

Demand forecasting for supply processes in consideration of pricing and market information

Gerald Reiner¹, Johannes Fichtinger²

We develop a dynamic model that can be used to evaluate supply chain process improvements, e. g. different forecast methods. In particular we use for evaluation a bullwhip effect measure, the service level (fill rate) and the average on hold inventory. We define and apply a robustness criterion to enable the comparison of different process alternatives, i. e. the range of observation periods above a certain service level. This criterion can help managers to reduce risks and furthermore variability by applying robust process improvements. Furthermore we are able to demonstrate with our research results that the bullwhip effect is an important but not the only performance measure that should be used to evaluate process improvements.

Introduction

This paper deals with the evaluation of supply chain process improvements under special consideration of demand forecasting. Forecasting is an important lever of performance management of supply chain processes. To fulfill the customer requirements on delivery performance demand forecasts are necessary, e. g. to acquire resources (capital, equipment, labor). In this context an important question arises. How should the performance of different demand forecast alternatives be evaluated under consideration of the supply chain process. Lee et al. (2004) present the bullwhip effect (i. e. the amplification of demand variability upstream the supply chain) as a consequence of the use of quantitative forecast methods in multiple echelons in the supply chain. The main problem is that the forecasts are based on demand information generated by inventory policies of the downstream stage in the supply chain. Some papers show how integration of additional demand information improves the accuracy of demand forecasting (Natter et al., 2007). Price variation is a further cause of the bullwhip effect that is interesting in the context of our research. Under consideration of an integrated demand and supply chain management, forecasting and pricing are also related to each other.

¹University of Neuchâtel, Faculty of Economics, Enterprise Institute, Rue A. L. Breguet 1, 2000 Neuchâtel, Switzerland

²Cranfield School of Management, Cranfield, Bedford, MK43 0AL, United Kingdom

So far, efforts for a joint optimization of the supply (capacity reservation, planned safety stock and safety time) and demand forecasting have tried to predict customer demand based on historical demand patterns. These models have neglected additional available information for demand side forecasting like prices and/or reference prices. Therefore one goal of this paper is to present a demand forecast and inventory model that can be used to evaluate the performance improvements based on the integration of this information. The dependencies between demand forecast quality, and the drivers of inventory holding costs in make to stock and the drivers of production capacity reservation costs in make to order environments (ideal utilization for given variability) should be analyzed via this model. Finally, the evaluation of the effects of forecast errors based on the bullwhip effect and further “necessary” performance measures will be discussed. In this context a further research question will be answered: are there any additional performance measures required or do the classical bullwhip effect measures cover all relevant performance aspects?

In particular, we develop in this work an extended dynamic demand forecast and inventory model for a two stage supply chain process, assuming purchase decisions are made based on rational actors. The last partner (retailer) in the supply chain faces consumer demand. We will illustrate our approach with an empirical reference dataset of an Austrian retail chain company. We illustrate how the coordinated application of our model can be used to evaluate performance of the supply process.

In Section we review relevant literature in the field of supply chain management with focus on the bullwhip phenomenon and demand management with emphasis on extended price information. Section describes our estimation and evaluation models while in Section the results with respect to the reference dataset are shown. Section concludes the paper and gives an outline of further research activities.

Literature Review

We will give a short overview about the relevant articles for our presented research work in the context of an integrated supply and demand management. Two major topics are discussed, bullwhip effect and reference prices.

A pointed definition of the bullwhip effect is provided by de Kok et al. (2005): “The bullwhip is the metaphor for the phenomenon that variability increases as one moves up a supply chain”. There are different approaches to identifying the causes of the bullwhip effect. Sterman (1989) sees wrong decisions made by human decision makers as the major cause of the bullwhip effect, while Lee et al. (2004) show that this effect occurs even in a supply chain where all decisions are made in a completely rational way. Notwithstanding these different approaches, it is obvious that the effect can be reduced by better communication between the elements making up the chain and through the chance for the manufacturer to see the real (unaltered) customer demand (Lee et al., 2004, Sterman, 1989). Further research studies compare the benefits of information sharing with lead time reduction. The results obtained show that in some supply chain settings the reduction in lead time can have a greater impact on supply chain performance than information sharing (Cachon and Fisher, 2000).

It is necessary to take the dynamic dependency between bullwhip effect and lead time into account by evaluating process alternatives. It is obvious that the bullwhip effect has disturbing performance influence up- and downstream the supply chain process. Chen et al. (2000) investigates the dependencies between forecasting, lead times and information in a simple supply chain, i. e. the lead time is an input parameter and not calculated within the model.

