Excess shelf space in retail stores: An analytical model and empirical assessment

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Marketing and operations responsibilities meet in retail stores on the shelves. The shelf is the location where any product meets the consumer, whereas the shelf is also the final inventory location in the retail supply chain. Marketing assumes that the presence of inventory drives demand and therefore requires excellent operations. In operations, the main concern is with the trade-off between inventory holding cost on the shelf and the cost of replenishment. We gathered empirical data at a grocery retail chain and were able to combine marketing and operations data into a single database. This provided us the opportunity to conduct a unique analysis. We could compare the results of the space allocation decisions of the marketers with a basic analytic model that incorporates aspects of marketing and operations. Based on this comparison, we argue that significant amounts of excess shelf space exist for a large part of the assortment of a retailer. Excess shelf space is retail space that is not required to carry out the current operations with respect to customer service and costs. We also observed that the cost of replenishment is non-linear and dominates the inventory holding cost. Therefore, excess shelf space cannot easily be eliminated. Instead, excess shelf space in the presence of a non-linear cost of replenishment offers enormous opportunities for the development of new supply chain coordination mechanisms.

1. Introduction

To achieve excellence in operations, retailers must balance inventory holding cost and cost of replenishment. Marketing research addresses the issue of determining the number of facings and determining minimum display levels under the assumption that the presence of inventory drives demand. Examples are the studies by Hansen and Heinsbroek (1979), Corstjens and Doyle (1981), Urban (1998) and Yang (2001). The inventory modeling literature addresses the issue how to optimally use the available shelf space. Models analyze the optimal ordering policies that minimize the cost involved, considering linear inventory, backorder, and shelf space costs, and excluding handling cost (e.g., Cachon, 2001). Handling costs are generally not included in the models. This is a fair assumption if the case pack size is very small compared to the shelf space, since then it can be assumed that increasing or decreasing the shelf space has limited effect on the handling cost incurred for stacking the shelves.

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In our paper, we hypothesize that shelf space is not determined as part of the replenishment decision, but is primarily a consequence of marketing decisions: the determination of the number of facings and the merchandising category to which the product belongs. For example, if two products are positioned next to one another on the shelf, the actual space allocated for one of the products cannot be decided on independently, since the depth of the shelf for both products is identical. Furthermore, we hypothesize that the case pack size and existing shelf dimensions have a considerable impact on the operational cost, in particular the cost of stacking the shelves. One of the probable reasons why these hypotheses have not been investigated before in reality is the difficulty in obtaining data. In most retail companies, the data needed for such a study (e.g. Point of Sale data, planograms, replenishment orders, promotions) are not available electronically or spread across multiple different databases (cash registers, space management system, inventory system, warehouse management system). The effort to collect and combine these datasets over an extended period of time into a single database is substantial and prohibitive in many research or company projects. This paper describes and analyses the results of the first published study in which these different empirical datasets have been combined into a single database for joint analysis. Studying empirical data based on specific modeling insights to test our hypotheses lead us to conduct model-based empirical research (Bertrand and Fransoo, 2001).

The initial insight from combining the data is that the space allocated to a specific product on the shelf and its demand level is not necessarily correlated. Furthermore, we find that shelf space is more abundant than typically assumed in the literature, and define the concept of *Excess Shelf Space (ESS)* as shelf space that is not required to carry out the current operations with respect to customer service and costs. We demonstrate, based on our empirical data set and analysis of the structure of the problem based on different modeling assumptions, that this is not a coincidence for the specific set of stores that we analyzed, but that this is a structural property of retail shelves, which is due to case pack sizes, consumers unit dimensions and shelf space dimensions. Typically, these variables are largely exogenous to the store manager's decision space, and hence, the size of the Excess Shelf Space for a particular product is a predominantly exogenous parameter of each SKU. Furthermore, we observed that the cost of replenishment, especially for handling, is non-linear and dominates inventory-holding cost. An importance consequence of our findings is that a new class of replenishment policies needs to be considered for those

products for which Excess Shelf Space is abundant. For example, we could base the replenishment policy primarily on using ESS such that shelf-stacking costs are minimized.

In the next sections, we first describe the replenishment logic at the grocery retail chain and then the cost structure of the operation. In Section 4, we document in detail the data collection process we conducted. In Section 5, we discuss the main drivers of Excess Shelf Space. In Section 6, we further analyze the data and argue that the Excess Shelf Space we identified is not specific to the store we analyzed, but is caused by the fact that the main determinants of excess shelf space are exogenous to the shelf space allocation decision. In Section 7, we describe a number of possible strategies that make use of the existence of Excess Shelf Space in order to improve operational performance. We conclude in Section 8.

2. Store replenishment process

We collected data at a medium-sized, well operated Netherlands supermarket chain. The mission of the retail chain is to offer a large assortment while at the same time guaranteeing a high customer service.

The grid layout of the grocery stores of the chain with long *gondolas* of merchandise and aisles in a repetitive pattern minimizes the time spent for the customers and enhances the space productivity, according to Levy and Weitz (1995, p. 470). A gondola is an island type of self-service counter with tiers of shelves, bins, or pegs. Figure 1 illustrates the grid layout of the stores. Each Stock Keeping Unit (SKU) in the assortment of the retailer gets one or more slots in the gondolas. A slot is defined by location and allocated space. The assigned shelf and position on the shelf determine the location. Shelves are divided into *facings* and each facing can only carry a single SKU. The number of assigned facings and the *facing capacity* determine the space allocation. The facing capacity is defined as the number of consumer units that fit behind a facing on the shelf. We assume that the orientation of the SKU on the shelf is determined by marketing and therefore fixed. The distance between two shelves determines the possible stacking of the consumer units and is fixed for all SKU's assigned to the shelf. On a completely filled shelf, the consumer sees of each SKU the number of *fronts*, i.e., the number of facings multiplied by the stacking. The facing capacity at a location is determined by the stacking of the consumer units and the row depth, i.e. the number of consumer units that fit on the depth of the

shelf. The different dimensions of a SKU slot on the shelf are illustrated in Figure 2. A slot plan of all SKU's in a merchandising category is called a planogram.

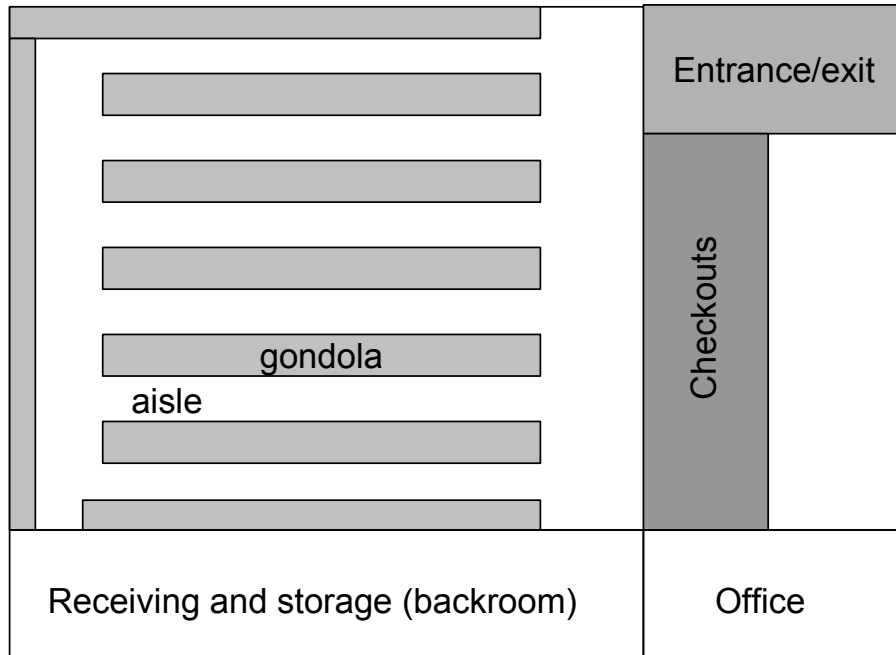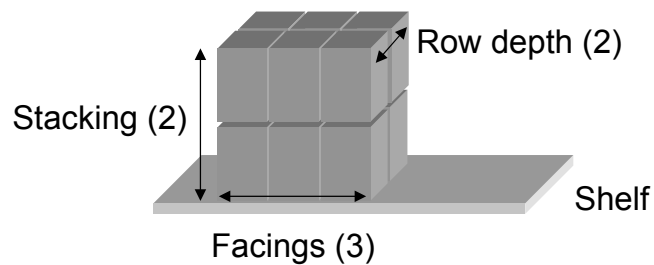Figure 1: A possible grid layout of a retail store.

