Information Sharing Strategies to Reduce Fluctuations and Bullwhip Effect in Supply Chains[1]

Baris Gunduz
Ford Otosan
Ankara Asf. 4.Km
Uskudar, Istanbul, Turkey
+90 216 326 70 60, x905
bgunduz@ford.com.tr

Yaman Barlas
Bogazici University
Department of Industrial Engineering
80850, Bebek, Istanbul, Turkey
+90 212 358 15 40, x2073
ybarlas@boun.edu.tr

Supply chain inventories are prone to fluctuations and instability. Known as bullwhip effect, small variations in end item demand create oscillations that amplify throughout the chain. We try to understand the underlying structure that generates bullwhip effect, and explore the effectiveness information sharing to eliminate this type of behavior, by using dynamic system simulation. Extensive parametric analysis is carried out for this purpose. Simulation results show that (i) a major root cause of bullwhip effect is independent demand forecasting performed at each stage of the supply chain and (ii) demand and forecast sharing strategies can significantly reduce but not completely eliminate the bullwhip effect. Our research continues with alternative ordering policies, supply networks and forecasting methods.

Keywords: supply chain, bullwhip effect, information sharing, coordination, demand forecasting, dynamic feedback simulation

Introduction

Supply chain inventories are prone to fluctuations and instability. Small changes in end item demand create inventory and order oscillations that amplify as one moves up in the supply chain. (Forrester 1961, Ch.12; Sterman 1989; and Sterman 2000, Ch. 17, 18). This phenomenon of amplification of oscillations through the supply chain is also known as the *bullwhip effect* (Lee *et al.* 1997; Chen *et al.* 1998, Xu *et al* 2001).

Lee *et al.* (1997) identifies four main causes of bullwhip effect as: demand signal processing, order batching, rationing game and price variations. Chen *et al.* (1998) argues that the bullwhip effect is due, in part, to the need to forecast demand. Sterman (2000, Ch.17 and 18) and Forrester (1961, Ch.12) show that delays inherent within the supply chain together with demand forecasting and distortion can create amplified oscillations.

Supply chain literature and management practice focus on coordination policies based on *information sharing* among supply chain members in order to reduce the bullwhip effect. Chen *et al.* (1998) argues that centralizing demand information could significantly reduce bullwhip effect. Xu *et al.* (2000) and Lee and Whang 1998 report that demand forecast and inventory information sharing is effective in reducing order fluctuations and safety stocks. Gavirneni *et al.* (1999) compares the no-information-sharing case against two different degrees of information sharing policies used by the

[1] Supported by Bogazici University Rereacrh Fund no. 02R102

retailer (partial and complete sharing), on a simple one retailer-one supplier chain. Gallego and Özer (2001) search optimal policies for with and without demand information sharing cases for a two stage supply chain, where retailer batches orders and faces Poisson demands. Jeong and Maday (1996) discuss the stability of a multi-echelon supply chain from a feedback control theoretic perspective. Silver *et al.* (1998) suggest demand sharing and *echelon inventory* policy implementations. Authors propose that each stage apply *echelon* (s,S) policy, in which an agent monitors its echelon inventory level (the total inventory position of the subsystem consisting of all downstream inventories, including the stage itself).

The purpose of this research is twofold: (1) to understand the underlying structures and factors that generate inventory fluctuations and bullwhip effect through the supply chain; and (2) to explore the effectiveness of some management strategies (in particular sharing demand and forecast information) in ameliorating this undesirable behavior. Dynamic feedback modeling is used as the research platform.

Model Structure

We consider a three-stage supply chain system consisting of identical agents where each agent (i) orders only from its upper agent (i+1). An agent ships goods immediately upon receiving the order if there is sufficient on-hand inventory. Orders may be partially fulfilled and unfulfilled orders are backlogged. Shipped goods arrive after a constant transit lead-time. Uppermost stage places orders to an infinite source. This model represents an uncapacitated producer-wholesaler-retailer setting. For consistency with inventory literature, time is assumed discrete (DT=1). The basic equations are (excluding the ordering heuristics to be analyzed later):

Local inventory increases with arrivals and decreases by shipments:

$$LI_{i,t} = LI_{i,t-1} + (A_{i,t} - S_{i,t})$$

where $A_{i,t}$ is the arrivals to stage i, and $S_{i,t}$ is the shipments from stage i in period t.

In transit inventory is the goods shipped by the upper stage, but has not yet arrived:

$$IT_{i,t} = IT_{i,t-1} + (S_{i+1,t} - A_{i,t})$$

Goods in transit arrive after an exponential delay structure:

$$A_{i,t} = IT_{i,t} / LT_i$$

where LT_i is the transit lead time needed for shipments by stage $(i+1)$ to reach stage i.

Shipment requirement (*SR*) for a stage i is the sum of demand faced ($D_{i, t}$) at time t and backlogged orders ($BL_{i, t}$):

$$SR_{i, t} = BL_{i, t} + D_{i, t}$$

If there is enough local inventory, the required amount is shipped immediately in one period. If not, the unfulfilled portion of orders are added to the backlog:

$$S_{i ,t} = \min (SR_{i, t}, LI_{i, t})$$

$$BL_{i, t+1} = BL_{i, t} + D_{i, t} - S_{i, t}$$

Net inventory (*NI*) is the local inventory after backlogs are subtracted:

$$NI_{i, t} = LI_{i, t} - BL_{i, t}$$

Agents are assumed to be unaware of the exact demand pattern they are facing, so they must forecast future demand. Simple exponential smoothing is used as the forecasting mechanism. Thus the expected demand is calculated by:

$$E_{i, t} = E_{i, t-1} + (1 / EAT_i) (D_{i, t-1} - E_{i, t-1})$$

where EAT_i is the expectation adjustment time used by stage *i*. $D_{i, t-1}$ is the demand faced by stage *i*. End demand D_1 is an external input to be described in the next section and demands D_2 and D_3 faced by stage two and three are actually the orders given by their lower stages. ($D_i = O_{i-1}$, where O_i are to be described in the following sections).

For any agent, the expected total demand during lead time ($\hat{D}_{i,L}$) is simply calculated by expected demand for one period multiplied by lead time:

$$\hat{D}_{i,L} = (LT_i)(E_{i, t})$$

Each agent continuously monitors her inventory position (IP), defined as the sum of her local inventory (LI), in transit goods from the upper stage (IT), backlog (BL) at the upper stage minus the backlog at her stage:

$$IP_i = LI_i + IT_i + BL_{i+1} - BL_i$$

The stock-flow diagrams for retailer, wholesaler and producer are shown in Figure 2 and Figure 3.

Demand Pattern

Three types of demand input are used: 1- deterministic 'step up and down' demand for testing/verification purposes, 2- iid random demand (Normal(20,2)) in some selected comparison runs, and 3- stationary autocorrelated demand (obtained by exponential smoothing of white noise, with an autocorrelation period of five) used in most runs in this paper, unless otherwise noted. (Figure 1 illustrates these demand patterns).

