

Exploring the bullwhip effect by means of spreadsheet simulation

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Abstract: One of the main supply chain deficiencies is the bullwhip effect: demand fluctuations increase as one moves up the supply chain from retailer to manufacturer. The Beer Distribution Game is widely known for illustrating these supply chain dynamics in class. In this paper we present a spreadsheet application, exploring the two key causes of the bullwhip effect: demand forecasting and the type of ordering policy. We restrict our attention to a single product two-echelon system and illustrate how tuning the parameters of the replenishment policy induces or reduces the bullwhip effect. We also demonstrate how bullwhip reduction (dampening the order variability) may have an adverse impact on inventory holdings and/or customer service. As such, the spreadsheets can be used as an educational tool to gain a clear insight into the use of inventory control policies and forecasting in relation to the bullwhip effect and customer service.

Keywords: Bullwhip effect, replenishment rules, forecasting techniques, spreadsheet simulation, Beer Distribution Game

1 Introduction: teaching the bullwhip effect

The bullwhip effect is a well-known phenomenon in supply chain management. In a simple, linear supply chain that consists of a manufacturer, a distributor, a wholesaler and a retailer, we observe that the retailer's orders to the wholesaler display greater variability than the end-consumer sales, the wholesaler's orders to its distributor show even more oscillation, and the distributor's orders to the manufacturer are most volatile.

The bullwhip effect and its dynamics are often illustrated in class by the "Beer Distribution Game", developed at MIT (Sternan 1989). It is by far the most popular simulation and the most widely used game in many business schools, supply chain electives and executive seminars. Simchi-Levi et al. (2003) developed a computerized version of the Beer Game, and several versions of the Beer Game are nowadays available, ranging from manual to computerized and even web-based versions (e.g. Machuca and Barajas 1997, Chen and Samroengraja 2000, Jacobs 2000).

Beyond the games, real cases are used as teaching tools to introduce and to address the bullwhip effect, e.g. the case study Barilla SpA (Hammond 1994), a major pasta producer in Italy, Campbell Soup's chicken noodle soup experience (Cachon and Fisher 1997), and more recently, Kuper and Branvold (2000), Hoyt (2001) and Peleg (2003).

In this paper we explore the two key causes of the bullwhip effect: demand forecasting and the type of ordering policy used (Lee et al. 1997a). An increasing number of studies has already been devoted to the adverse effects of demand signaling and improper forecasting. E.g. Watson and Zheng (2002) use formal models to address manager's over-reaction to demand changes and the misuse of forecasting approaches. Lee et al. (1997b) provide a mathematical proof that variance amplification takes place when the retailer adjusts his ordering decision based on demand signals. Dejonckheere et al. (2003) and Chen et al. (2000) demonstrate that the use of "non-optimal" forecasting schemes, such as the exponential smoothing and moving average forecast, always lead to bullwhip, independent of the observed demand pattern. Disney and Lambrecht (2008) offer a recent overview.

However, when elaborating on these concepts in class, students (and especially executives) dislike complex mathematics. They predominantly want to obtain insights in the dynamics of the bullwhip problem. Besides they prefer a one-fits-all solution rather than a dozen different formulas.

To meet these challenges, we developed a user-friendly and easy to understand spreadsheet application, designed in Microsoft Excel. Spreadsheets have been used among others by Munson et al. (2003) to teach the cost of uncoordinated supply chains. Our spreadsheets explore a series of base-stock (order-up-to) replenishment policies and forecasting methods confronted with different demand processes. Where available, we provide the analytical results that we have found in the literature. This way all available results from literature are grouped in one tool, which can easily be consulted by students and executives. The spreadsheets have been useful in core operations management courses at undergraduate and MBA level, and in supply chain electives.

The objective of this paper is threefold. First, the basic spreadsheet calculations help the students to obtain insights in the bullwhip dynamics. Second, all results that are currently available in the literature are collected into one tool. Third, using simulation analysis, we can go beyond the existing analytical results. As such, the spreadsheet models guide the decision maker through a fairly complicated interplay between order fluctuations, inventory fluctuations and customer service in a variety of demand process scenarios and forecasting techniques. One can easily evaluate the impact of different replenishment strategies: what often appears to be a rational policy of the decision maker may create tremendous order amplification. On the other hand, reducing the bullwhip effect may hurt customer service (Disney and Lambrecht 2008).