Facing capacity = Stacking · Row depth (2·2 = 4)
Fronts = Facings · Stacking (3·2 = 6)

Figure 2: Dimensions of a SKU slot on the shelf.

We observed the following replenishment process for the SKU's on the shelves:

1. According to a fixed ordering and delivery schedule, a store manager places an order for a SKU in multiples of case packs to meet a customer service target.

2. At the central warehouse, order pickers collect the SKU's from the storage locations.

3. All SKU's that have to be delivered to a store on the same delivery day are combined in one shipment. The shipment is transported by truck to the store.

4. After unloading the truck, the store clerks move the deliveries to the shelves, unpack the case packs and put the consumer units on the shelves. To promote *First In First Out* retrieval from the shelves by customers and to improve the display, the consumer units on the shelves are rearranged, putting the oldest inventory in front.

5. Leftovers, which are consumer units that do not fit in the available shelf space after unpacking, are moved to the backroom, where they are temporarily stored in crates.

6. At the end of each sales day, store clerks replenish the shelves from the leftover consumer units in the backroom.

The fixed delivery schedule results in a periodic review inventory policy with fixed lead-times.

3. Cost structure

The total relevant costs of the retail operations consist of the cost for shelf space, inventory, transportation and handling. Since we look at fixed assortments in existing stores, we assume that the costs for shelf space are sunk costs. An inventory holding cost h per unit time for each unit of SKU is defined at the store, but this does not include inventory-holding cost at the central warehouse or in the pipeline, since the stores cannot influence these costs.

The cost of transportation depends on the distance to the store, the delivery frequency, and the capacity of the truck. We assume single stop trips and constant load utilization. Given a fixed delivery schedule, the shelf space allocation will not change the number of trucks needed.

Handling cost is derived from labor cost and handling time estimates. Handling times depend on the productivity of the personnel and the type of warehouse operations. The large variety of case pack sizes at grocery stores makes automating the warehouse operations impractical. Assuming that a single order picker collects a store order and usually traverses all aisles in the warehouse, the number of order lines in the store order and the storage locations of the SKU's in the store order do not influence the walking time of an order picker. This situation

corresponds to the S-shape heuristic mentioned by Hall (1993) for routing order pickers. The resulting two cost factors for handling at the warehouse are the cost of grabbing a case pack g_W and the order line cost b_W for each SKU in a store order. The order line cost is charged for walking to and stopping at the storage location of a SKU. We use the same type of handling cost model at the store, but with different labor costs and handling times, resulting in g_S per case pack and b_S for each order line. At the store, the handling time needed for the order line is considerably higher than at the warehouse, since unpacking the case packs, disposing the empty packaging, and rearranging the consumer units on the shelf takes ample time in addition to the walking time.

A shelf space allocation that is insufficient to receive a full case pack size has a large influence on the cost of handling, because in that case the store has to replenish from the backroom. According to Raman *et al.* (2001), using a backroom decreases the inventory accuracy in the store. This is especially true for temporarily storing consumer units. By applying the same cost factors g_S and b_S for placing consumer units instead of case packs in the backroom and for replenishing shelves from the backroom, the considerable cost of leftovers can be modeled adequately.

To show the importance of handling cost compared to inventory cost, we give an example. If we assume an annual interest rate of 0.1, an average sales price of 15 \$/case pack, and an average inventory of 10 days, the inventory cost become 0.041 \$/case pack. According to Hughes (1999), the hourly wage of a store clerk is around 5.5 \$/h. During consulting projects and master thesis assignments at warehouses with manual order picking, we observed output norm productivities that varied between 120 cases/h and 180 cases/h for an order picker. At the retail chain in this study, the output norm productivity at the warehouse is on average three times higher than at the store, excluding the effect of leftovers. According to these observations, we believe that handling cost is at least three times higher than inventory cost. Therefore, we will model handling explicitly and we consider finding the optimal inventory policy less important. The cost structure at the retail chain is shown in Figure 3. In this instance, the handling costs are almost five times the inventory costs.
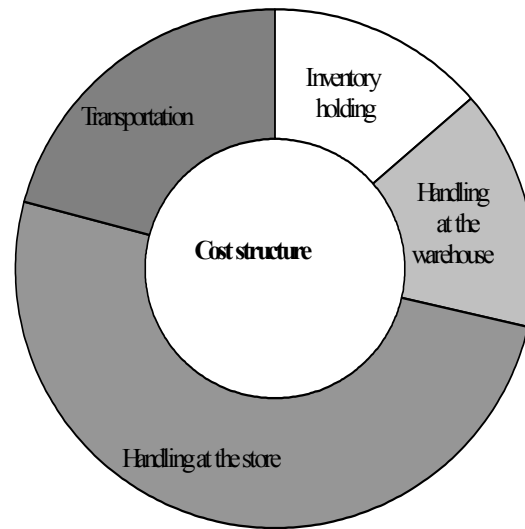
Figure 3: The cost structure at the retail chain.

4. Data collection

We obtained data on the operations of the retail chain in March 2003 during interviews with managers at the head office as well as the local managers of a selection of the stores. The managers at the head office were responsible for Marketing, Operations, and Logistics. Simultaneously, we downloaded data from the central (headquarters) and local (store) computer systems.

We obtained detailed sales and replenishment data from 50 stores of the retail chain over the year 2002. For our in-depth analysis we selected three stores based on selling space and turnover; at each of the stores, additional information was collected (see 4.2). These three stores were selected because the manager responsible for Operations considered them well operated. We will refer to the small store as A, the medium sized store as B and the large store as C. Measured in sales volume, store C ranked third, store B eighteenth, and store A thirty-first in our sample of 50 stores. The relative sales volume and sales area of the three selected stores are shown in Figure 4. The sales area of the stores in our sample varies between 500 m^2 and 1500 m^2, which corresponds to the range of sales areas of conventional supermarkets mentioned by Levy and Weitz (1995, p. 34).
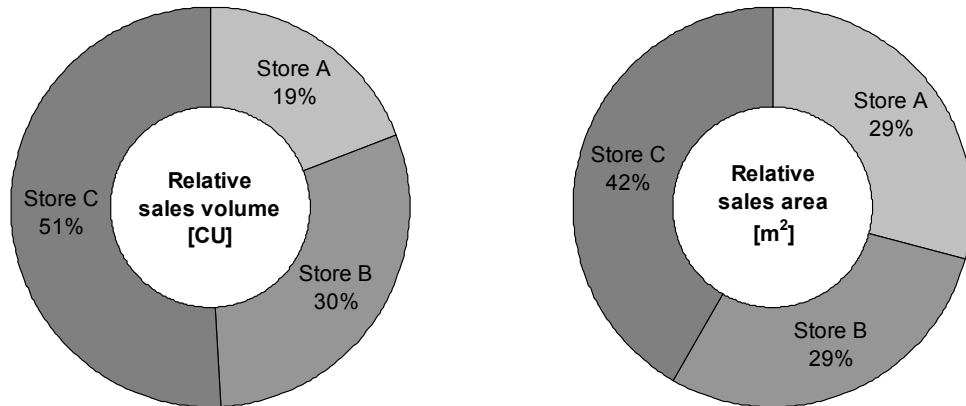
Figure 4: Characteristics of the three selected stores.

