2018

The Vendor in a Retail Setting: A Survey

Jesse LaPorte
Minnesota State University, Mankato

The Vendor in a Retail setting: A Survey

by

Jesse J. LaPorte

A Thesis Submitted in Partial Fulfillment of the Requirements for

Master of Arts

In Mathematics

Minnesota State University, Mankato

Mankato, Minnesota

April 2018

May, 2018

This Thesis has been examined and approved.

Examining Committee:

Dr. In-Jae Kim, Chairperson

Dr. Kyung Il Lee

Dr. Galkande (Iresha) Premarathna

Abstract

We consider the problem of managing nonperishable inventory as a vendor in a grocer setting. To manage inventory effectively, we must meet the demand of our customers as closely as we can. Too much inventory results in holding costs and ties up a large amount of capital and too little inventory results in lost sales or substitution. It is typical in a retail setting for the vendor to have access to past ordering data, but this data is only representative of the demand when we have sufficient inventory. Otherwise, the demand exceeds the inventory on hand and we lose, in addition to the sale, the observation of the true demand. However, we get ahead of ourselves since the ability for the vendor to even know if there is an out-of-stock situation is questionable. This can be addressed through cooperation with the store and access to point of sale systems. The setting is further complicated by such things as the presence of multiple products, a backroom, and positive lead times. We conduct a survey on these topics as well as others pertaining to a vendor-type situation such as periodic review, service level constraints, fixed order costs, and the joint replenishment problem.

Table of Contents

Chapter 1

Introduction

I am a merchandiser of Pepsi products for a local Pepsi distributor. Our business model, much like other vendors, is to provide the service of managing all aspects of the inventory we provide for our clients which include grocery stores, gas stations, and other convenience-type stores. Products commonly serviced by other vendors include other pops such as Coke and 7-UP, chips such as Frito-Lay and Old Dutch, and bread such as Country Hearth and Sarah Lee. Each of these vendor companies manages more than just the product immediately associated to their names. At Pepsi, for example, we also manage Lipton tea products, Starbucks products, Gatorade products, Rockstar Energy products, and several domestic, craft, and imported beers. While this list is rather large, the amount of these products in any given store is rather small. Thus, each merchandiser oversees several stores but typically no more than three. This is known as the *merchandiser's route*.

Every morning, except when a store is closed, the merchandiser visits each store on their route. They may receive an order placed on a previous day. They then replenish what is called in the literature "shelf space", but this can also include displays and coolers, with the product received in the order or from their dedicated area of the backroom of the store. In this area, we may place about 3 pallets. We will refer to these areas of the store as simply the *floor* and *backroom* respectively. Excess inventory is gathered, condensed, and placed in the backroom for future use. A review of the inventory is carried out, and an order placed accordingly. Depending on both the size and distance of the store from the warehouse, the number of orders able to be filled per week can vary but is usually no more than 5. Since orders might not be able to be picked on certain days such as weekends and holidays, there is some variability in the time between when an order is placed and when it arrives. This is known as the *lead time*.

The way in which we place orders is by manually visiting each part of the store containing our product and counting how many cases we ought to order to fill any gaps. We must take into consideration demand over the lead time. In addition, we must also order ahead for future promotions so that we can build the appropriate displays according to the stores floor plan. This ordering method is both subjective and time-consuming, taking about 30 minutes per store. This labor cost, in addition to the hardware costs necessary to submit the order, could be reduced greatly with the assistance of an automated inventory management tool.

If we consider the system through which we place an order, we have our past sales data. That is, we have the data on the orders we have placed and sold to the store, or, from the stores perspective, the incoming inventory. We also have several statistics for each item such as a 4-week moving average. The question is how we can automate ordering given this information?

What do we need? Well, the goal when managing inventory is to align supply and demand as closely as possible. Too much inventory, in this setting, results in overflow of the backroom, resulting in diminished good-will between the vendor and store. This can affect future sales as the store has some say over both the location and size of promotional displays, new product placement, and the ability to vulture space from competitors who underperform. Since the inventory upon arrival is sold to the store, the store may also request that it be returned, a costly thing for the vendor. Insufficient inventory results in lost sales and also a loss of good-will between the vendor and store. Part of the contract between the vendor and store also includes minimum service levels which is the level of service expected from the vendor, measured typically by the fraction of demand satisfied by on-hand inventory. To this end, we need to find a way to find the demand for our products so that we can match our order quantity as closely as possible.

Some additional assumptions that will be necessary going forward include:

1. Each product has an adequate number of facings and this number is known to the vendor and hence the vendor knows how many cases of product can fit on the floor. This is true in practice in the sense that often, the shelf-space is adequate for one period's demand. Note that stores do not typically allow vendors to change the number facings of products despite the vendor's expertise.

2. If product exists in our backroom area, then the floor is full when the vendor leaves the store.

3. Once the vendor has left the store, products in the backroom stay in the backroom. That is, the vendor exclusively handles the product.

4. The vendor visits each store on their route exactly once per day.

5. Substitution between a vendor's own products does not occur.

6. Orders are fulfilled from a single source, the warehouse. In practice, multiple sources may exist, e.g., a manufacturer.

On one hand, if we were to under-order a certain product, that is, there is none of that product remaining on the floor, then we have what is known as an *out-of-stock* (OOS) situation. Here, the demand must have been at least as large as the amount of product on the floor. In retail it is often the case that unmet demand is lost. (Corsten and Gruen, 2003) estimate that about 50% of the customers leave the store without buying the product, while the other half opts to substitute. Since we're ignoring substitution between our own products, we'll treat any unmet demand as lost. Hence unmet demand is not observed and is known as *censored demand*. Since there could be inventory yet in the backroom, an order immediately following an OOS situation need not be the same size as the floor capacity (here, the difference between the floor capacity and the quantity of product in the backroom would be needed but note we do not have the information on the quantity still in the backroom in our sales data). Hence one could not reliably detect OOS situations via ordering data. On the other hand, detecting over-ordering in ordering data is just as problematic as the only indication would be from either product returns or the absence of orders for a product for an abnormal amount of time. Thus, from our order history, we cannot reliably detect instances of either over or under ordering, let alone, the quantities by which we do so.