Our spreadsheet simulation model differs from the existing models (e.g. Simchi-Levi et al. 2003) in several ways. First, we bring several ‘demand signal processing’ methods together in a single spreadsheet application, ranging from the early work by Lee et al. (1997a), to the traditional (moving average and exponential smoothing) forecasting methods towards the more complex (merely academic) mean squared

error forecasting method. Second, we extend the traditional standard order-up-to replenishment policy to a generalized (or “smoothed”) order-up-to policy, which is able to dampen or smooth the order variability for any demand process. Finally, we consider both inventory related costs and production switching costs as performance measures. They should both be analyzed as the two measures are simultaneously affected by the replenishment rule.

In the next section we present our spreadsheet model. Section 3 analyses the impact of the standard order-up-to policy with different forecasting techniques on the bullwhip effect. Section 4 describes a smoothed order-up-to policy and we discuss its impact on customer service.

2 Description and use of the spreadsheet model

The spreadsheet model is designed to illustrate the ordering dynamics between two supply chain partners. We have previously used it in a debriefing session after having played the Beer Distribution Game, but also separately to illustrate the impact of the order-up-to replenishment policy in a supply chain context. Ideally, the students have already covered basic inventory management techniques, including the periodic review policy, where a variable amount of product is ordered at fixed periods (e.g. daily or weekly), as opposed to the EOQ policy (continuous review), where a fixed amount of product is ordered at variable time instants.

One may start the class by briefly recapitulating the periodic review order-up-to policy. If this technique has not been covered yet, the instructor may spend some time on it as this policy is common practice in retailing and is optimal when there is no fixed ordering cost and both holding and shortage costs are proportional to the volume of on-hand inventory or shortage (Zipkin 2000). These assumptions hold in many practical cases, as well as in the standard setup of the Beer Distribution Game.

Once it is clear how this ordering policy works, the instructor may guide the students through the simulation table for one or two periods (see section 2.1), and explain to them how this method ‘simulates’ a random demand and calculates the orders according to the chosen replenishment rule. The remaining of the session is then

devoted to analyzing the impact of tuning the parameters of the replenishment rule (see section 2.2) on the ordering behavior and supply chain performance (section 2.3). It is not needed to go through the simulation table after each run, but the students should know they can easily check the outcome by going through the same calculations. We suggest a story line at the end of each of the following sections, depending on what exactly the instructor wants to cover in class (sections 3.6 and 4.5).

The following has worked well. The instructor asks the students to recapitulate the periodic review order-up-to technique at home and to simulate a number of scenarios before class. The same sequence of scenarios can be used as described in sections 3.6 and 4.5. In class the instructor may spend time discussing their findings, the use of the parameters, and the rationale behind the results.

In the remainder of this section we briefly focus on (1) the simulation table, (2) the parameter selection (input section), and (3) the performance measurement (output section). The spreadsheet model can be downloaded here [*insert link to download the spreadsheet file*]. We refer to the student manual to tell the students how to simulate using the spreadsheet models [*insert link to download the student manual*] and to the instructor manual for the detailed mathematics [*insert link to download the instructor manual*].

2.1 Simulation table

Our model follows the standard setup of the Beer Distribution Game (Sterman 1989), where we have the following sequence of events in each period:

- (1) First, incoming shipments from the upstream supplier are received and placed in inventory. Assuming that the supplier has ample stock, these shipments correspond to the order placed $T_p + 1$ periods ago. T_p refers to the deterministic transportation delay and there is 1 period ordering delay (due to the sequence of events);
- (2) Next, a random customer demand is observed and either fulfilled (if enough on-hand inventory available) or placed in backlog. A positive net stock represents inventory immediately available to meet demand, whereas a negative net stock refers to a backlog (demand that could not be fulfilled and still has to be delivered). The

pipeline inventory represents the items ordered but not yet arrived due to the transportation lead time. The inventory position is the sum of the net stock and the pipeline inventory.

(3) Finally, a new order is placed to raise the inventory position to the order-up-to level:

$$\text{order quantity} = \text{order-up-to level} - (\text{net stock} + \text{pipeline inventory}) \quad (1)$$

These numbers can easily be tracked in the simulation table. We refer to the instructor manual for the exact mathematics behind the calculations [*insert link to download the instructor manual*]. In classroom it is sufficient to provide a screenshot of some periods only (see Figure 1). Note that the simulation table also contains the forecast of next period's demand. We need this number to calculate the order-up-to (OUT) level. In the next section we discuss in more detail how to obtain this demand forecast and the OUT level.

period	receive	demand	net stock	pipeline inventory	demand forecast	order-up-to level	order quantity	inventory costs	switching costs
10	108	110	19	225	110,36	353,60	110	9,50	6,00
11	112	113	18	223	110,89	355,18	114	9,00	8,00
12	113	122	9	224	113,11	361,85	129	4,50	30,00
13	110	120	-1	243	114,49	365,98	124	20,00	10,00
14	114	119	-6	253	115,39	368,69	122	120,00	4,00
15	129	117	6	246	115,71	369,66	118	3,00	8,00
16	124	120	10	240	116,57	372,23	122	5,00	8,00

Figure 1: Spreadsheet example of a standard OUT policy with $T_p = 2$

Finally, we compute the incurred costs. The inventory cost consists of a holding cost per unit in inventory (when net stock is positive) and a shortage cost per unit backlogged (negative net stock). The production switching cost is incurred for changing the level of production in a period. Assuming the production level is equal to the order quantity placed, the change in production is given by the difference in order quantity versus the previous period.