4.1 Operations

All products in the assortment of the retailer are bar-coded with a unique Uniform Article Code (UAC). The cash register systems of the stores report for each UAC the number of consumer units (CU) sold during a day. From the total assortment, only the SKU's delivered through the central warehouse are considered stock-keeping units (SKU). Therefore, direct deliveries such as newspapers are not included in our analysis. The Warehouse Management system (WMS) of the central warehouse contains the SKU data such as case pack size, case pack dimensions, and consumer unit dimension. Each SKU belongs to a planning group that determines the delivery schedule of that SKU to the stores. A SKU may have different uniform article codes, but each UAC identifies a unique product.

In the Netherlands, the sales during the week follow a typical pattern, with no sales on Sunday and peak sales of 30 % of weekly sales on Friday. This is shown in Figure 5. Similar patterns have been reported in other studies (see, e.g., Raman and Zotteri, 2000)
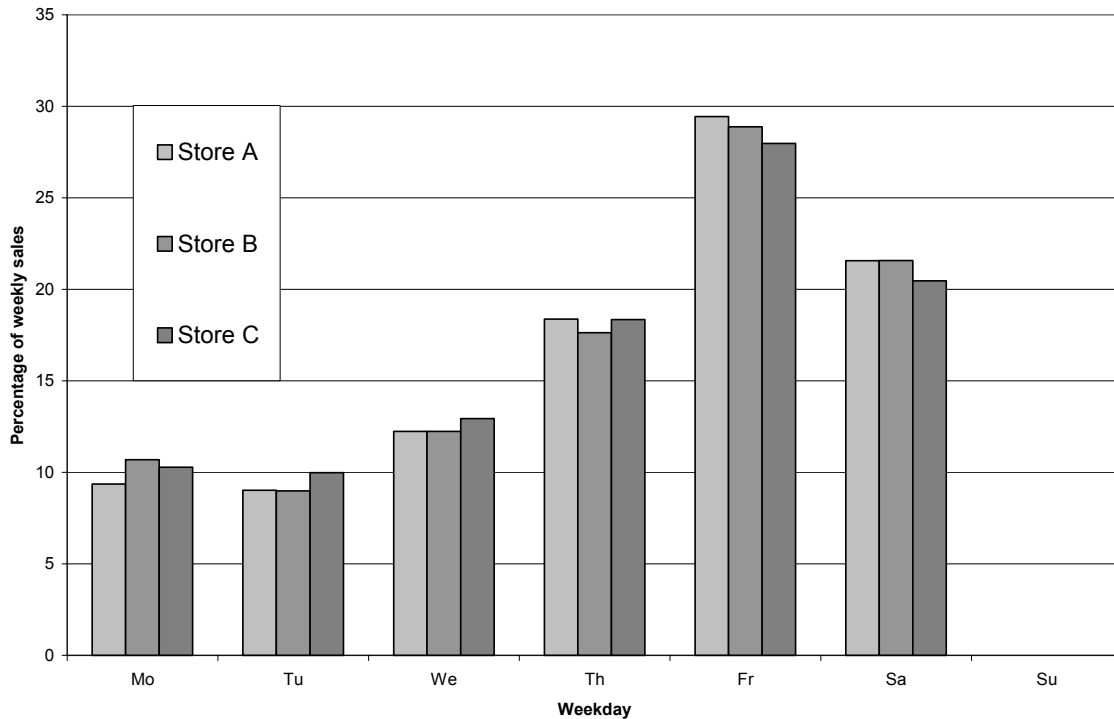
Figure 5: Weekly sales pattern in the selected three stores, measured in CU.

A store receives at most one delivery per day for each planning group. The delivery schedule determines for each store the days of the week on which a planning group can be ordered and will be delivered. A shipment to a store combines all goods from the planning groups that are delivered on that day. For all planning groups, orders that are received during the morning are delivered during the afternoon of the same day. The lead-time is therefore one sales day. From the invoices to the 50 stores, we collected the amount ordered and the amount delivered, measured in number of case packs for each SKU and each delivery from the central warehouse. For less than 2 % of the order lines, the central warehouse could not ship the ordered amount, indicating that product availability is not a big issue at the retail chain.

For reasons of confidentiality, we did not obtain the exact sales prices and profit margins from the invoices. Instead, the company provided us with margin data on a six-point scale, both for the absolute margin and the relative margin.

The Marketing department provided us with data on promotions initiated by the manufacturers. We distinguish two types of promotions: a price discount for the store and a price discount for the consumer. Promotions are identical across all stores of the retail chain and typically last a week.

Because of the fixed order and delivery schedules (based on the planning groups), the replenishment policies are based on periodic review. The ordering advice of the Automatic Store Ordering (ASO) system in use at the retail chain is based on a reorder level, which is equal to the sum of the minimum inventory level and the demand forecast during the review period plus lead-time. The minimum inventory level is measured in consumer units and is based on the number of facings, the average weekly demand and the maximum space available for the SKU in the planogram. The demand forecast is based on an exponential smoothing model. At each review period, the system checks if the inventory position is below the reorder level. If so, it advices to order a number of case packs such that the inventory position after ordering will be at or above the reorder level. This policy resembles a (R, s, nQ) policy with a dynamic reorder level s. The used minimum inventory levels in the ASO system resulted in satisfactory customer service levels according to the store managers.

4.2 Planograms

The merchandising managers use a PC-based space management system that is linked to the (central) warehouse management system to maintain the planograms. The space management system included data on the gondolas in use by the retail chain, such as depth of the shelves and the possible distances between the shelves. The space management system does not optimize the space allocation in the planograms but suggests plans based on guidelines set by the user.

We restricted our download to planograms of merchandising categories that had central planograms developed by the merchandising managers and that used the ASO system. We excluded tobacco and frozen food since in these categories a facing can be occupied by more than one SKU. The selected merchandising categories are listed in Table 1.

Table 1: Selected merchandising categories.

Sugar	Canned vegetables	Pet food
Coffee / tea	Canned fruits	Detergents

Flour / baking	Health food	Paper ware
Sauces / acids / oils	Baby food	Sanitary towels
Soups	Cookies	Household
Margarine / Butter	Sweets	Cosmetics
Crackers / Cereals	Chips / Nuts	Dairy daily fresh
Bread spreads	Coffee creamers	Dairy keepable
Meal components	Soft drinks / Beer	Eggs
Canned meat / fish	Wines	

A merchandising category can have different central planograms to accommodate different store sizes. A local planogram can differ from the assigned central planogram if the store manager decides to drop SKU's from the planogram and/or to add SKU's that are specific to his clientele. The local planograms were downloaded from the computer system at the stores. The actual gondolas in use by the store sometimes turned out to be different from the default gondolas used in the central planogram. We measured the depth of the shelves of all gondolas during visits to the stores in order to verify and correct the shelf depths in our database.

4.3 Resulting dataset

Focusing on SKU's in the 29 merchandising categories listed in Table 1 that were delivered from the central warehouse resulted in an (central) assortment of 6663 SKU's. This subset of the total assortment contained 30 % of the original assortment. More than 80 % of this subset consists of dry groceries. Store A carried 84 % of this subset, store B 76%, and store C 92 %.

