OPTIMAL STOCKING OF RETAIL OUTLETS: THE CASE OF WEEKLY DEMAND PATTERN

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Abstract

Retail stores sell products to consumers. Their ability to sell depends upon the availability of the planned assortment, i.e. every item is on shelf so that the consumer can buy it. In particular, for fast moving consumer goods, like food, the consumer expects that each item is on stock. The retailer's decisions on the length of replenishment cycles of stores, on the shelf-capacity allocated to each item, on the amount of inventory stored in the backroom of the store, on the minimum order quantity of each item, or on the case size affect the fill rate of the store.

This paper identifies a new aspect: With a demand fluctuating regularly according to a weekly pattern, the decision on which day to review inventory and to deliver stock has impact on the service level of the store. It analyzes the effect of the position of ordering cycles with respect to demand cycles on the out-of-stock rate. We simulate a retail scenario with different replenishment cycles, i.e. supermarkets with weekly seasonal demand can be supplied at different days of the week. We show -based on actual sales data of supermarkets– that the fill-rate depends heavily on the interaction between the weekly demand pattern and the inventory review and replenishment cycle. Futhermore, we demonstrate the role of item's case size in the performance of the supply chain. Numerical results for a periodic review, order-up-to-level inventory control system with batch-ordering and time-varying demand are presented.

Keywords: inventory management, retail operations, periodic review inventory control, seasonal demand, batch-ordering, case pack quantity

1. INTRODUCTION

Retailers serve consumers by providing a variety of products to them. Thereby they have to be able to sell any product at the demand of the consumer. Store-based retailers display their assortment in the store, i.e. grocers. In the foods segment the consumer expects to be able to buy at the moment he enters the store.[1] The desired item should be available and ready to buy, i.e. on shelf. Therefore, the on-shelf availability (OSA) is a key performance indicator of any retailer.

Reports on OSA show different values depending time, product category, type of stock (permanent, seasonal, promotional (e.g. one week)), retail format (e.g. supermarket, discount), day of the week, time of day (i.e. bakery products). The OSA ranges from below 80% with ultra fresh products (i.e. bakery, fruits, poultry, meat) to 98% (canned foods). Although 98% sounds like a good performance, given the intense competition and low margins in the retail sector, any slight increase of OSA relative to competitors will have large effect on sales and profit.

What happens if the item is not available? The consumer may leave the store to shop another store; he selects another item for substitution; he postpones his purchase till next time in this store. In general, the occurences of out-of-stocks reduce the retailer's and manufacturer's revenue. They are detrimental to consumer's loyalty and they deteriorate store's brand image.

Though we are not certain about a consumer's specific reaction to out-of-stock, it is clear that he does not like empty shelves. Consequently, retailers and manufacturers seek to increase OSA. Management of OSA is a supply chain problem as manufacturers and retailers contribute to OSA performance. Manufacturers improve OSA by timely delivery to retailers, by announcing new products timely, by providing case packs in the right size, etc. The retailer raises items' safety stocks to improve availability. However, this is not always feasible, as

[1]Many food products are sold as consumer packed goods. Due to frequent demand the consumer is accustomed to buy these products at arms length.

items compete with each other for scarce shelf-space.[2] Also, extra inventoring in the backroom is an option. Then, additional processes are required to identify the need to replenish shelves from backroom and to move items. Typically, a retailer has pre-determined the amount of shelf space allocated to each item and for each store.[3] Furthermore, the retailer sets the frequency of deliveries to the each store, e.g. a store will be supplied with dry foods every Monday and with fresh fruits and vegetables every day. The availability of the item depends on whether the order is large enough to protect the store from stockout between order arrival and arrival of the next order.

The objective of this paper is to determine the effect of the timing of inventory review in the presence of different daily demand that follows a characteristic pattern each week. The demand pattern repeats within the review cycle. For example the demand pattern repeats each week and replenishments are also scheduled once a week.

