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The information to share in upstream supply chains
dedicated to mass production of customized products
for allowing a decentralized management
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The information to share in upstream supply chains dedicated to mass production of customized products for allowing a decentralized management

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Abstract: *In an upstream supply chain (USC) dedicated to the mass production of customized products, decentralized management is possible and performing in the steady state, if all the links that precede the final assembly line use periodic replenishment policies. These policies require appropriate safety stocks of alternative or optional components. To achieve such performance in the real world, the supply chain must identify the source of any changes. Unexpected fluctuations in the production of USC plants suggest a bullwhip effect, yet most studies of the bullwhip effect fail to consider build-to-order supply chains. A double transformation of available information, derived from bill of materials explosions and time lags, is required to restore steady-state performance. It then remains to detect and quantify changes and, if a build-to-order strategy of alternative components is possible, use decision rules that are robust to such changes.*

Keywords: *Global supply chain management, bullwhip effect, information value, safety stock, upstream supply chain.*

1. Introduction

For the mass production of customized products (Anderson & Pine, 1997) using a build-to-order supply chain (BOSC, Gunasekarana & Ngaib, 2005, 2009), as exemplified by the automotive industry, differentiation results from the combination of n optional components (e.g., sunroofs) or alternative components (e.g., gearboxes). These components are taken from n different sets and assembled on n different workstations in an assembly line. The upstream supply chain (USC) then consists of units that contribute to the production of the vehicles assembled by the company. The various links of the chain are connected by flows of products and information. Eventually, the production decisions made by the last production link (i.e., the assembly line) pull production from the USC.

Two obstacles prevent centralized control of the USC by assembly lines: Many units belong to independent companies, and a link might belong to several supply chains (e.g., the supply chains monitored by PSA and Renault have many common links). The behavior of the chain, and thus its global performance, depends on the information and product exchanges that take place among the links, as well as the control rules used to make provisioning and production decisions.

The pernicious effects of decisions based on local information are well-known in the downstream supply chain, especially for low-cost, standardized, mass products (e.g., beer). They propagate oscillations of increasing amplitude along the supply chain, as highlighted by Forrester (1958) and later identified by name as the bullwhip effect.

Oscillations of production occur in USCs dedicated to the mass production of customized products too, but their causes and mechanisms are relatively unknown. For example, a car is assembled at the request of final customers or car dealers committed by commercial objectives. Because of the high price, each car is subject to individual tracking, which means the amplification effects observed in the distribution networks of low-cost, mass products are unlikely to occur. Upstream, production is organized to meet the demands of a single customer, the final assembly line. However, studies of the bullwhip effect generally ignore this type of situation, even though understanding the mechanisms that promote oscillations along the USC is a prerequisite for improving supply chain performance in terms of efficiency and effectiveness. We assume here that every link uses a periodic provisioning policy in its customer-supplier relationship.

An appropriate analysis of the steady state of periodic provisioning policies in the supply chain also must exist before we can understand why the steady state evolves or is disturbed. In another article (Camisullis *et al.*, 2010) we perform a formal analysis of the steady state of such a USC. In the type of USCs studied herein, the costs induced by a stock-out are so high that the use of an analytical model based on some expected cost function is useless; a periodic replenishment policy relies on a stock-out probability that is necessarily low. Whatever the stochastic sources of oscillation in the USC (e.g., random demand, quality problems, random lead times, packaging constraints, and restricted transport capacity), an exploitation of demand characteristics is possible. Therefore, the appropriate local application of the principles of periodic replenishment policies,

based on a judicious exploitation of the known and stochastic characteristics of demand, keeps stock-outs under control for each link of the USC. Thus, appropriate safety stocks divide the supply chain into independent subsystems, and each entity retains its managerial autonomy, which prevents the propagation of disturbances. In this contribution, we demonstrate how to run each link of the supply chain, according to properties found in the steady state, with appropriate periodical changes of the information and control rules.

We start (section 2) with a survey of literature that deals with the bullwhip effect. Few articles consider a complex supply chain though, and those that do mainly focus on the downstream part.