Note as well that it is possible to have demand censoring even if product is available. For instance, if there is a promotion accompanied by promotional space or display which, to the customer, is in an unintuitive location, customers may purchase all the product on the shelf but not the promotional space, leading to what customers assume is an OOS situation. This is called a *phantom stockout* and it accounts for an estimated 25% of OOS situations ((Ton and Raman, 2010), (Gruen et al., 2002)). In an OOS situation, as mentioned above, customers will either be unsatisfied or purchase a substitute product. This can further cause problems when estimating demand since substitution inflates the demand of the substituted item. Other problems arise when considering theft, inventory recording inaccuracies, and execution by the vendor ((DeHoratius and Raman, 2008), (Raman et al., 2001)).

To fill this information gap, we begin by seeking information regarding OOS occurrences. This can be done upon arrival to the store by taking note of when inventory on the floor is completely empty and assume an OOS situation has occurred on the previous day. Another type of information we can obtain is how much product has left the store. To measure this, the merchandiser would have to both record the inventory level of each product on the floor at the end of their visit and at the beginning of their next visit. Note that an OOS situation would be assumed when the inventory level of a product on the floor is zero in either case. Note as well that this is the minimum information required to assess over-ordering quantities as discussed above. From here, we only need information to be able to estimate lost sales.

Since the time it takes to gather this information could be more than how much we spend ordering already, this would not be an ideal means to our end. However, there is something already recording this information, although not directly nor as accurately since we can at the very least indirectly observe, but not attribute to, losses from things such as theft. This is, the point-of-sale (POS) system in the front end of the store i.e., the cash registers. In either case, this data gives us insight into the outgoing inventory. This outgoing inventory data is more detailed than the incoming inventory data since we can, at the very least, observe the date in which the demand for the item was realized whereas incoming inventory may be sold across multiple days. In addition, POS data has the information of the time in which demand is realized is recorded. With this *timestamp* data, we can both estimate when an OOS situation occurs by recording the last instance in which a product has been purchased and the quantity that was under-ordered by comparing days when an OOS situation occurred with days when it did not occur.

To reiterate our assumptions, we have:

- Censored Demand
- Access to Point of Sale (POS) Data
- Periodic Review
- Multiple Items
- A Backroom (This implicitly makes our items non-perishable)
- Variable Positive Lead Time
- Service Level Constraint
- Fixed Order Costs

The rest of the paper will go as follows: We will discuss reasons for the mismatch between supply and demand, then we will follow with a review of the literature discussing the above topics.

Chapter 2

Supply and Demand Variation

Gaps in supply and demand can be caused on either the supply side or the demand side. We discuss some of the causes of these gaps in either case.

2.1 Supply Side

Several studies have analyzed the behavior of inventory managers in a newsvendor setting. (Schweitzer and Cachon, 2000) find that humans consistently under-order products with high profitability. This is called the *pull-to-center bias*. (Bolton and Katok, 2008) as well as (Ho et al., 2010) find that almost no learning takes place by the inventory manager when the experiment is repeated. This demonstrates that experience is not a factor when it comes to pull-to-center bias (Bolton et al., 2012). There have been many attempts to explain this phenomenon. One is the inventory manager anchors on the mean demand out of convenience and adjusts insufficiently based on their observations ((Schweitzer and Cachon, 2000), (Schiffels et al., 2014)). Another identifies that overconfidence leads to an underestimation of the variance of demand which leads to orders closer to the mean than optimal (Ren and Croson, 2013). For further reading, see ((Kremer et al., 2014), (Su, 2008), (Kahneman and Tversky, 1979), (Becker-Peth et al., 2013), (Feiler et al., 2013), (Rudi and Drake, 2014), and (Kremer et al., 2011)).

2.2 Demand Side

There is much research in the area of demand forecasting. Here, we will discuss just some of the factors that explain variance in demand in our setting. Some of these are more easily adjusted for than others. Such things include price changes, day of the week, weather, and holidays. Price changes come in the form of promotions and clearance sales. Day of the week has an impact, Friday and Saturday tend to be the busiest days for a grocer and Monday and Tuesday tend to be the slowest. Weather plays a large role, particularly on beverages. Summer tends to be the busiest of the seasons for both food and drink ((Agnew and Palutikof, 1999), (Roslow et al., 2000)). However, rain and humidity can prevent outdoor activity leading to less consumption. Holidays play a large role and are often accompanied by promotions.

Chapter 3

Literature Review

3.1 Censored Demand and Point of Sale Data

(Bijvank and Vis, 2011) refers to studies by (Gruen et al., 2002) and (Verhoef and Sloot, 2010) and concludes that assuming excess demand is lost is more practical than assuming that it is backordered in a general retail environment. This is because in retail, it is estimated that 15% of customers in an OOS situation will later purchase the item whereas 40% will be lost, with the remaining 45% being substituted (Gruen et al., 2002). However, backorder assumptions receive more attention in literature partly because order-up-to policies are proven to be optimal for backorder models with periodic reviews ((Karlin and Scarf, 1958), (Scarf, 1960)). Using backordering models in a lost-sales setting has shown cost deviations of up to 30% (Zipkin, 2008). Work by (Huh et al., 2009) shows that it is possible to use backordering models in a lost-sales setting effectively but only under strict conditions.