Boute et al. (2007) show for a two-echelon supply chain how the bullwhip effect could be dampened under consideration of lead times. Hosoda and Disney (2006) analyze the variance amplification in a three echelon supply chain model under the assumption of a first-order autoregressive consumer demand. In this context they were able to obtain analytical results. Motivated by their research we investigate the influence of demand modelling on supply chain process performance by comparing different demand models.

By observing actual and past prices customers develop price expectations, or reference prices, which become the benchmark against which current prices are compared (Popescu and Wu, 2007). Observed prices lower than the customers' reference price are perceived to be low by the customer and therefore lead to higher demand compared to a setting where price expectation and observed price are equal. Observed prices higher than the reference price consequently result in reduced customer demand. Traditional simplistic demand functions, where demand $D(p)$ is a decreasing function in price p are extended to demand functions $D(p, r)$ decreasing in price p and increasing in reference price r .

In the literature there are numerous reference pricing models used for e.g. forecasting of future demand, describing actual demand patterns or optimization of prices and/or inventory decisions. A recent review is given e.g. in Mazumdar et al. (2005) and Briesch et al. (1997) presented empirical results of different reference price models and show that using "past prices of a brand is the best model of reference price". Exponential smoothing of reference prices (eq. 1) is very common in literature (Winer, 1986, Greenleaf, 1995, Kopalle et al., 1996, Fibich et al., 2003, Popescu and Wu, 2007) and empirically validated (Briesch et al., 1997).

$$r_t = \alpha r_{t-1} + (1 - \alpha)p_{t-1} + \varepsilon_t, \text{ for } 0 \leq \alpha < 1. \quad (1)$$

Since reference prices are not directly observable, they have to be calculated or estimated. It is possible to use

- historical sales and price data to estimate reference prices using time series analysis,
- if historical data are not available or difficult to collect reference prices could be estimated once by using conjoint analysis (see Jedidi and Zhang, 2002, for a similar model to estimate reservation prices) and updated using the formation mechanism in Eq. (1) or
- external references like indices if available.

While parts of the literature deal with dynamic pricing to optimize current and future profits (e.g. Greenleaf, 1995, or Kopalle et al., 1996, developed pricing models for retailers and manufactures), we concentrate in our work on the influence of the price effect on demand forecasting and assume pricing decisions to be exogenously.

Popescu and Wu (2007) provide analytical insights in the reference effect on demand. They describe a Gain-Loss Asymmetry which implies that customers react differently on discounts or surcharges. For a loss averse customer, a surcharge reduces demand more than a discount of the same magnitude increases demand and vice versa. Empirical evidence for risk averse pricing behaviour can be found in Ho and Zhang (2004).