2.2 Parameter selection

In the input section, the user defines the parameters of the customer demand process and the forecasting technique. The cells of the parameters that can be changed are shaded. We blocked the cells with automatic calculations in the spreadsheets in order

to avoid mistakes and miscalculations. The protection can easily be removed using the Unprotect Sheet command (Excel 2003: Tools menu, Protection submenu – Excel 2007: from the *Ribbon*, select the **Review** command tab). We refer to the student manual for the description how to input the parameters, and to the instructor manual for the mathematics behind the input section.

2.3 Performance measurement

We define three types of performance measures of the simulation analysis: (1) the variance amplification ratios ‘bullwhip effect’ and ‘net stock amplification’; (2) the average inventory and switching costs per period; and (3) the customer service measures ‘customer service level’ and ‘fill rate’.

(1) We define the bullwhip effect as follows:

$$\text{Bullwhip} = \frac{\text{Variance of orders}}{\text{Variance of demand}}.$$

A bullwhip measurement equal to one implies that the order variance is equal to the demand variance, or in other words, there is no variance amplification. A bullwhip measurement larger than one indicates that the bullwhip effect is present (*amplification*), whereas a bullwhip measurement smaller than one is referred to as a “smoothing” scenario, meaning that the orders are smoothed (less variable) compared to the demand pattern (*dampening*).

Our focus is not only on the bullwhip measure. In this paper we also check the variance of the net stock since this has a significant impact on customer service (the higher the variance of net stock, the more safety stock required). Therefore we measure the amplification of the inventory variance, NSAmp, as:

$$\text{NSAmp} = \frac{\text{Variance of net stock}}{\text{Variance of demand}}.$$

(2) The inventory and switching costs are related to these variance amplification measures. A high bullwhip measure implies a wildly fluctuating order pattern, meaning that the production level has to change frequently, resulting in a higher average production switching cost per period. An increased inventory variance results in higher combined holding and backlog costs.

(3) Finally, we provide the customer service level and fill rate resulting from the simulation analysis. The customer service level represents the probability that customer demand is met from stock, while the fill rate measures the proportion of demand that is immediately fulfilled from the inventory on-hand.

3 Impact of forecasting on the bullwhip effect

In the previous section we introduced the standard order-up-to policy: we place an order equal to the deficit between the OUT level and the inventory position (Eq. (1)). According to the theory, the OUT level, which we denote by S_t , covers the forecasted average demand during the protection interval and a safety stock. The protection interval L equals the physical lead time plus the review period.

$$S_t = \hat{D}_t^L + SS, \quad (2)$$

with \hat{D}_t^L the forecasted demand over L periods and SS the safety stock (either equal to $z\sigma_L$ or set to an arbitrary value). We will now review a number of forecasting techniques and illustrate their impact on the bullwhip effect by means of our spreadsheet models.

3.1 Mean demand forecasting

If the decision maker knows that the demand is IID, then the best possible forecast of all future demands is simply the long-term average demand, \bar{D} . As a consequence, the forecasted lead time demand equals $\hat{D}_t^L = L\bar{D}$, and the OUT level S_t given by Eq. (2) remains constant over time, so that Eq. (1) becomes

$$O_t = S_t - (S_{t-1} - D_t) = D_t. \quad (3)$$

We simply place an order equal to the observed demand; we call this policy the “chase sales policy”. In this setting, the variability of the replenishment orders is exactly the same as the variability of the original demand and the bullwhip effect does not exist.

By selecting in the spreadsheet model the “mean demand forecasting” technique, the user can observe how the generated orders are equal to the demand, with a bullwhip measure equal to one as a result. Although we do not discuss in this section the net stock amplification, it is worthwhile to check that number as well.