The remainder of this article is organized as follows. In section 2, a review of the literature is given. In section 3, we describe the model of the shelf replenishment process and the parameters of the simulation model. We present the results of the numerical simulation and draw conclusions from the results. Section 4 presents major results and managerial insights. It concludes by a guide for future research ideas.

2. REVIEW OF THE LITERATURE

The problem we address in this study refers to the area of inventory management. The literature on inventory theory is very extensive. Therefore, we restrict our review on publications directly addressing the inventory management problem at retail stores.

2.1. Contributions to the replenishment problem of the retailer and out-of-stock

Corsten and Gruen (2005) provide an overview of the problem to increase on shelf availability. They report on their own empirical findings at retailers and review other studies between 1996 and 2003. The average out-of-stock rates (OOS rate) were found in those studies about 7 to 10 percent. The rates are different depending on the product category, e.g. fresh food categories (perishables) tend to have higher rates. However, the figures are subject to the measurement methods applied, also. Gruen and Corsten (2007) review different methods that define and measure OOS. Aastrup and Kotzab (2010) review two research streams dealing with OOS. The first is about consumer responses to OOS, the second is about the root causes of OOS: They propose to seek for the optimal level of OOS in terms of cost and gains instead of striving to a minimal OOS rate. Trautrims et al. (2009) contribute to this gap. They explore the relation and trade-off between on-shelf availability and profitability of a retailer.

Van Donselaar et al. (2005) suggest a framework to divide the assortment of a retailer into five categories and to devise different inventory management procedures for each category. These categories are: products with short life cycle or short shelf life. They have to be inventoried carefully to due the risk of obsolescence. Promotion items realize increased sales due to marketing activities, one-time-items take advantage of special buying or selling opportunities (no replenishment), and capacity driven items that can be used to complement store operations at times of low sales rate and low frequency of consumers' arrival to smooth operations. For example, stores are replenished daily with fresh fruits and vegetables but only once a week with dry food at a day with low sales rate.

2.2. Contributions to instore logistics and inventory

There are some papers dealing with the case size of items (number of units per retail shipping container) and two storage areas of items: shelf and backroom. The shelf is the preferred area as products are sold from shelf. The second place to locate inventory is in the backroom, where the consumer has no access. It serves to backup the shelf. However, the shelf replenishment process from the backroom is more costly as direct replenishment from arriving order. Furthermore, in real instances this process appears more unreliable since the backroom inventory is not tracked in every supermarket. Raman, DeHoratius, and Ton (2001) report on diverse reasons why store level operations are unrealiable and inventory records are inaccurate. With insufficient data on stocks automated ordering procedures are likely to fail.

[2]Online retailing differs from store-based retailing as in the latter the items are assigned to specific areas of the shelf restricting the capacity for this item. The consumer learns the position of the item. The online retailer is more flexible to assign storage place for items as the consumer has no direct contact to the storage.

[3]These allocations are sketched in a planogram. It determines the location of the item on the shelf, the number of facings, and the allocated shelf space for this item (maximum number of units of the item).

Waller, Tangari, and Williams (2008) research on the question whether the case size has an impact on market share of the manufacturer. Their results indicate that the impact depends on the inventory turnover (demand). Items selling relatively slow compared to their case size and to their assigned shelf-capacity, will end up with lower market share for the supplier as the too large cases cause additional stock-outs at the retail level. These stock-outs are derived as being a consequence of an unreliable replenishment process between backroom and shelf.

Eroglu, Williams, and Waller (2013) also build upon the existence of a backroom as secondary storage. They extend the continuous review (s,q)-model to account for inventory in the backroom as well as on the shelf. In their model the case size determines the order quantity (q). If upon arrival of the order there is not enough shelf capacity available the excess inventory goes to the backroom. They derive a closed form solution for the total cost function as a function of reorder point (s) that includes the cost of carrying backroom inventory plus the cost for the replenishment of shelf from backroom inventory. The resulting model finds a lower reorder point at the optimum compared to a scenario not modeling the backroom storage. This is due to the additional cost of the backroom inventory that increases with case size since with larger case size it is more likely that part of the order goes through backroom storage at higher cost. The model does not account for lost sales but instead models backorders.

