significantly impact on performance of the supply chains characterised by low information sharing level.*

A high value of the smoothing parameter, within the studied range, is generally associated to better process performance (ORVrRatio, InvVrRatio, GZR and Global Average Inventory). The customer service level shows an opposite trend: a monotonic reduction of Average Fill Rate is associated to increasing smoothing parameter values. This result is more evident in the TL model, due to the fact that in this model the only bullwhip avoidance technique consists on the use of a smoothing replenishment rule. In TL, among the empirical rules used to determine the value of smoothing parameter, the more efficient reduction of demand amplification and inventory stability is obtained by setting the smoothing parameter as the double of the physical lead time, while the worst bullwhip dampening is obtained when the smoothing parameters are equal to the value of lead time.

As smoothing parameters increase, the supply chain process performance improves and the customer service level worsens. This opposite trend noticeably decreases as information sharing level increases.

As in the TL, the most efficient reduction of the bullwhip is obtained in SCDI by setting the smoothing parameter as the double of the physical lead time. The process performance and the customer service level present the same opposite trend as the TL model with relation to the increase of smoothing parameters. However, the magnitude of this trend noticeably decreases: the SCDI supply chain generally outperforms the TL using a replenishment order policy supported by shared point-of-sale forecasts. In SCDI an improved process performance is achieved and a higher customer service level is guaranteed. The conjoint adoption of smoothing replenishment rules and shared demand forecast information enhances the supply chain ability to dampen demand amplification.

Data analysis shows how in VMI the four echelons for every parameter vector do not show significant differences in performance. VMI configuration enables the most effective bullwhip avoidance, inventory stability, and enhanced customer service level regardless of smoothing parameter variations. Shared real-time point-of-sales information, sales forecasts, inventory order policies and inventory reports represent a robust solution to bullwhip, inventory instability and poor customer service. The results presented in this study highlight that, *amongst the bullwhip dampening techniques, deeper information sharing weights more than the value of smoothing parameters*.

4 CONCLUSIONS AND FUTURE RESEARCH

The aim of this paper was to investigate how different smoothing parameter values of the Automatic Pipeline Inventory and Order Based Production Control System replenishment rule impact on the bullwhip dampening efficacy under progressive information sharing strategies.

Continuous time differential equation methodology was used to model three different four-echelon base-stock policy supply chains: Traditional Linked structure, Sharing Customer Demand Information structure and Vendor Managed Inventory structure. The models have been simulated in continuous time domain for assessing the response of the progressively information-integrated structures to demand variations in terms of bullwhip effect and customer service level.

The main result of this work are:

1. *The smoothing parameter variations significantly impact on performance of the supply chains characterised by low information sharing level*
2. *As smoothing parameters increase, the supply chain process performance improves and the customer service level worsens. This opposite trend noticeably decreases as information sharing level increases.*
3. *Amongst the bullwhip dampening techniques, deeper information sharing weights more than the value of smoothing parameters*

Future research will involve testing the efficacy of the smoothing parameters under several real supply chain conditions as production plant constraints and interruptions.

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AUTHOR BIOGRAPHIES

SALVATORE CANNELLA holds a master's degree in Management Engineering from the University of Palermo, 2005. He has been committed to several international cooperation research projects and training programmes supported by the European Commission, the National Research Council of Italy, the Spanish Ministry of Education and Science, the Italian Ministry of University and Research, the Italian Ministry of Foreign Affairs and the Council of Italian Universities. He is member of Production Engineering Research workGroup (Pergroup) and of the Italian Association of Management Engineering (AiIG). He is now Ph.D. student at Department of Manufacturing, Industrial and Management Engineering of the University of Palermo, and visiting at Department of Industrial Management, High School of Engineering, University of Seville, Spain. His research is focusing on bullwhip effect reducing approaches, supply chain reengineering, replenishment rules and what-if simulation in operations management.

ELENA CIANCIMINO holds a master's degree from the University of Palermo in Management Engineering. She has been committed to several international cooperation research projects and training programmes supported by the European Commission, the National Research Council of Italy, the Italian Ministry of University and Research, the Italian Ministry of Economic Development. She is currently a Ph.D. student at Department of Manufacturing, Industrial and Management Engineering of the University of Palermo, and visiting at Department of Industrial Management, High School of Engineering, University of Seville, Spain. Her research interests include supply chain modelling and performance metrics, IT-enabled practices and healthcare management.