Assuming we're working in cooperation with the store and have access to their POS system, we can use the timestamp data to give an estimate of the censored demand. Here, we present the approach used in (Sachs and Minner, 2014).

Since we have the timestamp data, we have the ability to see the time at which demand was realized for our product. Let V be a set of samples representing different weeks of data. Then $v \in V$ is a week of $T = 7$ periods (days). For every product i, group the days $t \in T$ into the sets F_i and C_i depending on if demand was fully observed or censored for that day respectively. For days in C_i, let k_{ivt} denote the time the OOS situation began.

For each day in F_i, divide the day into $j = 1, \ldots, J$ hours ($J = 24$). For each j, the sales h_{ivtj} are recorded. Let H_{ivtj} denote the cumulative sales where $H_{ivtJ} = d_{ivt}$. Hence, the ratio of the mean of cumulative sales $\overline{H}_{iJ}$ to mean demand $\overline{D}_i$ of all demand observations is:

$$\frac{\overline{H}_{iJ}}{\overline{D}_i} = 1. \tag{3.1}$$

The ratio of cumulative demand H_{iJ} to total demand one hour before closing can be calculated as the complete ratio less demand h_{iJ} that will occur in the meantime:

$$\frac{\overline{H}_{i(J-1)}}{\overline{D}_i} = 1 - \frac{\overline{h}_{iJ}}{\overline{D}_i}. \tag{3.2}$$

The ratios of the preceding time intervals j can then be obtained recursively as

$$\frac{\overline{H}_{ij}}{\overline{D}_i} = \frac{\overline{H}_{i(j+1)}}{\overline{D}_i} - \frac{\overline{H}_{i(j+1)}}{\overline{D}_i} \cdot \frac{\overline{h}_{i(j+1)}}{\overline{H}_{i(j+1)}} = \frac{\overline{H}_{i(j+1)}}{\overline{D}_i} \cdot (1 - \frac{\overline{h}_{i(j+1)}}{\overline{H}_{i(j+1)}}) = \frac{1}{K_{ij}}. \tag{3.3}$$

It follows that $K_{ij} = \frac{K_{i(j+1)}}{(1-\frac{\overline{h}_{i(j+1)}}{\overline{H}_{i(j+1)}})}$ with $K_{iJ} = 1$.

The cumulative demand for all days with censored observations can then be estimated by interpolating the corresponding ratios before and after the stockout occurred in k_{ivt}. Hence, we can approximate the lost sales by:

$$H_{ik_{ivt}} \frac{(K_{ik_{ivt}} + K_{i(k_{ivt}-1)})}{2}. \tag{3.4}$$

Using this and taking into consideration external factors such as temperature, humidity, price, holidays, and day of the week, and assuming that these factors have a linear effect on the demand of an item, (Sachs and Minner, 2014) construct a linear program and optimize the weights of these external factors to create an inventory function. This is similar to a linear regression, but the overestimation and underestimation are weighted differently due to the under- and over-ordering costs. Extending this work by allowing the non-linearity of external factors, (Huber et al., 2017) use artificial neural networks to construct a non-linear program.

3.2 Vendor Managed Inventory and the Sharing of Data

There is a category of literature devoted to the study of vendor managed inventories (VMI). Typically, these take a more supply chain or macro view whereas this paper considers the store level or micro view. It is well documented that the sharing of information between stores and vendors gives the best results. As stated in (Southard and Swenseth, 2008), in all documented cases of organizations using VMI, there was some connection between the members in order to facilitate the exchange of information on inventory levels, product usage and re-supply issues. Generally, this connection is provided with electronic data interchange (EDI) (Emigh, 1999). (Haavik, 2000) stated that using electronic data exchange tools were needed to realize the full benefits of VMI. (Vigtil, 2007) described a set of five case studies that indicated sales forecasts and inventory positions were the most valuable information provided to suppliers by the buyers in a VMI relationship. (Kuk, 2004) found that VMI benefited smaller organizations more than larger ones.

Note that this is consistent with the view taken in this paper.

3.3 Periodic Review

There are two kinds of review periods, one is periodic and the other is continuous. A review period can be considered to be the time when we are at our store. A continuous review assumption means that we are at the store at all times and hence we may place an order for a product the moment it reaches the reorder point. In addition, instantaneous replenishment from the backroom when necessary is generally assumed. When ordering, if there is negligible or no fixed costs for our orders, our multi-product problems becomes a single product problem for each product. Otherwise, ordering multiple products at the same time, or joint ordering, is less costly since this fixed cost is spread across these multiple products.

Clearly, we instead find ourselves in a periodic review setting. Note that in a retail setting, it is also generally assumed that instantaneous replenishment from the backroom takes place throughout the day as necessary but as we are in a VMI situation, we have the flexibility to assume otherwise. (Bijvank and Vis, 2011) concludes that the main focus of lost-sales models in a periodic review setting is seeking near-optimal policies and deriving bounds for the optimal order quantities. These bounds are then used in a myopic policy although they do not always perform well. Optimality results for the backordering case are well known (Bijvank and Vis, 2011).

3.4 The Backroom

The backroom in retail exists as a hedge against uncertainty in product demand. Another benefit of the backroom is that product can be replenished throughout the day and so less floor space is needed per product. This means in the same amount of space, we may have a larger product assortment which can increase sales. However, the backroom can have its disadvantages as well.