Simulation is a very powerful tool to analyze complex business processes under uncertainty. Routroy and Bhausaheb (2010) model inventory control by a discrete event simulation with ARENA software tool. It incorporates periodic review inventory control and tracking shelf life of items that are subject to obsolescence.

Items or cases tagged with RFID technology can be used to track inventory movements in store. Condea, Thiesse, and Fleisch (2011) develop a heuristic periodic review inventory control procedure that accounts for failures of RFID equipment in detecting each movement of cases between backroom storage and sales floor. They present results of a simulation.

Kotzab, Reiner, and Teller (2007) describe their findings from an analysis of processes in stores. They identify a generic in-store process and conduct a survey on the parameters of the in-store processes of 113 stores like distances between backroom storage areas and shelves. Then these parameters were used to simulate the sales process and inventory replenishment process.

2.3. Contributions to perishability of inventory

Perishable items, i.e. products with relatively short shelf lifes, have found extended attention in recent years. For example, yogurt is suggested to be consumed within 30 days after production wheras canned food has a best before period (sometimes called shelf life) of about 12 months or more. Perishability of items imposes more restrictions on handling, as the potential of loss is higher. If the products are overstocked, the retailer might not sell them within the shelf life and they have to be discarded. The review of Goyal and Giri (2001) classifies deteriorating inventory models according to the items lifetime, e.g. fixed (short) lifetime or random lifetime (e.g. for fresh fruits like strawberries), and the type of demand, e.g. stock-dependent, price-dependent or stochastic demand.

The book of Nahmias (2011) brings together a concise review of models for managing inventory of perishables. Van Donselaar et al. (2006) classifies items in grocery retail and discusses inventory control rules for perishables that are applied in practice. For example, items with shelf lives below 1 to 5 days need short lead times to reduce uncertainty within the protection period and restricted assortments to keep up daily sales. The automated store ordering system (ASO) observed in their study applies periodic review inventory control with reorder level and reorder size as a multiple of case size. In order to cope with varying demand, the reorder level is adjusted by a forecast for the period of leadtime plus review (protection period).

With perishable items it is necessary to monitor the age of items in inventory. Broekmeulen and van Donselaar (2009) suggest a model tracking the age of inventoried items. They conduct a discrete event simulation for a single product single store scenario. The model has daily review of inventory after closing the store, removing out of date inventory and ordering for the next day. Facing different ages of items on display the consumer selects the item with preferred age. The simulation applies LIFO and FIFO item selection from inventory to model the consumer's decision on which product to buy from a stock of items with different remaing shelf lives.

2.4. Contributions to multi-stage inventories and supply chain design

Kanchanasuntorn and Techanitisawad (2006) simulate a two-echelon distribution system with perishable items under periodic review policy. On the first stage, at the central warehouse, items are backordered, whereas on the second stage, the retail level, unsatisfied demand is lost.

Cardós and García-Sabater (2006) model the design of the retailers supply system, i.e. from central warehouse to stores, that comprises vehicle routing decisions, delivery frequency and inventory management (here periodic review order up to level). Also Sternbeck and Kuhn (2014) describe an application that determines store delivery patterns based on an analysis of central warehouse operations, transportation to stores, and instore handling for a grocery retail chain. Agrawal and Smith (2013) point on the problem that demand of items is different from store to store. In their 2-period-model a given stock of items has to allocated to stores. Since demand is correlated they propose an updating procedure for demand forecasts to improve inventory allocation to individual stores in the second period.

Lütke Entrup (2005) researches on the consequences of restricted shelf life of items on the production at the manufacturer. It suggests extensions of manufacturer's advanced planning system for some food industries with perishables, e.g. yogurt or sausages.