In section 3, we start by assuming that the supply chain runs in a steady state environment. We also assume that every link uses a periodic provisioning policy in its customer–supplier relationship. Then we identify precisely which information is needed by a link from downstream partners to run its production and provisioning with sufficient risk protection. This information is much more complex than that suggested by prior bullwhip literature. The transmitted information cannot be the same for each link; rather, it must undergo a double transformation, using bill of materials (BOM) explosion and time lags. Yet environment stability never lasts very long. Thus, we also analyze the mechanisms of time lags that can account for detected changes. In turn, the firm can adapt steady state policies to preserve its performance. Currently, information that comes from BOM explosion and time lags is not propagated along the USC, which means USC performance cannot rely on decentralized decisions. A lack of cooperation and reports of poor effectiveness or efficiency may encourage managers to modify their provisioning policies through trial and error, which can trigger new problems along the supply chain. Finally, we examine the problem of detecting changes. Some changes may be induced by company decisions, such as pricing actions, limited series, or the introduction or withdrawal of products. Usually companies anticipate the impacts of those decisions, before they come into effect, though these forecasts tend to be less than reliable for distant periods. Another type of change results from shifts in customers' demands for alternative components. We propose a means to detect this form of change and automatically adapt the parameters of replenishment policies accordingly. To complete this analysis, we note that such changes may alter the effectiveness of monitoring rules used in the BOSC system, such as the synchronous production of alternative components and the definition of sufficient safety stock, especially if the ordered quantity must be a multiple of the transport container size.

2. The Bullwhip Effect in the USC

We provide a short review of the bullwhip effect that reveals USC-oriented investigations are very rare and usually pertain to first-tier suppliers. We then analyze the causes of disturbances in an upstream BOSC.

2.1. The Bullwhip Effect

The bullwhip effect is a well-known phenomenon in industrial dynamics (Forrester 1958); it was regarded as inevitable in historical systems of production. The dynamics among firms in supply chains caused volatility that kept increasing for operations farther upstream. In the effect described by Forrester (1958), real demand information from the end of the chain got distorted by various interpretations, processing, and movement up the supply chain.

Extensive research attempts to identify the major causes, and demonstrate the huge costs, of the bullwhip effect. It usually centers on a downstream supply chain, with the goal of (1) analytically demonstrating the existence of a bullwhip effect for the mass production of standard products, (2) encouraging the use of forecasting and production mechanisms among members of a distribution network based on information from point-of-sales data, or (3) sharing valuable information about independent, identically distributed demand in a downstream supply chain.

The bullwhip effect also has been recognized in many diverse markets (Lee et al. 2004) associated with mass or standard production and volatile markets. For example, in an inventory management context, Sterman (1989) reports evidence of a bullwhip effect for a standard product: beer. The experiment involved four players who made independent inventory decisions, without consultation, and revealed systematic, irrational behavior. Using data about the consumption of high-tech and durable goods, Hanssens (1998) also quantifies the impact of the bullwhip effect and demonstrates that the use of retail sales information can improve the precision of upstream forecasts. In modeling the possible distortion of demand, most prior research considers standard products with high potential volatility, such that the pricing actions assume an eventual economy of scale due to mass production, which is very specific to a distribution supply chain.

The distribution supply chain is situated downstream of the manufacturing center, and its simple configuration supports analyses of the bullwhip effect. Chen et al. (2000) attempt to quantify the impact of demand forecasting on the bullwhip effect for a simple, two-stage supply chain that consists of a single retailer and a single manufacturer. The retailer does not know the true distribution of demand and therefore uses a simple moving average forecast to estimate its mean and variance. The retailer uses these estimates to form a simple order-up-to level. These results

generalize to multistage supply chains, in the case of both centralized and decentralized customer demand information. However, the question remains whether they generalize to an upstream chain, especially in the case of BOSC.

Coordination mechanisms in the supply chain rely on the flow of information among its members. We note that in assessing the value of information sharing, most studies assume the supplier has full knowledge of the underlying demand. Information flows can have direct impacts on the inventory, control flow, and delivery plans of individual members of a supply chain. Yet most studies of the distortion of demand information only model a retail store's sales of one product, such that the retailer issues orders to manufacturers (Lee et al. 1997). In these studies, the bullwhip effect is an outcome of strategic interactions among rational supply chain members. Cachon and Fisher (2000) also investigate the value of information in capacitated supply chains with one supplier, N identical retailers, and independent and identically distributed demands. With a moving average demand forecast, Chen et al. (2000) reduce the bullwhip effect by centralizing demand information. These studies consistently assume that the supplier has full knowledge of the underlying demand model and the order policy used by the retailer, though in reality, this assumption is unrealistic for the downstream supply chain.