In case the Beer Distribution Game has been played in class, the instructor could pop up the question why the students did not play like this, or in other words, why do we observe variance amplification. If the Beer Distribution Game has not been played in class, the instructor could question why this policy would not work in the real world. The answer is that decision makers do not know the demand (over the lead time) and consequently they forecast demand and constantly adjust the OUT levels. Suppose the demand is not characterized by an IID process, but rather a correlated or a non-stationary process, it is preferable to use the knowledge of the current demand to forecast next period’s demand. Because of the fact that the true underlying distribution of demand is not directly observed (only the actual demand values are observed) many inventory theory researchers suggest the use of adaptive inventory control mechanisms. This is also how many students play the Beer Distribution Game. Unfortunately, these adjustments create bullwhip. We now discuss some possible adjustments that are frequently used.

3.2 Demand signal processing

Lee et al (1997a) introduce the term “demand signal processing”, which refers to the situation where decision makers use past demand information to update their demand forecast. As a result, the order-up-to level does not remain constant, instead it becomes *adaptive*. Suppose that the retailer experiences a surge of demand in one

period. It will be interpreted as a signal of high future demand; the demand forecast will be adjusted and a larger order will be placed. In other words, the order-up-to level is adjusted based on the demand signal:

$$S_t = S_{t-1} + \chi(D_t - D_{t-1}),$$

which results in the following order size:

$$O_t = O_{t-1} + \chi(D_t - D_{t-1}), \quad (4)$$

where χ is the *signaling factor*, a constant between zero and one. A value $\chi = 1$ implies that we fully adjust the order quantity by the increase (decrease) in demand from period to period.

This ordering policy can be explained to the students as follows (Cachon and Terwiesch 2006). An increase in demand could signal that demand has shifted, suggesting the product's actual expected demand is higher than previously thought. Then the retailer should increase his order quantity to cover additional future demand, otherwise he will quickly stock out. In other words, it is rational for a retailer to increase his order quantity when faced with an unusually high demand observation. These reactions by the retailer, however, contribute to the bullwhip effect. Suppose the retailer's high demand observation occurred merely due to random fluctuation. As a result, future demand will not be higher than expected even though the retailer reacted to this information by ordering more inventory. Hence, the retailer will need to reduce future orders so that the excess inventory just purchased can be drawn down. Ordering more than needed now and less than needed later implies the retailer's orders are more volatile than the retailer's demand, which is the bullwhip effect.

Suppose we select "demand signal processing" in our spreadsheet (the "Define a demand forecasting technique" window), then we immediately observe demand amplification. If we set $\chi = 1$, the bullwhip effect increases to a value around 5. If we anticipate to a lesser degree to the change of the demand, for example by setting $\chi =$

0.2, the bullwhip effect remains, but tempers to a value around 1.48. Observe that the switching costs also increase together with the bullwhip measure.

3.3 Moving average forecast

When the retailer does not know the true demand process, he can also use simple methods to forecast demand, such as the moving average or exponential smoothing technique. This way future demand forecasts are continuously updated in face of new demand realizations (sometimes students keep track of historical demand data in order to forecast future demand when they play the Beer Distribution Game). Adjusting the demand forecasts every period, the order-up-to level becomes *adaptive* (see Eq. (2)). The computerized Beer Game developed by Simchi-Levi et al. (2003) offers the players different replenishment policy options. One of them is an adaptive order-up-to policy based on a moving average forecast of demand.

The *moving average* forecast (MA) takes the average of the observed demand in the previous periods, with T_m the number of (historical) periods used in the forecast. The forecast of the lead time demand is obtained by multiplying the next period's demand forecast by the lead time L , $\hat{D}_t^L = L\hat{D}_t$, which determines the OUT level in Eq. (2).

By selecting the “moving average” forecasting technique in our spreadsheet models, we observe the impact of this forecast method on the order behavior. Assuming an IID demand and a physical lead time of 2 periods, the bullwhip effect equals 3.63 for $T_m = 4$ (if one period corresponds to a week, then we use the demand data of the past 4 weeks or 1 month to compute the forecast). By using the data of 1 year or $T_m=52$, we obtain a much smaller bullwhip of 1.12 and we approach the chase sales policy. Indeed, the more data we use from the past, the closer our forecast will approach the average demand, and our results coincide with mean demand forecasting.

The spreadsheets also allow us to illustrate the effect of the lead times on the bullwhip effect. Doubling the physical lead time to 4 periods for example, the bullwhip measure increases to 6.63 with $T_m = 4$. We observe the same dynamics when demand is correlated (AR demand process). Note that the degree of bullwhip is impacted by

the specific demand structure, but the dynamics when we start forecasting are the same, irrespective of the correlative structure of the demand process. We find that there is always bullwhip for all values of ρ and L . This result is worthwhile to stress in class: no matter the lead time or specific demand process, the bullwhip will always be present.

