Order Advancement in a Multi-Item Two-Echelon System: Theory and Case study

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Abstract

Motivated by a case at a large retail chain in the Netherlands, we study short-term order advancement in a multi-item, two-echelon system consisting of a distribution center (DC) and many stores. Application of traditional inventory replenishment rules may lead to a strongly fluctuating workload for order picking, and thus capacity problems, at the DC. By advancing replenishments for slow movers, we can balance the workload at the DC without negative impact on the service levels towards the final customer. In addition, we also have to deal with limited shelf- and storage space at the stores and balancing the workload for order receipt at each individual store. We develop a performance evaluation method and an optimization heuristic suitable for large problem instances (i.e., hundreds of stores and thousands of stock keeping units). Application to case data from the retail chain shows a reduction of 50% in the capacity shortage at the DC without causing major issues at store level. Sensitivity analysis shows that the capacity shortage could be reduced by up to 70% if backroom inventory is increased slightly. Reducing the capacity shortage at the DC decreases the improvement potential of workload balancing at the stores at the expense of a minor (almost negligible) increase in the backroom usage at the stores.

Keywords: Inventory; multi-echelon; workload balancing; order advancement; retail.

1. Introduction

Most retail chains use professional software for demand forecasting and inventory management at their stores and distribution center(s) (DC) that typically deploy traditional and proven methods (cf. Silver et al., 2017). Basically, these methods focus on balancing service levels to the final customer, such as fill rates, with the costs of ordering and holding inventory. However, the resulting short-term replenishment decisions also impact the workload at the DC (picking and dispatching) and at the stores (order receipt). This is typically not considered when releasing replenishment orders, which may lead to capacity overloads at the DC and in the stores. This is also caused by demand patterns that vary over days in the week (e.g., considerably more sales on a Saturday than on a Monday). Therefore, pooling replenishment orders over many stock keeping units and stores does not level out the DC workload.

We encountered this situation in a large retail chain in the Netherlands consisting of a single DC and around 1,500 stores. Despite the use of professional software, capacity problems occur at the DC where on some days many more order lines need to be picked and dispatched than on other days. As a consequence, a part of the order lines is delayed because demand exceeds pick capacity. This ultimately has an impact on product availability in the stores and thus on customer service levels. A simple solution seems to be to adapt capacity to demand. However, this turned out to be infeasible, because the labour market is tight and qualified personnel is very difficult to find. The alternative is to adapt replenishment demand to capacity without harming service levels at the stores. This means controlled advancing of replenishment orders instead of uncontrolled delay (with the risk of negatively affecting the service level).

Advancing replenishment orders needs to be done carefully to avoid negative impact on the stores. First, stores also have finite capacity to handle inbound deliveries, so they desire a decent allocation of the workload over days in the week. Second, advancing replenishment orders means that a store receives products earlier than originally planned, and possibly the products do not fit in the reserved shelf space on arrival. Of course, this situation is not desirable. As a partial solution, a store may keep some items in a backroom until shelf space has become available after customer demand has been satisfied, but that space is extremely limited: stores are often located in urban areas at expensive sites, so it is best for the retailer to use most space for the shopping area and as little as possible for non-commercial activities.

Any professional inventory management system will determine the parameters of the inventory control policies, such as reorder points that trigger a replenishment when the inventory position (inventory on hand plus amount on order minus backorders) drops to or below the reorder point (depending on the application). Combining these inventory policies with demand forecasts generated by the same system gives insight in the number of replenishment orders that we can expect for the upcoming period (say, one or two weeks), both at the DC and at all the stores. This means that we can identify capacity conflicts in the short run and try to avoid them by moving some replenishment orders to an earlier point in time, the *order advancement*. Thereby we have to make a trade-off between the costs of (i) demand exceeding DC capacity, (ii) order receipts exceeding handling capacity at the stores, (iii) backroom usage due to exceeded shelf space at the stores.

The number of possible order advancement actions to be considered is very large, as these include all combination of stores, stock keeping units (SKUs) and days within the planning horizon. Therefore, we reduce the number of options by considering the following aspects:

(i) To optimize transportation between DC and stores, the retailer uses fixed order- and delivery schedules to the stores (see Section 3 for details). That is, each store is assigned a set of two or three days in the week on which it can release and receive replenishment orders. For each store, we can only advance replenishment orders to a preceding replenishment opportunity.

(ii) Given the delivery schedules, fast-moving SKUs are typically replenished at almost every opportunity. So, advancing replenishment orders for these SKUs is not very beneficial and would likely lead to shelf space issues. Therefore, we focus on slow movers, where most improvement potential is expected. Besides, most SKUs at retail stores tend to be slow movers.

Summarizing, we consider order advancement in a multi-item, two-echelon inventory system for slow movers, aiming to balance capacities at both the DC and the stores in terms of order line handling and shelf space.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and gives an explicit contribution statement. In Section 3, we describe the problem derived from our retail case in detail. We present our model, assumptions, notation, and the analysis of a given scenario in Section 4. In Section 5, we develop heuristics to solve our model. Next, in Section 6, we develop numerical experiments based on the case data and provide numerical results. Finally, we give conclusions, managerial implications, and suggestions for future research in Section 7.

2. Literature review

Although retail operations is widely studied in literature, only few papers address operational inventory management decisions taking into account DC and in-store handling effort. Mou et al. (2017) provide a review of literature regarding in-store logistics and inventory distribution models. They find that, despite the fact that handling effort is a major entity in retail, it is rarely considered in the decision-making for inventory retail problems.

Several papers reveal that in-store handling (e.g., replenishing shelves) has a significant impact on the operational efficiency (Kuhn and Sternbeck, 2013; Van Zelst et al., 2009). Hence, it is necessary to include this in determining inventory policy parameters to increase the operational efficiency (Reiner et al., 2013). Van Donselaar et al. (2010) consider in-store handling in a European supermarket chain. They find that store managers significantly override order advices generated by inventory management systems by shifting some recommended peak-day orders to preceding nonpeak days. The authors also identified that store managers aim to balance in-store workload and improve product availability.

The main driver of in-store handling is the use of backroom inventory if the assigned shelf space is exceeded (van Zelst et al., 2009; Kuhn and Sternbeck, 2013). Drawbacks of backroom inventory are (1) increased labour costs due to double handling of items, (2) inventory inaccuracy (Raman et al. 2001), and (3) reduced service levels due to "phantom products", i.e., products that are available in the store but not on the shelf and hence are not visible for customers (Corsten and Gruen, 2003; DeHoratius and Raman, 2008). Although the use of backroom is common in retail stores, only few papers take its effects into account (Pires et al., 2015). Eroglu et al. (2013) are the first to quantify the expected amount of backroom inventory. They introduce the backroom effect as a consequence of misalignment of case pack size, shelf space capacity and inventory control policy. The authors show that ignoring the existence of a backroom effect results in significantly higher reorder points and total costs.

Next to in-store handling, the workload at the DC for order picking and dispatch also plays an important role in retail supply chain efficiency. Papers considering DC handling effort typically focus on the tactical or strategic level (e.g., optimizing delivery patterns, determining the unpack location of case packs or the size of case packs), see e.g., Sternbeck and Kuhn, 2016; Gaur and Fisher, 2004; Wenn et al., 2012; Broekmeulen et al., 2017. In contrast, we focus on the operational level, i.e., short-term order advancement. Moreover, most papers model a single-item problem and/or assume demand to be deterministic and stationary over time (see e.g., Sternbeck and Kuhn, 2016; Gaur and Fisher, 2004; Wenn et al., 2012; Broekmeulen et al., 2017; Van Woensel et al., 2013). However, this does not reflect the real situation retail sector (Ehrenthal et al., 2014; Taube and Minner, 2017). Our work differs from these papers by considering multiple items in a multi-echelon setting with stochastic, non-stationary demand.

To show our contribution to literature, we compare our paper to the closest related papers that consider instore and/or DC handling effort as well as backroom usage in Table 1. Summarized, we develop a method to advance replenishment orders according to tactical decision rules, such that we balance (i) handling workload at the DC for order picking and dispatch, (ii) handling workload at store level for order receipt, (iii) backroom usage for inventory exceeding dedicated shelf space. We are not aware of any study considering this trade-off, which highlights the contribution of our work. As explained in the introduction, we focus on slow movers with non-stationary stochastic demand. Moreover, we use a real-life data set with many stores, whereas most previous studies focus on a small number of stores. Given the large problem size, we need a computationally efficient optimization method.

Related papers	In-store		DC	Review type		Problem / model setting							Use of Case Data				
						Items	Echelon level	Demand			Planning			Number of stores			
	Backroom inventory	*Handling variability*	*Distribution center workload*	*Periodic*	*Continuous*	*Number of items*	*Number of echelons*	*Deterministic / stochastic*	*Distribution*	*Stationary / non-stationary*	*Planning horizon*	*Hierarchical planning level*	*Company data*	*1*	*2 - 50*	*51 - 200*	*> 200*
Van Donselaar et al. (2010)		✓		✓		Multi	Single	Stochastic	General	Stationary	Finite (rolling)	Operational	Supermarket chain		✓		
Sternbeck & Kuhn (2016)		✓	✓	✓		Single	Two	Deterministic	General	Stationary	Finite	Tactical	Supermarket chain		✓		
Gaur & Fisher (2004)			✓	✓		Single	Two	Deterministic	General	Stationary	Finite	Tactical	Supermarket chain				✓
Eroglu et al. (2013)	✓				✓	Single	Single	Deterministic	Gamma	Stationary	Finite	Tactical	Store audits		✓		
Broekmeulen et al. (2017)	✓	✓	✓	✓		Single	Two	Deterministic	Poisson	Stationary	Finite	Strategic	European retail chain		✓		
Taube et al. (2018)	✓		✓	✓		Multi	Two	Stochastic	Poisson	Non-stationary	Finite	Tactical		✓			
Van Woensel et al. (2013)		✓		✓		Single	Single	Stochastic	General	Stationary	Finite	Tactical	Supermarket chain	✓			
Wen et al. (2012)		✓	✓	✓		Multi	Two	Deterministic	General	Stationary	Finite	Strategic	US retail chain				✓
Taube & Minner (2017)		✓	✓	✓		Multi	Two	Stochastic	General	Non-stationary	Finite	Tactical	Retail chain			✓	
This paper	✓	✓	✓	✓		Multi	Two	Stochastic	Poisson	Non-stationary	Finite (rolling)	Operational	European retail chain				✓

Table 1. Papers considering handling effort and are closely related to our paper.

3. Case study

A large retailer specialized in health and beauty consumer goods in the Netherlands is studied in this paper. We explain the supply chain structure Subsection 3.1. Subsection 3.2 deals with the replenishment policies and the in-store handing, whereas Subsection 3.3 describes the DC handling.

3.1 Retail supply chain structure

The retail supply chain (Figure 1) consists of one central DC from which around 1,500 stores located in the Netherlands and Belgium are supplied. The largest part (i.e., around 80%) of the assortment consists of products with low demand.