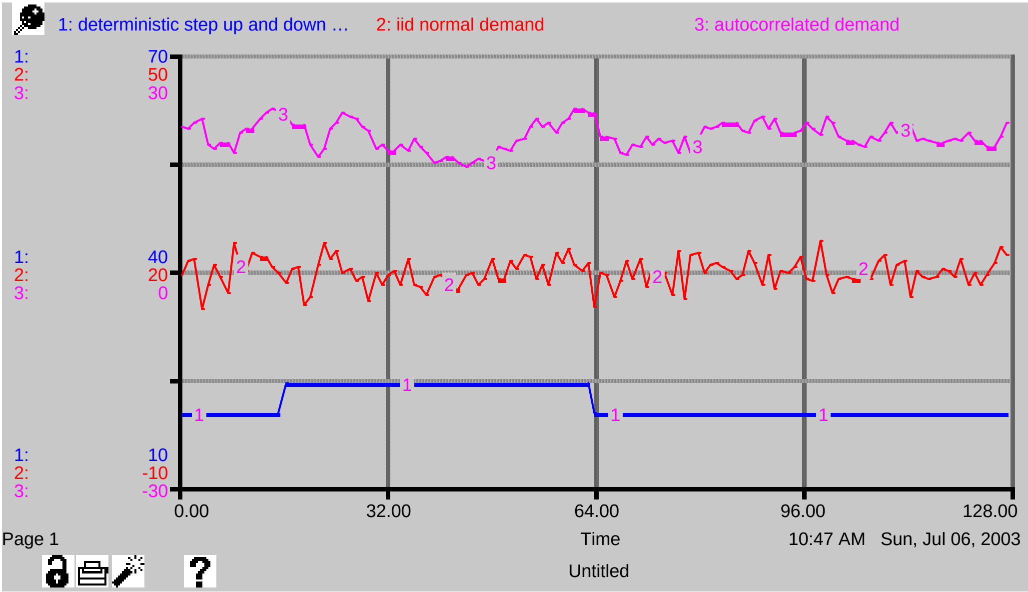

Figure 1. Three different demand patterns used in simulation experiments

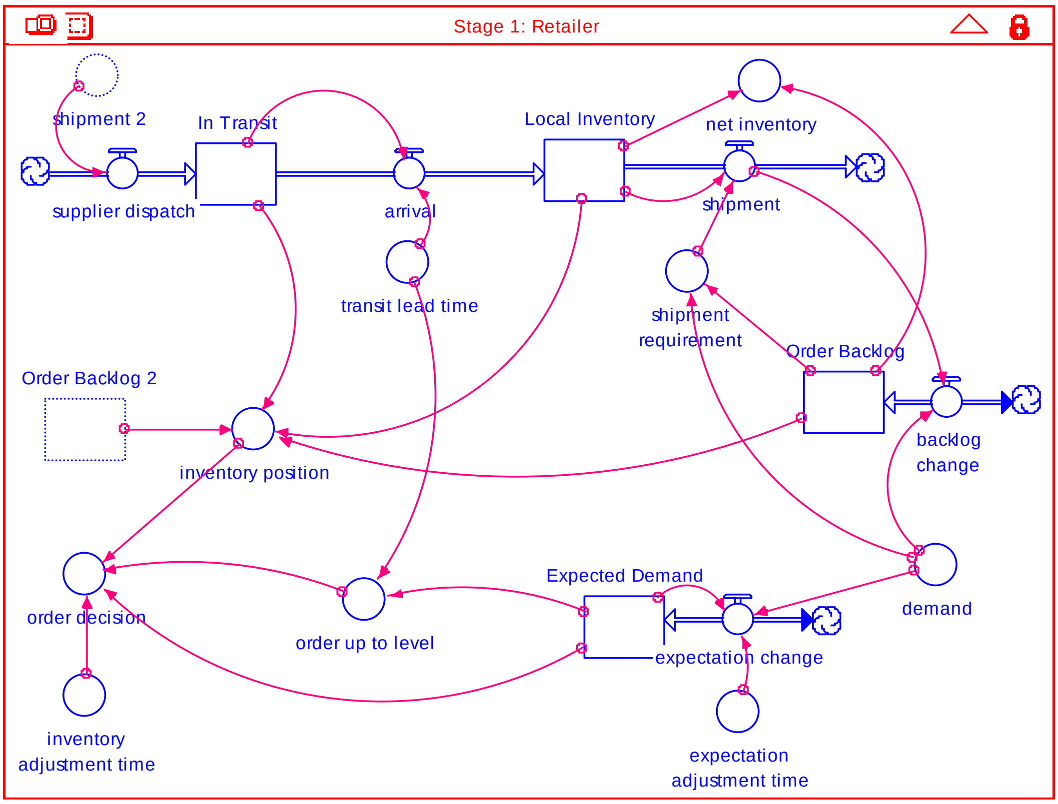

Figure 2. General stock-flow diagram of the supply chain model: stage one, retailer