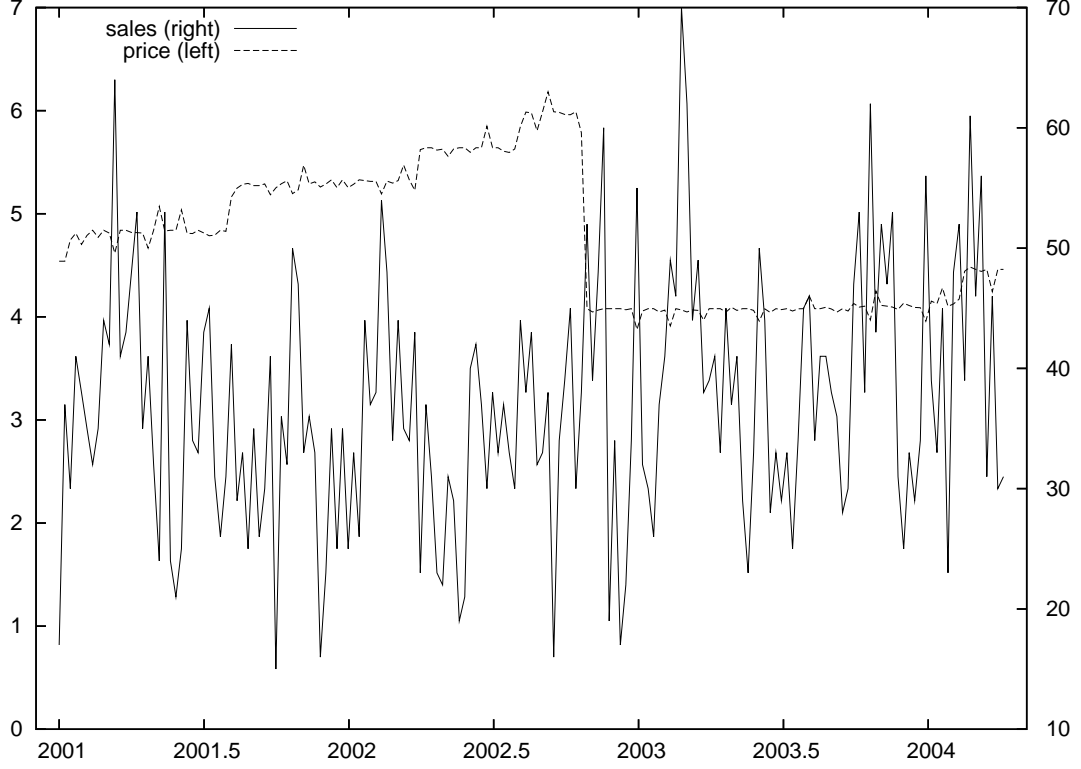


Figure 1: Sales (units sold) and price data 2001/01/01 to 2004/04/05

Estimation and basic model

Description of used sales data

For our analysis we use aggregated weekly empirical sales (units sold) and pricing data over 171 periods (2001/01/01 to 2004/04/05). The available sales data do not exactly correspond with the real demand, since stockouts are not recorded. However, in this study these specific sales data can be considered as an indicator for demand. To evaluate the quality of forecasting with respect to a mean squared error (MSE) we use a subset of 95 periods (2001/01/01 to 2002/10/21) of all data for in-sample forecasting. Figure 1 shows the price-dependent sales for all periods. Note that the latent reference price r is not observable but was calculated using the updating mechanism described in Eq. (1) and is shown for illustration. For further analysis of data d can be treated as stationary (has no unit root based on augmented Dickey-Fuller test) and with time-independent variance. See Hackl (2005) for details on OLS-techniques.

Description and estimation of demand models

Based on the above presented literature review, we use the following basic demand definition in our framework

$$D_t(p_t, r_t) = c + \beta_1 p_t + \beta_2 (r_t - p_t)^+ + \beta_3 (r_t - p_t)^- + \varepsilon_t \quad (2)$$

where $(r_t - p_t)^+ = \max(r_t - p_t, 0)$ is the positive gap between reference price and observed price and $(r_t - p_t)^- = \min(r_t - p_t, 0)$ is the negative reference price gap. The separation of the positive and negative gap allows us to model the risk preferences (risk aversion) of customers. The updating of reference price r follows Eq. (1) but with periodically updated α_t :

$$r_t = \alpha_t r_{t-1} + (1 - \alpha_t) p_{t-1} + \varepsilon_t. \quad (3)$$

Note that a similar reference price model can be found e.g. in Natter et al. (2007). An updating mechanism of reference prices based on Eq. (1) is used.

We compare the performance of the following five estimation models. Two of them include reference price r and price p while the other two depend on price p only, the simple moving average model 0 used by Chen et al. (2000) is evaluated as benchmark. Furthermore we compare the performance of models using auto-regressive terms with non-time-series models.

Parameters β_{1t} are expected to be negative implying decreasing d in p while β_{2t} and β_{3t} are expected to be positive. The estimation is done using an OLS technique with a finite grid of α in 0.01 steps evaluated against the minimum sum of squared errors by using the GNU Regression, Econometric and Time-series library ‘‘Gretl’’ (Cottrell and Lucchetti, 2007). The R^2 measures are similar to other empirical studies of this type (see e.g. Winer 1986).

Model 0 Simple moving average model for n periods used by Chen et al. (2000). Average goodness of fit: $R^2 = 0.06$, $\sum e^2 = 13943$.

$$\hat{D}_t = \frac{\sum_{i=1}^n D_{t-i}}{n} \quad (4)$$

Model 1 Time-series model including reference prices ($R^2 = 0.17$, $\sum e^2 = 7951$):

$$\hat{D}_t = c_t + \delta_t D_{t-1} + \beta_{1t} p_t + \beta_{2t} (r_t - p_t)^+ + \beta_{3t} (r_t - p_t)^- \quad (5)$$

Model 2 Time-series model without reference prices ($R^2 = 0.13$, $\sum e^2 = 8331$):

$$\hat{D}_t = c_t + \delta_t D_{t-1} + \beta_{1t} p_t \quad (6)$$

Model 3 Simple regression model including reference prices ($R^2 = 0.11$, $\sum e^2 = 8541$):

$$\hat{D}_t = c_t + \beta_{1t} p_t + \beta_{2t} (r_t - p_t)^+ + \beta_{3t} (r_t - p_t)^- \quad (7)$$