Often because of constraints due to scheduling or scale economies, the size of the batch also plays an essential part in explaining the bullwhip effect. Large batch sizes, moving from the downstream partners upstream in chains, result in a difference between the volume requested and production (Lee et al. 2004). Cachon (1999) studies the optimal balance in order policies in a supply chain model with several retailers. The bullwhip effect depends partly on the periodicity of the order and the size on batch. Therefore, to minimize this effect, Cachon recommends reducing the size of the batch and increasing the intervals between orders to reduce the variability of the requests to the supplier.

Moreover, variation in prices, including the effects of promotions at the end of the chain, can cause anticipation of future sales. Price promotions do not create significant new consumption though and therefore generate overproduction cascades along the supply chain. Similarly, the anticipation of rising prices can generate overproduction that gets accentuated moving upstream. Another price effect stems from the generalization of promotional agreements in transactions with customers and suppliers. Companies order goods in great quantities to profit from substantial price reductions, but the levels of these orders are not representative of patterns of spending, and the variation in the bought quantities is much greater than the variation of consumption. In batch-based orders, variation in prices generates

artificial peaks, followed by drastic valleys (Lee et al. 2004).

2.2. Causes of Disturbances in Upstream BOSC

The causes of upstream disturbances are somewhat different. Fluctuations mainly are triggered by decisions made by the company, which lead to a BOSC strategy. Pricing actions aim to boost demand, such that they modify not only sales and production volumes but also the requirements for optional or alternative components, depending on the product segments affected by the price changes. Limited series of homogenous products provide another tactic to maintain or boost demand and have similar effects on demand levels and requirements for optional or alternative components. We also cannot ignore the impact of the introduction or withdrawal of products.

Therefore, the causes of disturbances in an upstream BOSC cannot be the same as those cited in prior bullwhip literature, mainly because the BOSC is pulled by each unique customer, such as an automotive assembly line. This customer reacts to changes in final demand, though its immediate production level and detailed production schedule already have been defined. Changes in final demand may trigger commercial actions, such as pricing tactics or limited series, to boost that demand. The introduction or withdrawal of car models also should have effects. That is, these decisions likely have an impact on the level of daily production and the structure of the demand for alternative components, which the members of the supply chain should study in advance. Because a limited series offers no variety, the impact on demand for alternative components should depend only on the fraction of daily production dedicated to the limited series and the degree of cannibalization of other model configurations.

From a practical point of view though, this information rarely gets propagated along the USC; on the contrary, we show it is quite useless. Thus USC plants react or overreact to "weak signals" from the BOSC leader, which induces stock-outs and excessive stocks and triggers massive disturbances along the USC.

3. Restoring Steady-State Performance in a Changing Environment

If managers of upstream USC links can adapt their decision rules quickly using information transmitted from the final assembly line, steady-state performance can be restored even if the environment changes. We explain why the information necessarily is the result of a double transformation that relies on mechanisms associated with the bill of materials (BOM) explosion and time lags. The latter relate to the growing delay of moving upstream in the supply chain, that is, between the date of production of a component by one link and its integration into the end product in the final assembly line. Without this double transformation, the

information transmitted lacks any value. In the steady state, the time lag mechanism does not play an important role, because when the decision rules have been defined using appropriate information, there is no reason to change them. If every link receives appropriate information and uses it to control stock-outs, disturbances in the supply chain should be rare, and the managerial independence of each link of the USC can be guaranteed. We therefore move on to check various implementation problems.

3.1. Double Transformation of Information

We begin by determining the information required by each link of the USC, according to the steady-state assumption, to establish production and replenishment rules that will allow for both management independence and smooth USC functioning. Such rules also indicate the initial calibration of the steady state of the USC. We then show that knowledge of current or previous changes can support an adaptation of the monitoring rules and make steady-state performance possible. This point leads to our extended conceptualization of the order penetration point.

3.1.1 Mandatory use of planning BOM to define information to send upstream

Different forms of information sharing are useful for decreasing costs and risks in short-term decision making (Chandra et al. 2007). Firms can share raw information, such as sales histories, orders, inventory positions, and deliveries, or they might share processed information that deals with planned or forecast demand (Ryu et al. 2009). The latter form of information might be the output of a collaborative process that represents a first step toward centralized management of the supply chain.

The value of shared information depends on not only its possible but also its effective uses, which aim to share cost savings across the supply chain. Even in the steady state, transmitting detailed information about daily production or end-user demand to upstream echelons is useless: Products exchanged between links in the USC are different than those that represent the focus of the downstream supply chain, due to the classic mechanism of BOM explosion. For example, demand for a component gets pulled by the one of the alternative parts mounted in a workstation used in the final assembly line, such that the same piston might be found in various motors on the car assembly line.