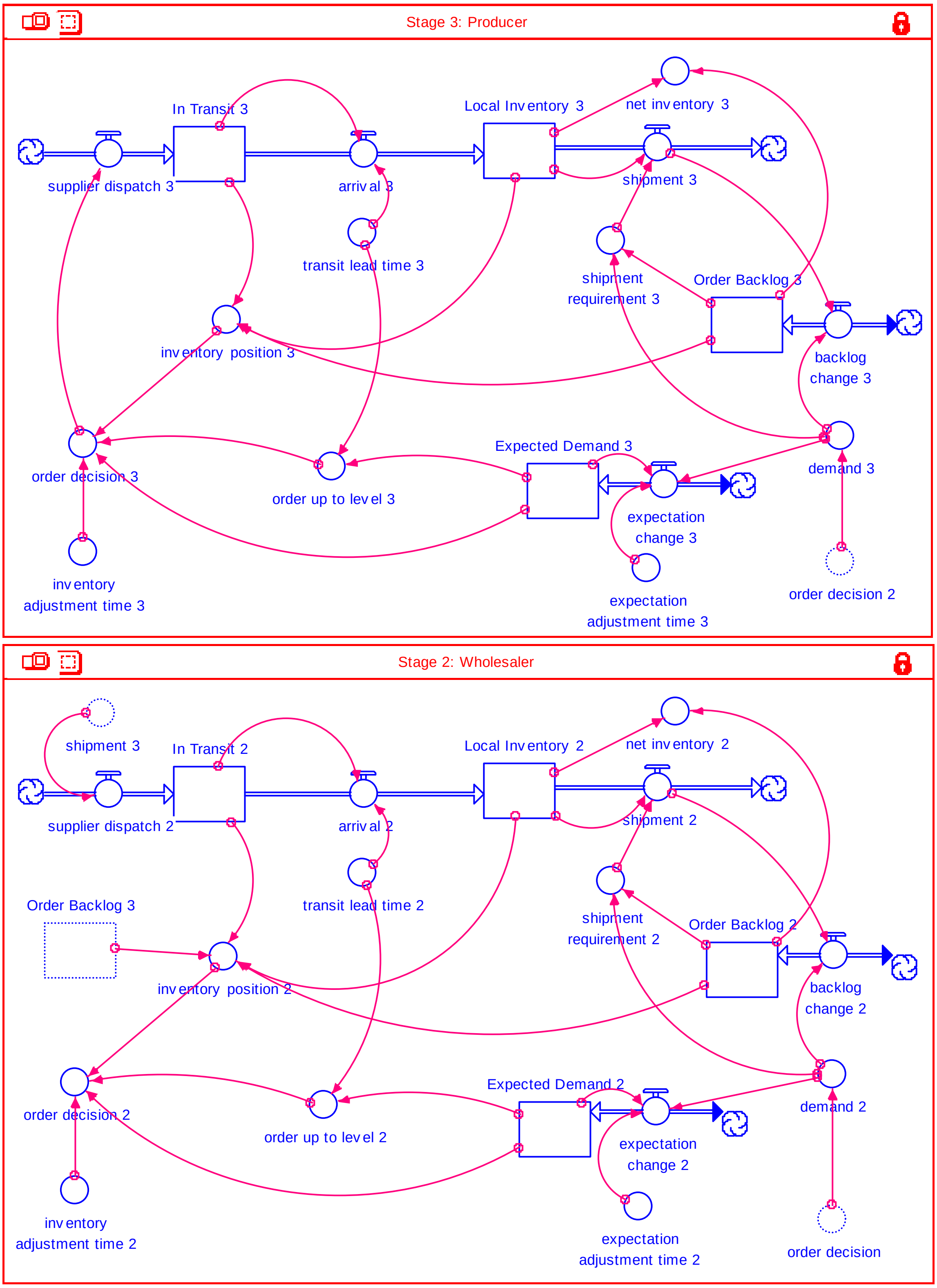

Figure 3. Stock-flow diagram of stage two and three: wholesaler and producer

Ordering Policies

Three basic inventory management policies are tested within the supply chain model: Order-up-to-S policy, standard system dynamics order policy (anchor-and-adjust policy), and (s,S) policy. As all stages are assumed identical, for each selected policy, all stages use the same policy with the same parameters. In reference runs, each stage locally decides on the order quantity without considering the overall supply chain.

Order-up-to-S Policy

Order-up-to-S Policy is the well-known base stock policy where an agent orders the quantity needed to bring its inventory position up to a base stock level S whenever it falls below S. The associated ordering equation is:

$$O_{i,\,t} = \max((S_{i,\,t} - IP_{i,\,t})/IAT_i,\, 0)$$

where $O_{i,\,t}$ is the order decision, $S_{i,\,t}$ is the order-up-to-level, $IP_{i,\,t}$ is the inventory position, and IAT_i is the inventory adjustment time. In the standard up-to-S policy, the discrepancy is immediately ordered, so we set inventory adjustment time IAT to one.

The order-up-to-level ($S_{i,\,t}$) can be set in different ways. (One approach is to compute it by $S = \hat{D}_L + k\sigma_L$, where $\hat{D}_L$ is expected demand during lead time; $k\sigma_L$ is safety stock where σ_L is standard deviation of forecast errors of lead time demand, and k is a constant selected according to desired service level. In any case, the idea is to set S at a level greater than $\hat{D}_L$ to account for demand variation. A suitable constant S is another simple choice. See Gündüz 2003). A practical formula suggested for S is to 'inflate' the shipment lead time LT by a factor K, to account for the variation. The formula is:

$$S_{i,\,t} = (LT_i + K_i)\, E_{i,\,t}$$

where LT_i is the transit lead time for stage *i*, K_i is the 'lead time inflation constant', and $E_{i,\,t}$ is the expected demand (or expected order of stage i-1) estimated by stage *i*. (Recall that $\hat{D}_{i,L} = (LT_i)(E_{i,\,t})$ anyway, so that the term $(K_i)E_{i,}$ is the extra addition to $\hat{D}_L$ to account for the variation).

In this policy, the order-up-to-level S is updated each period, as the expected demand is updated. The resulting inventory dynamics (with autocorrelated demand), $LT_i = 3$, $K_i = 2$ is seen in Figure 4. Note the oscillations and bullwhip effect (amplification) along the supply chain, as one moves from the retail end toward the producer.

System Dynamics Anchor-and-Adjust Policy

This is the anchor-and-adjust policy widely used in System Dynamics literature. This policy tries to keep local inventory constant at a desired level. The associated order equation is the following:

$$O_{i,\,t} = \max(\, (I^*_{i,\,t} - I_{i,\,t}) / IAT_i + (SL_{i,\,t}^{\,*} - SL_{i,\,t}) / SLAT_i + E_{i,\,t},\, 0)$$

where $I^*_{i,\,t}$ is the desired inventory level and $SL_{i,\,t}^{\,*}$ is the desired supply line; *IAT* and *SLAT* are inventory adjustment time and supply line adjustment time respectively.

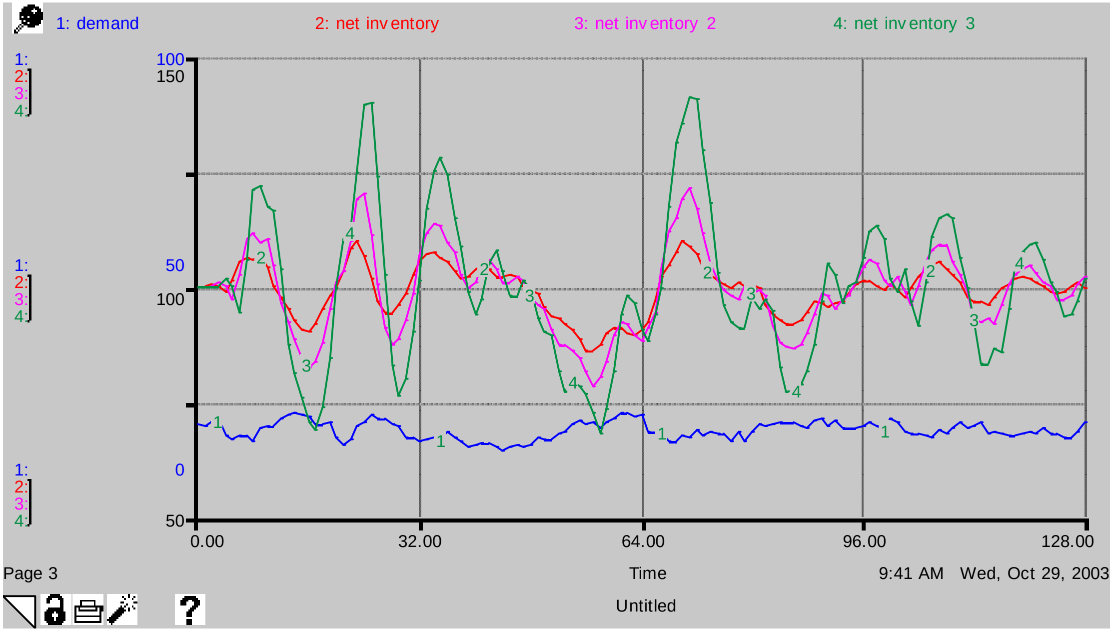

Figure 4. Net inventories when order-up-to-S policy is applied (2: retail; 3:wholesaler; 3: producer)

$I_{i,t}$ and $SL_{i,t}$ represent inventory level and supply line, which are defined as follows:

$$I_{i,t} = LI_{i,t} - BL_{i,t}$$
$$SL_{i,t} = IT_{i,t} + BL_{i+1,t}$$

The desired levels of inventory and supply line are determined by:

$$SL_{i,t}^{*} = LT_i * E_{i,t}$$
$$I^{*}_{i,t} = M$$

where M is some constant.