The backroom effect (BRE) was coined by (Eroglu et al., 2013) who studied the interaction between case pack size, shelf space, and the reorder point and the poor alignment between them. This is due to the fact that all three of these aspects are decided by different independent parties. Case pack size is decided by the manufacturer, shelf space is decided by the merchandising department of the store and is only updated a few times per year, and the reorder point is decided by the inventory manager. It is common in retail to have a backroom and this poor alignment leads to costs that otherwise are overlooked. Increased costs come from the necessity to monitor backroom inventories in addition to floor inventory. Another cost increase comes from the double-handling that takes place when excess inventory gets handled the first time when it initially arrives at the store and there is no space for it on the floor and when it gets handled at least one more time in a subsequent period. It is estimated that 38% of operational logistical costs in retail are due to product handling at the store level (Zelst et al., 2009). Items may also be misplaced or forgotten, leading to inventory recording inaccuracies. Case pack size affects store operations as noted by ((Ferguson and Ketzenberg, 2006), (Ketzenberg and Ferguson, 2008)) since large case packs reduce the replenishment frequency which improves the fill rate but also increases the chance the order will not all fit on the floor. The more inventory is in the backroom, the worse the fill rate becomes due to the unreliability to fill the floor from the backroom ((Raman et al., 2001), (Waller et al., 2008)). There are many reasons this is the case, such as misplacement, insufficient labor, or poorly designed business processes ((Gruen and Corsten, 2007), (McKinnon et al., 2007), (Waller et al., 2008), and (Waller et al., 2010)). The numerical study carried out by (Eroglu et al., 2013) shows that ignoring the BRE give higher reorder points and higher total costs.

3.5 Service Level Constraints

As mentioned above, contracts between vendors and their clients typically include service level constraints. Thus, it is important to include these in our model. There is an additional benefit here as well. It is easier to define an acceptable service level compared to defining penalty costs, such as a good-will cost. We will refer to models with penalty costs as *cost models* and models with service level costs as *service models*.

The three most common definitions of service level are the α, β, and γ type. The α type is simply the probability of an item not having an OOS situation in a given period. The α type is also known as a cycle service level. The β type is the fraction of demand satisfied directly from stock on hand. This is also known as a fill-rate and it considers the size of the backorders or lost sales. The γ type service level is a time-based measure and is the fraction $(1 - \gamma)$ of the demand being on backorder each period. The β type is the most common.

Cost models are usually studied and in practice service level constrains are common. Work by (Bijvank, 2014) gives a comparison of service level constraints in periodic review inventory systems with optimal replenishment policies and shows a difference of 0.64%. The heuristic procedure developed in the paper guarantees the satisfaction of the service level constraint and their experiment shows a cost deviation of about 1-2% compared to the best (s,S) policy. Here, s denotes the reorder point and S denotes the order-up-to level. In (Bijvank and Vis, 2012), a similar study is carried out in a periodic review, lost sales setting with the (R,s,S) and optimal policies and finds a difference of 1.2% in the case of fixed order costs. Here, R denotes a constant time between orders.

The approaches taken in (Bijvank, 2014) and (Bijvank and Vis, 2012) improve on the standard two-dimensional search procedures to find the control variables s and S. Since the state space is unbounded, the general approach is to place bounds on S. However, in our scenario S can be found directly by considering the floor space assigned by the store. Note that it would still be beneficial for a vendor to know an appropriate value for S when it comes to negotiation of floor space, i.e., assortment planning.

(Donselaar and Broekmeulen, 2013) studies the calculation of safety stock ss levels in a (R,s,nQ) policy under a lost sales environment with positive lead time and β service levels for a fixed quantity size Q and $n \in \mathbb{N}$. In practice, the quantity Q can take different forms such as case packs, layers of a pallet, or pallets themselves. They take a linear regression approach that achieves an approximation error of 0.0028 and a standard deviation of the approximation error of 0.0045. The approach is also very fast and so the safety stock level can be set in a way to achieve target service levels. Here, $s = (L + R)\mu + ss$ for lead time L and average demand μ.

3.6 Fixed Order Costs

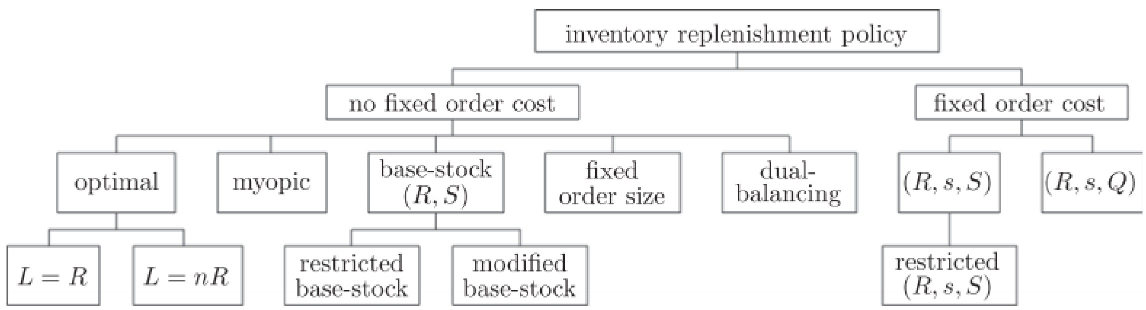

Figure 3.1: Categorization of periodic review lost-sales models (Fig. 2 in (Bijvank and Vis, 2011))

With no fixed-ordering costs, many models are available. See Figure 3.1. With a fixed ordering cost in a lost-sales setting with periodic review, the (R,s,S) policy is proven to be optimal when the lead time is zero ((Veinott Jr and Wagner, 1965), (Veinott, 1966), (Shreve, 1976), (Bensoussan et al., 1983), (Cheng and Sethi, 1999), and (Xu et al., 2010)). When the lead time is positive, no simple policy is optimal. In this case, (Hill and Johansen, 2006) demonstrates that the optimal policy is neither an order up to policy, (R,s,S), nor a fixed quantity ordering policy, (R,s,Q), yet both are close to optimal and are easy to implement.