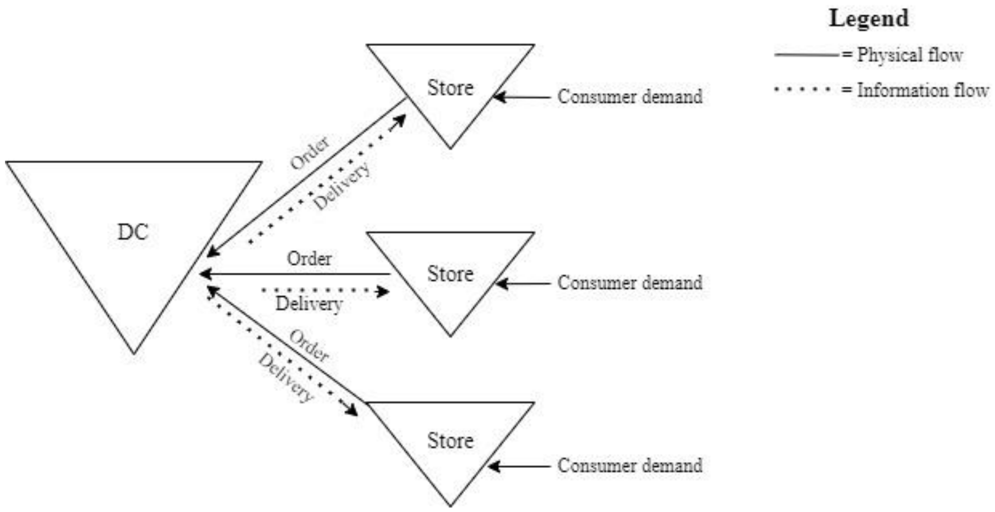

Figure 1. Retail supply chain in case study.

Every store is assigned to a fixed weekly order and delivery schedule for sake of transportation efficiency (i.e., transportation routes are optimized on these schedules). This schedule dictates on which days in the week the store can place replenishment orders. These orders will be picked the next day at the DC and delivered to the store the day thereafter (skipping the Sunday). So, the lead times are deterministic. Each store has two to four delivery moments per week, see Figure 2 for an example. The corresponding replenishment orders have to be placed two days in advance (skipping the Sunday).

D: Delivery day

Store	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
1	D	-	-	-	D	-
2	D	D	D	-	D	-
3	-	-	D	-	D	-
4	-	D	-	D	-	D
5	D	-	D	-	-	-
…						
1,500	-	D	D	-	D	-

Figure 2. Example store delivery pattern.

3.2 In-store operations and replenishment policy

The in-store process (see Figure 3) starts with a replenishment order that is delivered from the DC on a roll container two days later. The roll containers are taken over by store employees and brought to the sales room where initial shelf stacking takes places. In case the allocated shelf space for an SKU is insufficient for all items, the excess items have to be stored in the backroom until shelf space becomes available after consumer purchases. This leads to additional costs caused by (i) monitoring shelf space until backroom inventory is depleted, and (ii) additional handling effort due to moving items to and from the backroom instead of to the shelf immediately. Since stores have certain labour capacity available to restock shelves, they prefer a balanced handling workload over the delivery days, for similar reason as in the DC. We consider the allocation of shelf space to SKUs in the stores – a tactical decision - as given.

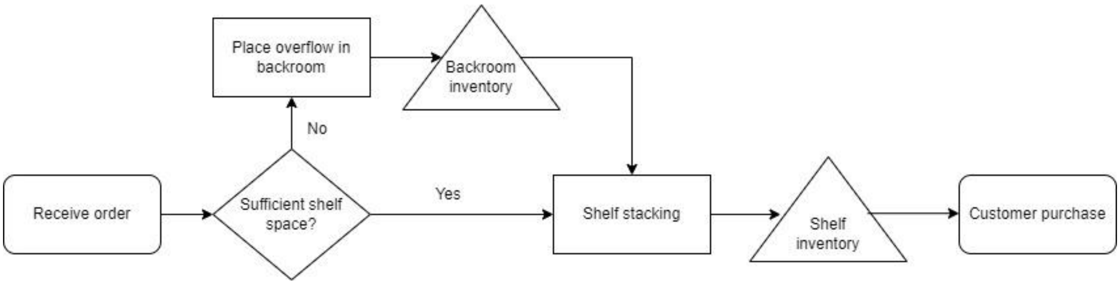

Figure 3. In-store processes

Given the fixed order and delivery schedule per store, each SKU is replenished according to a periodic dynamic replenishment policy with fixed lead times. The automated store replenishment system places orders according to a dynamic (R, s, nQ)-policy (cf. Silver et al., 2017). This means that every R periods the system is reviewed, where the review period R varies over time in our case. If the inventory position of an SKU is strictly below the reorder point s upon review, a replenishment order is created with size nQ such that the inventory position after ordering is equal to or larger than the reorder point. Here Q represents the case pack size. The reorder points of SKU-store combinations are dynamic, as the consist of the forecast demand during the two-day lead time plus a review period and the safety stock. The safety stock is determined based on a target service level, cf. Silver et al. (2017).

3.3 Order handling at the distribution center

An order placed at a store is received the next day at the DC. In general, a specific SKU-store order is denoted as an *order line*. A store order consists of many order lines, one for each specific SKU ordered. Each order line requires labour-intensive operations, i.e., orientation time, order picker traveling to the location of the SKU location in the DC and picking the case pack(s) and placing it on the load carrier for store delivery. Therefore, we use the number of order lines to be processed on a day as indicator for the workload at the DC. Because demand and therefore also store replenishments are stochastic, the total DC workload is stochastic as well. Besides, the DC workload may fluctuate heavily over the weekdays, which may lead to capacity shortages on specific days. Then, some replenishment orders have to be delayed until the next delivery opportunity. This leads to an increasing stock-out probability at the stores, which entails lower customer satisfaction and a lower profit margin because of lost sales.

Stores have finite labour capacity available to restock shelves, and limited space in backroom. As a result, stores are interested in minimizing backroom usage and balancing handling workload over the delivery days. However, they lack knowledge in considering this when placing a replenishment order. Since both the stores and the DC have finite capacity, short-term replenishment decisions need to be coordinated over all stores and over the DC without worsening customer service levels. Therefore, replenishment orders as scheduled by the automated system may be advanced in time, but not delayed. In the next section, we provide a detailed description of the model with its assumptions, notation, and mathematical expressions for the analysis of a scenario.

4. Model

This section formulates the performance evaluation model for the problem defined in the previous sections. In Section 4.1, we give a model outline with the key assumptions. The notation (Table 2) and is introduced in Subsection 4.2, followed by the derivation of expressions for several performance measurements given a scenario (reorder points) in Subsection 4.3, these being required to formulate the overall cost function in Subsection 4.4.

4.1 Model outline and assumptions

We consider a periodic-review, finite-horizon, multi-item, two-echelon inventory system consisting of a single DC and multiple stores. The inventories at the stores are controlled using an (R, s, nQ) inventory policy, where the (dynamic) policy parameters and the demand forecasts are given. This information is generated by the automated forecasting and inventory control system used by the retailer. We estimate for each combination of store, SKU, and store-specific order day the probability that a replenishment order will be released on each day in a certain planning horizon (say T days) and calculate three key performance indicators:

1. The expected workload at the DC per day, expressed as expected number of order lines.
2. The expected backroom usage per combination of store, SKU, and day within the planning horizon.
3. The expected workload per store per day, expressed as the expected number of received order lines.

From these performance indicators, we compute the following cost factors:

1. The costs of DC workload exceeding capacity with fixed penalty cost per order line.
2. The costs of backroom usage per store with fixed penalty cost per item.
3. The costs of workload variability over the delivery days in the planning horizon per store.

We can influence these cost factors by advancing orders. That is, we may temporarily increase a reorder point for each combination of store, SKU, and order day if this decreases overall costs.

Our model proceeds from the following assumptions:

1. The demand of each SKU-store combination follows a non-stationary Poisson distribution with known mean and is independent over SKUs, stores, and days. This is realistic due to the focus on slow movers for which it makes sense to advance orders, as these are irregularly ordered. Fast movers are typically ordered almost every order day, so order advancement does not make sense.
2. Demand that cannot be satisfied from stock on hand is lost.
3. The replenishment quantity is fixed. In principle, multiple case packs can be ordered, but for slow movers typically not more than one case pack is ordered.
4. The lead time between ordering and receipt at each store is deterministic. For sake of simplicity, we use in our expressions a lead time of two days, but this is straightforward to generalize.
5. Any store will replenish the same SKU only once during the planning horizon. This is reasonable since slow movers are not sold very frequently.
6. All store orders released will be picked at the DC the next day (which is trivial to generalize).
7. Inventories at the DC are always sufficient to fill the replenishment orders of the stores.
8. In case of order advancement, the size of the order will not be adapted.
9. The backroom area is sufficiently large to temporarily store the overflow when the delivery does not entirely fit onto the shelves. In our optimization method, we will penalize the use of backroom capacity thereby reducing its usage. Also, we will measure in the numerical experiments whether backroom usage is not excessive.
10. Costs for order picking at the DC and order receipt at the storages only depend on the number of order lines, irrespective of SKU characteristics like volume or weight. Most slow movers at the retailer are small items.

4.2 Notation

Below we describe the notation that we will use, and we refer to Table 2 for an overview of key notation. We denote the periods in the planning horizon by $t = 1, \ldots, T$, the retail stores by $j = 1, \ldots, J$, and the SKUs by $i = 1, \ldots, I$. We denote by D_{i,j,t_1,t_2} the cumulative demand for SKU *i* at store *j* over the periods $t_1, \ldots, t_2$, having mean μ_{i,j,t_1,t_2}.

Table 2. Overview of notation.

Symbol	Description
Indices:	
i	Index for SKUs (*i* = 1,..,*I*)
j	Index for stores (*j* = 1,..,*J*)
t	Index for days in planning horizon (*t* = 1,..,*T*)
n	Replenishment opportunity (n = 1,..,N_j)
Parameters:	
PC_t^{DC}	Pick capacity available at the DC on day *t* in number of order lines
V_{ij}	Shelf space of SKU *i* at store *j* in number of items
D_{i,j,t_1,t_2}	Cumulative demand for SKU *i* at store *j* over day t_1 up to and including day t_2 (Poisson distributed with mean μ_{i,j,t_1,t_2})
Q_i	Fixed lot size of SKU *i* (equal to the MOQ)
s_{ijt}	Reorder point of SKU *i* at store *j* on day *t*
OH_{ijt}	On hand inventory of SKU *i* at store *j* at the start of the planning period
$OO(k)_{ij}$	On order amount of SKU *i* at store *j* at the start of the planning period (end of day 0, to be received at the end of day *k*, where *k* = 1,2)
SOD_{jt}	Indicates if store *j* can order on day *t*
τ_{jn}	Number of days until replenishment opportunity *n* at store *j* since the start of the planning period
Decision variables:	
s'_{ijt}	Modified reorder point of SKU *i* at store *j* on day *t*
Auxiliary variables:	
IP_{ijt}	Inventory position of item *i* in store *s* at the end of day *t*, (**a random variable**)
p_{ijt}	Probability that store *j* will order SKU *i* at the end of day *t*
q_{nm}	Probability that demand in [1, τ_n] equals *m* and no replenishment order has been released up to τ_{n-1}
W_{jt}	Expected total number of order lines received at store *i* on day *t*
$\bar{W}_j$	Average number of order lines over the days which can be influenced at store *j*
W_t^{DC}	Expected total number of order lines to be picked at the DC on day *t*
CS_t	Expected number of order lines exceeding DC capacity on day *t*
Z_j	Costs of variability in the number of order lines received per day for store *j*
OH_{ijt}	On-hand stock of item i in store *j* at the end of day *t*, (**a random variable**)
B_{ijt}	Expected number of SKUs *i* in the backroom of retail store *j* at the end of day *t*
Cost factors:	
C_{ij}^{BR}	Backroom storage cost, which is the same for all items per store
$C^{OL_{DC}}$	Penalty costs of order lines exceeding the capacity of the DC per order line
C_j^{H+}	Penalty costs per order line above the weekly average number of order lines at store *j*
C_j^{H-}	Penalty costs per order line below the weekly average number of order lines at store *j*

4.2 Calculations for a given scenario

To evaluate a scenario, we proceed as follows. First, we derive the probability distribution for the timing of a replenishment order for each SKU-store combination within the planning horizon, including the probability that no replenishment order will be placed at all. Next, we discuss the performance evaluation at the DC and at store level, respectively. Combining all cost factors gives us the goal function to optimize in Subsection 4.3.