3.4 Exponential smoothing forecast

The *exponential smoothing* (ES) forecast is another forecasting technique. In this case the next period's demand forecast is adjusted with a fraction (α) of the forecasting error. Analogously to the moving average forecasting method, we multiply the next period's demand forecast by the lead time L to obtain a measure of the lead time demand forecast.

The impact of this forecasting method can be illustrated with the spreadsheets. When demand is IID and $T_p=2$, a smoothing factor $\alpha=0.4$ generates a bullwhip measure of 5.20. We observe that an increase of α increases the bullwhip effect, since more weight is given to a single observation in the forecast. Similar to the MA forecast, we observe that an increase in the lead time results in a higher bullwhip measure.

3.5 Minimum Mean Squared Error forecast

Finally we consider the *minimum mean squared error* (MSE) forecasting method, which is mathematically more complex than the previous methods. With this forecasting technique, we explicitly exploit the underlying nature of the demand pattern to predict future demand (Box and Jenkins 1976). To calculate the forecast of the demand over the lead time horizon L , we do not simply multiply the next period's forecast with the lead time, but instead we explicitly forecast the demand of τ periods ahead. We refer to the instructor manual for the detailed math.

Because the MSE method minimizes the variance of the forecasting error among all linear forecasting methods, it leads to the lowest average cost among the three forecasting approaches (Zhang 2004). It explicitly takes the demand structure into account (e.g. a first-order autoregressive pattern), which is not the case in the MA and

ES techniques. It assumes, however, that the underlying parameters of the demand process are known or that an infinite number of demand data is available to estimate these parameters accurately.

We illustrate the impact of this forecasting method with our spreadsheets, and again assume $T_p = 2$. The results obtained are different from the previous results. In this case, when demand is negatively correlated, there is no bullwhip effect. When for instance $\rho = -0.5$, we obtain a bullwhip measure of 0.30, meaning that the order variability is dampened compared to the customer demand, instead of being amplified. We refer to Alwan et al. (2003) for a theoretical justification. When $\rho = 0.5$, we obtain a bullwhip measure of 2.64, indicating that the bullwhip effect is present for positively correlated demand. Note that when $\rho = 0$, the demand process is IID and the MSE forecast boils down to the mean demand forecast, resulting in a bullwhip measure of one. Furthermore, we again observe that increasing the lead time results in a higher bullwhip measure.

3.6 Insights for classroom purposes

We have contrasted five different forecasting methods to replenish inventory with the standard order-up-to policy for both IID and AR(1) demand. The findings indicate that different forecasting methods lead to different bullwhip measures. The bullwhip measure also varies according to the lead time and demand process.

The spreadsheet application helps the student to evaluate the impact of forecasting on the variability of the material flow. In class, we advise to start with forecasting demand by its long-term average, in which case there is no bullwhip effect. The instructor may then ask how realistic this policy is. If students don't come up immediately with the *adaptive* proposal, the instructor may ask them what they should do in case demand doubles from one period to another and you don't change your policy. Next the instructor can show how demand signal processing adjusts the order-up-to level every period, and why it results in the bullwhip effect. He tells them that an alternative way to process demand signals, is to use forecasting methods, such as the simple exponential smoothing or moving average technique. The students should observe that using these methods the standard order-up-to policy will always result in

a bullwhip effect, independent of the demand process. The impact of lead times can also be investigated.

Finally the instructor may discuss the MSE forecasting technique, which takes the nature of the demand process explicitly into account. This method is clearly the winner among the forecast methods, because it chases sales when demand is an IID process and it dampens the order variability when demand is negatively correlated. Moreover, it minimizes the variance of the forecasting error among all linear forecasting methods, and therefore it leads to the lowest inventory costs. Nevertheless, the students should be aware that this forecast method requires an elaborate study to discover the parameters of the demand process, is generally more complex to calculate and therefore (unfortunately) less frequently used for practical purposes.

The instructor may conclude that improper forecasting may have a devastating impact on the bullwhip effect. As a consequence, inventory and production switching costs may increase significantly. This observation puts forecasting in a totally different perspective. A vivid discussion on a proper use of forecasting and demand management techniques may arise.

4 Impact of bullwhip reduction on customer service

In the previous section we illustrated that the bullwhip effect may arise when using the standard order-up-to policy with traditional forecasting methods. In this section we introduce a smoothed order-up-to policy that avoids variance amplification and succeeds in generating smooth ordering patterns, even when demand has to be forecasted.

Smoothing models have a long tradition. A smoothing policy is justified when production (ordering) and inventory costs are convex (e.g. quadratic costs) or when there is a production switching cost. In such an environment it is preferable not to accept large deviations, instead some form of “averaging” is optimal. Generally, there are one or two students who come up with this idea of smoothing the order pattern when searching for solutions to cope with the bullwhip effect. It often occurs that students, who have played the Beer Distribution Game before, don’t want to fall into

the bullwhip ‘trap’, and keep their orders constant. To their own surprise, their inventory costs turn out not be lower at all. In the debriefing of the game, it is therefore worthwhile to elaborate on this smoothing strategy.