Another research direction with short lived products focuses on information sharing between retailer and supplier to increase the remaing shelf life of inventoried items at the point of sale. Ferguson and Ketzenberg (2006) simulate a periodic review inventory control rule with short shelf life and information sharing of items expiry date from the supplier to the retailer before ordering with a periodic review inventory control scheme. The value of this information is estimated as change in net profit given that inventory of outdated products must be discarded. The proposed methodology is tested in a simulation. Eksoza, Mansouri, and Bourlakis (2014) review the literature on collaborative forecasting and information sharing in the food supply chain.

Chen, Geunes, and Mishra (2012) research on a specific type of case pack, the distribution case pack. Contrary to a regular case pack that contains more than one unit of a given product, a distribution case pack contains a variety of different items. A store that stocks a distribution case pack will be able to offer a variety of products in a single shelf space thereby reducing handling requirements in the store as well as in the upstream supply chain. The article models the trade-off between reduced order handling costs and higher inventory-related costs under dynamic, deterministic demand using dynamic programming.

Bischak et al. (2014) derive an expected cost function and approximate optimal solution of a periodic review inventory model with potential crossover in replenishment deliveries. Puts (2013) researches the inventory control rules at a Dutch food retailer with focus on items with low sales rate. The thesis provides detailed operational details and insights.

3. ANALYSIS OF A RETAILER’S LIMITED SHELF CAPACITY BATCH ORDERING POLICY

Todays grocery retail market is dominated by large retailers operating chain stores. They operate hundreds or even thousands of stores under one or sometimes two or more banners, i.e. retail formats like supermarkets or hypermarkets. Thereby they can achieve economies of scale in their operations. Stores appear similar, have similar assortments and are operated by the same processes. For example, they operate central warehouses where products from manufacturers are consolidated, stored and then picked to replenish the stock at the outlets. There the goods are presented on shelfs and other display furniture to be sold to the consumer.

3.1. General setting and assumptions of the model

We model the inventory level on shelf at a single store. We restrict our model to a single SKU (stock-keeping unit), as we assume that the selling and restocking process is independent of other items. Then the sales of other items in the assortment do not affect the item under study.

We assume that items shipped to the store will be immediatly available on shelf. The inventory review, the delivery process, and the in-store handling process are deterministic and without failure. Any stock ordered will be ready on shelf in the planned period.

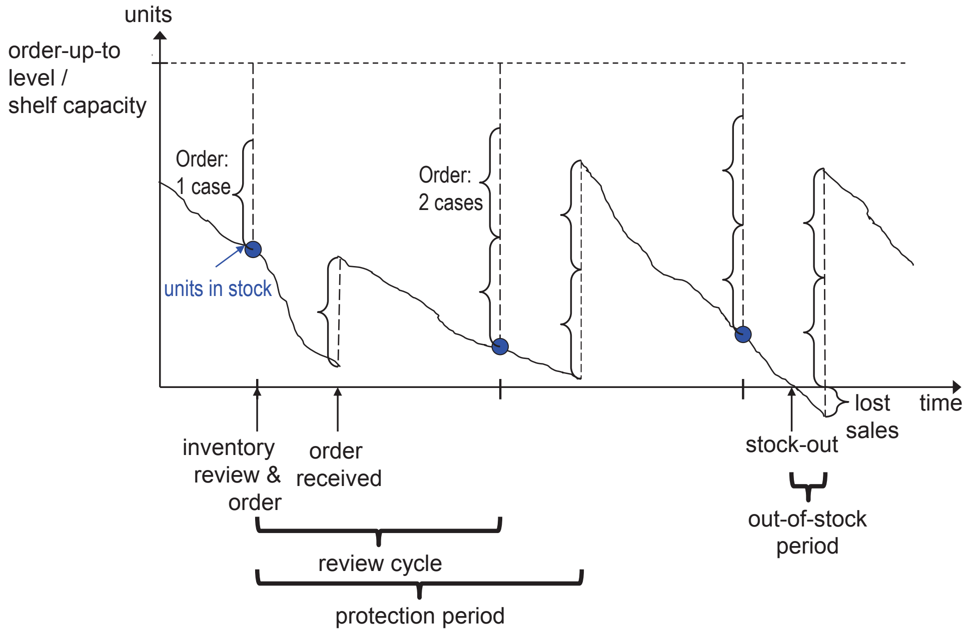
The inventory is replenished based on an order-up-to-level, periodic review inventory control. However, only case packs can be ordered, i.e. the either one, two, three, etc. case packs of the item can be ordered given that the order size will fit into shelf. The batch size of orders is the case size or multiples of it.