4.2.1. Probability distribution of the timing of replenishment orders

Assumption 5 states that we can place at most one replenishment order during the planning horizon. The timing of this order is uncertain, as it depends on demand to be realized. In the expressions below, we focus on a single SKU *i* at a single store *j*. For sake of readability, we drop the SKU and store index in this subsection. Without having placed any replenishment order, the inventory position at any day *t* equals the initial inventory position minus the cumulative demand, so $IP_t = IP_0 - D_{1t}$. The first opportunity to place a replenishment order is at day τ_1. The probability that we use this opportunity, denoted by p_{τ_1}, equals the probability that the inventory position falls below the reorder point, so:

$$p_{\tau_1} = P\{IP_{it} \leq s_t - 1\} = P\{D_{1t} \geq IP_0 - s_t + 1\} = 1 - F_{Pois}(IP_{i0} - s_{it} \mid \mu_{1t}) \qquad (1)$$

where $F_{Pois}(n|\mu)$ denotes the cumulative Poisson distribution with mean μ in the point n. Obviously, $p_t = 0$ if day *t* is not a replenishment opportunity, so if $SOD_t = 0$.

For any further replenishment opportunity, we condition on the event that no earlier replenishment opportunity has been used. For convenience, we use the shorthand notation $q_{n-1,m}$ for the probability that demand in $[1, \tau_{n-1}]$ equals m and no replenishment order has been released before. If we know these probabilities, we find the probability that a replenishment order will be placed at the n^{th} replenishment opportunity in the planning horizon by conditioning on the event that no replenishment order has been released up to opportunity $n - 1$, and the demand up to τ_{n-1} equals m. Analogously to Equation (1), we see that we will use replenishment opportunity *n* at τ_n if the total demand up to τ_n is at least equal to $IP_0 - s_t + 1$, which means that the demand on the days $\tau_{n-1} + 1$ until τ_n should at least equal $IP_0 - s_t + 1 - m$. So we find:

$$p_{\tau_n} = \sum_{m=0}^{IP_0 - s_{\tau_{n-1}}} q_{n-1,m} \left\{1 - F_{Pois}\left(IP_0 - s_{\tau_n} - m \middle| \mu_{\tau_{n-1}+1,\tau_{n,}}\right)\right\} \qquad (2)$$

We can compute the probabilities $q_{n,m}$ recursively. For the first replenishment opportunity, no replenishment order can have been placed before τ_1 by definition. Therefore, $q_{1,m}$ is simply a Poisson density with mean μ_{τ_1}. For replenishment opportunity *n* at τ_n, we find that the total demand equals *m* and no replenishment order has been issued (so at least $m \leq IP_0 - s_{\tau_n}$), if (i) no replenishment opportunity has been used up to τ_{n-1} and demand up to that replenishment opportunity equals $k \leq min\{m, IP_0 - s_{\tau_{n-1}}\}$, and (ii) cumulative demand on day $\tau_{n-1}+1, .., \tau_{n,}$ equals $m-k$, with $m \leq IP_0 - s_{\tau_n}$ (otherwise we use replenishment opportunity *n*). Denoting the Poisson density with mean μ in the point *m* by $f_{Pois}(m|\mu)$, we thus find the following recursive expression:

$$q_{n,m} = \sum_{k=0}^{IP_0 - s_{\tau_{n-1}}} q_{n-1,k}\, f_{Pois}\left(m-k|\mu_{\tau_{n-1}+1,\tau_{n,}}\right) \text{ if } m \leq IP_0 - s_{\tau_n} \tag{3}$$

where $f_{Pois}\left(x|\mu_{\tau_{n-1}+1,\tau_{n,}}\right) = 0$ if $x < 0$.

<u>Remark:</u> For a constant reorder point *s*, the order probabilities simplify to $p_{\tau_1} = 1 - F_{Pois}\left(IP_0 - s|\mu_{1,\tau_{1,}}\right)$ and $p_{\tau_n} = F_{Pois}\left(IP_0 - s|\mu_{1,\tau_{n,}}\right)$-$F_{Pois}\left(IP_0 - s|\mu_{1,\tau_{n-1,}}\right), n > 1$. Given the demand patterns (e.g. more sales on Saturday than on Monday), store reorder points tend to vary in time, however.

4.2.2. Performance at the DC

Now we have from equations (2) and (3) the probability distribution p_{τ_n} for the timing of the replenishment order within the planning horizon, where the probability that no replenishment order is issued within the planning horizon obviously equals $1 - \sum_{n=1}^{N_j} p_{\tau_n}$. Now let us add the item index *i* and store index *j* again. We use these probabilities to estimate the workload at the DC per day, noting that SKUs ordered in the store on day $t-1$ are picked in the DC on day t. As a result, the expected workload in the DC at time t is the sum of items ordered in all stores at time $t-1$, which is equal to:

$$W_t^{DC} = \sum_{i=1}^{I} \sum_{j=i}^{J} p_{ij,t-1} \qquad \forall t \geq 2 \tag{4}$$

The number of order lines exceeding picking capacity is a random variable. However, the uncertainty will be low due to the pooling effect over many SKUs and stores. Therefore, we ignore this uncertainty when calculating the number of order lines exceeding the capacity of the DC at day *t*, denoted by CS_t:

$$CS_t \approx (W_t^{DC} - PC_t^{DC})^+ \tag{5}$$

where x^+ is a shorthand notation for $\max\{x, 0\}$.

4.2.3. Performance at the stores

The performance at the stores consists of two components: (i) variability in the workload for receiving and storing products, (ii) backroom usage. First, note that the workload for receiving products, expressed in the number of order lines, depends on the number of replenishment orders issued two days before. Therefore, the expected number of order lines received by store j at day t equals:

$$W_{jt} = \sum_{i=1}^{I} p_{ij,t-2} \qquad \forall\, t \geq 3 \tag{6}$$

and the costs of varying workload within store j over the days that replenishments can be received are:

$$Z_j = \sum_{t=3}^{T} SOD_{jt} \left\{ C_j^{H+} \left(W_{jt} - \overline{W}_j \right)^+ + C_j^{H-} \left(\overline{W}_j - W_{jt} \right)^+ \right\} \tag{7}$$

where $\overline{W}_j$ denotes the average number of order lines per day that replenishments can be received, calculated as:

$$\overline{W}_j = \frac{1}{\sum_{t=3}^{T} SOD_{jt}} \sum_{t=3}^{T} W_{jt} \tag{8}$$

Now let us turn to the backroom usage. Note that we skip the first two days for the calculation of the backroom usage, as this is the result of earlier replenishments before the start of the planning horizon and can thus not be influenced. So, the first relevant day is $t = 3$. To evaluate backroom usage, we need the on-hand stock for each combination of SKU, store, and day in combination with the shelf space V_{ij}. The on-hand stock on day t depends on the timing of the replenishment order: If a replenishment order has been released latest two days before t, we have added a lot size Q_i to inventory, otherwise not. Let us denote the day that store j receives the replenishment order for SKU i by $\theta_{i,j}$ (i.e., the replenishment order is placed at the end of day $\theta_{i,j} - 2$). For $3 \leq t < \theta_{i,j}$, the on-hand stock of SKU i in retail store j at the end of day t (a random variable) then equals:

$$OH_{ijt} = IP_{ij0} - D_{ij1t} \tag{9}$$

Now the expected number of items i in the backroom of retail store j at the end of day t equals:

$$B_{ijt}^{(1)} = E\left[\left(OH_{ijt} - V_{ij} \right)^+ \right] = E\left[\left(IP_{ij0} - V_{ij} - D_{ij1t} \right)^+ \right] \tag{10}$$

In fact, $B_{ijt}^{(1)}$ can only be positive if there is a shelf space problem at the start of the planning period, resulting from previous order advancements. However, when $t \geq \theta_{i,j}$, the on-hand stock of SKU i in store j at the end of day t (random variable), ignoring lost sales, equals:

$$OH_{ijt} = IP_{ij0} + Q_i - D_{ij1t} \tag{11}$$

Then the expected number of SKUs i in the backroom of retail store j at the end of day t equals:

$$B_{ijt}^{(2)} = E\left[\left(OH_{ijt} - V_{ij}\right)^+\right] = E\left[\left(OH_{ij0} + Q_i - V_{ij} - D_{ij1t}\right)^+\right] \tag{12}$$

The expected number of SKUs stored in the backroom on day t (B_{ijt}) is a weighted average of $B_{ijt}^{(1)}$ and $B_{ijt}^{(2)}$, with as weights w_{ijt} the probabilities that the replenishment order is placed after t (or not at all):

$$B_{ijt} = \left(1 - w_{ijt}\right)B_{ijt}^{(1)} + w_{ijt}B_{ijt}^{(2)} \tag{13}$$

Here the weights are given by $w_{ijt} = \sum_{t=1}^{T-2} p_{ijt}\, \forall t \geq 3$. To evaluate (10) and (12), we need $E[(a - D)^+]$, where a is a constant and D is a Poisson distributed random variable with some mean value λ. In (10), $a = OH_{ij0} - V_{ij}$ and $a = OH_{ij0} + Q_i - V_{ij}$ in (11). Straightforward calculus reveals:

$$E[(a - D)^+] = aF_{Pois}(a|\lambda) - \lambda F_{Pois}(a - 1|\lambda) \tag{14}$$

4.3 Total cost function

The total cost function consists of the following factors:

- The costs of exceeding the DC handling capacity at $C^{OL_{DC}}$ per order line.
- The costs of workload variability at the stores, specified by Equation (7).
- The costs of the backroom usage during the planning horizon.
- The impact of backroom usage remaining at the end of the planning horizon.

The latter two cost factors require further specification. We have derived the backroom usage per combination of SKU, store, and day in (13) using (10) and (12). But the backroom size typically depends on the store size Larger stores tend to have larger backrooms, but then the impact of one additional product in the backroom should be less than for a small neighbourhood store. We measure the relative size of store j (rs_j) by the fraction of total yearly historical demand (HD_j) handled by that store:

$$rs_j = \frac{HD_j}{\sum_{j=1}^{J} HD_j} \tag{15}$$

Then we use as backroom usage cost factor per store:

$$C_j^{BR} = \left(\frac{\left(\frac{1}{J}\right)}{rs_j}\right) * \bar{C}^{BR} \qquad \forall j \tag{16}$$

where $\bar{C}^{BR}$ denotes the input backroom cost factor.

Backroom inventory remaining at the end of the planning period will lead to costs for days after the planning period. We also include these costs, assuming a linear decline in the backroom usage. These costs must be included in the total cost function. To determine these costs, the inventory is gradually decreased. The average days of backroom (DBR) still on hand at the of the planning period is:

$$DBR_{ij} = \frac{B_{ij,T}}{\mu_{ij}} \tag{17}$$

The costs of inventory in the backroom at the end of the planning period is therefore:

$$BC_{ij} = \sum_{t=1}^{DBR} (B_{ij,T-t} * \mu_{ij}) * C_j^{BR} \tag{18}$$

Combining all four cost factors mentioned at the start of this subsection, we find as total cost function:

$$TC = C^{OL_{DC}} \sum_{t=2}^{T} CS_t + \sum_{t=3}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} C_j^{BR} B_{ijt} + \sum_{j=1}^{J} Z_j + \sum_{i=1}^{I} \sum_{j=1}^{J} BC_{ij} \tag{19}$$

This is the objective function that we aim to minimize in the next section.