According to (Bijvank and Vis, 2011), the majority of models that include the lost sales in a periodic review setting assume small fixed ordering costs and hence an order is placed every period so that we focus on minimizing the holding and either penalty costs or maintaining service levels. Conversely, high fixed-ordering costs lead to an irregular ordering schedule. Intuitively, if the store is at a large distance from our warehouse, it may not be cost effective to send a truck there every day. Since these distances vary, neither scenario is uncommon in practice. However, companies tend to impose regularity on the availability of order delivery since this is more efficient from a logistical standpoint. This, of course, means that sometimes it is sub-optimal from an inventory management perspective. The delivery schedule is another thing taken into consideration when negotiating backroom space for our product.

3.7 Joint Replenishment Problems

The joint replenishment problem (JRP) is the result of a multi-item, fixed ordering cost context when one considers the option of ordering items that have not fallen below their reorder level in addition to an item already below its reorder level provided the items are supplied by the same source. Intuitively, this leads to a lower cost policy as the fixed ordering costs are spread out over more items in an order. (Salameh et al., 2014) shows that the JRP guarantees a total cost reduction compared to single item ordering policies. Some types of joint replenishment policies are time-based, however, (Kang et al., 2017) finds that quantity-based models are superior.

(Turgut et al., 2018) uses a periodic review (s,c,S,nq) policy with case pack size q. This is a JRP that is considered a *can-order policy* (COP) (Balintfy, 1964). The idea incorporates major and minor ordering costs where a major cost can be thought of as the costs of transporting the order via truck. This is viewed as a fixed cost. The minor ordering costs can be thought of as the initial handling costs for each individual item. Major ordering costs occur when an item falls below the reorder point s. Other items are then ordered jointly if their inventory level is below the can-order point c where the appropriate minor ordering costs are included for each item in the order. (Turgut et al., 2018) also includes case sizes in their model since this misalignment between floor space and case quantities are part of the backroom effect. Note that in our nonperishable product setting, it is optimal to have $c = S - q$.

Additional assumptions made by (Turgut et al., 2018) are that we have uncensored demand, influence of demand by the retailer through promotions and advertising are excluded, the order lead time is zero (there is a modification for positive lead time as well), and the shelf is replenished throughout the day from the backroom. We will present the model found in (Turgut et al., 2018) with the modification for positive lead time.

For each $t \in T$, let I_{ivt} be the inventory level of item $i \in I$ at the beginning of period t. If an order occurs due to an item falling below the reorder point s_{it}, each item i is included in the order if $I_{ivt} < c_{it}$ and the quantity ordered is such that the inventory is replenished to at least the order-up-to level S_{it}. Let SC denote the major setup costs and sc denote the minor set-up cost per product and let p_i denote the variable ordering cost of item i. When replenishment occurs and the floor capacity cap_i is exceeded, we have both a major and minor backroom cost K and k_i per unit. These two factors reflect the non-linearity handling costs in retail ((Broekmeulen et al., 2004), (Curseu - Stefanut et al., 2009), (Zelst et al., 2009), and (Sternbeck and Kuhn, 2014)). Any demand d_{ivt} that goes unmet l_{ivt} incurs lost sale penalty ls_i per unit and any inventory at the end of a period incurs a holding cost h_i per unit.

The calibration of the model takes the standard approach of optimizing the parameters s_{it}, c_{it}, S_{it} using an uncensored demand history via mixed integer linear programming (MILP).

Let y_{ivt} be a binary variable indicating if an order is triggered by reorder point s_{it} and let n_{ivt} be the number of cases q_i of item i ordered when $u_{it} = 1$. Let Y_{vt} denote the major ordering event and u_{it} denote a minor ordering event. Let excess inventory be denoted by w_{ivt} and Z_{ivt} be the binary variable indicating a major overflow event. Let b_{ivt} be the satisfied demand and l_{ivt} be the unmet demand. For the MILP formulation, a sufficiently large number $M_i = \max_{v \in V}(\sum_{t \in T} d_{ivt}/q_i) \cdot q_i)$ is needed.

The extension to positive lead times in (Turgut et al., 2018) is achieved by changing n_{ivt} in (4) to $n_{it\lambda(v-L)}$ where

$$\lambda(a) = \begin{cases} a & a \geq 0 \\ |T| - a & a < 0 \end{cases}$$

and changing I_{ivt} in (1), (5), (6), (11)-(14) to $I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)}$.

Minimize:

$$\begin{aligned} &\sum_{i \in I} \sum_{v \in V} \sum_{t \in T} (p_i \cdot n_{it\lambda(v-L)} \cdot q_i + sc \cdot u_{ivt} + k_i \cdot w_{ivt} + ls_i \cdot l_{ivt}) \\ &+ \sum_{v \in V} \sum_{t \in T} (SC \cdot Y_{vt} + K \cdot Z_{vt}) + \sum_{i \in I} \sum_{v \in V} \sum_{t \in T} h_i \cdot (I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)}) \\ &+ \sum_{v \in V} \sum_{i \in I} |T| \cdot hi \cdot \sum_{t \in T} (n_{it\lambda(v-L)} \cdot q_i - b_{ivt}) \end{aligned} \tag{3.5}$$