Note that, in this policy, although desired supply line is adjusted according to expected demand, desired inventory level is taken constant. Inventory behavior in this case (with autocorrelated demand, M=100, LT=3 and $IAT_i = SLAT_i = 1$) is seen in Figure 5. Just like with the order-up-to-level S policy, we observe oscillations and bullwhip effect (amplification) through the supply chain, from the retailer to the wholesaler and then to the producer. (Comparing Figures 4 and 5, also note that the behavior patterns of orders and inventories with order-up-to-S policy and anchor-and-adjust system dynamics policy are quite similar). As an alternative, the desired inventory in the adjustment equation above can be defined proportional to the expected demand, i.e. $m * E_{i,t}$. In this case, both the oscillation amplitudes and the bullwhip effect are increased as a result of stronger (double) effect of the expected demand on orders. We are unable to provide the corresponding graphs due to space limitation. (The reader is referred to Gündüz 2003).

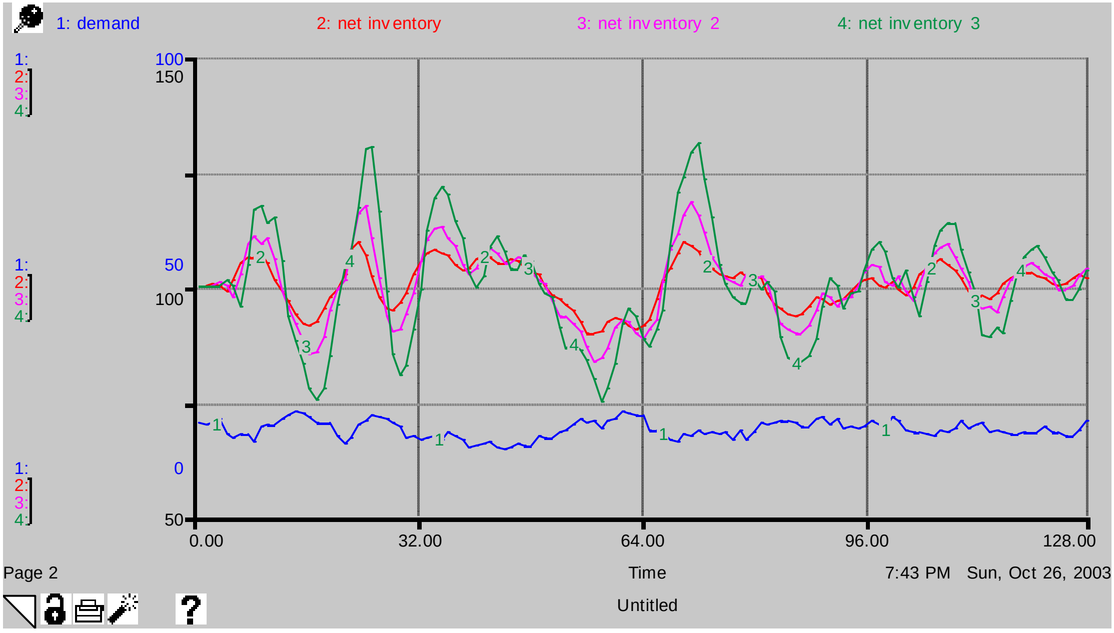

Figure 5. Net inventories when 'anchor and adjust' policy is applied

(s,S) Policy

(s,S) Policy is a review policy where orders are placed to raise the inventory position to order-up-to-level S, whenever the inventory position drops to the reorder point s or below. The order equation is as follows:

$$O_{i,t} = (S_{i,t} - IP_{i,t})/IAT_i \qquad \text{if } IP_{i,t} \leq s_{i,t}$$

$$O_{i,t} = 0 \qquad \text{otherwise}$$

In the standard (s,S) policy, the discrepancy is immediately ordered, so we set inventory adjustment time IAT to one. The reorder point $s_{i,t}$, and the the order-up-to-level $S_{i,t}$ for stage *i* at time *t*, can be computed by the following equations:

$$s_{i,t} = (LT_i)(E_{i,t}) + SS_i$$
$$S_{i,t} = s_{i,t} + q\,E_{i,t}$$

where SS_i is constant safety stock and *q* is a constant order quantity multiplier, to provide a buffer for the variation in demand. (S could also be determined by s + EOQ, where EOQ the optimal 'economic order quantity' to be calculated for given inventory holding and backlog costs. But such optimal level computations are irrelevant to the purpose of this article. Since it is known in general that EOQ is an increasing function of estimated demand $E_{i,t}$, using $q\,E_{i,t}$ in lieue of EOQ is reasonable).

The inventory dynamics with LT=3, SS=240 and q=3 is shown in Figure 6. Once again, we observe oscillations and bullwhip effect along the supply chain. Note further that the level of amplification in this case is stronger than the previous two cases (the amplitude of oscillations more than doubles with each stage). As will be seen later, this finding is consistent with the Lee *et al.* (1997) result that 'order batching' is one of the main causes of the bullwhip effect. (In (s,S) policy, orders are in effect batched).

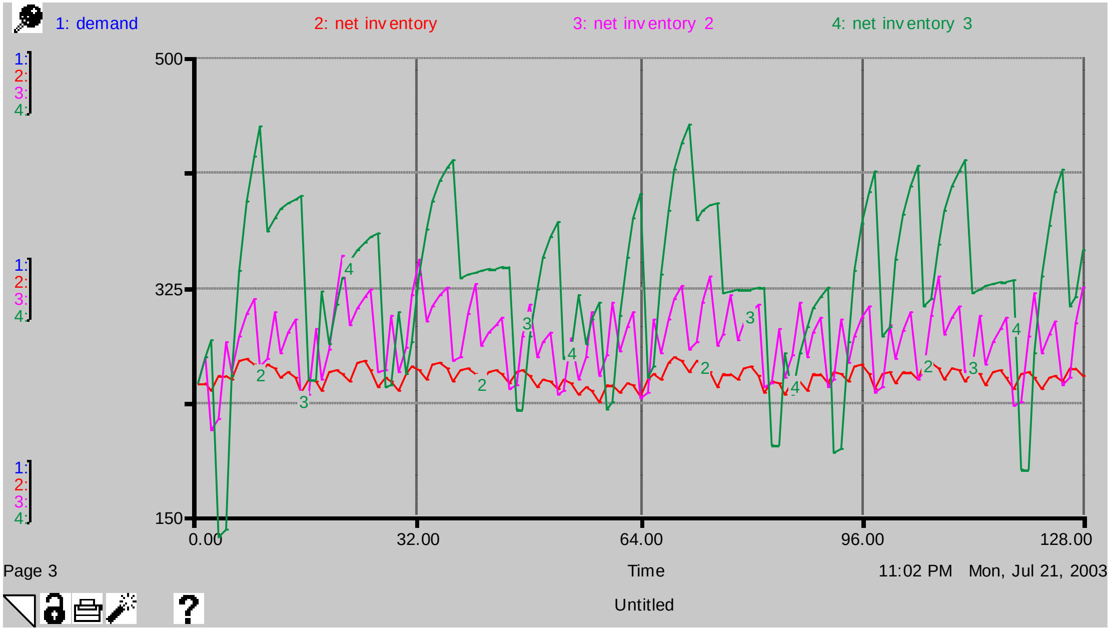

Figure 6. Net inventories when (s,S) policy is applied (SS=240, q=3)

Analysis of Sources of Bullwhip Effect

Numerous simulation experiments are carried out using each of the three ordering policies described above. (Some variants of these policies and other policies like (s,Q) have been tested as well, but we skip them due to space limitations. See Gündüz 2003). These experiments can be grouped in two: Policy-independent parameters of the supply chain and policy-specific parameters.

