Contribution for ECR Europe Student Awards

Reducing Out-of-Stock for Promotions

An investigation to the causes of promotion OOS and the development of a demand forecast model and model for logistical control at a large Dutch supermarket organization to reduce OOS

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In times of severe competition, many retailers recognize the importance of efficiently maximize their customer service. In recent years, the reasons for Dutch consumers to choose for a particular supermarket shifted from quality related aspects to price related aspects (low prices, attractive promotions, et cetera). Since the start of a price war between Dutch supermarket organizations in 2003 a battle for consumers has emerged. This makes fulfilling all demand of the consumers extremely important. It was observed that for a large Dutch grocery retail chain the Out-of-Stock (OOS) rates for promoted products in the stores were significantly larger than the OOS for non-promoted products. From the literature, it is known that OOS of regular products may have several consequences: store switching, product switching, delay of purchase, canceling the purchase, category switching or brand switching (see e.g. Sloot et al., 2002; Gruen et al., 2002). Store switching and purchase cancellation will directly lead to lost sales. All other consequences might lead to lost sales as unsatisfied customers could choose another supermarket next time. For OOS of promotions the same behavior is expected (but the importance of the consequences might be different). These observations are the starting points of the conducted research.

First, the impact of OOS is measured by collecting data on the demand patterns during several weeks in a number of shops. The experiment was set up such that there would be no OOS in the store (i.e. by pushing enough inventory in the store). During the period each store registered its sales for promotions. Products that by accident did go out OOS are filtered out from the sales data. This resulted in pure demand patterns, which did not incur any OOS. These demand patterns were used in calculating what could have been sold (i.e. if there were no OOS) in weeks before the experiment: in regular promotion weeks with OOS. In this way the lost sales could be determined. It seems that promotion sales in the grocery assortment can be increased by at least seventeen percent if OOS rates could go to zero. This means that, per year, over all stores, tens of millions of euros are lost on promotion sales. However, sales are not only lost on promotions, but on the regular assortment too. Some consumers will go to another store for all their purchases if they do not find the (price) promoted product they are looking for. It is estimated that several millions of euros are lost directly due to store switching and purchase cancellation behavior of customers. So OOS reduction of (price) promoted products will lead to increased promotion sales, as well as to increased non-promotion sales.

This paper makes the following contributions:

1. The *causes* of the Out-of-Stocks for promotions are analyzed.
2. A *promotions demand forecasting model* is developed based on an extensive dataset of 78 weeks of past promotions.
3. A model for the *logistics control function* is constructed using the forecasting model.

A good forecast of demand is still an estimate of a future event. It is thus clear in advance that this forecast will be wrong. Therefore, a proper logistical control for promotions will improve further the match between demand and supply. Developing an appropriate logistics control policy in accordance with an accurate demand forecasting tool is a promising way to reduce OOS of promotions. The paper will be structured in the same order as the contributions listed above.