Subject To:

$$0 \leq \sum_{t \in T} (n_{ivt} \cdot q_i - b_{ivt}) \leq M_i \quad \forall i \in I, v \in V \tag{3.6}$$

$$d_{ivt} = b_{ivt} + l_{ivt} \quad \forall i \in I, v \in V, t \in T \tag{3.7}$$

$$I_{iv(t+1)} = I_{ivt} + n_{ivt} \cdot q_i - b_{ivt} \quad \forall i \in I, v \in V, t \in T \tag{3.8}$$

$$I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)} - s_{it} + 1 \leq M_i \cdot (1 - y_{ivt}) \quad \forall i \in I, v \in V, t \in T \tag{3.9}$$

$$s_{it} - (I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)}) \leq M_i \cdot y_{ivt} \quad \forall i \in I, v \in V, t \in T \tag{3.10}$$

$$n_{ivt} \leq \frac{M_i}{q_i} \cdot u_{ivt} \quad \forall i \in I, v \in V, t \in T \tag{3.11}$$

$$u_{ivt} \leq Y_{vt} \quad \forall i \in I, v \in V, t \in T \tag{3.12}$$

$$Y_{vt} \geq y_{ivt} \quad \forall i \in I, v \in V, t \in T \tag{3.13}$$

$$Y_{vt} \leq \sum_{i \in I} y_{ivt} \quad \forall v \in V, t \in T \tag{3.14}$$

$$I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)} - c_{it} + 1 \leq M_i \cdot (1 - u_{ivt}) \quad \forall i \in I, v \in V, t \in T \tag{3.15}$$

$$c_{it} - (I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)}) \leq M_i \cdot (1 - Y_{vt} + u_{ivt}) \quad \forall i \in I, v \in V, t \in T \tag{3.16}$$

$$I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)} + n_{ivt} \cdot q_i \geq S_{it} - M_i \cdot (1 - u_{ivt}) \quad \forall i \in I, v \in V, t \in T \tag{3.17}$$

$$I_{ivt} + \sum_{r=1}^{L-1} n_{it\lambda(v-r)} + n_{ivt} \cdot q_i \leq (S_{it} + q_i - 1) + M_i \cdot (1 - u_{ivt}) \quad \forall i \in I, v \in V, t \in T \tag{3.18}$$

$$w_{ivt} \geq (I_{ivt} + n_{ivt} \cdot q_i - cap_i) - M_i \cdot (1 - u_{ivt}) \quad \forall i \in I, v \in V, t \in T \tag{3.19}$$

$$w_{ivt} \leq M_i \cdot Z_{vt} \quad \forall i \in I, v \in V, t \in T \tag{3.20}$$

$$S_{it} \geq s_{it} + 1 \quad \forall i \in I, t \in T \tag{3.21}$$

$$S_{it} \geq c_{it} + 1 \quad \forall i \in I, t \in T \tag{3.22}$$

$$s_{it} \leq c_{it} \quad \forall i \in I, t \in T \tag{3.23}$$

$$n_{ivt} \in N_0 \quad \forall i \in I, v \in V, t \in T \tag{3.24}$$

$$y_{ivt}, Y_{vt}, u_{ivt}, Z_{vt} \in \{0, 1\} \quad \forall i \in I, v \in V, t \in T \tag{3.25}$$

$$s_{it}, c_{it}, S_{it}, w_{ivt}, b_{ivt}, l_{ivt} \geq 0 \quad \forall i \in I, v \in V, t \in T \tag{3.26}$$

$$I_{ivt} \geq 0 \quad \forall i \in I, v \in V, t \in T \cup \{|T| + 1\} \tag{3.27}$$

See (Turgut et al., 2018) for a detailed description of the constraints.

Their findings show that consideration of the BRE has a median cost savings of .96%. Consideration of the JRP results in a median cost savings of 17.99%.

Chapter 4

Summary

We explored the limitations of a vendor in a grocer setting. Without information other than ordering data, we noted that we cannot reliably obtain information regarding quantities by which we under- and over-order. Without this, it is impossible to close the gap between supply and demand due to human bias. To this end, we gathered additional information so that we can build an automated inventory management tool. We noted that we had two options, either to gather information regarding inventory quantities manually or, in a cooperative arrangement with the store, through the store's point of sale system. From there, we surveyed the various aspects of the proposed setting. Namely, we studied the nonperishable, multi-product, periodic review problem with positive lead times, service level constraints, fixed costs, and a backroom.

In the literature, we found that with timestamp data from the store's POS system, a good approximation for lost-sales can be obtained. For the backroom, we studied the backroom effect and the costs involved with double-handling. Service level constraints were found to be an easily implemented alternative to standard under-ordering costs. When considering positive lead times in addition to fixed ordering costs, no simple policies exist but it has been demonstrated to be neither, but close to, the easily implemented policies (R,s,S) and (R,s,Q). Last, we found a joint replenishment model that captures our situation well and can provide a foundation for future implementation.

References

Agnew, M.D. and J.P. Palutikof. 1999. *The impacts of climate on retailing in the uk with particular reference to the anomalously hot summer of 1995*, International Journal of Climatology **19**, no. 13, 1493–1507.

Balintfy, Joseph L. 1964. *On a basic class of multi-item inventory problems*, Management Science **10**, no. 2, 287–297, available at `https://doi.org/10.1287/mnsc.10.2.287`.

Becker-Peth, Michael, Elena Katok, and Ulrich W. Thonemann. 2013. *Designing buyback contracts for irrational but predictable newsvendors*, Management Science **59**, no. 8, 1800–1816, available at `https://doi.org/10.1287/mnsc.1120.1662`.

Bensoussan, Alain, Michel Crouhy, and Jean-Marie Proth. 1983. *Mathematical theory of production planning*, North-Holland.

Bijvank, Marco. 2014. *Periodic review inventory systems with a service level criterion*, Journal of the Operational Research Society **65**, no. 12, 1853–1863, available at `https://doi.org/10.1057/jors.2013.160`.

Bijvank, Marco and Iris F.A. Vis. 2011. *Lost-sales inventory theory: A review*, European Journal of Operational Research **215**, no. 1, 1–13.

———. 2012. *Lost-sales inventory systems with a service level criterion*, European Journal of Operational Research **220**, no. 3, 610–618.