For example, under a case size of 6 and a maximum assigned shelf space of 8 units: If there are 2 units of product on shelf of the item, the ASO will order 1 case of 6 units. If there are 3 units of product on shelf no case will be ordered.

Our survey among different German retailers (Edeka, Rewe, Aldi, Globus) in Germany showed that the orders for the category of dry food have a lead time of one day. The inventory on shelf is reviewed in the evening on day 1, the orders are transmitted to the central warehouse and delivered on day 3 before opening the store. E.g. an order that is placed on Tuesday will be delivered and ready for sale on Thursday, an order placed on Friday will be delivered by Monday. The stores are closed on Sundays, also there are no deliveries to stores on Sundays. An example of opening hours of grocers in Germany is: Monday through Saturday from 8 a.m. to 10 p.m.

For ease of presentation, we assume that the inventory level on shelf is known at the time of closing of the store on day 1 so that the order can be placed. Also, the replenished stock is available immediately from opening at day 3. So, the lead time is 1 day. This is also the span of time during which the remaining stock on shelf should be sufficient to cover demand. However, the total protection period of the stock is between two consecutive reviews plus the lead time. For example, if the store is delivered once a week, the protection period of the stock is 7 selling days. So, if we review on shelf-inventory on Monday and do not place an order (for Wednesday) the stock has to be enough to fulfill the demands till Wednesday the following week. Otherwise there will be unsatisfied demands (lost sales). Figure 1 depicts the order-up to inventory policy with batch-ordering. Obviously, the units on hand will not reach the maximum inventory level unless the difference between order-up-to-level and the inventory level at the time of review is an integer multiple of the case size and there are no sales in the order lead time, i.e. till the receiving and restocking shelf.

Figure 1 Order-up to inventory policy with batch-ordering



Source: Author

When the consumer arrives and the desired item is not on shelf, his demand cannot be satisfied. We account for this situation as lost sales. As we track only one item in our model we do not consider any substitute sales (the consumer selects another product).

When calculating the order quantity, the order quantity is based on shelf space only and not augmented by a demand forecast. We want to be sure that the ordered quantity will fit into the shelf. If we increase the order to account for units that are likely to be sold during lead time, we may end up with overflow inventory if demand is lower than forcasted. Items in excess of shelf space could be stored at a different place like the backroom but at the cost of a more complex refill process.

Consumers can shop the stores six days a week. But they do not buy in the same intensity every day. The number of customers and their shopping baskets vary over the week. The daily sales of a store are not constant. Each store shows a more or less regular pattern of sales during the week. In many instances Fridays and Saturdays are the strongest selling days during the week. Also the monthly sales are seasonal, as the first days of the month are usually stronger. The yearly sales pattern, for example is that there is seasonality with peaks around Christmas season, after summer holidays and the Easter Season. However, for the weekly stocking decision monthly and yearly patterns are less important.[4] Therefore, we model a weekly demand pattern only.

3.2. Model settings and numerical results

We consider a single SKU with an average demand of 1 unit per day and a standard deviation of 0,67 units. Daily demand is assumed to follow an independently identical Normal distribution (before adjusting for the weekly demand pattern).[5] The lead time is 1 day, so that between review and availability of new stock is one selling day. We have six selling days per week. The weekly demand is assumed to have an increasing daily