The planning bill of materials (PBOM) describes related options or modules that constitute an average end item. Applied to a set of R alternative components r that might be mounted in a given station of the assembly line (e. g. motors) the PBOM coefficients p_r ($0 < p_r < 1$; $\sum_r p_r = 1$) represent the steady-state probabilities of a multinomial distribution, in which the number of trials n equals daily production of cars. These alternative components belong to the level 1 of the BOM. The daily demand X_{1r} of the alternative

component r follows the binomial distribution $\mathcal{B}(n, p_r)$, because in each n trials, the event “alternative component r is mounted” is tested against the event “component r is not mounted”. Component r may include $a_{rs} > 0$ units of the component s (e. g. piston set) in the level 2. The daily demand X_{2rs} of that component s , as induced by the daily requirement X_{1r} , is $a_{rs} \cdot X_{1r}$. If that component s can be used by several alternative components $r' \in R_s$, the total demand X_{2s} is $\sum_{r' \in R_s} X_{2r's} = \sum_{r' \in R_s} a_{r's} \cdot X_{1r'}$.

The knowledge of the distribution of X_{2s} is necessary to define the appropriate order-up-to level of that component s , associated with the preferred stock-out risk and thus its safety stock. The distribution of that sum of weighted binomial variables can be easily defined by using a Monte Carlo simulation. Those Gross Requirements are random variables and not fixed values as in the MPR computation of planned orders.

In turn, that component s of level 2 (e. g. a given piston set) uses $b_{su} (> 0)$ components u of level 3 (e. g. a given piston head) but it may be not the only one ($\rightarrow s' \in S_u$). The previous reasoning applies again, after linking component u to component r : as previously, the demand X_{3u} is a weighted sum of a subset of demands of components of level 1:

$$X_{3u} = \sum_{s' \in S_u} b_{s'u} \cdot X_{2s'} \\ = \sum_{s' \in S_u} b_{s'u} \sum_{r' \in R_{s'}} a_{r's'} \cdot X_{1r'}$$

Again, its distribution can only be defined by using a Monte Carlo simulation.

Let's illustrate this mechanism with an example. For a given set of 6 alternative motors ($r = 1 \dots 6$) that can be mounted in a given workstation of a car assembly line. The motors PBOM is $\{M_1, 54\%; M_2, 13\%; M_3, 4\%; M_4, 22\%; M_5, 5\%; M_6, 2\%\}$. The line production is a 962 cars per day ($\rightarrow n = 962$). The daily requirement X_{1r} of the alternative component r follows the binomial distribution $\mathcal{B}(962; p_r)$, that is to say $X_{1,1} \sim \mathcal{B}(962; 54\%)$, for the motor 1, and $X_{1,5} \sim \mathcal{B}(962; 5\%)$, for the motor 5. Thus, in the steady state with a risk of 0.1%, the safety stocks of motors 1 and 5 are 47 and 23. If, according to the BOM, only motors M_1 and M_5 include the piston set P_1 ($s = 1$) and if M_1 needs 4 piston sets while M_5 needs 6 piston sets ($a_{1,1} = 4$; $a_{5,1} = 6$), the daily requirement of that piston set P_1 is $X_{2,1} = 4X_{1,1} + 6X_{1,5}$, which is an even discrete variable, starting from 4 for the positive values ($X_{2,1} = 0, 4, 6, 8, \dots$ as $X_{1,1}$ and $X_{1,5}$ are discrete non-negative values). Using the Monte Carlo simulation, one finds a reorder point of 2622 (for a risk of 0.1%,) and a demand average of 2392; then the safety stock of piston sets is 230. If only piston sets P_1 and P_3 include the piston head H_1 , component ($u = 1$) of level 3. If only piston sets P_1 and P_3 include the piston head H_1 and if P_3 is mounted only in motors M_2 and M_6 , the daily requirement of that piston set P_3

is $X_{2,3} = 4X_{1,2} + 4X_{1,6}$. With $b_{1,1} = b_{1,3} = 1$, the daily requirement of H_1 is a sum of weighted binomial variables $X_{3,1} = 1 \cdot (4X_{1,1} + 6X_{1,5}) + 1 \cdot (4X_{1,2} + 4X_{1,6}) = 4X_{1,1} + 4X_{1,2} + 6X_{1,5} + 4X_{1,6}$, with $X_{1,1} \sim \mathcal{B}(962; 54\%)$, $X_{1,5} \sim \mathcal{B}(962; 5\%)$, $X_{1,2} \sim \mathcal{B}(962; 13\%)$ and $X_{1,6} \sim \mathcal{B}(962; 2\%)$. Using again the Monte Carlo simulation, it is easy to show that, in the steady state, the average demand of piston heads H_1 is 2944 and the safety stock, 470.