Policy-independent Parameter Analysis

Simulation experiments are performed with different settings of demand pattern (autocorrelation degree), lead time (LT), nature of delays; and demand estimation adjustment time (EAT). Some important results can be summarized as follows. (Only one example behavior graph is shown due to space limitation. See Gündüz 2003).

• If the end item demand is *autocorrelated*, the base (retail) oscillations and bullwhip effect both increase, especially when order-up-to-S policy or anchor and adjust policy is used. (With (s,S) policy, autocorrelation does not have substantial effect on inventory oscillations, because significant 'batching' of orders in (s,S) makes it insensitive to demand autocorrelation. But this batching has a bullwhip effect as will be seen later).

• The bullwhip effect increases with an increase in *lead time LT*. This is essentially caused by the fact that the up-to-order level S and the desired supply line $SL_{i,t}^{*}$ are both proportinall to the lead time (delay). The orders and the resulting inventory oscillations are hence amplified. (The same is not true with (s,S) policy, where the order quantity and the frequency are not effected by lead time).

• In the basic model, the only delay is the material delay on the supply line ('lead time'). In reality, there can be other delays like *information delay* in placing orders. The effects of including such additional information delays in the ordering mechanisms have been investigated. In all three policies, the bullwhip effect significantly increases with inclusion of order information delays. This is consistent with the above result about the bullwhip effects of increased lead time, since additional information delays effectively increase the lead times between placing and receiving or orders.

• Base retail oscillations and bullwhip both *decrease* significantly with an increase in the demand *estimation adjustment times (EAT)*, for all three policies. (Compare Figure 7 below, with Figure 4 above, as an illustration). The explanation is that, the larger the estimation adjustment time, the *less* responsive the model becomes to changes in demand (or incoming orders). Since uncoordinated demand forecasting is a main cause of the bullwhip effect (Lee *et al.* 1997), larger estimation adjustment times, meaning less responsive (or almost 'no') forecasts, naturally lead to decreased bullwhip effect. This result is important in the sense that it reveals one of the major causes of the bullwhip phenomena: uncoordinated demand forecasting (as will be discussed below).

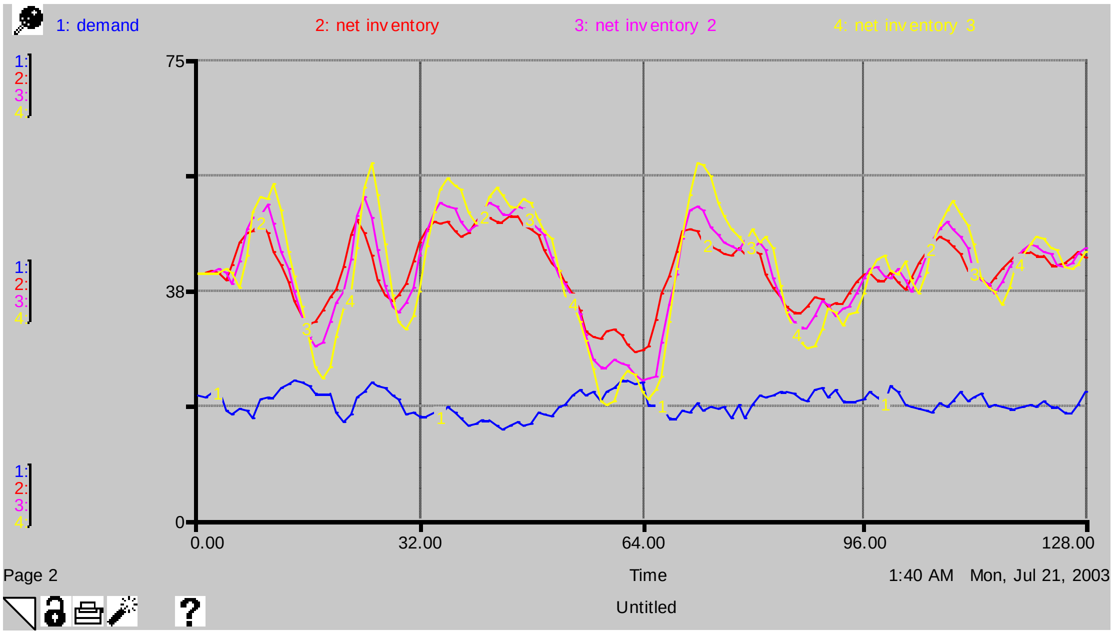

Figure 7. Net inventories with order-up-to-S policy and EAT increased to 10.

Policy-specific Parameter Analysis

In the second set of runs, we experiment with policy-dependent parameters such as: lead time inflation constant K in the order-up-to-S policy, order quantity multiplier q in (s,S) policy and the desired inventory coverage constant m in the anchor and adjust policy. (See the associated equations of each policy, above).

• Experiments show that when the lead time inflation constant *K* (in the order-up-to-S policy) is increased, the bullwhip effect also increases. Note that *K* is a multiplier of the expected demand in the order-up-to level computation in this policy; so it represents the weight of the expected demand in the order decisions.

• When the order quantity multiplier *q* (in (s,S) policy) is increased, the bullwhip effect and magnitude of oscillations both increase. (Compare Figures 8 and 6). Note again that *q* is a multiplier of the expected demand in the order-up-to level (S) computation in this policy; it represents the strength of the demand forecast in the order decisions.

• When the desired inventory coverage constant *m* (in the anchor and adjust policy) is increased, the bullwhip effect and magnitude of oscillations both increase. Note once again that in this policy (with variable desired inventory), the desired inventory is obtained by multiplying the demand forecasts with the coverage constant *m*, so that the latter represents again the weight of demand expectations in order decisions.