Model 4 Simple regression model without reference prices ($R^2 = 0.06$, $\sum e^2 = 8979$):

$$\hat{D}_t = c_t + \beta_{1t} p_t \quad (8)$$

Supply Chain Model

Figure 2 depicts the most important relationships in our model that is used as an evaluation framework for different forecast methods. In detail we use a two stage supply chain process with a supplier and a retailer. The supplier produces mainly with a make-to-order production strategy fulfilling retailer orders unless capacity is inadequate. Many performance problems of the supplier arise due to inaccurate demand forecasts. In our model delivery performance is

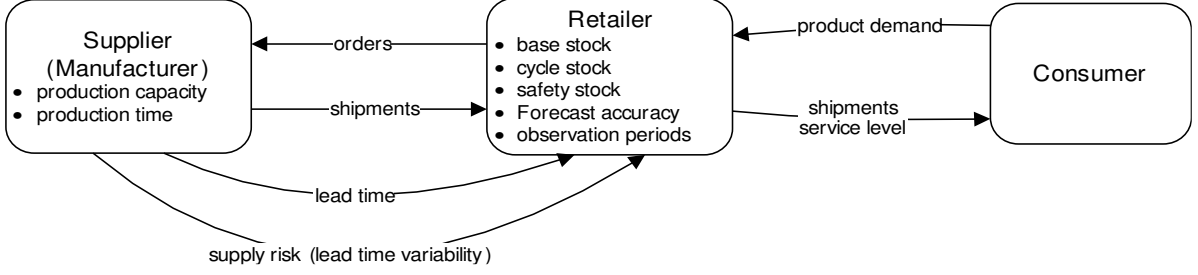


Figure 2: Model of a simple two stage supply chain

mainly dependent on lead time which is influenced by forecast accuracy. The retailer uses an adapted base stock inventory policy.

Formal description The supplier has to apply a make-to-order production strategy. Therefore, we use a general distributed queuing model (G/G/1) for the supplier (one product is produced at one assembly line which is reserved for the retailer) to determine the replenishment lead time L for the retailer (eq. 10) (Hopp and Spearman, 1996). This is an estimation of the “real” lead time. For the production process only approximate values of the parameters of lead time can be computed, like the mean lead time which is composed of a variability component, a utilization component and a capacity component. The queuing model (G/G/1) seems to be a quite hard approximation of reality. However, an empirical study by Klassen and Menor (2007) show that it is a good indicator if no other lead time data are available. Therefore, the relevant input parameters are about

- the arrival and service process, e. g., arrival rate R_a and service time T_p ,
- forecast accuracy (standard deviation of the forecast error / mean forecast error, ca) and
- the service time coefficient of variation cp .

The most relevant output parameter is $L =$ waiting time T_a + service time T_p but queue length I_a and utilization ρ (eq. 9) are still relevant, e. g. to determine the right utilization to fulfill the customer requirements.

$$\rho = R_a T_p \quad (9)$$

$$I_a = \frac{\rho^2}{1 - \rho} \cdot \frac{ca^2 + cp^2}{2} \quad (10)$$

$$L = \frac{I_a}{R_a} + T_p = T_a + T_p \quad (11)$$

The retailer uses an adapted base stock policy as presented in the following equations. Furthermore, we explain some restrictions of the operations which have to be taken into account. The theoretical safety stock s_t (eq. 18) is calculated like the classical base stock policy (Neale et al., 2003) with SF denoting the safety factor. In general, for each planning period an order is placed to boost the inventory position (inventory currently on-hand plus on-order) up to the base stock level.

The base stock y_t (eq. 12) determination takes the demand forecast, \hat{D}_t , for period t into account. This forecast is based on the different forecast alternatives described in Section . A further requirement is to calculate the average replenishment lead time for the retailer \bar{L}_t (eq. 13) at time t , the replenishment lead time standard deviation for the retailer σ_{L_t} (eq. 14), the average demand \bar{D}_t (eq. 15) per time period t and the average demand standard deviation σ_{D_t} (eq. 16) based on the observations from the previous n periods.