3.1.2. Mandatory use of time-lag mechanisms for a non persistent steady state

The steady state never lasts more than few weeks, but environmental changes often are slow enough to suggest that the “real world” is defined by a succession of slightly different steady states. From one state to the next, changes involve the level of production and the structure of demand for each set of alternative components. Consider a component launched in production at time t in a USC echelon, and integrated in a vehicle at time $t + \delta$.

To make good decisions at time t , the echelon needs appropriate information for time $t + \delta$, such that δ represents the information lag. This lag plays a similar role to the lead-time one in the MRP but within the wider perimeter of the USC. Another difference with the MRP system is that we assume here we are beyond the Order Penetration Point ($\delta > \text{OPP}$), defined hereafter, and then beyond the MRP frozen horizon. The mechanism described in the previous section therefore must be adapted. To simplify the mechanism description, we assume that components productions are launched every day for all the components produced in the USC; the replacement of that assumption is easy but yields a more complex formulation. The demand $X_{1r,t}$ of the alternative component r of level 1 for the day t , to launch in production on that day, follows the binomial distribution $\mathcal{B}(n_{1r,t+\delta_r}; p_{1r,t+\delta_r})$, as those components will be integrated in a vehicle at time $t + \delta_r$. The demand X_{2st} of the alternative component s of level 2 for the day t , and used by several alternative components $r' \in R_s$ is a weighted sum of a subset of daily productions of components of level 1: $\sum_{r' \in R_s} a_{r's} \cdot X_{1r',t+\delta_{r'}}$. That component s of level 2 uses component u of level 3, as some other ones ($\rightarrow s' \in S_u$). After linking component u to component r : as previously, the demand X_{3ut} is again a weighted sum of a subset of daily productions of components of level 1:

$$X_{3ut} = \sum_{s' \in S_u} b_{s'u} \sum_{r' \in R_{s'}} a_{r's'} \cdot X_{1r',t+\delta_{r'}}$$

Again, all those distributions can easily be defined by using a Monte Carlo simulation.

Let's adapt our previous example. The current day t is 1. The motors 1 and 5 are respectively characterized by a time-lag of 2 and 3 days (\rightarrow motors 1 and 5 produced on day t will be mounted in the assembly

line respectively on days $t+2$ and $t+3$). The Multinomial distribution and production level don't change the first two days. On the following ones, the daily production decrease from 962 to 605 and the motors PBOM becomes $\{M_1, 49\%; M_2, 10\%; M_3, 3\%; M_4, 25\%; M_5, 11\%; M_6, 2\%\}$. With this information, the production of motors 1 and 5 to launch on day t are the requirement of the assembly line for days $t+2$ and $t+3$: $X_{1,1,t+2} \sim \mathcal{B}(962; 54\%)$ and $X_{1,5,t+3} \sim \mathcal{B}(605; 11\%)$. With a risk of 0.1%, the safety stock is still 47 for motors 1 and 24 for motor 5. If, for the production of piston sets H_1 , the delay between planned order and delivery is 2 days, the part of the production of day t , sent for producing motor M_1 , will be set in a car using motor M_1 4 days later (information lag); the other part is sent for producing motor M_5 , 5 days later. Then, the demand of that piston set P_1 for day t is $X_{2,1,t} = 4X_{1,1,t+4} + 6X_{1,5,t+5}$, where $X_{1,1,t+4} \sim \mathcal{B}(605; 49\%)$ and $X_{1,5,t+5} \sim \mathcal{B}(605; 11\%)$. Using the Monte Carlo simulation, the safety stock of piston sets is 184 for that production day (with an average demand of 1488).