The smoothed order-up-to policy described in this section allows order dampening. Make clear to the students that this is a heuristic; optimality is not claimed. Finding the optimal policy is far from a trivial exercise (see Sobel 1969). Modigliani and Hohn (1955) offer another well known discrete time smoothing policy.

4.1 Smoothed order-up-to policy

We present a generalized order-up-to policy with the intention of dampening the order variability or *smoothing* the order pattern. It can be easily derived from the standard order-up-to policy. Substituting Eq. (2) into Eq. (1) we obtain

$$\begin{aligned} O_t &= \text{order-up-to level} - \text{inventory position} \\ &= \hat{D}_t^L + SS - IP_t = L\hat{D}_t + SS - IP_t \\ &= (T_p + 1)\hat{D}_t + SS - IP_t = \hat{D}_t + [T_p\hat{D}_t + SS - IP_t], \end{aligned} \quad (5)$$

where $T_p\hat{D}_t + SS$ can be seen as the *desired* inventory position DIP, which is the sum of the desired pipeline stock $T_p\hat{D}_t$ and the desired net stock or safety stock SS. The difference between the desired and actual inventory position $[DIP - IP_t]$ is denoted as the *inventory deficit*.

Introducing a proportional controller β for the inventory deficit, results in the following *smoothed* order-up-to policy:

$$O_t = \hat{D}_t + \beta \cdot [DIP - IP_t], \quad (6)$$

with $0 < \beta < 2$. Forrester (1961) refers to $1/\beta$ as the “adjustment time”. When $\beta < 1$ the user explicitly acknowledges that the deficit recovery should be spread out over time, whereas $\beta > 1$ implies an overreaction to the inventory deficit. Hence, when $\beta < 1$, the

inventory deficit is only partially recovered during the next ordering period. This fractional adjustment is second nature to control engineers. It is the reason why the decision rule given by Eq. (6) may generate a “smooth” ordering pattern.

We developed a spreadsheet simulation of this smoothed inventory policy (this model can be found in a second worksheet of the same file). The model is similar to the spreadsheet simulation of the standard OUT policy, but with a few important modifications. We additionally input a value for the smoothing parameter β (since the control engineer literature prefers to use the inverse of β , namely $T_i = 1/\beta$, we also mention the T_i parameter in the input section).

In Figure 2 we illustrate the impact on the order pattern when we choose a value $\beta = 0.5$, demand is IID and forecasted with its long-term average. The fractional controller indeed has a dampened or “peak-shaving” impact on the order pattern; the resulting bullwhip measure equals 0.33.