Bolton, Gary E. and Elena Katok. 2008. *Learning by doing in the newsvendor problem: A laboratory investigation of the role of experience and feedback*, Manufacturing & Service Operations Management **10**, no. 3, 519–538, available at https://pubsonline.informs.org/doi/pdf/10.1287/msom.1060.0190.

Bolton, Gary E., Axel Ockenfels, and Ulrich W. Thonemann. 2012. *Managers and students as newsvendors*, Management Science **58**, no. 12, 2225–2233, available at https://doi.org/10.1287/mnsc.1120.1550.

Broekmeulen, R.A.C.M., K.H. Van Donselaar, J.C. Fransoo, and T. Van Woensel. 2004. *Excess shelf space in retail stores : an analytical model and empirical assessment*, BETA publicatie : working papers.

Cheng, Feng and Suresh P Sethi. 1999. *Optimality of state-dependent (s, s) policies in inventory models with markov-modulated demand and lost sales*, Production and operations management **8**, no. 2, 183–192.

Corsten, Daniel and Thomas Gruen. 2003. *Desperately seeking shelf availability: an examination of the extent, the causes, and the efforts to address retail outofstocks*, International Journal of Retail & Distribution Management **31**, no. 12, 605–617, available at https://doi.org/10.1108/09590550310507731.

Curseu - Stefanut, A., T. Van Woensel, J.C. Fransoo, K.H. Van Donselaar, and R.A.C.M. Broekmeulen. 2009. *Modelling handling operations in grocery retail stores : an empirical analysis*, Journal of the Operational Research Society **60**, no. 2, 200–214.

DeHoratius, Nicole and Ananth Raman. 2008. *Inventory record inaccuracy: An empirical analysis*, Management Science **54**, no. 4, 627–641, available at https://doi.org/10.1287/mnsc.1070.0789.

Donselaar, Karel H. Van and Rob A.C.M. Broekmeulen. 2013. *Determination of safety stocks in a lost sales inventory system with periodic review, positive lead-time, lot-sizing and a target fill rate*, International Journal of Production Economics **143**, no. 2, 440–448.

Emigh, J. 1999. *Vendor-managed inventory: Financial and business concepts in brief*, Computerworld **33**, no. 34, 52.

Eroglu, Cuneyt, Brent D. Williams, and Matthew A. Waller. 2013. *The backroom effect in retail operations*, Production and Operations Management **22**, no. 4, 915–923, available at https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1937-5956.2012.01393.x.

Feiler, Daniel C., Jordan D. Tong, and Richard P. Larrick. 2013. *Biased judgment in censored environments*, Management Science **59**, no. 3, 573–591, available at https://doi.org/10.1287/mnsc.1120.1612.

Ferguson, Mark and Michael E Ketzenberg. 2006. *Information sharing to improve retail product freshness of perishables*, Production and Operations Management **15**, no. 1, 57.

Gruen, Thomas W and Daniel S Corsten. 2007. *A comprehensive guide to retail out-of-stock reduction in the fast-moving consumer goods industry*.

Gruen, Thomas W, Daniel S Corsten, and Sundar Bharadwaj. 2002. *Retail out of stocks: A worldwide examination of extent, causes, and consumer responses*.

Haavik, S. 2000. *Building a demand-driven, vendor-managed supply chain.*, Healthcare financial management : journal of the Healthcare Financial Management Association **54**, no. 2, 56–61.

Hill, Roger M and Søren Glud Johansen. 2006. *Optimal and near-optimal policies for lost sales inventory models with at most one replenishment order outstanding*, European journal of operational research **169**, no. 1, 111–132.

Ho, Teck-Hua, Lim Noah, and Tony Haitao Cui. 2010. *Reference dependence in multilocation newsvendor models: A structural analysis*, Management Science **56**, no. 11, 1891–1910, available at https://doi.org/10.1287/mnsc.1100.1225.

Huber, Jakob, Sebastian Müller, Moritz Fleischmann, and Heiner Stuckenschmidt. 2017. *A data-driven newsvendor problem: From data to decision*.

Huh, Woonghee Tim, Ganesh Janakiraman, John A. Muckstadt, and Paat Rusmevichientong. 2009. *Asymptotic optimality of order-up-to policies in lost sales inventory systems*, Management Science **55**, no. 3, 404–420, available at https://doi.org/10.1287/mnsc.1080.0945.

Kahneman, Daniel and Amos Tversky. 1979. *Prospect theory: An analysis of decision under risk*, Econometrica **47**, no. 2, 263–291.

Kang, Kyunghoon, Ki-sung Hong, Ki Hong Kim, and Chulung Lee. 2017. *Shipment consolidation policy under uncertainty of customer order for sustainable supply chain management*, Sustainability **9**, no. 9, 1–17.

Karlin, Samuel and Herbert Scarf. 1958. *Inventory models of the arrow-harris-marschak type with time lag*, Studies in the mathematical theory of inventory and production **1**, 155.

Ketzenberg, Michael and Mark E. Ferguson. 2008. *Managing slowmoving perishables in the grocery industry*, Production and Operations Management **17**, no. 5, 513–521, available at `https://onlinelibrary.wiley.com/doi/pdf/10.3401/poms.1080.0052`.

Kremer, Mirko, Stefan Minner, and Luk N. Van Wassenhove. 2014. *On the preference to avoid ex post inventory errors*, Production and Operations Management **23**, no. 5, 773–787, available at `https://onlinelibrary.wiley.com/doi/pdf/10.1111/poms.12071`.

Kremer, Mirko, Brent Moritz, and Enno Siemsen. 2011. *Demand forecasting behavior: System neglect and change detection*, Management Science **57**, no. 10, 1827–1843, available at `https://doi.org/10.1287/mnsc.1110.1382`.