If the information lags for the motors M_2 and M_6 that include piston P_3 are respectively 2 days and 1 day, the demand of piston P_3 for day t is $X_{2,3,t} = 4X_{1,2,t+2} + 4X_{1,6,t+1}$. Using the same delay between planned order of H_1 and its delivery (2 days), the demand of the piston heads H_1 used by P_3 to be mounted in motors M_2 and M_6 is $X_{2,3,t} = 1 \cdot 4X_{1,2,t+4} + 1 \cdot 4X_{1,6,t+3}$. Then the daily requirement of that piston head H_1 is $X_{3,1,t} = 1(4X_{1,1,t+4} + 6X_{1,5,t+5}) + 1(4X_{1,2,t+4} + 4X_{1,6,t+3}) = 4X_{1,1,t+4} + 4X_{1,2,t+4} + 6X_{1,5,t+5} + 4X_{1,6,t+3}$. Using again the Monte Carlo simulation, it is easy to show that, in the steady state, the average demand of piston heads H_1 is 1876 and the safety stock, 235.

In turn, we must emphasize three important operational consequences. First, the final assembly line, which is the BOSC leader, drives information sharing, because the relevance of the information depends on the reliability of the volume and structure forecasts, as well as the anticipated impacts of pricing actions and launches of limited series. Beyond a certain horizon, information reliability weakens and decreases interest in information sharing among units that are farther away in the USC. To counter this effect, the unit should increase the probabilities of demand for alternative components and the production level. The loss of efficiency is the price to pay to achieve a certain effectiveness, knowing that the stock-out risk is not really under control.

Second, information sharing involves minimal cooperation between the enterprises of the USC, because the lag δ between the production of a component and its inclusion in the car in the final assembly line equals the sum of the intermediate lags

observed between each pair of echelons in the path that links the final assembly line to the echelon that produces the component. The reliability of the intermediate lags transmitted to the BOSC leader also influences the relevance of the information sharing and thus the decentralization of decisions. Furthermore, because the value of shared information depends on its effective use, all members of the USC must “play the game”; if not, uncontrollable disturbances cannot be avoided.

Third, it is desirable that information lags are weak to improve the chances of controlling the whole USC. Savings from a distant provision process may be balanced by a loss of global coordination of the USC.

3.1.3 Extended conceptualization of the order penetration point

The displacement of the order penetration point (OPP) suggests the possibility of increasing the proportion of production, which in turn may improve effectiveness and efficiency in certain demand conditions. The OPP has been used since 1920 but was formalized on in the 1950s (Alderson, 1950). Olhager and Östlung (1990) discuss the use of push and pull systems relative to the position of the OPP, arguing that pull systems necessarily apply upstream of the OPP, whereas push systems involve downstream operations. This approach could differ in the supply chain, depending on the vision, whether global or local (Giard and Mendi, 2008).

Orders sent upstream to the OPP cannot be produced to order if the time between order arrival and the delivery shipment is insufficient. The production units must produce to stock, which they can do without any information. However, if they lack information, no scientific basis supports the rules, and stock-out risk cannot be controlled. In a supply chain, it leads to major disturbances and poor efficiency. To achieve scientific-based monitoring, plants need information about demand levels and stochastic structures. As we showed for the USC, such information results from the double mechanism of the BOM explosion and time lags. These mechanisms require that the planning horizon of the final assembly line exceeds the lag δ that separates the production of a component from its inclusion in the final product. Therefore, we define an extended order penetration point (EOPP), beyond the “ordinary” OPP, and divide USC units into plants that can use information to mitigate stock-out risk and others. These others, which are outside the EOPP, must make decisions with unreliable information, which can lead to stock-outs that may be propagated downstream in the USC.

3.2. Implementation

To achieve the wanted performance, firms must be able to detect changes before making adaptations.

3.2.1 Detection of changes

The necessary changes to consider include commercial actions (e.g., pricing, limited series) and production or logistic actions (e.g., delivery frequencies, container sizes). Such actions should be communicated to managers in charge of supply chain monitoring. Other changes require detection devices.

–*Commercial actions.* Commercial actions, such as discounts or limited series offers, can affect the level and structure of demand. Therefore, it becomes necessary to conduct preliminary studies of these actions to gather information about the volume spread over operations and assumptions about the level of cannibalization. The changes are observable in the structure of requests for alternative components (i.e., weighted average of structures for series of sold products).

–*Production and logistics actions.* In this category, three actions are pertinent. First, actions could relate to necessary adjustments of the production capacity to face evolutions of demand. For example, adding or reducing shifts may have a direct impact on the structure of demand. Forecasting these changes is beyond the scope of this study, but these adjustment decisions should be made weeks in advance to enable appropriate staff management. Second, some actions relate to transportation. For example, changes in the periodicity and duration of transports among links should be taken into consideration because they modify the probability distributions used to define the order-up-to levels. Third, in relation to transport containers, any modification in the size of specific containers must be known in advance, because it likely affects safety stocks.