The Entity-Relationship diagram of the resulting database is shown in Appendix 1.

5. Key Drivers of Excess Shelf Space

We will first discuss how marketing management at the central and store level sets the shelf space allocation. Based on that allocation, we investigate how this space allocation influences the operations of the retailer.

5.1 Space allocation from a marketing perspective

Merchandising management involves the following key decisions:

- Assortment. Which SKU's does a store carry?
- Location. Where are the SKU's displayed?
- Allocation. How much space is devoted to a SKU?

The shelf space allocation problem (SSAP) tries to find a set of allocations for the SKU's that maximizes total profit, subject to capacity constraints on the shelves and lower and upper bounds on the space allocations of the SKU's. Expected profit is the difference between the expected proceeds from sales and the cost of operations. Hansen and Heinsbroek (1979), Corstjens and Doyle (1981), Urban (1998) and Yang (2001) describe models that incorporate these decisions. A central assumption in these models is that sales depend on the location and the space allocation of the SKU's in the store. Hiring out the shelf space to the manufacturer is also linked to the assumption that exposure influences sales. Drèze *et al*. (1994) found in their experimental study that location is more important than space if allocated space is above a certain threshold. The model of Urban (1998) reformulates the basic model of Corstjens and Doyle by making sales dependent on displayed inventory instead of allocated space. An additional facing will only increase sales when inventory is present at that facing. This can be achieved by setting a lower bound on the displayed inventory or presentation stock that is dependent on the number of facings. Yang (2001) describes an alternative model formulation and an efficient solution procedure for this non-linear integer problem.

While the space management system at the retail chain does not use optimization, we will use the existing models for the SSAP as a benchmark. In our analysis of the shelf space usage, we will restrict ourselves to the slotting decisions, thus without assortment planning decisions. Given an assortment of size N and a fixed store layout with K shelves, we want to find for each SKU i an allocation of a number of facings on a shelf k, i.e. x_{ik}. The total length of a shelf k is W_k and each facing of SKU i has a width w_i. For marketing reasons, each SKU can have a lower bound LF_i and an upper bound UF_i on the number of allocated facings. Since we look at a fixed assortment in which each SKU has at least one facing allocated, the lower bound LF_i for the allocation is at least 1, i.e. $LF_i \geq 1$. Assuming no interdependencies due to substitution and complementarity, as in the models of Hansen and Heinsbroek (1979) and Yang (2001), we can formulate the SSAP as follows:

$$\max P = \sum_{i=1}^{N} \sum_{k=1}^{K} \text{Profit}_{ik}(x_{ik}) \tag{1}$$

subject to

$$\forall k : \sum_{i=1}^{N} w_i x_{ik} \leq W_k \tag{2}$$

$$\forall i : LF_i \leq \sum_{k=1}^{K} x_{ik} \leq UF_i \tag{3}$$

$$\forall i, k : x_{ik} \text{ integer} \tag{4}$$

In the objective function (1), the total store profit P is maximized. Constraint (2) ensures that the allocation respects the available shelf length. The lower and upper bounds in Constraint (3) helps the merchandizing manager to steer the solution towards acceptable solutions regarding the product mix. In the models of Urban (1998) and Yang (2001), these lower and upper bounds on the space allocation are considered exogenous. Remark that a SKU can be allocated facings on more than one shelf.

5.2 Space allocation from an operations perspective

Operations are driven by costs given a customer service constraint. After selecting an appropriate customer service measure, we will define additional constraints on the shelf space allocation problem that assist in achieving a high customer service level and low costs of replenishment.

Selecting a level of availability of a SKU is a trade-off between the cost of stock outs and the holding cost of inventory. At the retail level, the consumer response to a stock out determines the cost of a stock out. According to Zinn and Liu (2001), a consumer experiencing a stock out for a SKU may substitute the sought SKU, delay the purchase to a later visit or leave the store without the SKU and no plan to buy it at a later time. In the last case the demand is lost for the store. The long-term effect of stock outs may be that fewer consumers select the store for their shopping trips. The possible impact of stock outs is substantial, but determining the consumer response is very difficult. Following Hansen and Heinsbroek (1979), we assume in our analysis that a stock out will lead to lost sales, ignoring the effects of substitution and delay. We choose *fill rate* as measure of customer service from the operations perspective. The *ready rate* would be more appropriate from the marketing perspective, since it gives an indication of the actual

displayed inventory, which is used in the space allocation model of Urban (1998). As long as the customer service, measured by the *fill rate*, is high, it is reasonable to assume that sales are equal to demand.

The basic SSAP model, stated in (1)-(4), mentions only facings, where retail operations deal with consumer units and case packs. We want to extend the basic model with a constraint that gives a lower bound on the shelf space allocation in order to handle:

- Displayed inventory or presentation stock;
- Demand during the review period or the review period plus lead-time;
- Case pack size.

By assuming that each shelf has the same depth and that each facing has the same capacity, previous models have overlooked the effect of the case pack size, the dimensions of the consumer unit and the layout of the gondolas. The facing capacity v_{ik} of a SKU i at location k depends on the unit dimensions of the SKU, the type of gondola, and the location in the gondola. The bottom shelf has typically a greater shelf depth than the higher shelves.

In Figure 6 we show the distribution of the facing capacities for the SKU's at their current locations for the selected three stores. The average facing capacity is 18.8 consumer units and the median 12 consumer units. The facing capacity is proportional with the reciprocal of the consumer unit volume with coefficients of correlation for the three stores between 0.74 and 0.78. The minimum displayed inventory level or presentation stock is on average three times the number of allocated facings. This presentation stock always fits in the allocated shelf space. The space allocation S_i (measured in consumer units) is equal to the number of allocated facings x_{ik} multiplied by the facing capacity at the location v_{ik}, i.e., $S_i = \sum_{k=1}^{K} v_{ik} x_{ik}$.