$$y_t = \hat{D}_t (R + \bar{L}_t) + s_t \quad (12)$$

$$\bar{L}_t = \begin{cases} \frac{\sum_{i=t-n+1}^t L_{i-1}}{n} & \text{for } t > n, \\ \frac{(n-t)L_0 + \sum_{i=1}^t L_{i-1}}{n} & \text{for } 1 \leq t \leq n \end{cases} \quad (13)$$

$$\sigma_{L_t} = \begin{cases} \sqrt{\frac{\sum_{i=t-n+1}^t (L_i - \bar{L}_i)^2}{n-1}} & \text{for } t > n, \\ \sqrt{\frac{(n-t)a_0^2 + \sum_{i=1}^t (L_i - \bar{L}_i)^2}{n-1}} & \text{for } 1 \leq t \leq n \end{cases} \quad (14)$$

$$\bar{D}_t = \begin{cases} \frac{\sum_{i=t-n+1}^t D_{i-1}}{n} & \text{for } t > n, \\ \frac{(n-t)\bar{D}_0 + \sum_{i=1}^t D_{i-1}}{n} & \text{for } 1 \leq t \leq n \end{cases} \quad (15)$$

$$\sigma_{D_t} = \begin{cases} \sqrt{\frac{\sum_{i=t-n+1}^t (e_{i-1})^2}{n-1}} & \text{for } t > n, \\ \sqrt{\frac{(n-t)e_0^2 + \sum_{i=1}^t (e_{i-1})^2}{n-1}} & \text{for } 1 \leq t \leq n \end{cases} \quad \text{with } e_t = D_t - \hat{D}_t \quad (16)$$

Additionally to the planning parameters, we also present the calculation of the observed values for the base stock y_t^o (eq. 17) at time t . In addition to the safety stock s_t (eq. 18), the observed inventory position y_t^o represents the connection to the supplier because deliveries of the supplier x_t (eq. 19) increase the y_t^o and the fulfillment of customer demand D_t decreases the y_t^o . Waiting replenishment orders, WRO_t , which have not been arrived at the inventory yet have to be also taken into account (eq. 20). Deliveries of the supplier in period t are identical to the retailer orders x_{t-1-L_t} (eq. 19). The service level of the retailer (fill rate) SL_t (eq. 21) is calculated under consideration of the observed safety stock s_t^o (eq. 23) and demand D_t .

We calculate the average on-hand inventory OHI_t (eq. 22) based on the observed safety stock s_t^o .

$$y_t^o = \begin{cases} y_{t-1}^o + x_{t-L_t} - D_{t-1} & \text{for } t > 0 \\ y_0 - WRO_0 & \text{for } t = 0 \end{cases} \quad (17)$$

$$s_t = SF \sqrt{\sigma_D^2 (R + \bar{L}_t) + \sigma_{L_t}^2 \bar{D}_t^2} \quad (18)$$

$$x_t = \max(y_t - s_t^o - WRO_t, 0) \text{ for } t > 0 \quad (19)$$

$$WRO_t = \begin{cases} \sum_{i=t-L_t}^t x_{i-1} & \text{for } t > 1 + L_0 \\ (L_0 - t + 1) \bar{D}_0 + \sum_{i=0}^{t-1} x_i & \text{for } 1 \leq t \leq 1 + L_0 \\ L_0 \cdot \bar{D}_0 & \text{for } t = 0 \end{cases} \quad (20)$$

$$SL_t = 1 - \frac{\sum_{i=1}^t \max(D_t - s_t^o, 0)}{\sum_{i=1}^t D_t} \text{ for } t \geq 1 \quad (21)$$

$$OHI_t = \frac{\sum_{i=1}^t \max(s_i^o, 0)}{t} \text{ for } t \geq 1 \quad (22)$$

$$s_t^o = y_t^o - D_t \text{ for } t > 0 \quad (23)$$

Finally, we analyze in detail the bullwhip effect mentioned. We calculate a measure W in Eq. (24) that shows how demand is amplified at each echelon (e. g., W_r = retailer). We measure the bullwhip effect at a particular echelon in the supply chain as the quotient of the coefficient of variation of demand (orders) generated by this echelon (D_{out}) and the coefficient of demand received by this echelon (D_{in}) (Fransoo and Wouters, 2000).

$$W = \frac{c_{out}}{c_{in}} \text{ with} \quad (24)$$

$$c_{out} = \frac{\sigma(D_{out}(t, t+T))}{\mu(D_{out}(t, t+T))}, \quad c_{in} = \frac{\sigma(D_{in}(t, t+T))}{\mu(D_{in}(t, t+T))}$$

Motivated by Boute et al. (2007) we extended our model by introducing a bullwhip dampening parameter ζ . This adoption causes the following modification of the retail order x_t for any $t > 0$ ($\zeta = 1$ for $t = 0$):

$$x_t = (1 - \zeta) x_{t-1} + \zeta (\max(y_t - s_t^o - WRO_t, 0)) \quad (25)$$

Model parameters

Input parameters are based on discussions with managers of different suppliers and retailers. The initial values are based on a carefully conducted sensitivity analysis. The verification as well as validation results are used for calibrating of the systems dynamics model, e. g. lead time initial value L_0 , forecast error initial value e_0 or average demand initial value D_0 (see table 1). The time interval Δt and the duration of the simulation T are motivated by the empirical data, by the forecast process and the requirements to show dynamic effects over multiple periods.