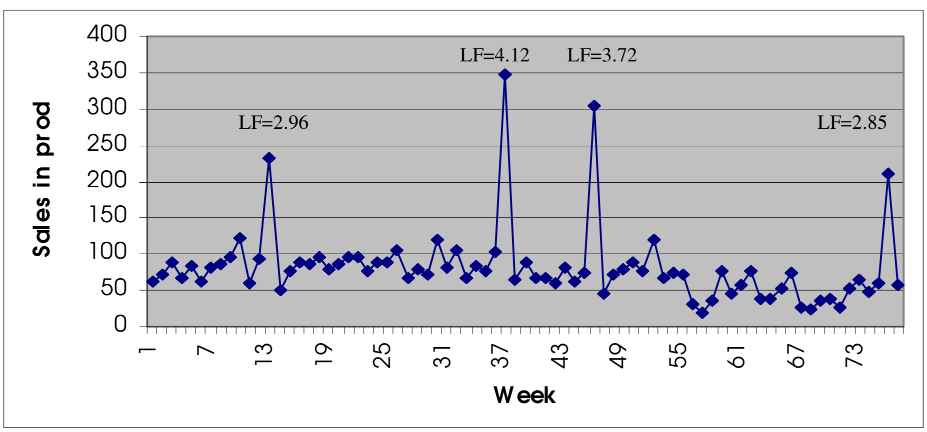
Causes of Promotions Out-of-Stock

The order for promotions is placed several weeks before the promotion period due to the supplier's production time. In the literature such situations are referred to as single period news vendor problems (Silver et al., 1998). Depending on the profit margin (sometimes negative), stores order more aggressive or less. Multiple causes exist that lead to ordering problems for promotions. These causes can be divided over nine main groups, which will be listed here accompanied with a short explanation or example. (1) Difficult demand forecasting due to variables that determine demand of promotions. Currently the forecasts are made several weeks before the promotion period. Too many factors play a role and affect each other in determining demand for (price) promoted products, to make human forecasting accurate. (2) Difficult demand forecasting due to a lack of data and experience. Forecasts are made per store and are mainly based on experience. Many of the (price) promoted products are in promotion once or twice a year. So very less (product specific) data is available to base forecasts on. (3) An inflexible logistical system. The orders are placed six weeks in advance of the promotion and stores get in the promotion period exactly what they ordered at that time. Next to that, the safety stocks (if any, because only products that are in the regular grocery assortment have a safety stock) are not dependent of demand or product characteristics. (4) Presence of totally unpredictable, external factors. These include situations as local parties or supplier advertisements. (5) Problems at supply chain (SC) partners. Sometimes the suppliers are not able to fulfill the order. In that case the distribution centers (DC's) will get OOS and so will the stores. Next to that, in the DC's mistakes can be made in the order picking process. (6) Bad inventory control in the stores. In some cases customers find a product OOS at the shelf, while it is still available in the warehouse of the supermarket. (7) Imperfect administration of performances during previous promotion periods. Administration has to be maintained manually. That is why multiple stores do not collect information about OOS, overstocks, et cetera, during promotions. (8) Insufficient care with which the products are ordered. It takes quite a time to order the (price) promoted products. So some stores do not pay much attention in ordering the products. Sometimes they just order "the same quantity as ever" while the promotion characteristics or trade units may be changed. (9) Intentional inaccurate ordering. Several drivers exist for the store managers too order to less or too much. Forward buying because of the low purchase prices, and defensively buying because of negative margins or fear for overstocks.

Promotions Demand Forecasting Model

To meet the customer demand with a high service level, an accurate forecast for the short-term promotions sales is needed. Here, the sales increase caused by a promotion compared to the regular sales level is used as a dependent variable. This latter is defined as the lift factor (LF). An extensive database including 78 sales weeks on promotions and their specific characteristics (e.g. advertising and display characteristics, weather, holidays, magnitude of the price cut, and product characteristics) was built. After outlier elimination a sample with LF' s in the range between 1 and 35 is obtained (the average LF is 8.5). Figure 1 shows an example of the idea of LF's for an arbitrary product.

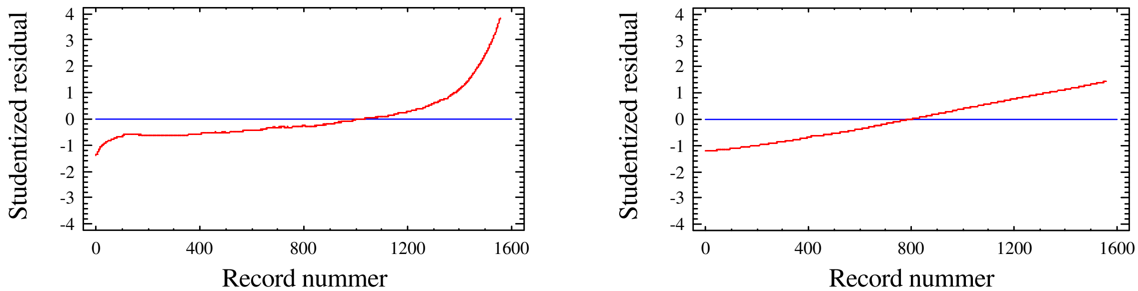
Figure 1: Demand pattern of a product with promotions in weeks 13, 37, 46, and 76



Multiple linear regression models are used to determine the effect of all related variables on the dependent variable. The dataset is split up in a calibration set (a year) and a validation set (remaining half year). The total dataset has information on 21,401 Stock Keeping Units (SKU's). All SKU's where we did not have historical sales records or prices are eliminated (the typical in-out products which are added exceptionally, e.g. Easter eggs). This leaves us with a good-sized dataset of 21183 SKU's.