The manufacturer determines the case pack size Q_i of a SKU i. The relative occurrences of case pack sizes in the assortment of the retail chain are shown in Figure 7. The case pack sizes range from 1 consumer unit to 120 consumer units per case pack with a median of 10 consumer units.
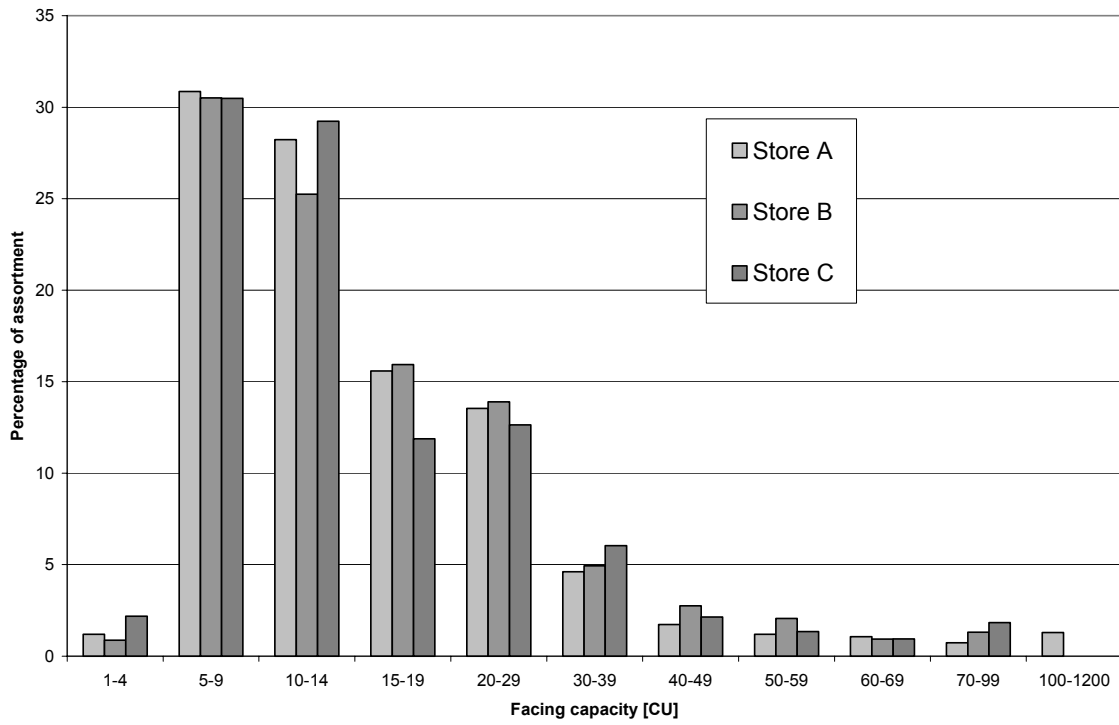
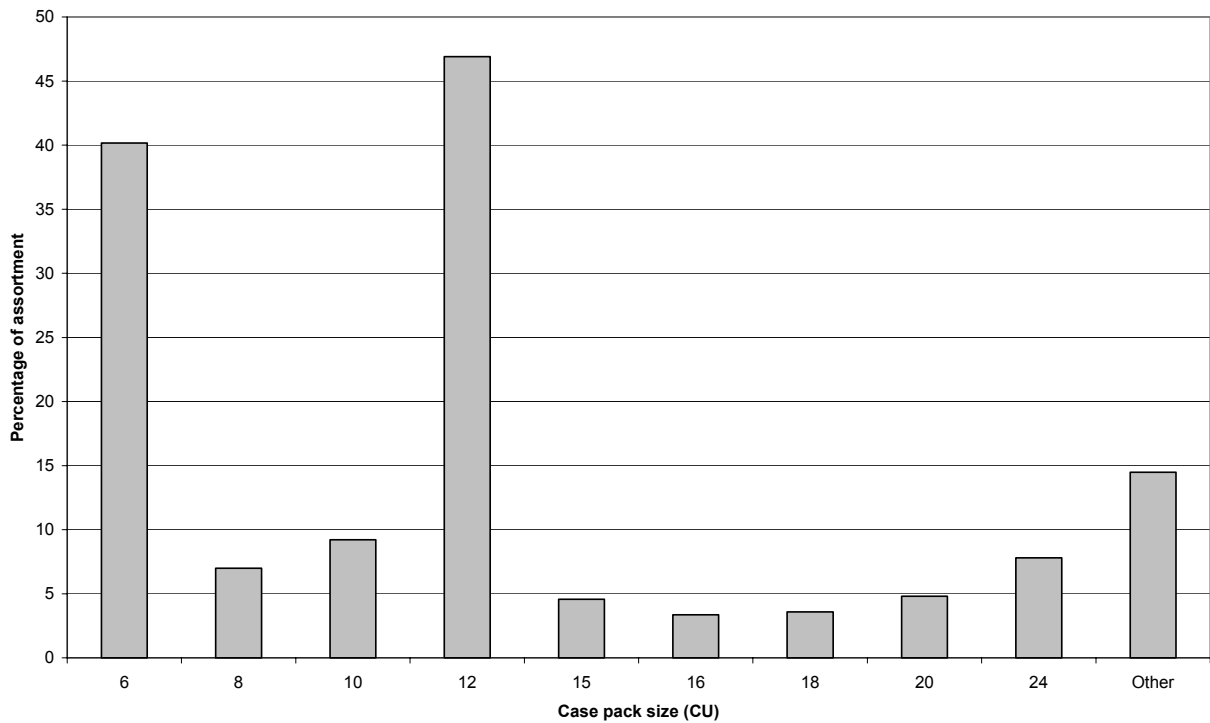Figure 6: Facing capacities at the three selected stores.

Figure 7: Distribution of case pack sizes.

Let us assume the inventory of SKU i is controlled with a (R, s, nQ) policy and a replenishment order is created only when the inventory position at a review moment is strictly below reorder level s_i. The value of n is chosen such that the inventory position just after a replenishment decision is at or above s_i, but strictly less than $s_i + Q_i$. So the maximum inventory position just after a replenishment decision is $s_i + Q_i - 1$, since we are dealing with discrete products. The inventory on hand is at its maximum just after a delivery is made. This is L (the lead-time) periods after the replenishment decision was made. The review period depends on the delivery schedule to a store for a planning group to which a SKU belongs, but the lead-time for the SKU's that are delivered from the central warehouse is always the same. Therefore we have for the maximum inventory on hand $\hat{S}_i$,

$$\hat{S}_i = s_i + Q_i - 1 - (\text{demand during L periods}) \tag{5}$$

If we assume that demand is deterministic and time-varying due to the week pattern, being constant for a particular day t in the week, but different on different days within the week, we have $s_i = M_i^d + \underset{t}{Max}\{D_{it}^{L+R}\}$, with M_i^d the minimun displayed inventory (due to commercial requirements) and D_{it}^{L+R} the known demand during the lead-time plus review period for a weekday t. As a result, the maximum inventory on hand is

$$\hat{S}_i^D = M_i^d + \underset{t}{Max}\{D_{it}^{L+R} - D_{it}^L\} + Q_i - 1 \tag{6}$$

So in this case the maximum depends on the delivery schedule for the SKU, which may depende not only on the SKU, but also on the store, and on the weekly sales pattern. Note that this quantity becomes independent of the lead-time when demand is constant, i.e., $\hat{S}_i^D = M_i^d + \underset{t}{Max}\{D_{it}^R\} + Q_i - 1$.

In the case that demand is stochastic and time-varying due to the week pattern, we have $s_i = M_i^s + \underset{t}{Max}\{E(D_{it}^{L+R})\}$, with M_i^s the minimum inventory norm, covering both the minimum displayed inventory requirements and the requirement to meet a target customer level. The current level for M_i^s in the ASO system of the retail chain resulted in adequate customer service levels according to management of the retail chain. The expected demand during the lead-time

plus the review period for a weekday t is expressed by $E(D_{it}^{L+R})$. This in combination with Equation (5) gives

$$\hat{S}_i^S = M_i^s + \underset{t}{Max}\{E(D_{it}^{L+R})\} + Q_i - 1 - (\text{demand during L periods}) \qquad (7)$$

Since demand during L periods is stochastic, the only thing we can say with certainty is that this demand is non-negative. Therefore the maximum inventory on hand in case demand demand is stochastic and time-varying is

$$\hat{S}_i^S = M_i^s + \underset{t}{Max}\{E(D_{it}^{L+R})\} + Q_i - 1 \qquad (8)$$

This is $E(D_{it}^L)$ higher when compared with the maximum inventory on hand in the deterministic setting. The lead-time is equal to one day for the SKU's delivered from the central warehouse in most grocery stores in the Netherlands.

Based on Equation (8), we propose an additional constraint to the SSAP that makes it possible to include the operations perspective in the space allocation decisions.

$$\forall i : M_i^s + \underset{t}{Max}\{E(D_{it}^{L+R})\} + Q_i - 1 \le \sum_{k=1}^{K} v_{ik} x_{ik} \qquad (9)$$

6. Empirical Evidence of Excess Shelf Space

We define Excess Shelf Space (ESS) as the part of the total shelf space for a SKU (expressed in number of consumer units) that is not necessary for carrying out the current operations with respect to customer service and costs. With current operations we mean the current inventory control policy for the SKU, considering the target customer service, the review period and the case pack size. An important assumption for having excess shelf space is that a facing is reserved for one SKU, i.e., SKU's do not share a facing on the shelf. The excess shelf space E_i is the difference between the allocated shelf space and the required shelf space, i.e.,

$$E_i = S_i - \hat{S}_i \qquad (10)$$

We calculated all demand data, such as $E(D_{it}^{L+R})$, from point-of-sale data, excluding periods with promotions. The sales during promotions (in CU) remained below 3 % of total sales in the three selected stores.