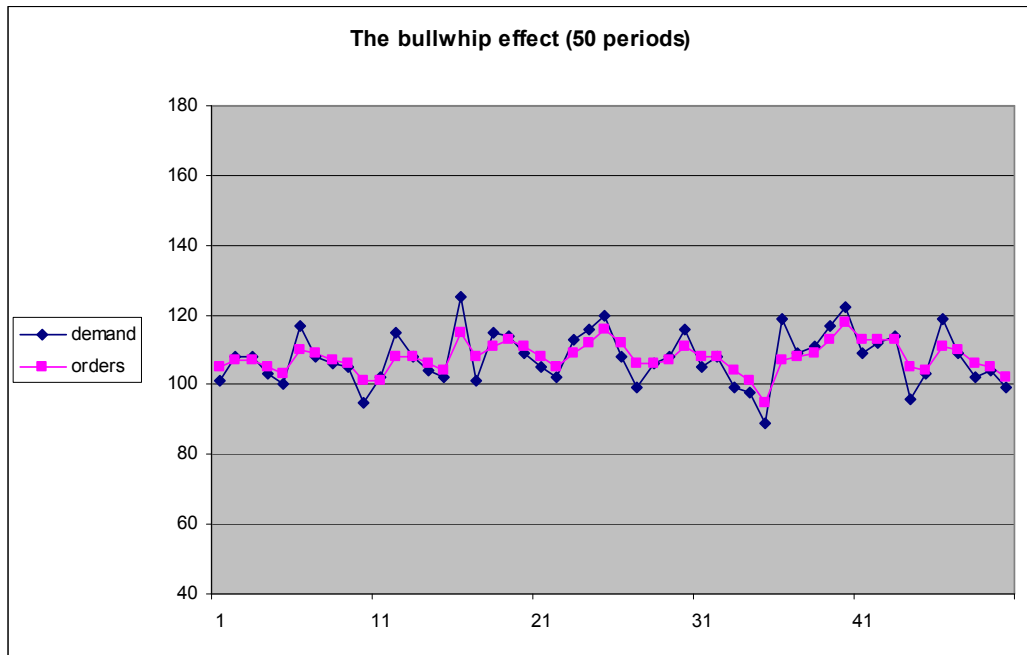


Figure 2: Generated order pattern when $\beta = 0.5$

4.2 Trade-off between bullwhip and inventory variance

So far we have been concentrating on the variance of orders placed. Smoothing the order pattern may indeed provide a solution to counter the bullwhip effect. This is, however, only one side of the coin. When students smooth the order pattern in the Beer Distribution Game, they do not necessarily obtain lower inventory costs, even to the contrary. In developing a replenishment rule one has to consider the impact on the inventory variance as well, because that variance will have an immediate effect on customer service: the higher the variance, the more stock will be needed to maintain customer service at the target level. We therefore measure the net stock amplification (NSAmp), which equals the ratio of the inventory variance over the demand variance. Net stock variance (let alone variance amplification) is not a common supply chain measure, but we need it to calculate the fill rate, which is a popular customer service measure (see Disney et al. 2006).

Hence, we take into consideration the two following factors: on the one hand, the bullwhip effect which is related to the order variability and the switching costs; on the other hand the net stock amplification which is related to investment in inventories and the customer service.

Intuitively, we expect smooth ordering patterns will result in higher inventory fluctuations since the inventory buffer absorbs all the demand fluctuations, resulting in a poorer fill rate. This can be illustrated with the spreadsheets. Suppose we assume an IID demand, mean demand forecasting and $T_p=2$. A chase sales strategy with $\beta=1$ results in an NSAmp value of 3. Smoothing with $\beta=0.5$ reduces the bullwhip measure to 0.33, and equivalently decreases switching costs. On the other hand, it increases the NSAmp measure to 3.33, together with an increase in inventory and backlogging costs. We are able to smooth the order pattern, but pay the price of higher inventory fluctuations and more inventory and backlogging costs.

These observations lead to a trade-off between bullwhip and customer service (as measured by net stock variance amplification). The question we should ask ourselves is to what extent production rates can be smoothed in order to minimize production adaptation costs, without adversely increasing our inventory related costs too much.

Disney et al. (2004) show that when demand is IID and we forecast demand with its mean, then the sum of bullwhip and NSamp is minimized at $\beta = 0.618$, which can be seen as “the best of both worlds” solution. This remarkable result is the “Golden Section”, also known as the Golden Mean, Golden Ratio or Divine Proportion. By adding up the bullwhip effect metric and the net stock amplification metric, we assume that both factors are equally important. It is clear that in the real world companies apply weights to the bullwhip-related costs and customer service-related costs. In this case the shape of the total cost curve may be different and the optimal smoothing parameter may no longer be “golden”.

4.3 Win-win solutions for some demand patterns

We demonstrated that bullwhip can be reduced by ordering a fraction of the inventory deficit, rather than recovering the entire deficit in one time period. When demand is IID, order smoothing comes at a price: in order to guarantee the same fill rate, more investment in safety stock is required due to an increased inventory variance. Disney et al. (2006) show that it is possible to actually achieve bullwhip reduction *and* inventory reduction together whilst maintaining customer service. This is a true win-win situation resulting from the smoothed OUT policy. However, this cannot be achieved in all cases as it depends on the demand pattern.

Consider a stochastic demand pattern with auto regressive and moving average (ARMA) components of order one, with ρ the correlation coefficient and δ the moving average coefficient (Box and Jenkins 1976). Then, depending on the specific values of ρ and δ , inventory variance can be reduced by smoothing the demand signal ($\beta < 1$). In other words, bullwhip can be removed whilst reducing net stock variance (when compared to the standard OUT policy). In other cases, lower inventory variability is achieved by over-reacting to the ARMA signal (i.e., $\beta > 1$). In that case bullwhip leads to lower inventory costs compared to the chase sales policy ($\beta = 1$).

Although the win-win issue is already a highly specialized issue (can be skipped in class), described in the literature by Disney et al. (2006), these situations can be easily illustrated with the spreadsheets. For instance, suppose that $\rho=0.5$, $\delta=1.8$ and we

forecast demand with its long-term average (“mean demand forecasting”). Then, a chase sales strategy ($\beta=1$) results in an NSamp measure of 6.73. A value of $\beta = 1.8$ increases the bullwhip measure to 1.33, but decreases the NSamp to 5.5 (observe that smoothing with $\beta = 0.5$ decreases the bullwhip to 0.66, but increases NSamp to 9.13). Hence, in this case lower inventory variability is achieved with bullwhip. When we consider another example where demand is characterized by $\rho=0.25$ and $\delta=0.25$, then a chase sales strategy ($\beta=1$) results in an NSamp of 1.46. Smoothing with $\beta = 0.5$ decreases the inventory variability to 1.15. Inventory variance is in this case reduced by smoothing the demand signal, which is a win-win solution. We refer to Disney et al. (2006) for a detailed analysis of potential win-win scenarios.