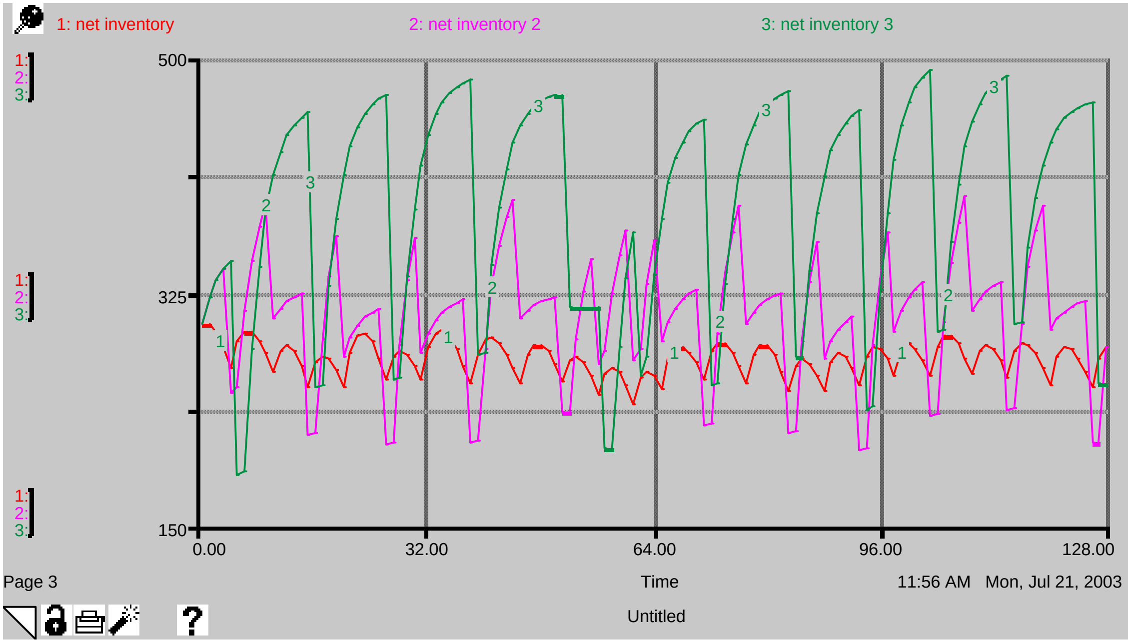

Figure 8. Net inventories when (s,S) policy is applied (SS=240, q=5)

The three policy-specific results all point to a single general result: The stronger the role of the demand forecasts in the order decisions, the stronger is the bullwhip effect (and sometimes the base retail oscillations). This result is consistent with Forrester (1961), Sterman (2000), Lee *et al.* (1997) and Chen *et al.* (1998). This result, together with the earlier result about the role of order batching in amplifying the bullwhip effect, leads to two important policy-oriented roots of the bullwhip.

Role of Order Batching

Among the policies tested, orders are batched in the (s,S) policy (since they are not placed in each period). We noted earlier that the effect of this batching is an increase in bullwhip effect (comparing the larger amplifications in Figure 6 with those in Figures 4 and 5). Yet, the other major cause of the bullwhip, i.e. demand/order forecasting, is also present in the (s,S) policy. In order to isolate and focus on the effect of order batching *only*, we tested (s,S) policy with *fixed* levels of *s* and *S*, which are not updated by any demand/order forecasts. Results in this case (Figure 9, compared to Figure 6) reveal that when demand forecasts are not used, bullwhip is *not* observed in (s,S) policy, although there is batching of orders. (The amplification from the retailer to the wholesaler is a result of initial conditions; noting that there is no amplification at all from wholesaler to producer. The same is true from any stage n to stage n+1). Thus, we conclude that batching of orders is not by itself sufficient for the bullwhip effect to emerge; order policy parameters must be updated by demand forecasts for the bullwhip to occur. But batching can further amplify the bullwhip effect, if the latter already exists as a result of demand/order forecasts.

Role of Demand/Order Forecasting

Analysis of the simulation results of no-demand-sharing cases reveals that the major cause of the bullwhip effect is the independent sequential demand forecasting performed at each stage of the supply chain, making use of previous stage's orders. As we have seen above, the weight of demand forecasts in ordering decisions determines the degree of the bullwhip experienced by the chain. All ordering policies that use demand forecasts in ordering equations multiply demand forecasts by a constant in order to obtain some 'target' order level. This constant is *K* for order-up-to-S policy, *m* for anchor-and-adjust policy, and *q* for (s,S) policy. (See equations above). Simulation runs show that the higher this multiplier constant is, the greater the magnitude of the bullwhip effect (See Figure 8 for example, for the (s,S) policy case).

Experiments with different expectation adjustment times (EAT) values also reveal that bullwhip effect decreases with the increase in EAT (Figure 7). Increase in expectation adjustment time means that demand forecasts are less responsive to changes in demand. A very high EAT effectively means no forecast updating, yielding 'almost constant' demand forecasts. At the extreme, constant ('no') demand forecasts result in zero bullwhip effect (Figure 9 and Gündüz, 2003 for more).

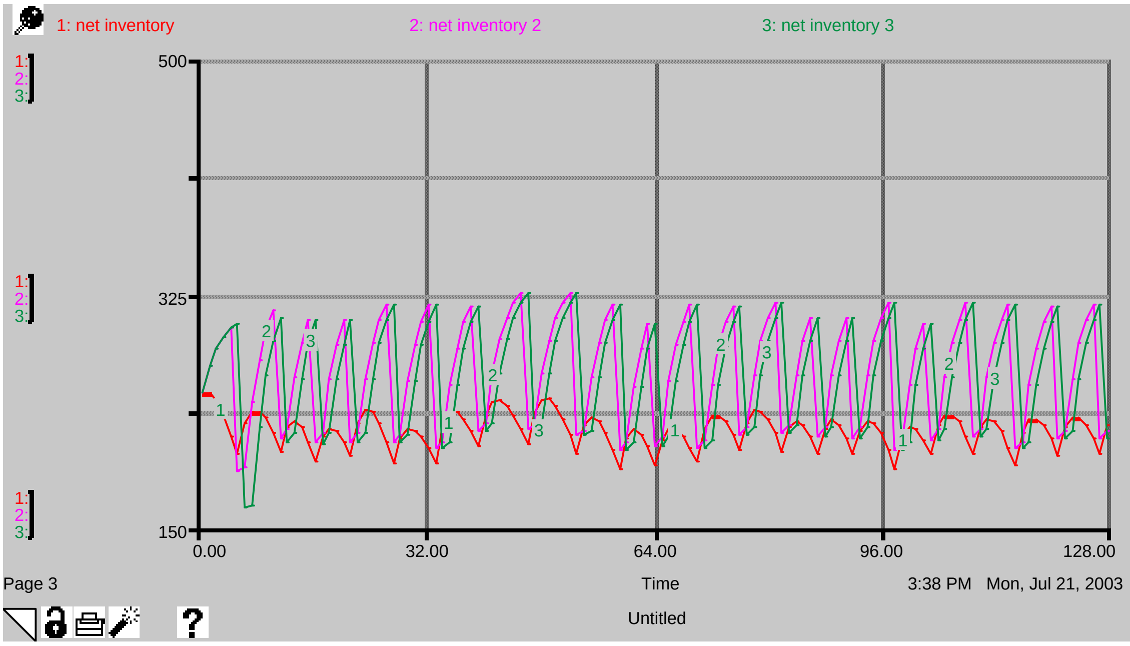

Figure 9. Net inventories under (s,S) policy, without using any forecasting

Improved Policy: Demand and Forecast Information Sharing

To here are several strategies suggested in the literature to tackle the bullwhip effect, as summarized in the introduction above. One such strategy, also implied by our earlier results, is sharing of demand and/or forecast information between agents on the supply chain. In order to explore the effects of this strategy on the behavior of the inventories, we modify he supply chain model to incorporate end-item demand sharing: Each stage uses end-item demand to forecast the future demand, rather than using orders of its lower stage. Hence, all stages use demand forecast obtained directly from end-item demand in their ordering decisions. (In the base case reported here, since all agents in the model all use the same forecasting mechanism with the same parameters, end-item demand sharing is the same as demand forecasts sharing. Given that the end item demand is shared, all stages effectively produce and use the same end item demand forecasts. If agents used different forecasting methods, then demand sharing and forecast sharing would be two different strategies).