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6.1 Current guidelines

The merchandising managers at the Marketing department told us that they follow two operations inspired guidelines to allocate sufficient space for a SKU in a planogram:

1. Service-oriented guideline: the allocated shelf space should be greater than or equal to 40% of the average weekly demand $\overline{D}_i^W$, such that the allocated space covers the peak demand during a week, assuming daily replenishments, and a safety stock of 10 % of weekly demand;

2. Handling cost oriented guideline: the allocated shelf space should be greater than or equal to 130 % of a case pack size, such that a whole case pack can be put into the allocated space.

The target required shelf space can now be formulated as

$$\hat{S}_i^M = Max\{0.4 \cdot \overline{D}_i^W, 1.3 \cdot Q_i\} \tag{11}$$

After examining the planograms in our download, we discovered that the operations inspired guidelines are not strictly followed. In the central planograms 84 % of the allocations follow the handling cost oriented guideline, compared to 74 % in the local planograms. If we relax this guideline to just 100 % of a case pack size, this numbers improved to 93 % for the central planograms and 84 % for the local planograms. In the local planograms, 95 % of the shelf space allocations followed the service-oriented guideline, and 71 % followed both guidelines. Note that the central planograms cannot be linked to demand information and therefore cannot be checked for the service-oriented guideline.

We suspected that the difference in following the handling cost guideline between the central and local planograms was caused by poor maintenance of the facing capacity data in the local planograms. The first problem with the planogram data that we encountered is the orientation of the SKU's. The orientation on the shelf is derived from the order in which the height, width and length of a SKU are entered in the Warehouse Management System. After close inspection of the planograms, we found that 7 % of the SKU's in our dataset had a too small row depth due to an incorrect orientation. The second problem was understating the stacking at a location in the local planograms. The management of the retail chain confirmed our suspicion by reporting us that the stores record only changes in the number of facings in the database. For the facing capacity the default value is entered in these cases, which is one. By increasing the stacking of

the SKU's in the local planograms, for which the allocation could not accommodate a full case pack, with one or two consumer units while respecting the available distance between the shelves, we could improve the matching between the local and central planograms. After increasing the stacking for 18 % of the facing capacities in the local planograms, 84 % of the allocations followed the handling cost guideline and 82 % both guidelines. The main difference that remained between the facing capacity in the local and central planograms is caused by the difference between the actual shelf and the default shelf dimensions.

The fact that 95% of the allocations reserved enough space to cover the average peak demand during the review period plus 25 %, i.e. $0.4 \cdot \overline{D}_i^W$, prompted us to look into the correlation between allocated shelf space and average peak demand during the review period. We found coefficients of correlation below 0.3, indicating that there is no significant relation.

6.2 Introducing the new target required shelf space

We can now compare our target required shelf space $\hat{S}_i^S$ with the target $\hat{S}_i^M$ used by the merchandising managers in their guidelines. The target $\hat{S}_i^S$ is on average 67 % higher (with a coefficient of correlation of 0.95) than the target $\hat{S}_i^M$ used by the merchandising managers. In 92 % of the cases the target $\hat{S}_i^M$ is dominated by the case pack size. For the target $\hat{S}_i^S$ the case pack size is greater than the reorder level in 64 % of the cases.

Given an operations based target for the facing allocation, we can distinguish three cases when we examine the local planograms.

- Overfacing: the planogram allocates more facings than required by the target, i.e., with fewer facings the target can still be met;
- Proper facing: the allocated facings in the planogram satisfy the target required shelf space without overfacing;
- Underfacing: the planogram allocates fewer facings than required by the target.

This is expressed in Equation (12).

$$\sum_{k=1}^{K} x_{ik} - \left\lceil \hat{S}_i \cdot \frac{\sum_{k=1}^{K} x_{ik}}{\sum_{k=1}^{K} v_{ik} x_{ik}} \right\rceil \begin{cases} > 0 & \text{overfacing} \\ = 0 & \text{proper facing} \\ < 0 & \text{underfacing} \end{cases} \qquad (12)$$

In Figure 8, we show the distribution of these three cases in relation to the number of facings allocated. With the merchandising guidelines, 17 % of the allocations have underfacing and with the target $\hat{S}_i^S$ this increases to 47 %. The most important cause for underfacing is the case pack size in relation to the facing capacity. Examples of underfacing are popular soft drinks. SKU's with underfacing were not bulkier than average and did not have a lower margin (coefficients of correlations below 0.2). We have the impression that we can reduce the number of SKU's with underfacing by improving the quality of the local planograms. According to the local planograms, the current allocation uses on average 60 % of the available volume in the gondolas. Looking at the planograms, we believe that we can increase the stacking further without deteriorating the accessibility for the customers.
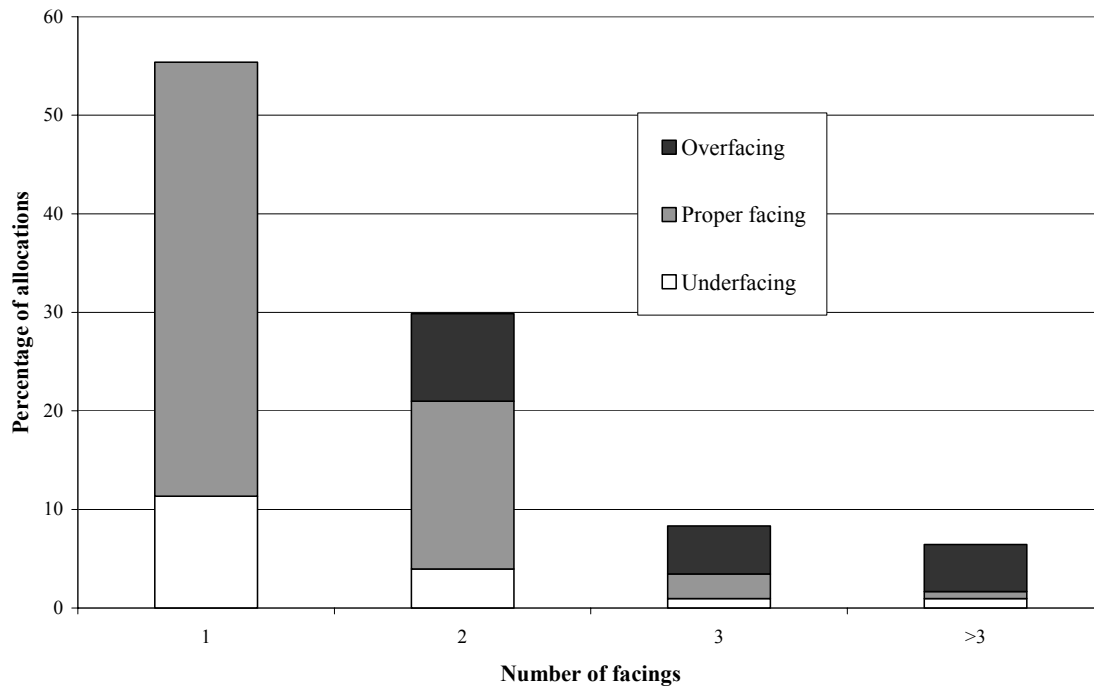

Figure 8: Distribution of facing allocations compared to the bound S_i^M.