5. Optimization heuristics

Since (i) the total number of decision variables is large (dimension: $I*J*T$ with potentially thousands of products, hundreds of stores, and planning horizon T around 10-20 days), and (ii) frequent optimization is necessary (we face an operational planning problem), speed of the optimization procedure is essential. Therefore, we focus on simple and fast heuristics based on greedy marginal analysis as applied by Vaez-Alaei et al. (2018) and Van Donselaar et al. (2021) for a simplified version of our model (multi-item, single-echelon). We will develop two variants in this section, to be evaluated on performance and run time in Section 6.

As mentioned in the previous section, advancing an order of SKU i at store j from t_2 to t_1, where $t_1 < t_2$, can be achieved by increasing the reorder point at time t_1 (s_{ijt_1}). In each step of our greedy heuristics, we increase a reorder point of the combination of SKU, store and day that gives the largest reduction in total costs. The difference between the two heuristics that we present in this section is the size of the increase that can be one unit (Heuristic H1) or a proper choice of multiple units that significantly reduces computational effort (Heuristic H2). This process is repeated until there is no decrease in total costs possible anymore. In Subsection 5.1 and 5.2 we give the impact of an increase in a reorder point for both heuristics, followed by the generic search procedure in Subsection 5.3.

5.1 Heuristic H1

To determine the impact of advancing an order of SKU i at store j by increasing the reorder point at day t_i by 1, we have to recalculate the replenishment probabilities p_{ijt} $\forall t \geq t_1$. Obviously, the replenishment probabilities for other SKU-store-day combinations remain the same. This results in a new set of replenishment probabilities p'_{ijt}. Now the change in expected order lines for SKU i to be received at store j on day $t \geq t_1$ due to an increase in in the reorder point at t_1 is simply

$$\Delta W_{ijt} = p'_{ij,t-2} - p_{ij,t-2} \qquad \forall t \geq t_1 + 2 \tag{20}$$

A similar expression applies to the number of order lines to be processed at the DC, where we have a delay of one day:

$$\Delta W_t^{DC} = p'_{ij,t-1} - p_{ij,t-1} \qquad \forall t \geq t_1 + 1 \tag{21}$$

Using these modifications, we can quickly find the impact on the number of order lines exceeding the DC capacity and the costs of varying workload. See equation (5) and (7). Regarding the backroom usage, we observe that $B_{ijt}^{(1)}$ and $B_{ijt}^{(2)}$ remain the same, only the weights w'_{ijt} change for $t \geq t_1 + 2$. So, we only have to re-evaluate (13).

5.2 Heuristic H2

As a faster heuristic, we can avoid recalculating any Poison probability at all. If we set $s'_{ijt} = IP_{i,j,0} + 1$, then a replenishment order is placed at $t_1$with certainty. This results in:

$$p'_{ijt} = \begin{cases} p_{ijt}, \ t < t_1 \\ 1 - \sum_{u=1}^{t_1-1} p_{iju}, \ t = t_1 \\ 0, \ t > t_1 \end{cases} \tag{22}$$

Now the change in number of order lines processed at store and DC level (new minus old) are:

$$\Delta W_{ijt} = \begin{cases} 0, \ t < t_1 + 2 \\ \left(1 - \sum_{u=1}^{t_1-1} p_{iju}\right) - p_{ij,t-2}, \ t = t_1 + 2 \\ -p_{ij,t-2}, \ t > t_1 + 2 \end{cases} \tag{23}$$

and

$$\Delta W_t^{DC} = \begin{cases} 0, \ t < t_1 + 1 \\ \left(1 - \sum_{u=1}^{t_1-1} p_{iju}\right) - p_{ij,t-1}, \ t = t_1 + 1 \\ -p_{ij,t-1}, \ t > t_1 + 1 \end{cases} \tag{24}$$

The change in average workload of store *j* equals:

$$\Delta \bar{W}_j = \frac{1}{\sum_{t=3}^{T} SOD_{jt}} \left\{1 - \sum_{u=1}^{T-2} p_{iju}\right\} \tag{25}$$

The expected workload increases, because a replenishment order for SKU i at store j is issued for sure now, whereas we had some nonnegative probability that no replenishment order would be released.

Regarding the backroom usage, we only have to modify the weights w'_{ijt}. The differences are:

$$\Delta w_{ijt} = w'_{ijt} - w_{ijt} = \begin{cases} 0, \ t < t_1 + 2 \\ 1 - \sum_{u=1}^{t_1} p_{iju}, \ t \geq t_1 + 2 \end{cases} \tag{26}$$

And so, the change in expected backroom usage is:

$$\Delta B_{ijt} = B'_{ijt} - B_{ijt} = \begin{cases} 0, \ t < t_1 + 2 \\ \left(-\sum_{u=1}^{t_1} p_{iju}\right) B_{ijt}^{(1)} + \left(1 - \sum_{u=1}^{t_1} p_{iju}\right) B_{ijt}^{(2)}, \ t \geq t_1 + 2 \end{cases} \tag{27}$$

5.3 Finding near-optimal reorder points

Figure 4 shows the flow of the steps in the optimization, proceeding from the reorder points provided by the automated reordering system. We will explain the details below.

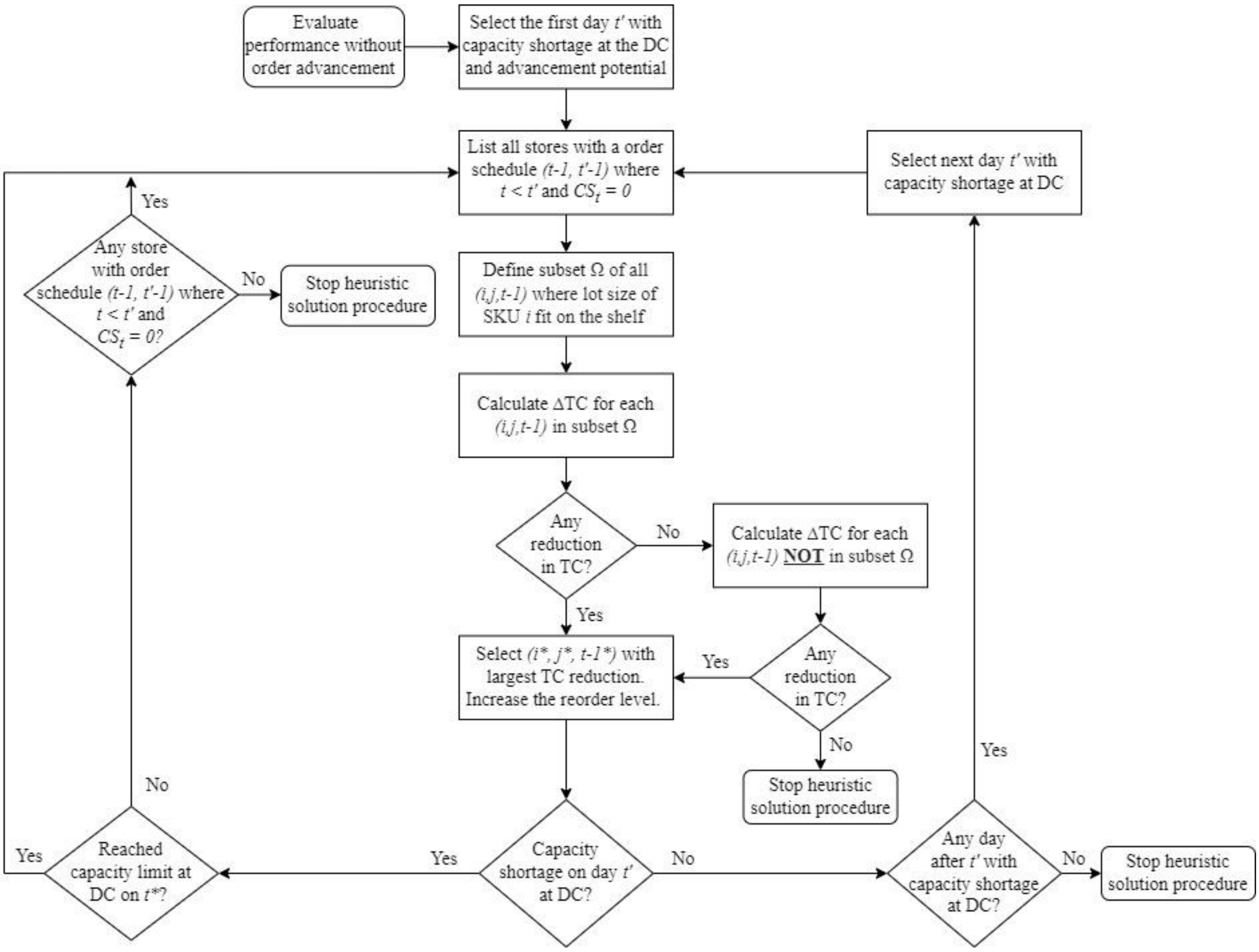

Figure 4. Flow diagram of greedy-heuristic solution procedure.

As a key bottleneck in the current way of working is insufficient handling capacity at the DC, we try to reduce DC capacity shortage first. That is, we select the first day t' with capacity shortage at the DC. We list all stores that are allowed to order both on day t' and on an earlier day $t < t'$ for which DC handling capacity is still available (call this subset *H*). For these stores, we search SKUs that have sufficient shelf space to store an early replenishment order for sure (even if no demand occurs), i.e., $IP_{ij0} + Q_i \leq V_{ij}$. The resulting store-SKU combinations are stored in a subset Ω.

The procedure first checks all SKU-store combinations in subset Ω and selects the tuple $(i^*, j^*, t-1^*)$ for which increasing the reorder point leads to the largest total costs reduction and implements this increase. We continue until the set Ω is empty, or no tuples $(i, j, t-1)$ within the set lead to a cost reduction anymore. The procedure then checks all SKU-store combinations not in subset Ω and increases the reorder point of the tuple $(i^*, j^*, t-1^*)$ that leads to the largest total costs reduction. We continue until no tuples $(i, j, t-1)$ lead to a cost reduction anymore.

Then we move to the next period t' in the planning period with capacity shortage at the DC and possible advancement opportunities given the order schedule. This process is repeated until all capacity shortages at the DC have been resolved, or no order advancement with cost benefit is feasible anymore.

6. Numerical experiments

In this section, we study the effectiveness and efficiency of our heuristics. We first define the experimental setup in Section 6.1. In 6.2, we discuss the basic scenario. Next, we perform an extensive sensitivity analysis and derive managerial insights in Section 6.3.

6.1 Experimental setup

We evaluated the heuristics on a real-world dataset with 65,745 SKU-store combinations from a large retailer in the Netherlands. The dataset consists of 214 retail stores supplied from one DC, and 342 SKUs. The number of SKUs differs per store. Each retail store is subjected to an order and delivery schedule similar to the examples in Figure 2. The SKUs are selected from two product categories (self-medication and baby food) with as criterion classification 'slow mover' in the automated replenishment system. Within this classification the average expected demand is not more than 0.69 per day. Demand forecasts, lot sizes and reorder points are supplied by the automated replenishment system the retailer uses. We selected four weeks of data, from 23 May until 19 June 2022. Table 3 shows the descriptive statistics for some key variables.

Table 3. Case study descriptive statistics.