Table 1: Standard input parameters of the analyzed supply chain process

\bar{D}_0	average demand initial value	39 consumer orders
a_0^2	squared lead time volatility initial value	10
ζ	bullwhip dampening parameter	0.5
ca	demand volatility	σ_{D_t}/\bar{D}_t
cp	production time volatility	0
Δt	time interval	1 week
e_0^2	squared forecast error initial value	130
\hat{D}_0	average forecasted demand initial value	39 consumer orders
n	number of observation periods	7 – 22
ρ	average utilization of the supplier (manufacturer)	65%
R	review period (time between successive orders)	1 week
SF	safety factor	2.33
T	number of time steps (product class life time)	76 weeks
L_0	replenishment lead time initial value	2 weeks
δ_t	autocorrelation parameter in period t	model estimation
β_{it}	model parameters in period t	model estimation
c_t	constant in period t	model estimation
D_t	product demand in period t	see fig. 1
p_t	product price in period t	see fig. 1

Results

We use a subset of 76 periods (2002/10/28 to 2004/04/05) of all data for out of sample forecasting to evaluate the forecast quality with respect to our evaluation model. Performance is measured in terms of the bullwhip effect (eq. 24), service level (eq. 21) and inventory measures (eq. 22).

The analyzed models result in the following $\sum e^2$ for the forecast \hat{D}_t :

Table 2: Resulting forecast errors

	$\sum e^2$
Model 0	10723
Model 1	9256
Model 2	9186
Model 3	9892
Model 4	9889

The characteristic of the analyzed empirical data set has also a major influence on our described results. Especially the low price variability compared to the volatile demand could lead to the identified small (missing) improvement potential of forecast methods under consideration of reference prices.

First we investigate the performance of the analyzed forecast methods under consideration of our basic model without additional dampening of the order variability. The results in Figures 3, 4 and 5 show that the time series models (model 1 and model 2) perform better than the regression models (model 3 and model 4). Additionally, we compared the basic model 0 with the other models. It could be shown that model 0 shows a similar result as the group of the regression models.