With a fixed assortment, a SKU has at least one facing allocated. At the retail chain, 56 % of the assortment has exactly one facing allocated and for these SKU's overfacing cannot occur. For SKU's in the highest two absolute and/or relative margin classes overfacing occurs twice as

often compared to SKU's in the lowest two classes. Examples of overfacings are recently introduced SKU's such as new flavors of soft drinks.

The majority of the allocations have a proper amount of facings. The median excess shelf space for allocations with proper facing is 4.8 consumer units (10.9 average) in the case of the target $\hat{S}_i^M$ (based on the merchandising guidelines) and 5.1 (11.9 average) in the case of the target $\hat{S}_i^S$. This is a significant amount compared to the median facing capacity of 12 consumer units (18.8 average) in the local planograms. The cumulative distribution of the excess shelf space based on the merchandising guidelines is shown in Figure 9.
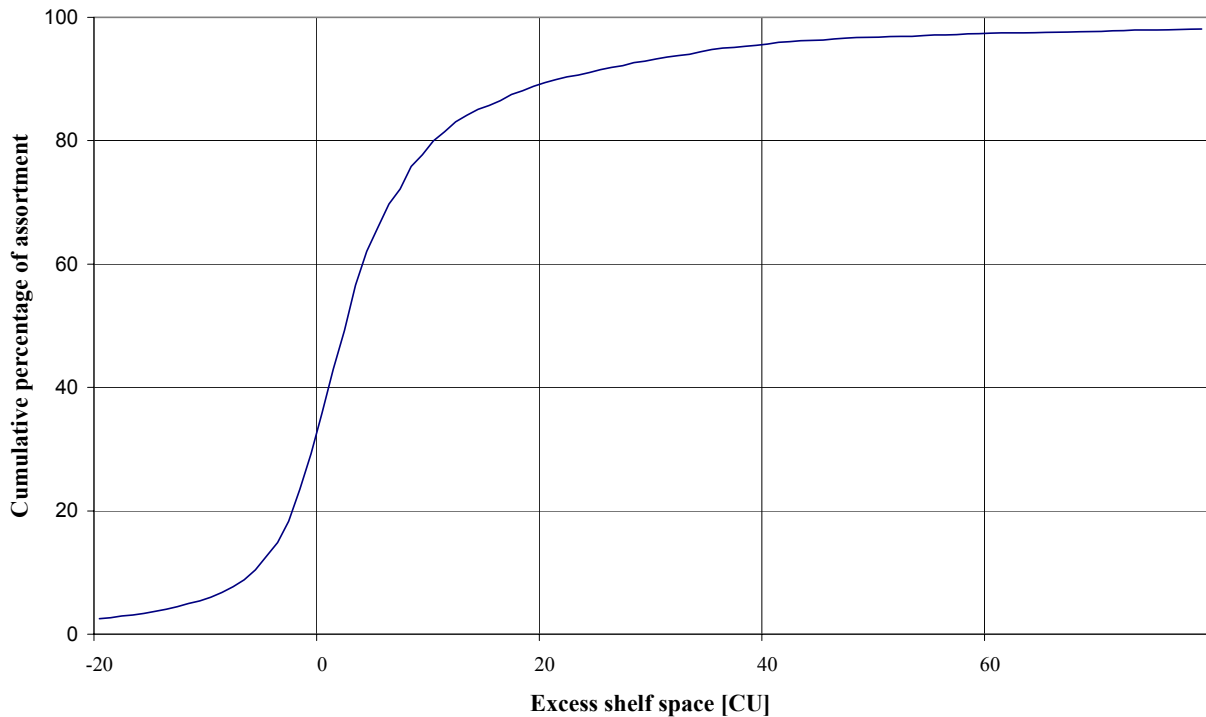

Figure 9: Cumulative distribution of excess shelf space at store B based on the target S_i^M.

Given the low percentage of overfacing (18 % with $\hat{S}_i^M$ and 5 % with $\hat{S}_i^S$), we can conclude that the occurrence of excess shelf space is mainly caused by rounding the shelf space capacity to the nearest integer number of facings and not by allocating additional facings to a SKU. Since the case pack sizes, the dimensions of the consumer units, and the shelf depth in the gondolas are

mostly exogenous to the retailer, we conclude that excess shelf space exists at grocery retail stores for a significant percentage of the assortment.

7. Using Excess Shelf Space to improve operations

In the previous section we have shown that excess shelf space is inevitable due to the way inventory is displayed at retailers. We will discuss how changes in the inventory policy and supply of the stores can benefit from the existence of excess shelf space.

7.1 Inventory policy

According to Cachon (2001), a common policy to achieve high customer service levels is the *full service* or (R, S) inventory policy. With this periodic review policy, one or more case packs are ordered up to the base stock level *S*, which in the retail setting is the shelf space capacity. When the shelf space allocation is at or above the optimal base stock level, the full service policy ensures that sufficient inventory is available to satisfy demand. Compared with the policy used by the ASO system of the retail chain in our study, we have a fixed reorder level instead of a dynamic reorder level, i.e., $s_i = S_i + 1 - Q_i$, since the shelf space allocation changes only once or twice a year. However, high variation in the demand will require unrealistically high shelf space allocations. With the current underfacing in the shelf space allocation, the full service policy will lead to unacceptable service levels. In these cases, the base stock level must be adjusted to allow ordering for the backroom, as is suggested by Urban (1998). In the ASO system, high demand forecasts will lead to an inventory position that exceeds the shelf space allocation and therefore results in leftovers for SKU's with underfacing. We proposed an extension of the (R, s, nQ) policy used in the ASO system that incorporates the shelf space allocation in the ordering advice such that it can take advantage of the excess shelf space. In the proposed (R, s, S, nQ) policy, the ordering advice is

$$ n = \begin{cases} Max\left\{ \left\lceil \dfrac{s_i - I_i}{Q_i} \right\rceil, \left\lfloor \dfrac{S_i - I_i}{Q_i} \right\rfloor \right\} & \text{if } I_i < s_i \\ 0 & \text{otherwise} \end{cases} \tag{13} $$

The advice from Equation (13) is to order only when the inventory position is below the reorder level. When that is the case, order the maximum of the ordering advice based on the demand forecast, and the ordering advice based on how many case packs will fit in the

unoccupied shelf space. With this extension we aim at reducing the average inventory level and the number of order lines at the same time. Further research is needed to establish a procedure to find the optimal reorder levels for this policy. Remark that the current minimum inventory level M_i^s is dominated by the presentation stock set by the Marketing department for a large percentage of the assortment. Since the handling costs are three to five times higher than the inventory costs, we believe that substantial cost reductions are possible with the current parameters.

7.2 Changing the review period for SKU's with excess shelf space

The previous section proposed to reduce the number of order lines by combining or consolidating several case packs in one delivery. When the excess shelf space is sufficient, we can structurally postpone the deliveries for a SKU by increasing the review period R_{it}. We define the expected demand during the lead-time plus review period $E\left(D_{it}^{L+R}\right)$ as the demand rate μ_{it} times the review period R_{it}, i.e., $E\left(D_{it}^{L+R}\right)=\mu_{it}\left(L+R_{it}\right)$, assuming a constant lead-time. Based on Equation (8), we get an expression for the maximum inventory on hand for each weekday t, i.e.,

$$\hat{S}_{it}^S = M_i^s + \mu_{it}\left(L + R_{it}\right) + Q_i - 1 \qquad (14)$$

Combining with Equation (10) result in a shelf allocation based review period R_{it}^S:

$$R_{it}^S = R_{it} + \frac{E_{it}}{\mu_{it}} = \frac{S_i - M_i - Q_i + 1}{\mu_i} - L \qquad (15)$$

If the lead-time is negligible and R_{it}^S is much greater than the current review period R_{it}, we can increase the review period of the SKU during that part of the week. However, changing the review period can lead to major problems in the current situation, since all SKU's in a merchandising category belong to the same planning group. We will need a sufficient number of SKU's to make this change worthwhile for the organization.