4.4 The smoothed order-up-to policy with demand forecasting

It is clear that the smoothed order-up-to policy described by Eq. (6) provides the opportunity to dampen the variability in orders compared to the demand pattern. Indeed, when an IID demand is forecasted with its long-term average, it is shown that for $0 < \beta < 1$ we generate a smooth replenishment pattern (dampening order variability) and for $1 < \beta < 2$ we create bullwhip (variance amplification).

However, when the smoothing rule is applied and demand is forecasted with e.g. the moving average or exponential smoothing technique, a feedback parameter $\beta < 1$ does not necessarily imply that the order variability is dampened. For instance, when demand is IID and forecasted with exponential smoothing and a smoothing parameter $\alpha = 0.5$, then a value $\beta = 0.5$ results in a bullwhip measure equal to 2.41. Hence the bullwhip effect is present, although the feedback parameter β is smaller than one. We need to reduce β down to 0.2 in order to obtain a smooth order pattern with a bullwhip measure smaller than one when using this particular forecast method. In other words, improper use of forecasting techniques may destroy the smoothing effect of the “smoothed” order-up-to policy.

These results are generally very complex and not always available in the literature. Using the spreadsheets, one can go beyond the existing analytical results and conduct several experiments to obtain insights into this complicated issue. The available results are added in the appendix of the instructor manual.

4.5 Insights for classroom purposes

When production is inflexible and significant costs are incurred by frequently switching production levels up and down, standard order-up-to policies with forecasting mechanisms may no longer be desirable. Because of the huge expenses, it may be important to avoid variance amplification or even to reduce variability of customer demand. Starting from the standard order-up-to policy, the instructor may derive the smoothed order-up-to decision rule. The crucial difference with the standard order-up-to policies is that the inventory deficit is only fractionally taken into account.

In using the smoothed order-up-to policy, the instructor should emphasize two aspects: the ordering behavior (as measured by the bullwhip effect), and the impact on its own net stock (as measured by the net stock amplification). The insights are clearest when demand is forecasted with its long-term average and demand is an IID process. In that case bullwhip reduction comes at a price. In order to guarantee the same fill rate, a larger safety stock is required. The instructor may ask the students to evaluate the impact of different values of β on inventory and switching costs.

The instructor may then point to the fact that the specific values of the demand parameters impact the ordering behavior. For ARMA(1,1) demand patterns, it is possible to end up in four different scenarios when compared to the standard OUT policy: (1) *win-win*, we can remove bullwhip and reduce inventory; (2) *win-lose*, sometimes bullwhip can only be removed at the expense of holding extra inventory; (3) *lose-win*, sometimes bullwhip can be endured because it results in a policy that requires less inventory to be held; (4) *lose-lose*, sometimes excessive bullwhip and inventory may exist. These scenarios depend on the statistical properties of the demand process. The exact conditions to end up in the different scenarios go far beyond the scope of the student's course, but we advise the students to play around with the parameters and come up with these scenarios. Generally, two to three scenarios are found by themselves.

When demand is forecasted using the exponential smoothing or moving average method, the results are much more complex. In class, the instructor may point to the fact that in that case a feedback parameter $\beta < 1$ does not necessarily imply that the order variability is dampened compared to the demand pattern. Using the spreadsheet application the students can experiment with order smoothing and forecasting and as such, they can evaluate the impact of different replenishment strategies on the fluctuations in both the order and inventory pattern.

5 Download information

The following files are available for download:

- *bullwhipexplorer.xls*: contains the spreadsheet file with two simulation models in two separate worksheets: standard OUT and smoothed OUT, referring to the standard order-up-to policy and the smoothed order-up-to policy. Both models work analogously. *[insert link to download the spreadsheet file]*
- *instructor manual.doc*: elaborates on the mathematics behind the input section, where the user selects the parameters of the model, and the simulation table, where the user can track the calculations of how orders are generated. In addition a summary is added of the analytical results available in the literature. *[insert link to download the instructor manual]*
- *student manual.doc*: describes on a step-by-step basis how to simulate using the spreadsheets. We omitted the mathematics behind the formulas. *[insert link to download the student manual]*

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