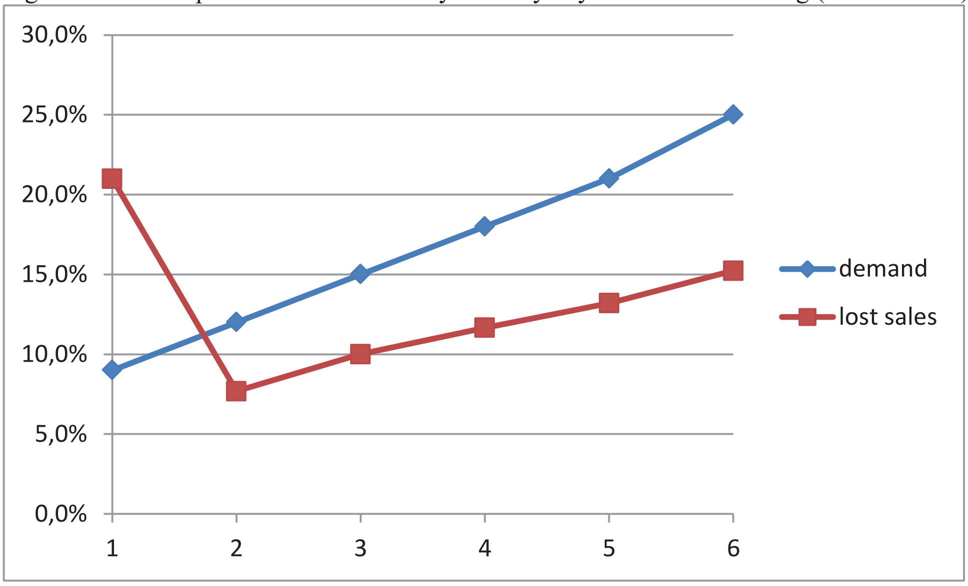
[4]In case of high demand before holidays the parameters of the inventory policy can be adjusted to increase the inventory on shelf. For example, if the order-up-to level is below shelf capacity for that item, it can be increased before beginning of the high sales period. Else, retailers implement shorter reorder cycles during that time.

[5]The random variable is truncated at zero.

demand from Monday through Saturday. The total weekly demand is distributed as 9% of weekly demand on Monday, 12% on Tuesday, 15% on Wednesday, 18% on Thursday, 21% on Friday, 25% on Saturday. The case size is 6 units and the allocated shelf space is 8 units, i.e. a reorder will be scheduled on the review day, if the actual stock is between 0 and 2 units.

Figure 2 exhibits the demand pattern. Demand is increasing from Monday (1 on x-axis), Tuesday (2) to Saturday (6). This demand pattern is repeated week by week. Figure 1 also shows the result of the simulation run in terms of lost sales. It provides a comparison of lost sales ratios. The lost sales ratio is associated with the delivery day of the week. It starts for Monday with a high rate of 21.0%. The lost sales are 21.0% if the store is delivered on Monday. The quantity delivered on Monday is based on the Friday closing stock on shelf. If under the same data the inventory review would have been on Saturday and delivery on Tuesday the lost sales would drop to 7.7% for the whole simulated time.

Figure 2 Demand pattern and lost sales by delivery day with batch-ordering (case size = 6)



Source: Own simulation

Table 1 shows how the lost sales ratio is composed of by day. It gives the sample lost sales for each day of the week. For example, if the delivery of order is on Monday (left column), there were no lost sales on Mondays, 0.2% lost sales occured on Tuesdays, 3.3% on Wednesdays, 5.2% on Fridays, 10.7% on Saturdays. In total there are 21.0% of lost sales. Note, that the lost sales ratios increase day-by-day in this example. But this must not be the case, as we account for lost sales only upon arrival of demand. If there is no demand on a specific day, it does not contribute to lost sales figure – though the shelf is empty till delivery. This is different to the concept of calculating a shelf-availability ratio that would account for the time the shelf is empty. This figure would rise in the same situation.