After a first rough analysis it appeared that for extreme values of LF, the forecast errors were higher (see figure 2(a) where a S-curve can be observed). This indicates that for small LF' s the overestimation increases and for large LF' s the underestimation increases. Therefore, a transformation of the dependent variable is done: P(LF), where P(LF) is the probability of observing such a LF value, which is obtained via the best fitting lognormal distribution. By transforming LF to P(LF), the observed S-curve relation between the dependent and independent variables in the multiple linear regression can be converted into a linear relationship (see figure 2(b)).

Figure 2:
Left 2(a): Forecast errors versus ascending LF' ,swith LF as dependent variable
Right 2(b): Forecast errors versus ascending LF' ,swith P(LF) as dependent variable



The regression models were built at two aggregation levels: the store level and the SC level. The literature on selecting the appropriate aggregation level is not conclusive. Some authors state that forecasting at store level is better because useful data is not lost and local information can be used (Foekens et al., 1994). Others find better forecasting performance at aggregate levels (Armstrong, 2001). Despite the loss of data, data on aggregate levels are less erratic and contain less noise. We assessed models based on both aggregation levels to evaluate which one is superior. All models are evaluated by using several performance indicators. The most important ones used are the Mean Absolute Percentage Error, the Standard Deviation of Absolute Percentage Error, the Coefficient of Variation and the R^2(DF), which is the R^2 adjusted for the degrees of freedom. Extensive testing and modeling taking into account non-linear relations between the dependent variable and the independent variables, the specific behavior of each variable, adding/dropping variables based on the significance, lead to the following best found model for our dataset:

P(LF) (for product i) =

$$C_1 + (C_2 + \alpha * AS_i) + (C_3 + \beta * AS_i) + \chi * RP_i + \delta * L_i + \varepsilon * PC_i + \phi * EMT + \sum_{l=1}^{l=4} (\varphi_l * A) + \sum_{k=1}^{k=K} (\gamma_k * G) + \sum_{t=1}^{t=8} (\eta_t * H)$$

Where:

C_1, C_2, C_3 =	Constant terms (may be negative)
AS =	Average sales
RP =	Regular sales price
L =	Length to previous promotion with same product
PC =	Price cut in percents
EMT =	Expected average maximum temperature in promotion period
A =	Dummy variable for kind of support. A=1 if the promoted product is displayed at the first page of the promotion flyer (if l=1), if it is supported by TV commercials (if l=2), if has visual in store advertising (if l=3), if it has audio in store advertising (if l=4). A=0 if it is not supported in one of the above ways.
G =	Dummy variable for product group. G=1 if the promoted product belongs to product group k. G=0 otherwise
H =	Dummy variable for period effects. H=1 if the promotion period is during Easter (if t=1), Queens day (if t=2), liberation day (if t=3), Pentecost (if t=4), Christmas (if t=5), Summer or Winter holiday (if t=6 or 7 respectively). H=0 if the promotion is not during one of these periods.
α =	Multiplier for impact of average sales for products with high average sales, 0 if average sales is below X, nonzero value if X is greater than or equal to X

β = Multiplier for impact of average sales for products with low average sales, 0 if average sales is greater than or equal to X, nonzero value if X is below X
χ = Multiplier for impact of regular sales price
δ = Multiplier for impact of length to previous promotion
ε = Multiplier for impact depth of price cut
ϕ = Multiplier for impact of weather conditions
φ_l = Multipliers for impact of product displayed at first page of promotion flyer (l=1), TV support (l=2), visual in store advertising (l=3), audio in store advertising (l=4)
γ_k = Multipliers for impact of product group where the promoted item belongs to
η_t = Multiplier for impact of Easter (t=1), Queens day (t=2), liberation day (t=3), Pentecost (t=4), Christmas (t=5), Summer holiday (t=6), Winter holiday (t=7)

The following general conclusions are made:
1. Forecasting on SC level leads to improved forecasting performance compared to forecasting on store level.
2. Using P(LF) instead of LF as dependent variable leads to an improved forecasting performance.
3. Adding more information by using dummy variables for stores and product groups leads to improved forecasting performance.