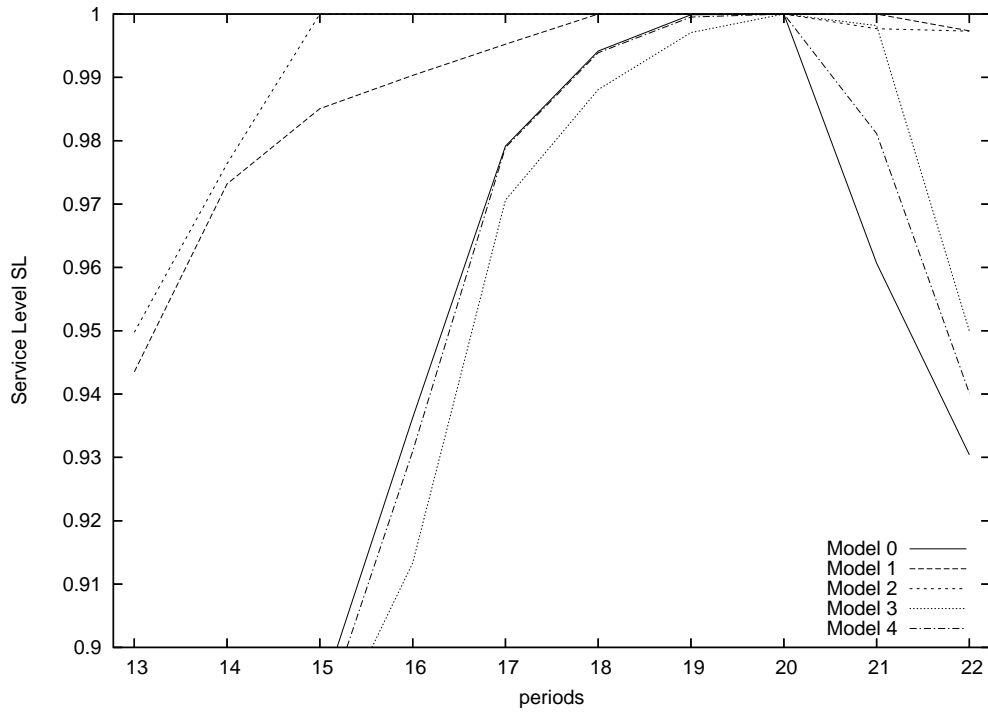


Figure 3: Service level SL_t

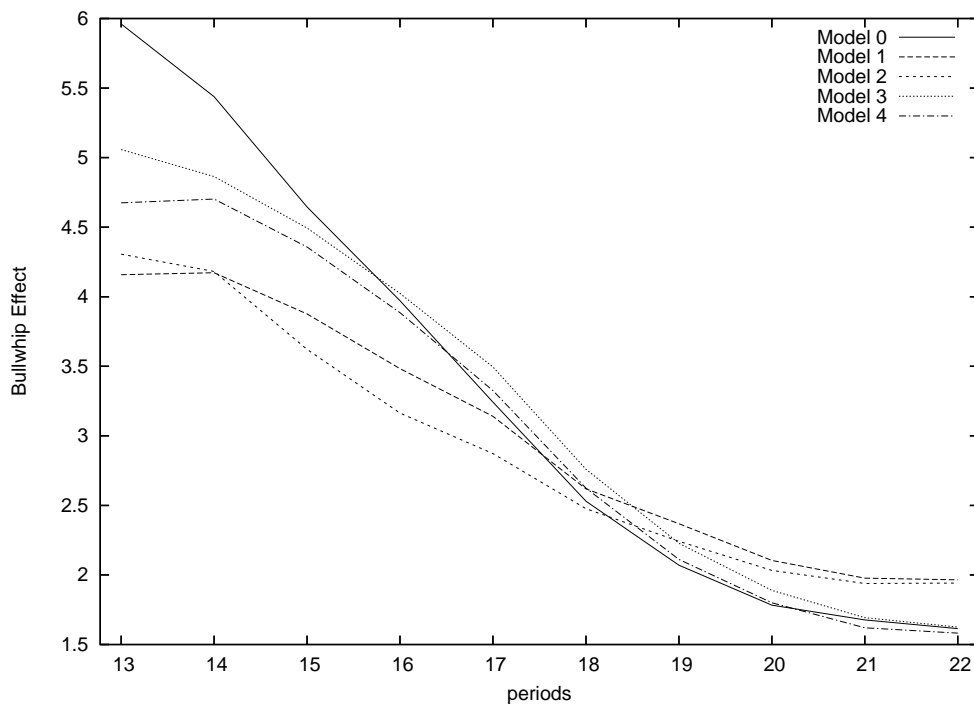


Figure 4: Bullwhip Effect W_t

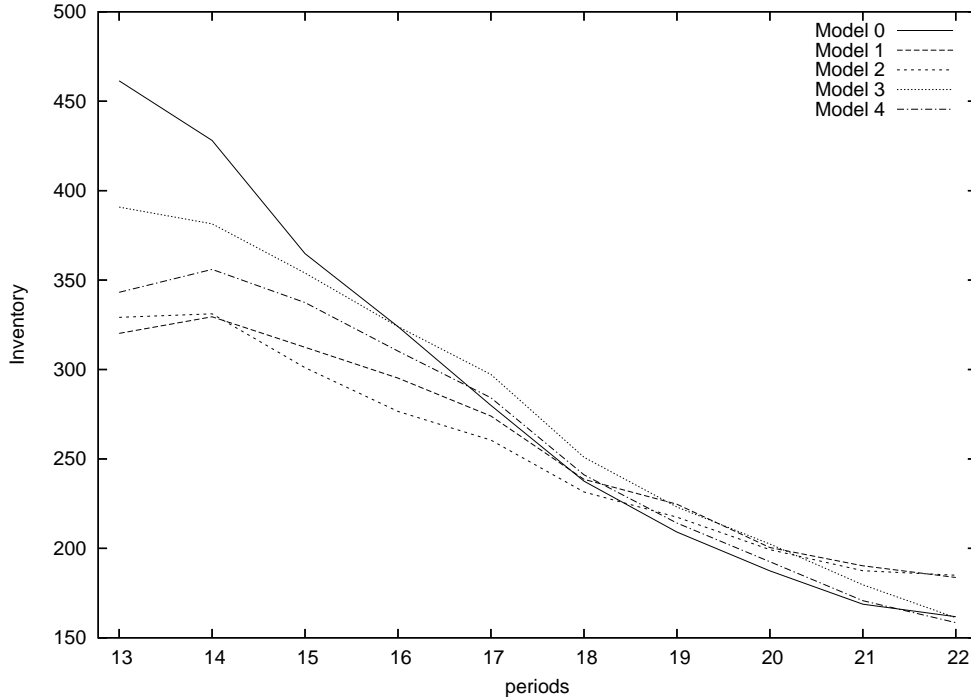


Figure 5: Average on-hand inventory OHI_t

The identification of the ideal forecast methods and inventory policy parameters (i.e. the number of calculation periods) is simple. We assume that all forecast methods cause the same handling cost. Therefore, an alternative with a simulated service level of 100% and the lowest average inventory should be selected. In particular, most models show their ideal performance with 20 observation periods, only model 1 shows best performance with 21 periods. Furthermore we are not able to identify any significant difference between the forecast methods under consideration of this criterion.

Let n^* denote the range of observation periods n with a simulated service level of 100%. This evaluation criterion is used to evaluate the robustness of the selected improvement alternatives. Model 2 presents the best performance with $n^* = 6$ (in observation periods $n = 15 \dots 20$), followed by model 1 with $n^* = 4$ ($n = 18 \dots 21$). Model 3 and model 4 result in $n^* = 1$ for the period $n = 20$, while model 0 results in $n^* = 2$ for the periods $n = 19 \dots 20$.

The analyzed product is characterized by a very long product life cycle. Nevertheless, the robustness criterion should occupy a major position by the selection of the forecast method, due to the fact that the optimal number of observation periods could only be determined ex post. If the number of observation periods is limited by a short life cycle this criterion will be an important factor.

The performance of the different forecast models is also determined by the assumptions of our illustration example, e.g. utilization, maximum allowed lead time and initial values. There is no significant difference in terms of the forecast error between the models including and not including reference prices (see table 2) but the caused lead time variability is higher for reference price models. Therefore flexibility (utilization, etc.) of the manufacturer has an important influence on the overall performance of the analyzed supply chain process.

Our research is based on the research work of Chen et al. (2000). They show how the bullwhip effect is influenced by the number of observation periods for the standard deviation

of the forecast error as well as the calculation of the forecasted demand. We considered additionally the lead time variability caused by the base stock inventory policy for different forecast methods. Our illustration example (see Figure 1) confirms this analytical result but under consideration of the service level it is obvious that the number of periods influences also the service level performance. We confirm also the restriction that an improvement of the bullwhip effect by increasing the number of observation periods is limited. In our illustration example period 21 (22 for model 1) leads to decreasing results, caused by the characteristic of the empirical data set.