Table 1 Lost sales by day of delivery

	lost sales if delivered on					
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Monday	0,0%	1,0%	0,7%	0,4%	0,3%	0,3%
Tuesday	0,2%	0,0%	3,7%	1,9%	1,5%	1,3%
Wednesday	1,5%	0,0%	0,0%	4,8%	2,6%	2,3%
Thursday	3,3%	0,2%	0,1%	0,0%	6,1%	3,1%
Friday	5,2%	1,6%	1,7%	0,9%	0,1%	7,5%
Saturday	10,7%	4,9%	3,9%	3,5%	2,7%	0,8%
sum (week)	21,0%	7,7%	10,0%	11,7%	13,2%	15,2%

Source: Own simulation

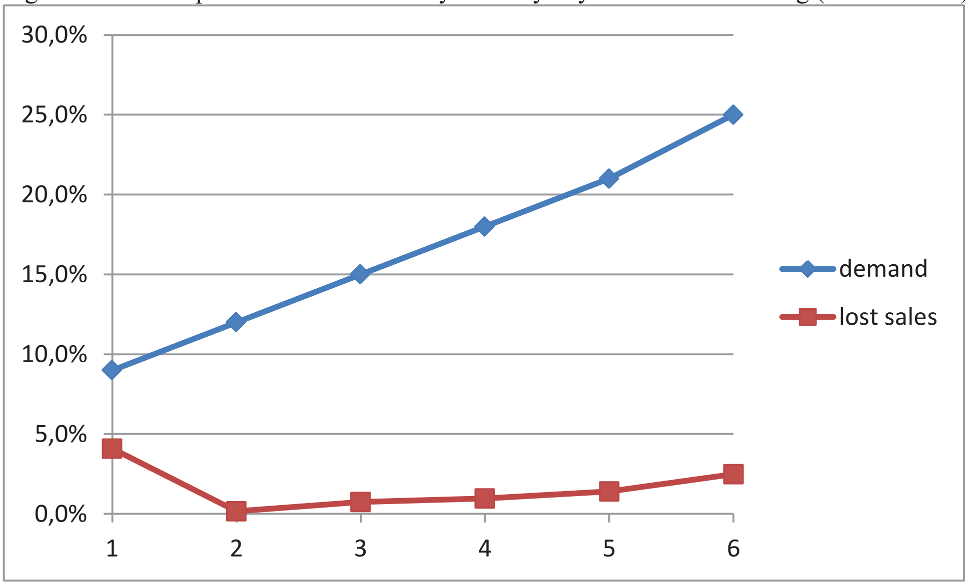
In this example, the lowest lost sales result from deliveries and restocking on Tuesdays, the highest lost sales is due to deliveries on Mondays. Regarding the demand pattern, the best results stem from replenishments on Tuesday followed by inventory reviews on Saturday. Since Saturday is the strongest selling day in our example, here it pays to see the demand on Saturday before decision to order. On Monday, demand drops to low level and rises again until Saturday. In more experiments, we have noticed that the drop of demand appears to be the driving factor for the lost sales ratio. For example, if sales on Saturday are slightly lower than on Friday and the big drop is to Monday, Saturday remains the optimal inventory review time.

3.3. Discussion of the simulation results

Hence, under time-varying demand with constant delivery cycles the occurences of lost sales depend on the timing of order review and deliveries with respect to the weekly repeating demand profile, i.e. demand peaks and lows during the week. We could show that the demand profile is a relevant parameter that affects the performance of the store's inventory policy. For example, it appears, that the inventory review should preferably carried out immediately after peak demand.

This result does not depend on case size. Figure 3 shows that with no restrictions on minimum order size (case size of 1), the lost sales ratios still depend on the demand pattern. Given the aforementioned demand pattern of this example, reviewing inventory at the demand peak on Saturday and delivery on Tuesday generates the highest fill rate.

Figure 3 Demand pattern and lost sales by delivery day with batch-ordering (case size = 1)



Source: Own simulation

The possibility to reorder only in cases carrying a fixed amount of items imposes further restrictions on efficient use of shelf space. However, the usage of cases simplifies handling in the supply chain. In the decision on case size, the effects on sales should be incorporated. Though manufacturers have factored in the effect of case size on shelf space assigned and the number of facings in the planogram, i.e. they hope that retailers assign larger shelf space to the item if there is a larger case, they may have not factored in the detrimental effect of case pack quantity on fill-rates of shelfs.