65,745 SKU-store combinations	Expected Demand [units/day]	Lot size (Q)	Shelf space [units]
Minimum	0.05	1.00	2.00
Mean	0.21	4.82	6.91
Maximum	0.69	46.00	54.00
Standard deviation	0.06	2.83	3.36

We consider the following key performance indicators: (1) number of order lines exceeding the DC capacity, (2) expected backroom usage as fraction of the shelf space, averaged over the stores; in this way we also consider the store size, (3) coefficient of variation (CV) of the workload on the delivery day for an average store (averaged over all stores).

In the basic scenario, we use relative cost factors for the optimization, since they are more useful for comparing the performance measurements to nominal values. We used cost ratios capacity shortage at the DC: backroom inventory: workload variability = 3:2:1. The DC handling capacity is chosen as the average DC workload in the planning horizon. In this way, we experience both capacity shortage and excess capacity, which makes it possible to test the order advancement model. The planning horizon is $T = 12$ days and is equal to the first 12 days in the dataset.

We programmed both heuristics in Python version 3.9, using the Anaconda Platform. The experiments were all conducted on a PC with an Intel Core i5-1147G7 processor, 16 Gigabyte RAM memory and Windows 10 64-bit installed. No restrictions were set on the computational time as each run was completed in acceptable time.

6.2 Numerical results and insights

We show the results of the performance evaluation method before optimization in 6.2.1. Next, we show the results of the basic scenario after optimization for both heuristics in 6.2.2.

6.2.1 Performance evaluation before optimization

In the basic scenario before the optimization heuristics there are 1060 order lines exceeding the capacity limit of the DC. The average CV of the approximated workload over the delivery days in the week over all stores is 0.54. This shows that the workload over the delivery days at the stores is unbalanced. Moreover, we observed that 11.04% of the all SKU-store combinations lead to backroom usage. The backroom usage of those SKU-store combinations is on average 7.91% of the allocated shelf space. This indicates that there could already be a misalignment between case pack size and shelf space. This can be explained by the fact that the case pack size and shelf space are set by different parties in the supply chain: The case pack size is determined by the supplier (production plant) which focuses on production costs (supplier profits), whereas the shelf space is set by the retailer with the focus on attracting customers (retail profits). Since there is already considerable backroom usage, we only show the backroom inventory increase for the SKU-store combinations with advanced orders in our analysis.

6.2.2 Basic scenario

Figure 5 shows the workload at the DC before and after optimization for both heuristics. Note that we cannot advance order lines from day 1 and 2 to earlier days, as moving an order from day 2 to day 1 at the DC would mean that the store should place the replenishment order at day 0, before the start of the planning horizon. So, we only use day 3-12 for the performance analysis.

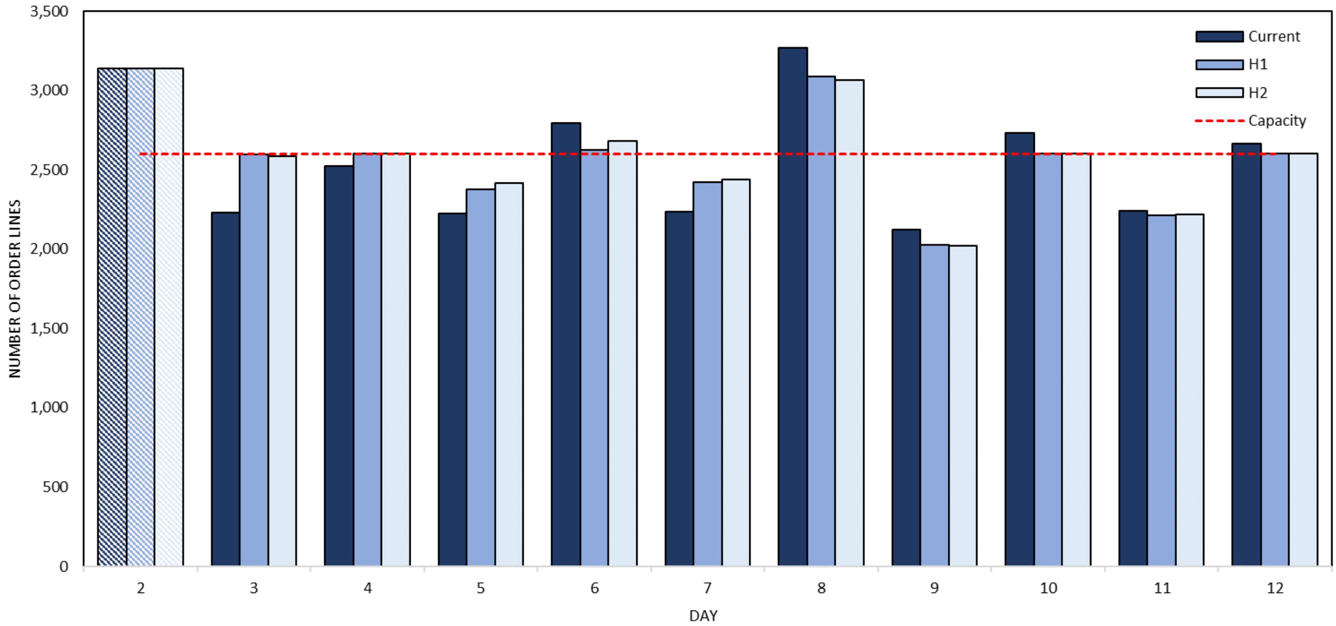

Figure 5. DC workload before optimization versus after H1 and after H2.

Heuristic H1 reduces the order lines exceeding DC capacity at the DC by 51.82%. There is still a capacity shortage on day 8 and excess space on day 5 and 7. The probability that we can advance from day 8 to day 7 is low because there are few stores with a delivery schedule that allows for deliveries on two consecutive days. We could also advance from day 8 to day 5, however, from in-depth analysis we see that the reduction in costs of order lines above the capacity on day eight does not outweigh the extra costs of backroom inventory on day five (= day four in the stores). We also find that the average expected backroom inventory does hardly increases under the current cost structure, which means that we mainly advance orders that directly fit into the shelves. The average CV of the approximated workload over the delivery days in the week over all stores is reduced with 0.042. In conclusion, the capacity shortage at the DC is decreased without any negative impact at store level. We provide the detailed results per performance measurement in Appendix A (Table A1).

Heuristic H2 performs almost as well as H1 regarding the reduction of order lines above the capacity at the DC (48.27%). The average expected backroom inventory of the advanced SKU-store combinations increases very slightly with 0.51% of the allocated shelf space. Also, the reduction in workload variability at store level is somewhat less (0.040 versus 0.042 for H1). Moreover, the overall expected workload in the short run increases, since we replenish for sure now. In the long run, this does not make any difference, since demand remains the same and the products have to be picked and received at some day anyway. Nevertheless, planners consider it an advantage to know for sure when to place a replenishment order.

We observe that we can advance many orders without exceeding the shelf space. As a result, we improve the in-store product availability, which is beneficial for reducing stockouts and stimulating demand as the customer perceives nice full shelves (cf. Van Donselaar et al., 2010). Figure 6 shows that the shelf utilization of the advanced orders increases by more than 10% for both heuristics. We conclude that we find results that are beneficial both at DC and store level.

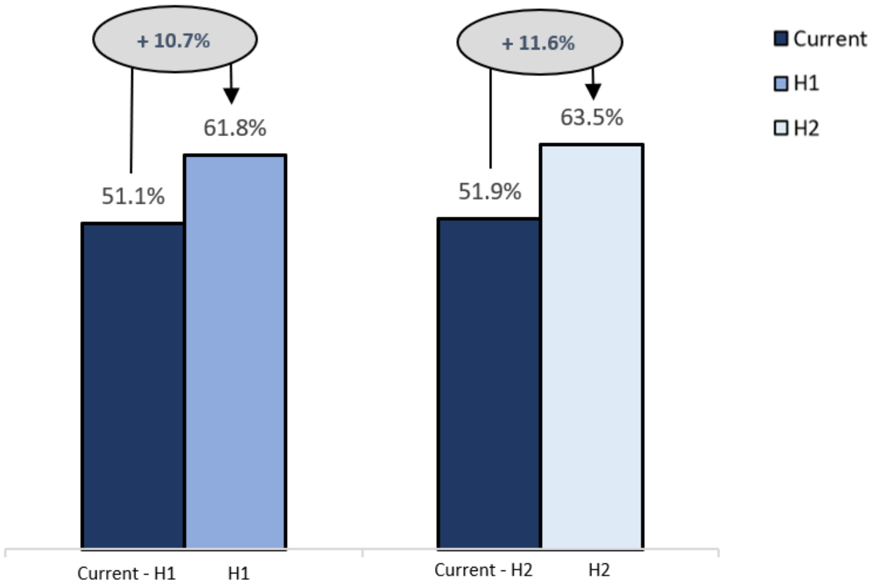

Figure 6. Shelf utilization of advanced orders - before optimization versus after H1 and H2.

The computation times of H1 and H2 in the basic scenario are 93 and 37 minutes, respectively. H2 requires fewer computations in every iteration (since the Poisson probabilities do not have to be recomputed), and typically uses less iterations as steps are larger. The major determinant of the computation time is the number of iterations, which are 3351 and 1653 for H1 and H2, respectively. So H2 performs slightly worse, but is considerably faster than H1. This may be an argument when moving to larger problem instances.

6.3 Sensitivity analysis and further insights

In this subsection, we perform a sensitivity analysis on DC capacity, length of planning horizon, shelf space, and cost factors:

- DC capacity: up to 10% more than in the basic scenario.
- Planning horizon varying between 8 and 24 days.
- Shelf spaces at the stores: 10% less or 10% more; given the structurally expanding product assortment, it could well be that the average shelf space available per SKU will decrease.
- Cost ratios for DC capacity shortage, workload variability at stores, and backroom usage: 5:1:1, 10:1:1, 1:5:1, 1:10:1, 1:1:5, and 1:1:10.

6.3.1 Sensitivity for DC capacity

In Figure 5 we saw that capacity is tight. We therefore increase the capacity limit at the DC stepwise by 1% until 10% additional capacity is reached and rerun the heuristics. We modify the capacity parameter with the aid of a scaling factor f(capacity). Figure 7 shows the impact of a marginal capacity increase on the reduction in capacity shortage.

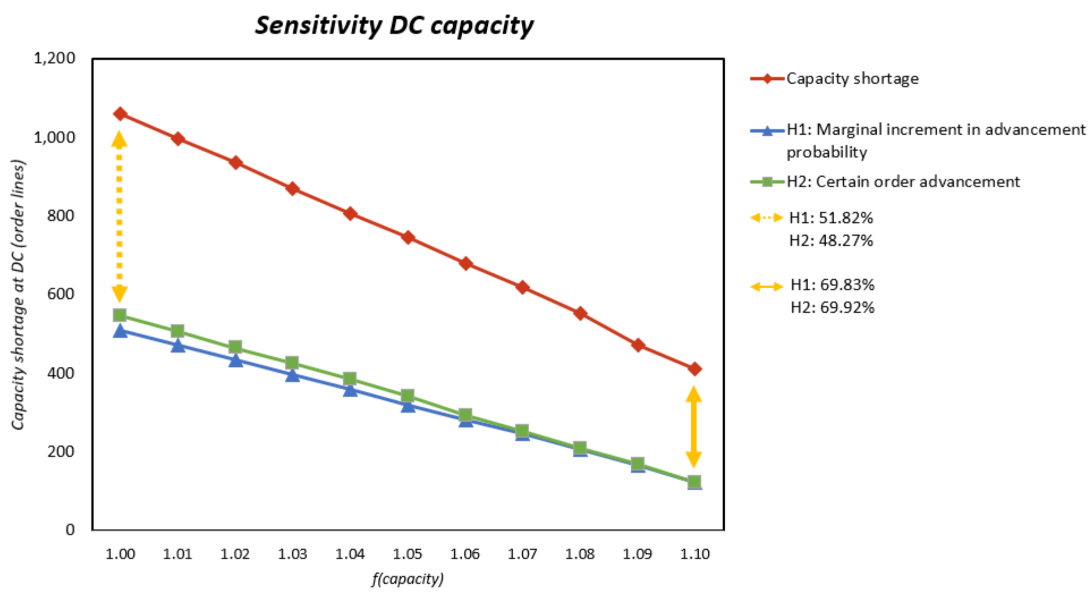

Figure 7. Impact of marginal capacity increases on reduction in capacity shortage.