–*Detection of changes in the demand structure.* In the preceding discussion, we based the solution on an implicit assumption of a steady state. Challenging this assumption does not pose a problem if the change relates to the global production level: Order-up-to levels adapt to the new steady-state characteristics and cause an increase or reduction of the safety stock, varying in the same direction as the level of production.

The change of demand structure also can be taken into account through single exponential smoothing. Assume the time series is locally stationary, and let \hat{p}_{jt} and p_{jt} denote the estimated probability of including the alternative component j in a car at time t and the associated observed percentage, respectively. The estimated \hat{p}_{jt} can be calculated as $\hat{p}_{jt} = \gamma \cdot p_{jt} + (1 - \gamma) \hat{p}_{jt-1}$. If the same smoothing technique is used for all alternative references, then:

$$\sum_j \hat{p}_{jt} = \sum_j \gamma \cdot p_{jt} + (1 - \gamma) \sum_j \hat{p}_{jt-1} = \gamma \sum_j p_{jt} + (1 - \gamma) \sum_j \hat{p}_{jt-1} = \gamma \cdot 1 + (1 - \gamma) \cdot 1 = 1.$$

The choice of the smoothing parameter γ implies a choice between high values (which allow faster adaptation to possible modifications of the structure of demand but imply overreactions to random variations) and low values (which mitigate the impact of random variations but take more time to detect changes). The

slow evolution of the demand structure favors a low coefficient, though it can also be determined by minimizing previous forecast errors ($\min \sum_{t' < t} (\hat{p}_{jt'} - \hat{p}_{j,t'+1})^2$) or some adaptive control of the smoothing parameter. Similar to all weighted moving averages, exponential smoothing suffers the disadvantage of generating oscillations due to the auto-correlation phenomenon (i.e., Slutsky-Yule effect). Such oscillations generate positive biases in the case of an excessive estimate of p_i and negative biases otherwise. A negative bias increases the risk of stock-outs and thereby leads to an increase in the current estimate, according to the known variance of the Slutsky-Yule error. In the case of positive bias, it means acceptance of overprotection. The analysis of the confidence interval of the daily requirements for part i may lead to the rejection of a hypothesis of oscillations generated only by the Slutsky-Yule effect. For example, the impact of the production of a limited series may require that the time series be corrected before forecasting. Most of the time though, it is induced by schedule constraints that introduce deviations between the daily demand structure and daily consumption by the assembly line, in which case it is preferable to use the forecast error deviation $\sqrt{\sum_{t'=2}^t (\hat{p}_{jt'} - \hat{p}_{j,t'+1})^2 / (t-1)}$ to define an upper limit of \hat{p}_{it} estimates.

3.2.2 Adaptation to changes

After the changes are detected, some adaptation of the monitoring rules must be implemented. Modifying the parameters of replenishment policies does not demand any particular comments. However, some changes influence other monitoring rules, including the production to order of alternative components with batch constraints and the safety stock involved when the transportation of an alternative component demands containers that contain only one type of part.

In the first case, possible need to change some monitoring rules used in the production to order. If the production capacity between two shipments is superior to ordered quantity, and the diversity demanded by batch size constraints cannot be met; therefore, inventories of alternative components should be implemented to avoid stock-out. Different rules can apply in this case (e.g., kanban system, order-up-to level periodic policy), but their parameters should be modified when the environment changes. A synchronous production method has been proposed (Giard and Mendy 2008) and benchmarked in the automotive industry; it helped avoid stock-outs and decreased safety stocks, even in the face of quality problems during the production process. Moreover, this new approach triggers the immediate adaptation of parameters to any variation in the demand structure, which is unlike most other approaches. Regardless of the rule used, a change in daily production provokes an adaptation of the parameters for those rules.

In the second case, transportation-related constraints may determine the amount of alternative components. We are interested in particular in a rule that demands the ordered quantity must be a multiple of the container size. This constraint is easy to take into account; it requires that the accepted stock-out risk be modified such that it can be managed automatically (see Camisullis *et al.* 2010). With a production-to-order system, this constraint implies that the sequence of alternative components preferred by the car assembly line will differ from the one that results from orders that must respect container constraints. Thus, the importance of an alternative component differs from its entrance rank in stock (i.e., shift of rank in the orders sent to the supplier). This rank change leads inevitably to stock-outs if the consumption rank occurs before the entrance rank. To avoid a situation in which the assembly line needs a component before it is available, safety stocks must support every alternative component, and their levels can be defined by simulation (Camisullis and Giard, 2008). Changes in the level of production and structure of demand thus imply a recalibration of safety stocks.