Second, we investigate the performance of the analyzed forecast methods under consideration of extended model with additional dampening of the order variability. The results are very similar to the basic model. On the one hand a little decrease of the bullwhip effect measures can be observed and on the other hand the average inventory can be decreased. The problem is that the service level will be also decreased. In particular the robustness criterion n^* shows the following results: $n^* = 2$ for model 1 and 2 ($n = 20 \dots 21$) and $n^* = 0$ for all other models. These results confirm that the bullwhip effect is an important but not the only performance measure that should be used to evaluate process improvements.

Conclusion

Based on analytical research work about the bullwhip effect (see Section) we developed a dynamic model that can be used to evaluate supply chain process improvements under consideration of different forecast methods. In particular we used for evaluation a bullwhip effect measure, the service level (fill rate) and the average on-hand inventory. We define and apply a robustness criterion to enable the comparison of different process alternatives. This criterion can help managers to reduce variability by applying robust process improvements because the optimal number of observation periods can be only determined ex post.

We could demonstrate with our illustration example that the evaluation of forecast methods should not be restricted to the classical performance indicators like MAD, MSE, MAPE, SAE, etc. but using our proposed robustness criterion provides further insights. These results confirm that the bullwhip effect is an important but not the only performance measure that should be used to evaluate process improvement. It can be recommended to apply also further measures like average on hold inventory and service level (e. g. fill rate).

Furthermore, dampening of the order variability in our illustration example decreases the bullwhip effect and the average on-hand inventory but with the problem of a decreasing service level.

Further research activities will deal with the dynamic effects in more detail, e. g. to identify the ideal (in terms of the overall supply chain process performance) number of observation periods ex-ante by a given demand characteristic forecast method, inventory policy and bullwhip dampening procedure.

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