The resulting inventory behaviors for order-up-to-S policy, SD policy, and (s,S) policy when demand is shared are shown in figures Figure 10, Figure 11, and Figure 12 respectively. Demand and forecast sharing eliminates uncoordinated and sequential forecasting mechanisms of the supply chain so that a stage no longer bases its orders on its forecasts of the lower stage's orders. Instead each stage directly uses end-item forecasts. Thus the bullwhip effect along the supply chain is significantly reduced. (Compare Figure 10 to Figure 4; Figure 11 to Figure 5; and Figure 12 to Figure 6).

Another strategy suggested against bullwhip is the *echelon* inventory policy, where each agent places orders based on echelon inventory position rather that its local The echelon inventory of a stage is defined as the inventory position of the subsystem consisting of the stage itself and all its downstream stages. Echelon policies result in a further decrease in bullwhip effect because they remove the order propagation delay from the supply chain. (We are unable to provide graphs and further discussion of echelon policies due to space limitations. See Gündüz 2003).

Order-up-to-S Policy

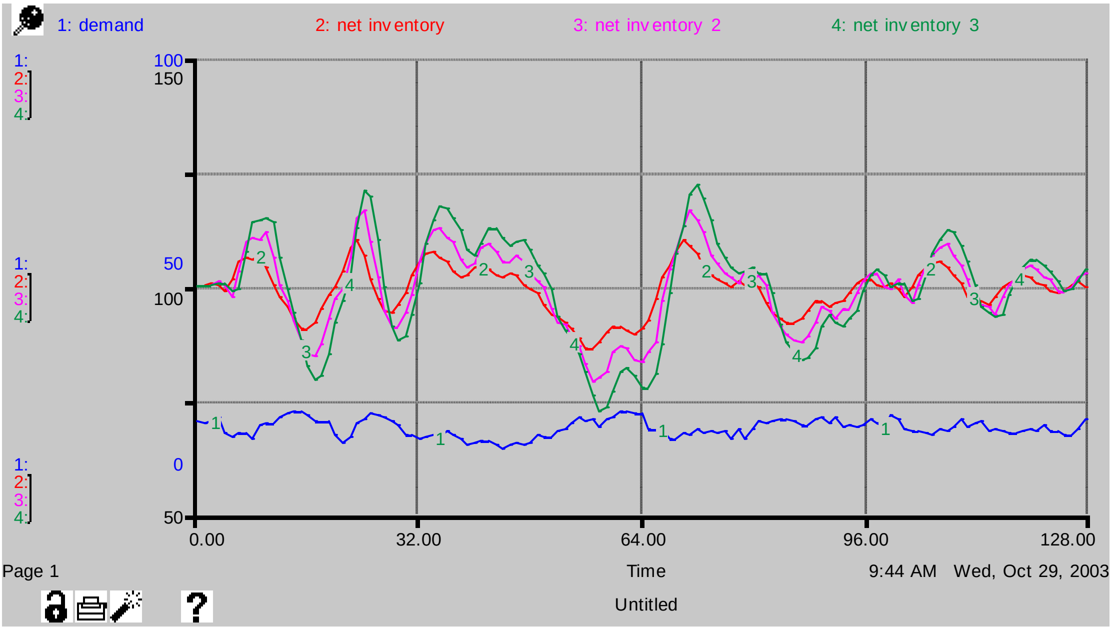

Figure 10. Net inventories when order up-to-S policy is applied and demand is shared

Anchor and Adjust Policy

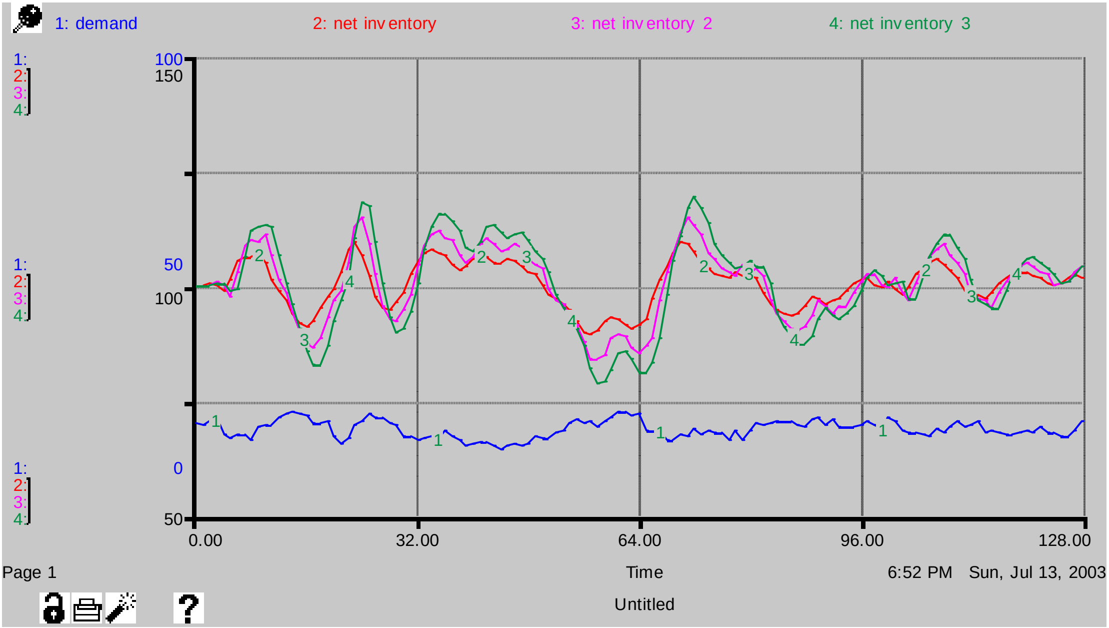

Figure 11. Net inventories when anchor and adjust policy is applied and demand is shared