Obviously, the capacity shortage is reduced when increasing the capacity limit of the DC. A more interesting observation is the relative increase of reduction in capacity shortage. This reduction can be explained by the fact that while increasing the capacity limit, there is relatively more excess space on earlier non-peak days which leads to a performance improvement of both heuristics. When increasing

DC capacity by 10%, the heuristics H1 and H2 can reduce the remaining capacity shortage by 69.83% and 69.92%, respectively. Notably, heuristic H1 works better when capacity is tight, but when there is ample capacity, H2 works slightly better. The impact on expected backroom inventory and CV of the workload over the delivery days is very small or even negligible.

6.3.2 Sensitivity for length of the planning horizon

We expect that a larger planning horizon increases the planning flexibility but will also increase run times. Therefore, it is useful to gain insight into the impact and benefit of considering a longer or shorter planning horizon. We consider horizons ranging from T = 8 days to T = 24 days, see Figure 8. Between T = 8 days and T = 14 days, the reduction in capacity shortage at the DC doubles. Further extension of the planning horizon does not help reducing capacity shortage. A drawback of increasing the planning horizon is the increase in computation times, see Table 4.

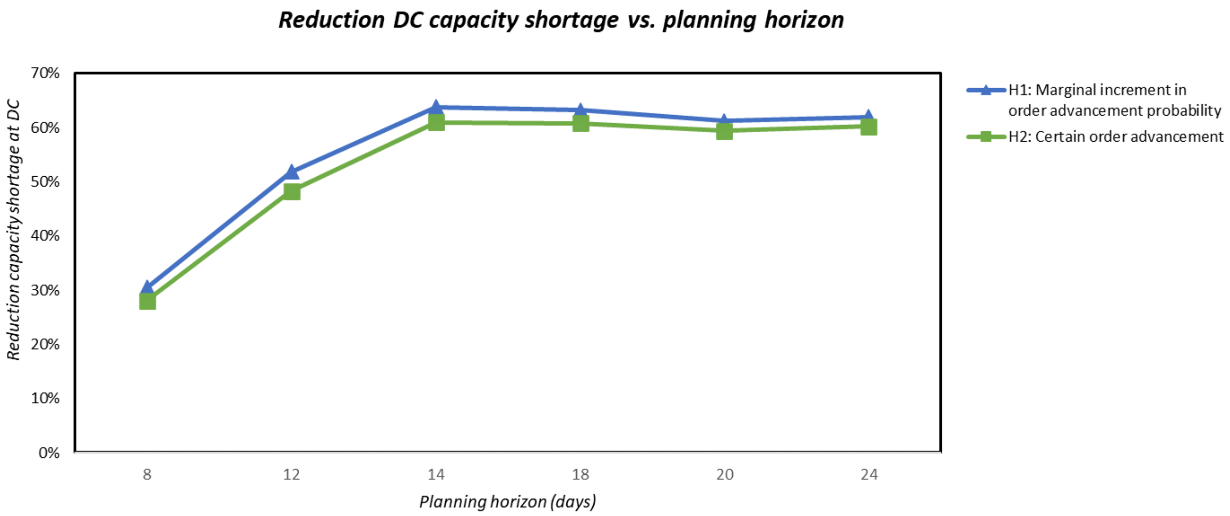

Figure 8. Impact of planning horizon on reduction in order lines exceeding the capacity limit.

Table 4. Computational times depending on the planning horizon (in minutes).

	Planning horizon T					
	8	12	14	18	20	24
H1	48.94	92.53	130.81	163.39	201.42	249.29
H2	33.14	37.01	44.73	67.00	81.93	96.04

6.3.3 Sensitivity for store shelf space

We expect that available shelf space may have a significant impact on the improvement potential, since it determines to which extent orders can be advanced without having to use backroom capacity. We therefore investigate two scenarios, one which 10% additional shelf space capacity and one with 10%

less shelf space capacity, see Figure 9. We modify the shelf space parameter with the aid of a scaling factor f(shelf space), where f(shelf space) = 1.0 indicates the basic scenario.

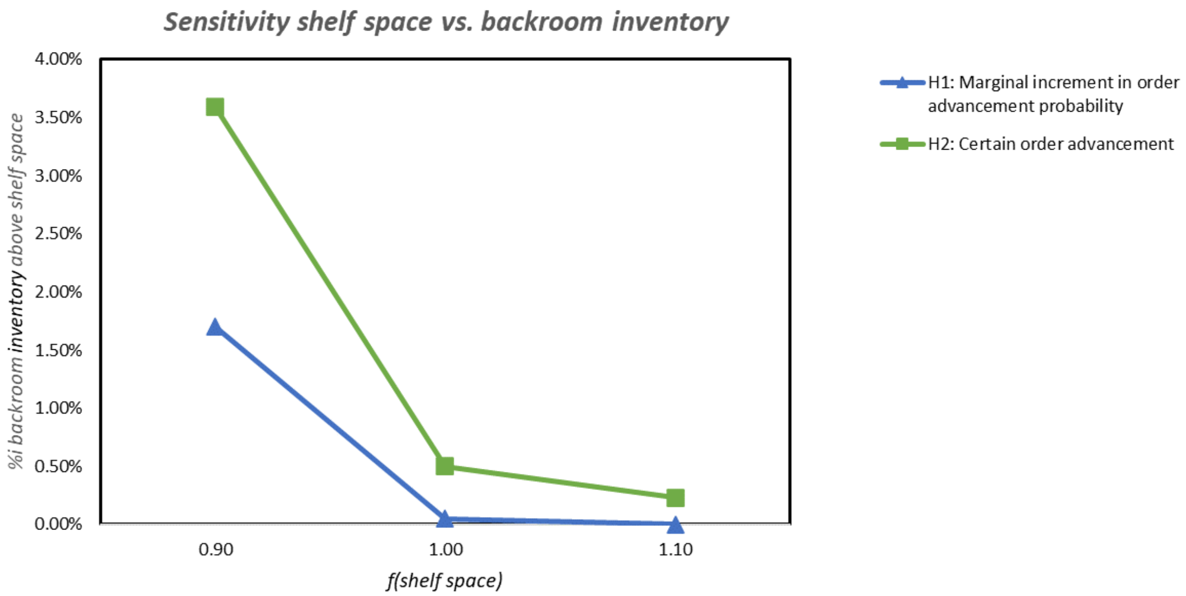

Figure 9. Impact of marginal capacity increases on reduction in capacity shortage.

We observe that a 10% reduction in shelf space leads to an increase of the expected backroom inventory. The impact of less shelf space is for H2 three times higher than for H1. Further, expected backroom inventory hardly decreases if we increase the shelf space. Also, 10% less shelf space leads to less reduction in DC capacity shortage (about 6%) with negligible impact on the CV of the store workload, see Table A1 in Appendix A for details.

6.3.4 Sensitivity analysis cost parameters

The cost parameters – in particular their ratio – are important inputs for the order advancement model. Therefore, to evaluate its robustness against different settings of ratios, a sensitivity analysis was carried out. So far, the basic problem instance assumed the original costs reported by the case company. In other words, $C^{OL_{DC}}$: $\bar{C}^{BR}$: C^{H+}: C^{H-} = 3:2:1:1. The parameter settings are chosen with the aid of a scaling factor f (.). The factor f(DC) modifies the DC workload cost parameter. The factor f(variability) changes the cost parameters for workload variability over the delivery days at the stores. Finally, the factor f(backroom) modifies the backroom inventory cost parameter. In each analysis the scaling factors are equal to 1 and one of the cost parameters is varied, so for example f(DC=5) gives a cost ratio $C^{OL_{DC}}$: $\bar{C}^{BR}$: C^{H+}: C^{H-} = 5:1:1:1. Since the difference in results of the sensitivity analysis for H1 and H2 is small, we only show the results of the sensitivity analysis of H1 in Figure 10.

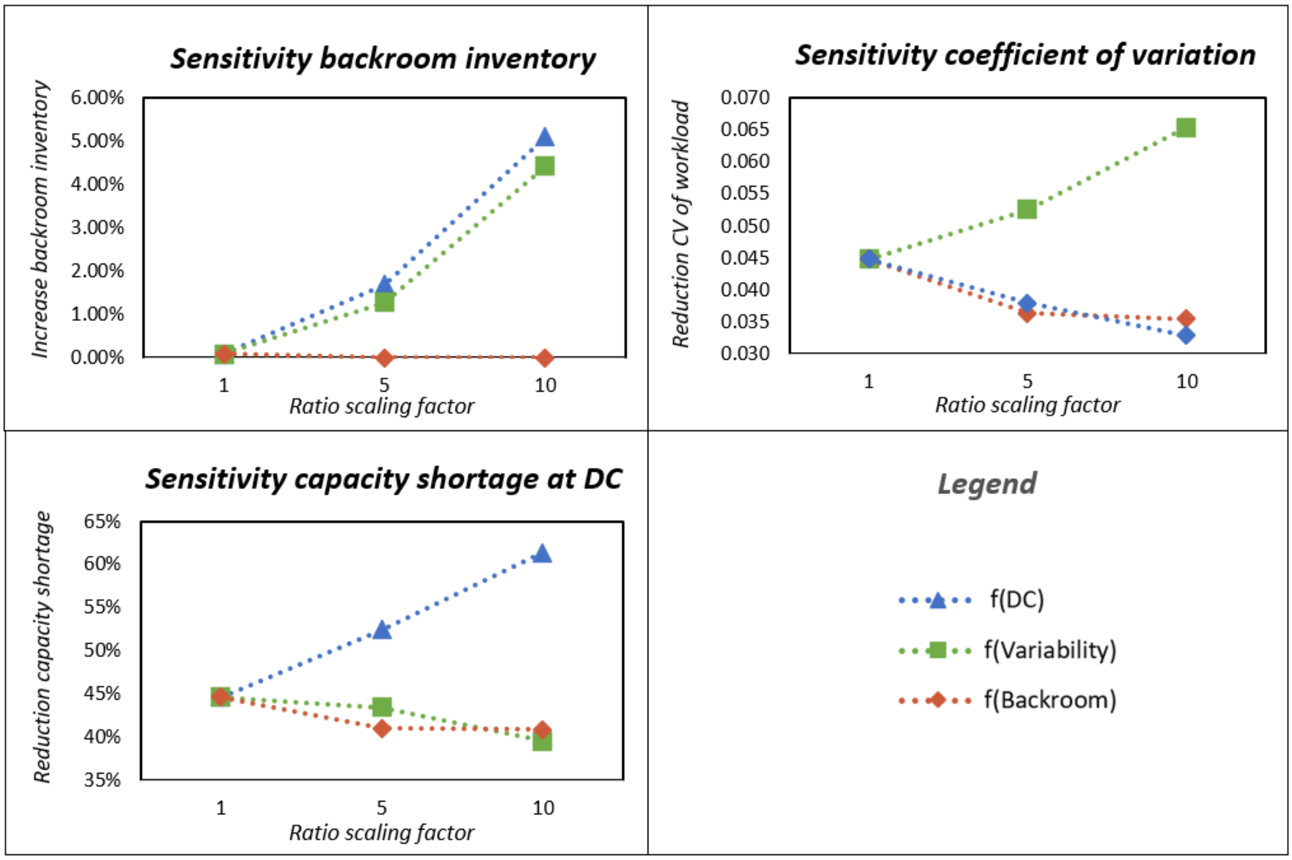

Figure 10. Impact of cost factors on performance measurements with heuristic H1.