So, the best models are models with P(LF) as dependent variable, on a SC level and with dummy variables for product groups.

Expert judgment over the output of the model is always necessary (as advocated by Silver et al. (1998)). Therefore guidelines are needed for proper human interpretation and adjustment of the forecast model's output. Several error analyses are carried out per variable. From these analyses insights could be obtained on whether a promotion with a particular variable is tended to be over or underestimated. These conclusions can then be used by experts in interpreting the output of the model. In interpreting and adjusting the forecast, experts could also take into account the following issues:
- Compare the forecast with observed LF's of previous promotions with the same product. What are the differences between those promotions and the current promotion?
- Did OOSs occur during previous promotions? If yes, then the realized LF of the promotion is not representative for the LF to be forecasted.
- Are complementary products, substitute products, or multiple variants of the same product on promotion? If yes, then the output may be increased (complementary) or decreased (substitute, multiple variants).
- Is the promoted product sensitive for weather conditions? If yes, then the output may be increased or decreased.
- Is the promoted product attractive for a specific group of consumers (for reasons such as without sugar or coloring)? This kind of products tends to react less heavily on promotions.

The model developed in this paper is compared to a commercial software package from ACNielsen to find out how it performs compared to already available forecast models. ACNielsen's SCAN*PRO tool is frequently used in practice in retailing environments (Van Heerde et al., 2002). It could be concluded that the model presented in this paper outperforms the ACNielsen model. Both the average and standard deviation of forecast errors are found to be lower with our model than with ACNielsen's model.

The Logistics Control Function

To improve the logistics control of the promotions, an appropriate inventory control policy is needed. Two strategies (push versus pull) are qualitatively evaluated on their compatibility with the forecasting model, their relation with the causes of OOS, flexibility, service level and multiple kinds of costs (inventory holding costs, handling costs, transportation costs, ordering costs, implementation costs and costs for lost sales). The push strategy scores higher on each aspect, except on implementation costs (this was expected because the pull strategy is currently used for promotions).

The push strategy was thus chosen for controlling the inventory of the promoted products. The consequence of the push strategy is that the total demand for a promotion period in all stores needs to be forecasted and ordered at a central level. This suits with the better forecast performance at the aggregate level. At that central point it is then determined which store gets how many products during the promotion period (i.e. allocation). The order quantity to the supplier should be based on combining the output of the forecast model, the adjustments of the experts and the required safety stocks. The safety stocks can be obtained by solving the news vendor problem.

During the promotion period the DC has to allocate its stock over the supermarkets. The allocation should be based on first setting the allocation fractions for all supermarkets based on minimizing imbalance in the chain and then determining the order-up-to levels per store. This is called Balanced Stock rationing (Van der Heijden et al., 1997). If the central stock is sufficient to fulfill demand of all stores, all order-up-to levels in the stores will be reached. If not, then the central stock has to be allocated by using allocation fractions as defined by De Kok and Fransoo (2003):

$$p_w = \frac{\mu_w^2}{2\sum_{m \in W} \mu_m^2} + \frac{\sigma_w^2}{2\sum_{m \in W} \sigma_m^2}$$

Where:
p_w = allocation fraction for store w of the amount short at the DC
μ_w = expected demand per period in store w
σ_w^2 = variance in demand per period in store w

In practice several pushes will be needed. For the first push, demand can be estimated by using historical sales data per supermarket. Demand for the succeeding pushes can be estimated by using early sales data from the stores in the current promotion week. This is also advocated by Fisher et al. (2001) and Bartezzaghi et al. (1999). At least two pushes per product are required to benefit from the flexibility of a push system (Fisher et al, 2001). Other important determinants for the number and size of pushes are available volume capacity in the chain (transportation and stores) and available labor capacity in the chain (DC and stores). It is concluded that each push should cover demand for as much as possible days under the restrictions of the minimum of two pushes and the capacity constraints. By combining all what is described above and by determining appropriate safety stocks in order to attain a certain service level the order-up-to levels per supermarket can be obtained.