7.3 Balancing the workload at the central warehouse and the stores

Instead of just increasing the review period, we can also try to shift the moment of delivery in such a way that it reduces the workload at the end of the week. By balancing the workload, the store manager can improve the use of its workforce. At the moment, shelves are stacked in the

evening to avoid hindrance of the consumers in the store. A high workload means that the work sometimes finishes after midnight, because the number of store clerks that can work in the store at the same time is restricted due to congestion in the aisles. In general, hourly labor costs are more expensive during the late evening than during the early evening. At the central warehouse, which has more permanent staff, a balanced workload can reduce the number of temporary order pickers needed. We want to further investigate the policies needed to balance the workload.

7.4 Reducing order picking costs at the central warehouse

Without coordination, the proposed extension of the inventory policy will reduce the number of order lines for the stores as well as for the central warehouse, which will reduce the handling costs. If we coordinate the orders for SKU's with excess shelf space, we can reduce the order picking costs even further, because this can lead to shorter order picking tour. According to Hall (1993), the number of SKU's that have to be visited in a tour determines the length of an order picking tour and therefore the total walking distance. Picking the assortment with sufficient excess shelf space only once or twice a week instead of almost every day makes it interesting to change the allocation of the SKU's such that this walking time reduction can be realized. Coordination opens the possibility for outsourcing the order picking of these less frequently picked SKU's to a third party logistic service provider, which has already been suggested by Wagar (1995).

8. Conclusions

In this study, we collected data at a retail grocery chain that encompasses all relevant data to model the entire store operation around the shelf. This enables us to relate the physical space on the shelf to the inventory replenishment policy. The available space on the shelf is strongly influenced by the physical dimensions of the product, the case pack size, and the shelf dimensions. Since these are exogenous to the replenishment process parameters, we conclude that excess shelf space is an important and relevant phenomenon in retail operations, which has not been documented before. We illustrate several opportunities for different replenishment policies and handling strategies that could reduce the cost of operations. The proposed policies need to be studied in more depth to fully assess their potential.
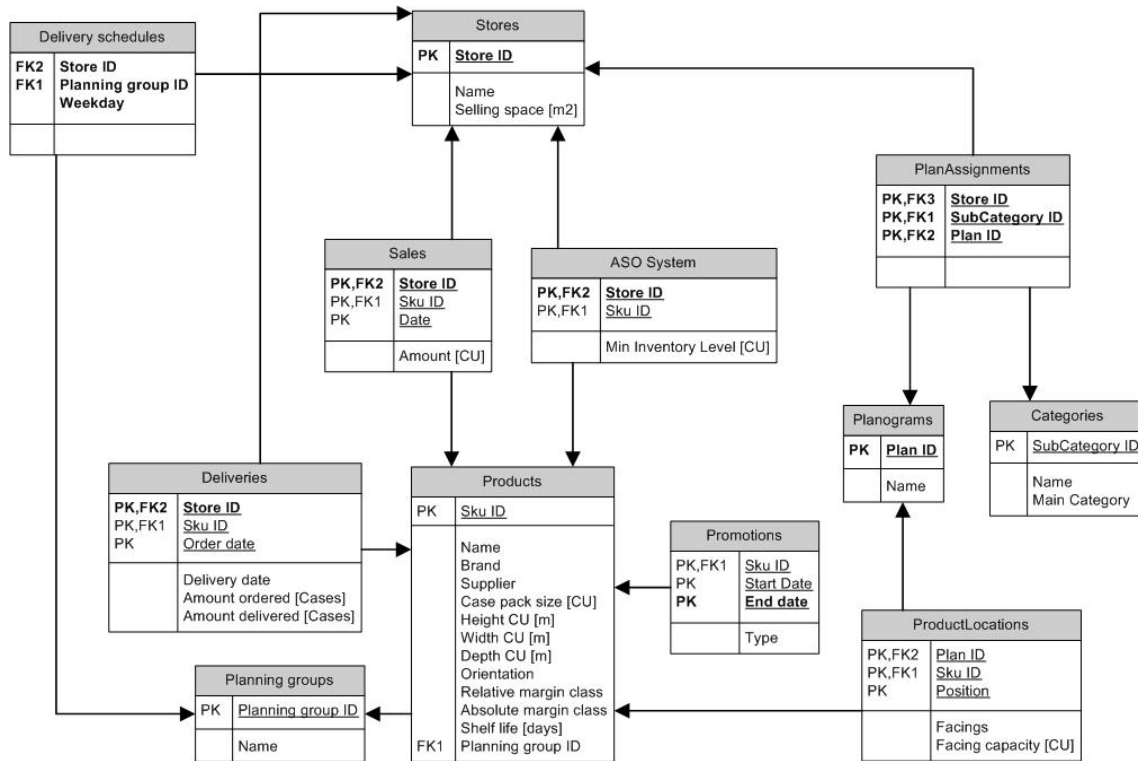
Appendix 1

Figure A1: Entity Relation diagram for the dataset.

Acknowledgments

References

Bertrand, J.W.M., J.C. Fransoo, 2001. Operations Management Research Methodologies Using Quantitative Modeling. *International Journal of Operations and Production Management* **22** 241-264.

Cachon, G. 2001. Managing a Retailer's Shelf Space, Inventory, and Transportation. *Manufacturing & Service Operations Management* **3**, 211-229.

Corstjens, M., P. Doyle. 1981. A model for optimizing retail space allocations. *Management Science* **27** 822-833.

Drèze, X., S.J. Hoch, M.E. Purk. 1994. Shelf management and space elasticity. *Journal of Retailing* **70** 301-326.

Hall, R.W. 1993. Distance approximations for routing manual pickers in a warehouse. *IIE Transactions* **25** 76-87.

Hansen, P., H. Heinsbroek. 1979. Product selection and space allocation in supermarkets. *European Journal of Operational Research* **3** 474-484.

Hughes, K.L. 1999. Supermarket Employment: Good Jobs at Good Wages? IEE Working Paper 11, Institute on Education and the Economy, Teachers College, New York.

Levy, M., B.A. Weitz. 1995. *Retailing management* (second ed.). Irwin, Chicago.

Raman, A., G. Zotteri. 2000, *Estimating retail demand and lost sales*, Harvard Business School Working Paper 01-006.

Raman, A., N. DeHoratius, Z. Ton. 2001. Execution: the missing link in retail operations. *California Management Review* **43** 136-152.

Silver, E.A., D.F. Pyke, R. Peterson. 1998. *Inventory Management and Production Planning and Scheduling* (third ed.). Wiley, Chichester.

Urban, T.L. 1998. An Inventory-Theoretic Approach to Product Assortment and Shelf-Space Allocation. *Journal of Retailing* **74** 15-35.

Yang, M.H., W.C. Chen. 1999. A study on shelf space allocation and management. *Int. J. Production Economics* **60-61** 309-317.

Yang, M.H. 2001. An efficient algorithm to allocate shelf space. *European Journal of Operational Research* **131** 107-118.

Wagar, K. 1995. The logic of flow-through logistics. *Supermarket Business* June 29-35.

Zinn, W., P.C. Chen. 2001. Consumer response to retail stockouts. *Journal of Business Logistics* **22** 49-71.