Kuk, George. 2004. *Effectiveness of vendor-managed inventory in the electronics industry: determinants and outcomes*, Information & Management **41**, no. 5, 645–654.

McKinnon, Alan C, Daniela Mendes, and M Nababteh. 2007. *In-store logistics: an analysis of on-shelf availability and stockout responses for three product groups*, International Journal of Logistics Research and Applications **10**, no. 3, 251–268.

Raman, Ananth, Nicole DeHoratius, and Zeynep Ton. 2001. *Execution: The missing link in retail operations*, California Management Review **43**, no. 3, 136–152, available at `https://doi.org/10.2307/41166093`.

Ren, Yufei and Rachel Croson. 2013. *Overconfidence in newsvendor orders: An experimental study*, Management Science **59**, no. 11, 2502–2517, available at `https://doi.org/10.1287/mnsc.2013.1715`.

Roslow, Sydney, Tiger Li, and J.A.F. Nicholls. 2000. *Impact of situational variables and demographic attributes in two seasons on purchase behaviour*, European Journal of Marketing **34**, no. 9/10, 1167–1180, available at `https://doi.org/10.1108/03090560010342548`.

Rudi, Nils and David Drake. 2014. *Observation bias: The impact of demand censoring on newsvendor level and adjustment behavior*, Management Science **60**, no. 5, 1334–1345, available at `https://doi.org/10.1287/mnsc.2013.1825`.

Sachs, Anna-Lena and Stefan Minner. 2014. *The data-driven newsvendor with censored demand observations*, International Journal of Production Economics **149**, 28–36. The Economics of Industrial Production.

Salameh, Moueen K., Ali A. Yassine, Bacel Maddah, and Likaa Ghaddar. 2014. *Joint replenishment model with substitution*, Applied Mathematical Modelling **38**, no. 14, 3662–3671.

Scarf, Herbert. 1960. *The optimality of (ss) policies in the dynamic inventory problem. mathematical methods in the social science, kj arrow, s. karlin, p. suppes, eds*, Stanford University Press, Stanford.

Schiffels, Sebastian, Andreas Fgener, Rainer Kolisch, and O. Jens Brunner. 2014. *On the assessment of costs in a newsvendor environment: Insights from an experimental study*, Omega **43**, no. Complete, 1–8.

Schweitzer, Maurice E. and Grard P. Cachon. 2000. *Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence*, Management Science **46**, no. 3, 404–420, available at `https://doi.org/10.1287/mnsc.46.3.404.12070`.

Shreve, SE. 1976. *Abbreviated proof [in the lost sales case]*, Dynamic programming and stochastic control, 105–106.

Southard, Peter B and Scott R Swenseth. 2008. *Evaluating vendor-managed inventory (vmi) in non-traditional environments using simulation*, International Journal of Production Economics **116**, no. 2, 275–287.

Sternbeck, Michael G. and Heinrich Kuhn. 2014. *An integrative approach to determine store delivery patterns in grocery retailing*, Transportation Research Part E: Logistics and Transportation Review **70**, 205–224.

Su, Xuanming. 2008. *Bounded rationality in newsvendor models*, Manufacturing & Service Operations Management **10**, no. 4, 566–589, available at https://pubsonline.informs.org/doi/pdf/10.1287/msom.1070.0200.

Ton, Zeynep and Ananth Raman. 2010. *The effect of product variety and inventory levels on retail store sales: A longitudinal study*, Production and Operations Management **19**, no. 5, 546–560, available at https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1937-5956.2010.01120.x.

Turgut, Özgün, Florian Taube, and Stefan Minner. 2018. *Data-driven retail inventory management with backroom effect*, OR Spectrum.

Veinott, Arthur F, Jr. 1966. *On the optimality of (s,s) inventory policies: New conditions and a new proof*, SIAM Journal on Applied Mathematics **14**, no. 5, 1067–1083.

Veinott Jr, Arthur F and Harvey M Wagner. 1965. *Computing optimal (s, s) inventory policies*, Management Science **11**, no. 5, 525–552.

Verhoef, Peter C. and Laurens M. Sloot. 2010. *Out-of-stock: Reactions, antecedents, management solutions, and a future perspective* (Manfred Krafft and Murali K. Mantrala, eds.), Springer Berlin Heidelberg, Berlin, Heidelberg.

Vigtil, Astrid. 2007. *Information exchange in vendor managed inventory*, International Journal of Physical Distribution & Logistics Management **37**, no. 2, 131–147, available at https://doi.org/10.1108/09600030710734848.

Waller, Matthew A., Andrea Heintz Tangari, and Brent D. Williams. 2008. *Case pack quantity's effect on retail market share: An examination of the backroom logistics effect and the storelevel fill rate effect*, International Journal of Physical Distribution & Logistics Management **38**, no. 6, 436–451, available at https://doi.org/10.1108/09600030810893508.

Waller, Matthew A, Brent D Williams, Andrea Heintz Tangari, and Scot Burton. 2010. *Marketing at the retail shelf: an examination of moderating effects of logistics on sku market share*, Journal of the Academy of Marketing Science **38**, no. 1, 105–117.

Xu, Yanyi, Arnab Bisi, and Maqbool Dada. 2010. *New structural properties of (s, s) policies for inventory models with lost sales*, Operations Research Letters **38**, no. 5, 441–449.

Zelst, Susan Van, Karel Van Donselaar, Tom Van Woensel, Rob Broekmeulen, and Jan Fransoo. 2009. *Logistics drivers for shelf stacking in grocery retail stores: Potential for efficiency improvement*, International Journal of Production Economics **121**, no. 2, 620–632.

Zipkin, Paul. 2008. *Old and new methods for lost-sales inventory systems*, Operations Research **56**, no. 5, 1256–1263, available at `https://doi.org/10.1287/opre.1070.0471`.