It is evident that an increase of the DC workload cost factor reduces the capacity shortage at the DC. However, this increase negatively impacts the expected backroom inventory and workload variability over the delivery days at the store. Especially for f(DC) > 5, the increase in expected backroom inventory at the stores is substantial. The workload variability over the delivery days at the stores decreases when the DC workload cost factor increases. This may be explained by the fact that increasing importance is dedicated to decreasing the capacity shortage at the DC instead of decreasing the workload variability over the delivery days at the stores. Moreover, we observe that the increase in expected backroom inventory is zero if we increase the backroom cost factor. This means that we only advance orders that do not require backroom inventory space. We see that this slightly negatively influences the reduction in capacity shortage at the DC. This may be explained by the fact that the order advancement optimization stops earlier, since there is no more reduction in total costs. When f(backroom) is larger than or equal to 5, there is no increase in expected backroom inventory anymore. Consequently, the reduction in capacity shortage does not change anymore. Further analysis shows that an increase of the variability cost factor reduces the CV of the workload over the delivery days at the stores, especially when f(variability) > 5. However, a drawback of this increase is that it negatively influences the expected backroom inventory and the workload variability over the delivery days at the stores. We observe that varying the variability cost factors at the stores between f(variability) = 1 and f(variability) = 10, reveals an increase of the expected backroom inventory by a factor of nine. The decrease of the reduction in capacity shortage at the DC can be explained by the fact mentioned above that increasing importance is dedicated to decreasing the workload variability over the delivery days at instead of decreasing the capacity shortage at the DC. However, we observe that the decrease of the reduction is relatively small. Lastly, we observe that increasing the cost factor f(DC) from 5 to 10 leads to an increased backroom usage and a reduced capacity shortage. Further analysis reveals that - for an extreme cost ratio - the capacity shortage can be reduced by 70% under 10% more backroom usage (as percentage of the allocated shelf space).

7. Conclusion

We presented a new operational order advancement decision model suitable for slow movers in a multi-item, two-echelon, periodic-review inventory system. Our decision model advances replenishments of slow movers from peak days to non-peak days, aiming to balance capacities at both the DC and the stores in terms of order line handling and shelf space. We furthermore derived two greedy marginal-analysis heuristics to optimize the reorder points for individual SKU-store-time period combinations. Based on or analysis, we draw the following key conclusions based on a case study for a Dutch retailer:

1. Advancing replenishment orders does not negatively affect the service to the stores and may increase product availability as observed by the higher shelf utilization.
2. The workload exceeding the capacity limit at the DC can by reduced by 50-70% (see Figure 7).
3. The workload over the delivery days at the stores can be more balanced, with a reduction in the coefficient of variation of order lines up to 0.065.
4. We can advance many orders without exceeding the shelf space, as confirmed by the limited backroom usage (see Figure 10).
5. By advancing orders we improve the in-store product availability by more than 10 percent points, which stimulates demand (see Figure 6).
6. Heuristic H2 that guarantees order advancement yields slightly lower performance at considerably higher computation speed (around a factor 3). The computation speed is an advantage when moving to larger problem instances. Besides, planners consider it an advantage to know for sure when to place a replenishment order.

The study has some limitations. First, our model only considers at most one replenishment order for a specific SKU-store in the planning period. This is justified as the model is applied on slow movers for which it is unrealistic that more than one replenishment is required within two weeks planning horizon. Second, we assume a Poisson distribution for the demand, also because we have little information on the exact shape of the demand distribution. Other demand distributions may lead to different results, although the modelling logic remains the same.

We foresee several opportunities for future research. For example, we could consider order postponement next to advancement only, insofar this does not seriously affect the service levels. Also, advancing orders over more than a single replenishment period only could be beneficial. Demand variability may be higher or lower for slow movers, and some SKUs facing intermittent demand exist in the assortment. The latter could for example be modelled by a compound Poisson distribution. Finally, other retail sectors may require specific model extensions, such as perishability of food products. In such a case, order advancement may have a negative impact on the fraction of products that need to be disposed.

Acknowledgements

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Appendix A. Experimental results

This appendix shows in Table A1 the experimental results. All percentage difference refer to the performance evaluation before optimization.

Table A1. Experimental results for each experiment. E[B] = Expected backroom inventory as fraction of the shelf space above the standard shelf space, CV = coefficient of variation of workload at the delivery days, CS = Capacity shortage at the DC.

Experiment	$\Delta E[B]$		ΔCV		ΔCS	
	H1	H2	H1	H2	H1	H2
Case problem setting	0.10%	0.51%	-0.042	-0.040	-51.82%	-48.27%
Sensitivity analysis						
Capacity + 10%	0.00%	0.38%	-0.045	-0.043	-69.83%	-69.92%
Shelf space - 10%	1.70%	3.59%	-0.040	-0.039	-44.62%	-42.79%
Shelf space +10%	0.00%	0.23%	-0.047	-0.044	-58.45%	-54.07%
T = 8	0.06%	0.43%	-0.031	-0.028	-30.49%	-28.10%
T = 14	0.11%	0.92%	-0.049	-0.047	-63.82%	-60.99%
T = 18	0.14%	2.57%	-0.060	-0.054	-63.2%	-60.8%
T = 20	0.16%	2.73%	-0.060	-0.062	-61.25%	-59.42%
T = 24	0.18%	2.67%	-0.061	-0.063	-61.99%	-60.20%
1:1:1:1	0.09%		-0.045		-44.62%	
5:1:1:1	1.69%		-0.038		-52.43%	
10:1:1:1	5.11%		-0.033		-61.40%	
1:5:1:1	0.00%		-0.036		-41.05%	
1:10:1:1	0.00%		-0.036		-40.85%	
1:1:5:5	1.29%		-0.053		-43.49%	
1:1:10:10	4.43%		-0.065		-39.53%	

slimstock

Guideline for order advancement implementation

Balancing the internal resource capacity requirements in the supply chain

experts in inventory optimisation

Introduction

This document serves as guideline for implementation of the master project ''Order Advancement in a Multi-Item Two-Echelon System: Theory and Case study'' conducted at Slimstock in 2022 by Quinziano ten Hagen. The goal of this project is to reduce the number of order lines exceeding the capacity limit at the DC. Therefore, we focus on optimizing replenishment orders from local stores to the distribution center (DC), by deciding upon which replenishment order of a specific store-item-day combination to advance to a preceding order moment (given the order- and delivery schedules).

An advantage of advancing order lines from peak days to non-peak days is that it does not adversely affect availability and thus on customer service levels. However, by advancing replenishment orders we have to satisfy multiple stores requirements; (1) stores also have finite capacity to handle inbound deliveries (i.e., they desire a decent allocation of the workload over the delivery days in the week) and (2) stores receive products earlier than originally planned, this can lead to situations where products do not fit in the reserved shelf space on arrival. In this situation, products that do not fit on the shelf could be temporarily stored in the backroom. However, this not desirable since the backroom capacity is limited and ensures double handling effort. Therefore, we have a trade-off between (i) the order lines exceeding the DC capacity, (ii) balancing the handling effort at the stores over the delivery days in the week planning horizon, and (iii) backroom inventory due to exceeded shelf space at the stores.

For the problem definitions/introduction, literature review, performance evaluation method, improvement heuristics, case study results, we refer to ''Order Advancement in a Multi-Item Two-Echelon System: Theory and Case study''.

The remainder of this document is structed as follows. Sections 1 provide the management summary. Section 2 elaborates on the practical implications of this research and provides an implementation plan. Finally, we provide our recommendations to Slimstock in Section 3.

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Contents

1. Management summary

Problem

This research on balancing the workload in a retail supply chain was done for Slimstock, an inventory optimization software and consultancy company. Typically, retail supply chains use professional software for demand forecasting and inventory management at their stores and distribution center(s). The main focus of this kind of professional software is on optimizing inventory management processes by balancing service levels to the final customer, such as fill rates, with the costs of ordering and holding inventory. However, optimizing the supply chain encompasses more than only the aspect of inventory management (e.g., handling). This is typically not considered when releasing replenishment orders at the stores. As a consequence, the replenishment orders of the stores fluctuate significantly over time. This leads to capacity problems at the distribution center where on some days many more order lines need to be picked and dispatched than on other days. This causes the workload for the order pickers in distribution centers to be highly unstable. Furthermore, capacity is limited and typically very flatly distributed through the week. As a consequence, a part of the order lines is delayed because demand exceeds capacity. This may ultimately have impact on product availability in the stores and thus on customer service levels.

Literature

Although retail operations is a widely studied area in literature, there is a limited number of papers that address inventory management decisions that consider both the DC handling effort and the in-store handling simultaneously. From literature review, we found several papers considering in-store handling. Those papers reveal that in-store handling has significant impact on the operational efficiency. The main driver of in-store handling is the use of backroom inventory if the assigned shelf space is exceeded. Although backroom is common in traditional retail stores, only a few papers take its effects into account. Next to in-store handling, the workload at the DC supplying the stores, for example for order picking and dispatch, also plays an important role in retail supply chain efficiency. Papers considering DC handling effort typically focus on tactical or strategic level and model a single-item problem and/or assume demand to be deterministic and stationary over time. Our research focuses on the operational level and considers multiple items with stochastic, non-stationary demand. In other words, to the best of our knowledge there are no models directly applicable to our research problem in the existing literature.

Model

After analysing relevant literature, we developed *Order Advancement*: a new model consisting of a performance evaluation method and optimization heuristics. Typically, professional inventory management system generates demand forecasts and determines the parameters of the inventory control policies. This gives the insight in the number of replenishment orders that we can expect for the upcoming period, both at the distribution center and at all the stores. In this way, capacity conflicts in the short and the long run can be identified and gives the opportunity to avoid them by moving replenishment orders to an earlier point in time (order advancement). Postponing replenishment orders is also possible, but this might yield service level loss and is therefore out-of-scope. With order advancement we have to make a trade-off between (i) reducing order lines exceeding DC capacity, (ii) order receipt handling effort at the stores over the delivery days in the week, and (iii) backroom inventory due to exceeded shelf space at the stores. To limit the available options, we consider only slow-movers and advancing to a single preceding replenishment opportunity. The order advancement model consists of two parts, (1) performance evaluation method and (2) optimizations heuristics. The performance evaluation method calculates the expected workload at the DC, handling workload at each individual store, and expected backroom inventory. Moreover, the performance evaluation method gives the total cost function which comprises three relevant cost components: DC capacity shortage penalty costs, store workload handling costs, and backroom inventory costs. Since we encounter a large problem instance and frequent optimization (e.g., daily, or weekly) is necessary, speed of the optimization procedure is essential. Therefore, we focused on a simple and fast heuristics based on greedy marginal analysis. We developed two variants of the greedy marginal heuristics. In each step of our greedy heuristics, we increase a reorder point of the combination of SKU, store and day that gives the largest reduction in total costs. The difference between the two heuristics that we present is the size of the increase in reorder point, that can be one unit (Heuristic H1), or a proper choice of multiple units that significantly reduces computational effort (Heuristic H2). This process is repeated until there is no decrease in total costs possible anymore.