Implementation and Improvement Opportunities
In order to obtain accurate as forecasts, it is most important to structurally collect all data related to promotions. The forecast model itself can be improved if more data comes available. Longer data series (i.e. more history) leads to more robust parameters. On top of that, new variables can be included in the model if data is collected. Variables that appear interesting, but could not be included in the model due to a lack of data are: promotions of competitors (Struse, 1987), radio support of promotions (Sethuraman et al., 2002), previous promotions with the same kind of products, and the number of variants of the same product in promotion. The last two aspects are closely related to cannibalizing demand of the promoted product by decisions made in the own organization. Cannibalization of demand is widely discussed in literature (e.g. Neslin, 1990).

The logistics control system assumes that complete information from each store to a central stocking point is provided. Real-time data on sales and inventory is required. Also key performance indicators such as OOS at each store during the promotion periods should be administrated at the central stocking point. Therefore the organization should facilitate the Electronic Data Interchange between stores, central stocking point and suppliers. Main point of attention during the implementation will be to create acceptance for the new ordering and delivery process for the store managers. At the end, they loose the responsibility of ordering their own promotional products. To create acceptance they should not only be involved in the development and implementation of the systems, but also a new benefit system should be developed in which the advantages and disadvantages of the new process will be divided fairly over all parties involved.

Conclusions

A price war in the Dutch supermarket industry makes improving the customer satisfaction of paramount importance. One of the main points of attention is reducing the Out-of-Stock (OOS) of promoted products. In this paper, tools are developed which help to reduce OOS for promotions. On the one hand a demand forecasting model based on multiple linear regressions is constructed. On the other hand an optimal control system is found, leading to appropriate inventory allocation decision rules.

This paper is based on the authors master's thesis for the study program "Industrial Engineering and Management Science" of the Eindhoven University of Technology in the Netherlands. It contains the main results of an eight-month project at a large Dutch supermarket organization. The complete report can be obtained via the university library (http://w3.tue.nl/en/services/library/).

References

- Armstrong, J.S. (2001). Principles of forecasting: a handbook for researchers and practitioners. Kluwer Academic Publishers, Dordrecht, the Netherlands
- Bartezzaghi, E., Verganti, R., Zotteri, G. (1999). A simulation framework for forecasting uncertain and lumpy demand. International Journal of Production Economics 59, 499-510
- De Kok, A.G., Fransoo, J.C. (2003). Planning supply chain operations: definition and comparison of planning concepts. In Handbook of operations research: supply chain management: design, coordination and operation. Technische Universiteit Eindhoven, the Netherlands
- Fisher, M.L., Rajaram, K., Raman, A. (2001). Optimizing inventory replenishment of retail fashion products. Manufacturing & Service Operations Management 3 (3), 230-241
- Foekens, E.W., Leeflang, P.S.H., Wittink, D.R. (1994). A comparison and an exploration of the forecasting accuracy of a loglinear model at different levels of aggregation. International Journal of Forecasting 10, 245-261
- Gruen T.W., Corsten, D.S., Bharadwaj, S. (2002). Retail out-of-stocks: A worldwide examination of extent, causes and consumer responses. Grocery Manufacturers of America
- Neslin, S.A. (1990). A market response model for coupon promotions. Marketing Science 9, 125-145
- Silver, E.A., Pyke, D.F., Peterson, R. (1998). Inventory management and production planning and scheduling. John Wiley and Sons Inc., 3rd edition
- Sethuraman, R., Tellis, G. (2002). Does manufacturer advertising suppress or stimulate retail price promotions? Analytical model and empirical analysis. Journal of Retailing 78, 253-263
- Sloot, L., Verhoef, P.C., Franses, P.H. (2002). The impact of brand and category characteristics on consumer stock-out reactions. ERIM Report Series Research in Management, ERS-2002-106-MKT, 1-42
- Struse, R.W. (1987). Commentary: approaches to promotion evaluation: a practitioner's viewpoint. Marketing Science 6, 150-151
- Van Heerde, H.J., Leeflang, P.S.H., Wittink, D.R. (2002). How promotions work: SCAN*PRO-Based evolutionary model building. Schmalenbach Business Review: ZFBF, 54 (3), 198-220
- Van der Heijden, M.C., Diks, E.B., De Kok, A.G. (1997). Stock allocation in general multi-echelon distribution systems with (R,S) order-up-to policies. International Journal of Production Economics 49, 157-174