We have assumed that demand is not forecasted at the moment of inventory review. This is no restriction on results, as the forecast would only serve to order less than the maximal integer multiple of cases such that the order fits into shelf space. As forecasts are not certain by nature we cannot be sure if we order more than actual shelf space that the order will fit into assigned shelf space. So, forecasts to increase the amount of inventory in store during the protection period would have to rely on additional storage, like a backroom storage.

4. CONCLUSION

On-shelf availability remains a management issue for each retailer. The fill-rates of stores still did not reach 99.9 percent, though the fast moving consumer goods industry has spent considerable effort on it. Out-of stock reduction is likely to be a management issue in the future. Increasing assortments of retailers contribute to this phenomenon. An increase in the number of stock-keeping units in a store will increase the uncertainty of demand. Then, to keep the same service level, the number of stored units per item has to be increased. Also the complexity of logistics systems increase. In the end, the decision on fill rate is an economic decision. Therefore, the need to improve the procedures in the retailer's supply chain will rest on the agenda.

4.1. Managerial implications

We showed that a simple alignment of the timing of stores inventory review and replenishment to the demand pattern of each store decreases the out-of-stock ratio considerably. Differences in daily demand during the replenishment cycle– no matter if we can forecast demand correctly or not- ask for selecting carefully the day of inventory review and replenishment. This result is very interesting as it holds independently on the reaction of consumer on stock-outs. Whether it is lost sales in an out-of-stock situation or the consumer selects a substitute is irrelevant. The retailer will be better off if he can improve the on-shelf availability with simple actions, like aligning the review and delivery schedules of the stores. This result is of high practical value as the impact on sales and consumer satisfaction can be dramatic.

Many chain retailers supply hundreds of supermarkets from one central warehouse. It should be easy to analyze weekly demand pattern of each store and to propose the store's optimal inventory review and replenishment schedule. This can be done regarding total sales pattern of the store or by category sales that are consolidated within one delivery. We expect that the optimal schedule will not be the same for all stores. For example, stores in the reach of residential areas may have peak demands on Friday or Saturday, stores located in proximity to business districts have higher demands during the week.

The decision to adjust the delivery schedules for the retailer is simple to implement, as it does not rely on decisions at other companies like changing the case size would. Of course, not all products will have the same demand pattern during the week. In an actual case, the set of products to be included into a single delivery would have to be evaluted by product.

Other options to increase availability like lowering the case pack size will have impacts at many steps in the supply chain: The manufacturer has to change packing including new machinery, the picking at the retailers warehouse becomes more costly as more cases have to be picked, the handling in store is more labor intensive since opening two 6-unit cases and putting to shelf is less time consuming than handling of three 4-unit cases. So, there would be high (inter)organizational barriers to implement different case sizes. For private label products it is an interesting consideration as the retailer decides himself on case pack quantity.

4.2. Further Research

The review of the literature showed that quite complex models have been developd to improve the OOS situation. However, our approach is quite simple. Therefore, the idea of this paper might be integrated in more complex models already described in the literature.

Our demand pattern was very simple for exploratory reasons. Using simulation it is straightforward to analyze specific patterns. Another research direction is to derive general results from a closed stochastic model that extends the literature by including a demand pattern.

As our model did not incorporate a reorder point this might provide further insights as we can control the number of replenishments by varying the reorder point. In some applications this option helps to control the number of stock-keeping units per delivery. This will have an effect on the cost of the instore shelf filling process. Also order picking and delivery schedules can be designed in face of scarce capacity, e.g. for larger stores two deliveries with disjunct assortments can be scheduled.

As the decisions to optimize OOS is at the cutting point of logistics and marketing, the effects of OOS on lost sales or substition could be integrated into the model. For example, stock-outs at high selling days with large frequency will have more impact on customer perception than on quiet days. The shopper who is not to buy a specific out-of-stock item will still take notice of empty shelves with negative effect on his store's brand image.

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