Results

We conclude that developed short-term order advancement model is beneficial for balancing the handling workload at both DC and stores. First of all, advancing replenishment order does not negatively affect the service to the stores. Second, advancing replenishment orders led to a more balanced workload at the DC, with a possible reduction of order lines exceeding the DC capacity of over 50%. Third, order advancement also led to a more balanced handling workload at the stores, with a coefficient of variation (CV) reduction up to 0.065. Next, order advancement also led to significant more fully stocked shelves, which improves the product availability and could be beneficial in reducing stockouts and stimulating demand. A drawback of order advancement is that it could slightly increase the total average backroom inventory in the stores. However, this increase is very small and does not outweigh the benefits.

Sensitivity analysis shows that we can increase the reduction of order lines exceeding the DC capacity limit up to 70%. Moreover, the heuristic in which we advance a certain order for sure makes larger steps in each iteration and fewer computations. This makes the heuristic three times faster than the marginal incremental heuristic, while the performance in reduction of order lines exceeding the DC capacity is almost similar. This makes the heuristic especially relevant in practical instances, where problem instances of traditional retail supply chains are enormous.

Recommendations

First, we recommend Slimstock to implement the order advancement model in the current replenishment method of slow-moving items according to the implementation plan. Slimstock should evaluate whether the order advancement model performs properly for all assortment categories as well as for multiple retail settings including events and promotions. Second, we recommend Slimstock to conduct further research on optimizing order- and delivery schedules of the stores. In this way, Slimstock could advise its clients about the stores' delivery schedules. Third, we advise Slimstock to update the data (e.g., shelf spaces) in the inventory management software frequently, as the quality of our order advancement model is determined by the quality of the input data. Fourth, we recommend Slimstock to create a dashboard that visualizes the performance indicators. Finally, we recommend Slimstock to determine the set of products for which the order advancement model is applicable and the customer specific ratio of the cost parameters. Future work can focus on more general supply chain structures, or applications to particular sectors (e.g., food retail), or extending the method to allow for other demand distributions to capture other demand classes.

2. Implementation plan

The goal of the order advancement model (i.e., performance evaluation method and greedy heuristics) is to reduce the order lines at the DC, by optimizing the reorder levels at SKU-store-day level, while also considering the impact at the stores for both delivery moments and backroom usage. In this section, we elaborate on how the suggested model can be implemented and what the first steps are Slimstock has to take after finalizing this research. In Subsection 2.1 we summarize which data are required of a client to implement the suggested order advancement model. Next, we explain the steps that has to be taken in the implementations phase in Subsection 2.2.

2.1. Input data

To implement the proposed order advancement model, data is required. First of all, we need of each SKU in every store the following data: current starting inventory position, replenishment policy and parameters such as: order- and delivery schedules, , minimum order quantity (MOQ), and fixed shelf space, historical demand transactions without promotions or events, daily demand forecast, backroom size, and daily DC order picking capacity.

In the proposed order advancement model, we assume one capacity limit for the entire DC. However, the DC could consist of several areas (e.g., dynamic picking system (DPS), sorter, volume, free storage) with its own order picking capacity limit. In this situation, the suggested order advance model requires a relatively small adjustment since we have several smaller problem instances instead of one large problem instance (i.e., one problem instance per area). One important assumption here is that each article is only picked from 1 picking area / method. Balancing between picking from different areas is out-of-scope. This could only make the optimization heuristics faster. In case the available pick capacity can be shifted between areas, we have again one large problem instance. Furthermore, as mentioned above, we need the daily demand forecast. Therefore, we advise Slimstock to determine daily demand forecast for slow-moving items.

To guarantee that the proposed model performs properly, the order advancement model should only be applied for retail clients who have the required data available and ensure it is accurate. Moreover, the proposed order advancement model is based on several assumptions. For the complete list of model assumptions we refer to ‘’Order Advancement in a Multi-Item Two-Echelon System: Theory and Case study’’.

2.2. Implementation steps

The implementations phase consists of several steps as shown in Figure 1.

Figure 1: Implementation phases

Broader experimentation

Although the first results and insights of the order advancement model seem to be beneficial, the implementation might come with some risks and challenges. First of all, we limited the scope to the retail supply chain structure explained, slow-moving items, two product groups (self-medication and baby food), and 234 stores. This means that the order advancement model has yet to be tested for other retail supply chain structures or sectors (e.g., food retail), demand classes and assortment categories. Therefore, it is necessary to perform additional experiments with other datasets as the first step of the implementation. The evaluation method and optimization heuristics are programmed in Python since Python is used by the research department of Slimstock. Therefore, experimentation with other datasets is possible immediately. Furthermore, in our study we included every SKU within the scope in the order advancement model. However, in general, retailers may set for any reason restrictions on which SKUs they absolutely don't want to advance (e.g., value, shelf life, promotion, etc.). As a consequence, business rules have to developed and tested for those restrictions. Moreover, the model is not tested on SKUs with promotions. However, promotions will only adapt the expected demand and could lead to extra order- and delivery moments. In this case, the solution procedure will not change, but the performance could change. Lastly, the heuristic in which we marginal increment the reorder point is solved in 37 minutes, whereas the heuristic in which we place an order for sure is solved in 93 minutes. Those computational times could decrease if the code could be programmed more efficiently.

Functional design

The second step of the implementation is the functional design. In this step, the employees of internal product support (IPS) and a consultant have to develop the design and user story in Slim4. The workload of both DC and stores on a throughout the week should be visualized in a dashboard (see Figure 2 for an example of a visualization of the workload at the DC). Furthermore, the daily DC picking capacity limit need to be defined. Moreover, the frequency with which the order advancement should be run, should be determined. The heuristic in which we place an order for sure is approximately three times faster than the heuristic where we marginally increase the reorder point, while the performance is almost similar. Besides, planners consider it an advantage to know for sure when to place a replenishment order. Therefore, we advise use this heuristic more often than the marginal increment heuristic.

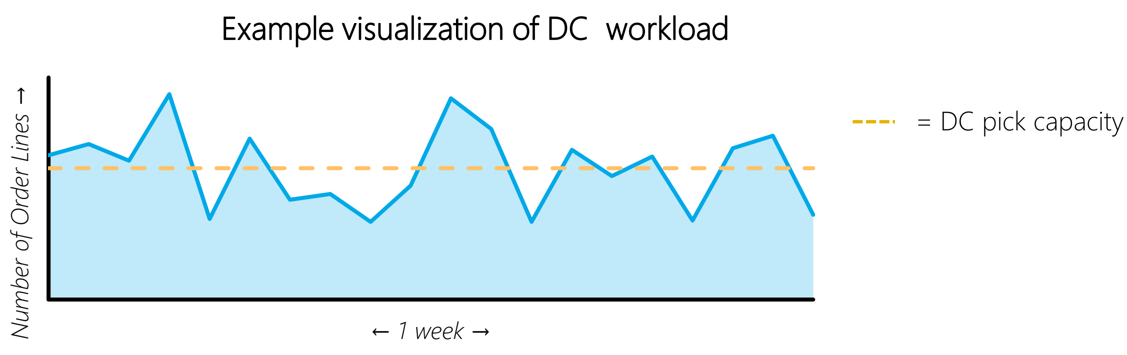

Figure 2: Example visualization of DC workload.

Technical design

The third step is to develop a pilot which will be tested in the next phase. The programmed order advancement model in Python should be programmed in the test environment.

Pilot-test and implementation in Slim4

The next step is to perform a pilot with the performance evaluation method and chosen optimization heuristic. The goal of the pilot is to investigate the impact of such as trends, seasonality, and promotions on the order advancement model. Our proposed order advancement model touches upon the core of inventory control, namely replenishment order advice generation. Therefore, it is important that the time period of the pilot is large enough. We propose to execute the pilot among retailers operating in different sectors (e.g., food retail). In case problems arise in the pilot, they have to be reviewed and solved in the previous phase (technical design). Whenever the results of the pilot seem satisfying, start implementing the order advancement model for both existing and new clients.

Evaluation

The last step is to evaluate the implementation of the performance evaluation method and chosen optimization heuristic. First of all, the cumulative capacity shortage at the DC should be monitored. When there is a trend in the cumulative capacity shortage at the DC, the tactical decisions have to be reviewed (e.g., order- and delivery schedule, parameters, etc.). Moreover, after implementation of the order advancement in the retail sector we have to determine whether a modified version of the proposed order advancement model is suitable for other industries such as pharmacy or wholesale. In this case, the client should have a backroom or an equivalent storage space.

3. Recommendations for Slimstock

Regarding the study: ''Order Advancement in a Multi-Item Two-Echelon System: Theory and Case study'', several recommendations for Slimstock are formulated:

1. Examine all steps and issues mentioned in the implementation plan.

First, we recommend Slimstock to implement the order advancement model in the current replenishment method of slow-moving items according to the implementation plan. Slimstock should evaluate whether the order advancement model performs properly for all assortment categories and cases including events and promotions. This is especially important since the proposed model is promising, but this is not guaranteed in other settings.

2. Review the order and delivery schedule.

Second, we recommend Slimstock to review the order- and delivery schedules of the stores. The delivery schedules of retailers are mainly based on long-term contracts with logistics service providers. Therefore, they form a restriction for Slimstock. However, we recommend Slimstock to investigate if the order- and delivery schedules are optimal from both inventory management as transportation perspective. In this way, Slimstock could advise its clients about the stores' delivery schedules.

3. Update the shelf space data frequently.

Third, we recommend Slimstock to update the shelf space data once every six months. Updating the data guarantees the accuracy. This will improve accuracy of the order advancement model and prevents stores for unexpected backroom inventory. We recommend to update the shelf space data once every six months since adopting the shelf spaces is a tactical decision and therefore does not change frequently.

4. Determine the set of products and stores that should be considered in the order advancement model.

Fourth, we recommend Slimstock to determine the set of products and stores that should be considered in the order advancement model. As mentioned earlier retailers may have restrictions on which SKUs they don't want to advance. Reasons for not advancing products might be the value, shelf life, and promotion. Furthermore, some stores might prefer to receive all slow-moving items on the same day in the week. In this situation, the proposed model should be modified with business rules.

5. Determine the customer specific ratio of the cost parameters.

Fifth, we recommend Slimstock to determine the customer specific ratio of the cost parameters. The ratio of the cost parameters depends on the focus of the retailer. For example, if the retailer wants zero increase in expected backroom the cost parameters of backroom have to set higher than the other cost parameters. In this way, the optimization heuristics will only advance replenishment orders that immediately fit on the shelf.

6. Create a dashboard to visualize the performance indicators.

Sixth, we recommend Slimstock to create a dashboard that visualizes the performance indicators. In the study: ''Order Advancement in a Multi-Item Two-Echelon System: Theory and Case study'', we created visualizations for some performance indicators. We recommend to create one unique dashboard with the results of the performance indicators to measure the effectiveness of balancing and business rules over time.

Based on wishes of the retailer, other performance indicators can be added to the dashboard. Moreover, cumulative capacity shortage at the DC should be monitored. In this way, trends could be observed which will lead to advises to review tactical decisions.

7. Analyze in detail the demand distributions.

Seventh, we recommend Slimstock to analyze the demand distributions in more detail. We recommend to analyze how frequent different demand distributions appear. The assortment of retailers also consists of SKUs facing intermittent demand. The latter could be modelled by a compound Poisson or negative Binomial distribution. The assortment also contains normal and frequent movers. For those items, further research has to be conducted on the demand distribution that best fits the data (e.g., Gamma)