(s,S) Policy

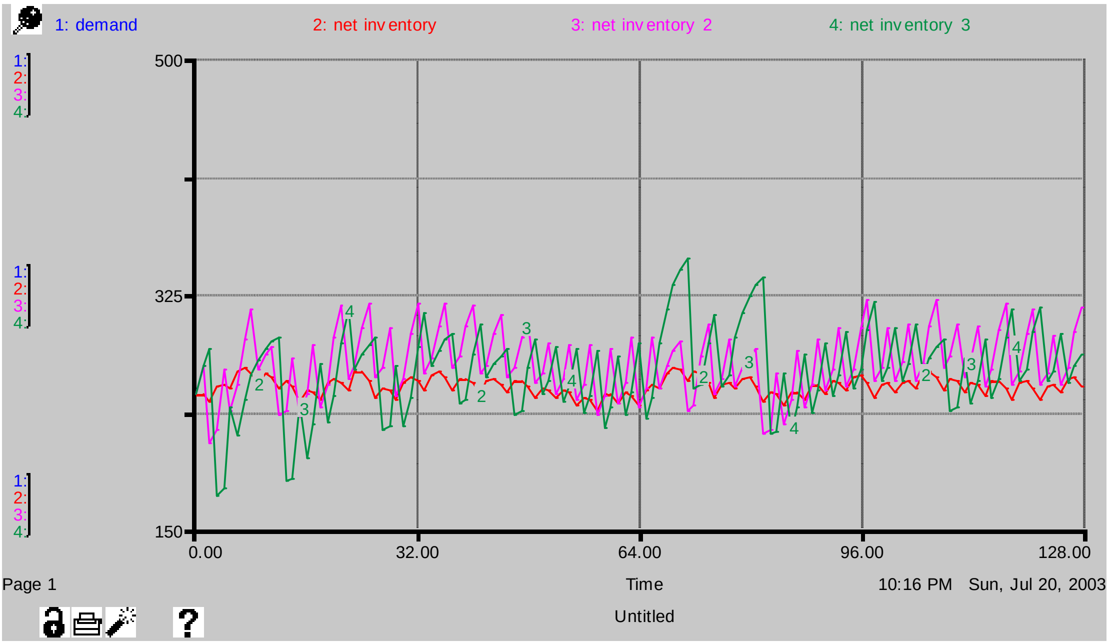

Figure 12. Net inventories when (s,S) policy is applied and demand is shared

Conclusions and Future Work

Three typical ordering policies are considered and modeled in the context of a supply chain. Numerous simulation experiments are carried out using each of the three policies. These experiments are grouped in two: Policy-independent parameters of the supply chain and policy-specific parameters for each policy. The most general conclusion of the experiments is that bullwhip effect (amplification of orders along the supply chain) results in all cases, with all parameter values, as long as each stage utilizes local demand forecasts based on incoming orders (or end demand). So, uncoordinated local demand forecasting is discovered as the main cause of the bullwhip effect. An extension of this result is that the level of' 'responsiveness' of forecasts to the demand influences the magnitude of bullwhip effect experienced. Forecasts that are highly responsive (meaning small estimation adjustment times) to changes in the demand increase the bullwhip effect, while less responsive forecasts decrease it.

Weight of demand forecast in the ordering equation is another important factor that determines the bullwhip effect. If the weight of demand forecasts in ordering equations is high, then the magnitude of bullwhip is high, too. If forecasts are not used in ordering equation at all (zero weight coefficient or very large estimation adjustment time), then bullwhip effect does not exist. Thus, if demand pattern is known and its mean does not change (or changes very slowly), bullwhip effect may be avoided by not using demand forecasts in ordering equations or by using very slow-response forecasts. As for the other factors such as *lead time* and *batching* of orders, experiments show that these factors are not by themselves sufficient to create the bullwhip effect. But given that there already is bullwhip effect caused by local demand forecasting, these factors do increase the amplification substantially. Increased level of batching of orders and increased lead time, both cause increased bullwhip effect in these cases.

Lastly, we tested demand and forecast information sharing strategies against the bullwhip effect, as suggested by the literature. These policies significantly reduce the bullwhip effect for all ordering policies. However, if forecasting plays a role in ordering equations, demand and forecast sharing cannot completely eliminate the bullwhip; it can only reduce it. Bullwhip effect will exist in the supply chain as long as the ordering policies incorporate demand forecasts. The information sharing strategy implies managerial practices like Collaborative Planning and Vendor Managed Inventories (VMI). It also implies information systems like Electronic Data Interchange (EDI) and Point of Sale (POS) systems. (Lee and Whang, 1998; Xu *et al.*, 2001; Sterman 2000). To avoid excessive batching, a contributor to bullwhip, Continuous Replenishment Programs (CRP) can be used. To shorten the lead time, another bullwhip amplifier, Quick Response (QR) systems can be implemented. (Aksogan and Barlas 1996).

There are two other major causes of bullwhip effect discussed in the literature: shortage (rationing) gaming and price variations. These two factors are beyond the scope of our study. For a realistic study of shortage gaming, the model should have multiple suppliers and retailers at the same stage, which we consider as a future research . (It is on the other hand possible to do a broad and rough study of shortage gaming even with single agent at each stage, provided that significant shortages occur. See for instance Sterman 2000, chapter 18, for such a rough shortage gaming modeling). As for the price variations, the model should include a price determination structure, which is again considered as further research. Finally, supply networks (rather than simple chains) will be modeled as a more realistic experimental setting.

References

Aksoğan, A. and Y. Barlas. 1996, "Product Diversification and Quick Response Order Strategies in Supply Chain Management", *Proceedings of the International System Dynamics Conference*, Boston, USA, pp. 51-54. (http://www.ie.boun.edu.tr/~barlas /wwwpape2.html)

Cetinkaya, S., Lee, C. Y. 2000. "Stock Replenishment and Shipment Scheduling for Vendor-Managed Inventory Systems", *Management Science,* Vol.46, No2.

Chen, F., Z. Drezner, J.K. Ryan, and D. Simchi-Levi. 1998. The Bullwhip Effect: Managerial Insights on the Impact of Forecasting and Information on Variability in a Supply Chain. in *Quantitative Models for Supply Chain Management*. Boston: Kluwer Academic Publishers.

Gallego, G. and Ö. Özer, 2001, "Optimal Use of Demand Information in Supply Chain Management", in J. Song, D.D. Yao (eds.), *Supply Chain Structures: Coordination, Information and Optimization,* pp. 127-168, Kluwer Academic Publishers, Boston.

Gavirneni, S., R. Kapuscinski, and S. Tayur, 1999, "Value of Information in Capacitated Supply Chains", *Management Science*, 45, pp. 16-24.

Gündüz, A.B., 2003. Strategies to Reduce Fluctuations in Supply Chains: A Dynamic Modeling Approach. *MS Thesis, Department of Industrial Engineering, Bogazici University*

Forrester, J. W. 1961. *Industrial Dynamics*. Waltham, Mass., Pegasus Communications.

Jeong, S. and C.J. Maday. 1996. Dynamic information control for multi-echelon production-distribution systems with constrained production capacity. System Dynamics Review Vol.12 (4): 331-343.

Lee, H.L., P. Padmanabhan, and S. Whang. 1997. Information Distortion in a Supply Chain: The Bullwhip Effect. *Management Science* 43:546-58.

Lee, H.L. and S. Whang, 1998, *Information Sharing in a Supply Chain*, Research Paper, Stanford University Graduate School of Business.

Özevin, G. and Y. Barlas, 2001, "Testing the Decision Making Rules Used in Stock Management Models", *Proceedings of the 19th International System Dynamics Conference*, Atlanta, Georgia, pp. 32-33. (http://www.ie.boun.edu.tr/~barlas/ BarlasOzevinISDC01.pdf)

Silver, E.A., D.F. Pyke, R. Peterson. 1998. *Inventory Management and Production Planning and Scheduling 3rd Ed*. New York: John Wiley & Sons.

Sterman, J. D.,1989. Modeling Managerial Behavior: Misperceptions of feedback in a dynamic decision experiment, *Management Science*, Vol. 35, 3 ,321-339.

Sterman, J.D. 2000. *Business Dynamics.* Boston: McGraw-Hill.

Xu, K., Y. Dong, P.T. Evers. 2001. Towards better coordination of the Supply Chain. *Transportation Research Part E* 37:35-54

Yaşarcan, H., 2003, *Feedback, Delays, and Nonlinearities in Decision Structures*, Ph.D. Dissertation, Boğaziçi University.

Zipkin, P.H. 2000. *Foundations of Inventory Management*. Irwin/McGraw-Hill.