4. Conclusion

We have shown that the disturbance mechanisms in upstream BOSC differ from those identified in prior bullwhip effect literature. The centralization of decisions in the BOSC is not probable, considering the multiplicity of unit owners and because one unit may support several supply chains. Thus, we require new coordination mechanisms that can guarantee the performance of a BOSC. In the steady state, decision autonomy is feasible if the stock-out risk is negligible, perhaps due to appropriate safety stocks, and if the right information is available to define the order-up-to levels. This information should result from a double transformation that relies on the BOM explosion and time lags associated with the interval between the production of a component and its effective inclusion in the final product. If all units in the USC use the information to adapt their decision rules, the USC is under control and efficient. The BOSC leader coordinates the upstream echelons by sending appropriate information; this leader also takes responsibility for detecting changes. The changes may demand shifts in monitoring the production to order of alternative components, as well as the adaptation of safety stocks to address the rank changes induced by constraints.

Although these mechanisms may be difficult to implement, alternative ones that achieve the same performance remain to be found.

5. References

Alderson, W. (1950), Marketing Efficiency and the Principle of Postponement, *Cost and Profit Outlook*.

- Anderson, D.M. & Pine, J. II (1997), *Agile Product Development for Mass Customization*, New York: McGraw-Hill.
- Cachon, G.P. (1999), Supply chain demand variability with scheduled ordering policies, *Management Science* 45 (6), 843-856.
- Cachon, G.P. & Fisher, M. (2000), Supply chain inventory management and the value of shared information, *Management Science* 46 (8), 1032-1048.
- Camisullis, C. & Giard, V., and Mendy Bilek, G.,(2010) The causes and determination of safety stocks in the upstream supply chain dedicated to the mass production of customized products, Conference ILS 2010 (International Conference on Information Systems, Logistics And *Supply Chain*), first working paper n°295 of LAMSADE (Laboratoire d'Analyse et Modélisation de Systèmes pour l'Aide la Décision - CNRS-Université Paris Dauphine).
- Camisullis, C. & Giard, V. (2008), A new need for safety stocks in a supply chain dedicated to customized mass production, *Supply Chain Forum: An International Journal*, 9, 88-96.
- Chandra, C., J. Grabis, A. Tumanyan (2007), Problem taxonomy: a step towards effective information sharing in supply chain management, *International Journal of Production Research* 45 (11), 2507-25.
- Chen, F., Drezner, Z., Ryan, J., & Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. *Management Science* 46 (3), 436-443
- Forrester, J.W. (1958). Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review* 36 (4), 37-66
- Giard, V. & Mendy G. (2008), Scheduling coordination in a supply chain using advance demand information, *Production Planning and Control* 19 (7), 655-667.
- Gunasekarana, A. & Ngai, E.W.T. (2005), Build-to-order supply chain management: a literature review and framework for development, *Journal of Operations Management* 23 (5), 423-451.
- Gunasekarana, A. & Ngaib, E.W.T. (2009), Modeling and analysis of build-to-order supply chains, *European Journal of Operational Research* 195 (2), 319-334.
- Hanssens, D. M. (1998), Order forecasts, retail sales, and the marketing mix for consumer durables, *Journal of Forecasting* 17 (3-4), 327-346.
- Lee, H.L, Padmanabhan, V., & Whang, S. (1997), Information distortion in a supply chain: The bullwhip effect. *Management Science* 43 (4), 546-558.
- Lee H.L, Padmanabhan, V., & Whang, S. (2004),. Information distortion in a supply chain: The bullwhip effect. *Management Science* 50 (12), 1875-1886.
- Olhager, J. and Östlund, B. (1990), An integrated push pull manufacturing strategy. *European Journal of Operational Research*, 45 (2-3), 135-142.
- Ryu, S.-J., T. Tsukishima, H. Onari (2009), A study on evaluation of demand information-sharing methods in supply chain, *International Journal of Production Economics* 120 (1), 162-175.
- Sterman J.D. (1989), Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment, *Management Science* 35, 321-339.