

A store-oriented approach to determine order packaging quantities in grocery retailing

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Published online: 7 October 2014
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Abstract Instore operations in bricks-and-mortar grocery retailing account for the highest share of operational logistics costs within the internal retail supply chain. The order packaging quantity (OPQ) is regarded as one important driver of instore logistics efficiency. We define the OPQ as the number of consumer units that are bundled into one order and distribution unit for supplying the individual stores. Therefore, the OPQ corresponds to the smallest possible order size and determines the possible granularity of order sizes with an impact on instore operations costs. In this paper, we develop a cost-minimization model including instore handling and inventory carrying costs to determine OPQs. The model developed builds on inventory management theory and is based on discrete probability distributions of consumer demand. We apply the model in an industry case study with real retail data for 39 stock keeping units and 1,180 stores of a European retail company. By applying the minimal-cost OPQ for all stores, the costs considered can be reduced by 9.4 %. This paper can be considered as a first in-depth analysis of the dormant instore efficiency potential in connection with adjusted OPQs that seems to be largely untapped in retail research and practice.

Keywords Retail operations · Instore logistics · Case pack size

JEL Classification L810 · M110

1 Introduction

Instore operations in bricks-and-mortar grocery retailing account for the highest share of operational logistics costs within the internal retail supply network, mainly

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due to the time-consuming manual handling processes of shelf stacking and restocking activities from the backroom (Kuhn and Sternbeck 2013; Saghiri and Jönsson 2001; van Zelst et al. 2009). Warehousing operations and the transportation of loaded carriers from distribution centers (DCs) to the stores taken together are about as expensive as instore operations. Instore handling includes the management of the store's backroom in which excess inventory is stored that has been delivered but for which there is not enough free shelf space at the time of delivery arrival (Eroglu et al. 2013). In the specific case of a major European grocery retailer, more than 30 % of the operational instore logistics costs—tens of millions of euros per annum—are due to the non-value-adding process of intermediately storing products in the store's backroom and its associated handling processes.

The order packaging quantity (OPQ) per stock keeping unit (SKU) is regarded as one driver of instore logistics efficiency (Waller et al. 2008; Eroglu et al. 2013; Wen et al. 2012). We define the OPQ as the number of consumer units (CUs) that are combined into one order and distribution unit for supplying the individual stores from retail-owned DCs. Therefore, the OPQ corresponds to the smallest possible order size of a store (Kuhn and Sternbeck 2013). The OPQ has to be distinguished from the case pack of a product, which corresponds to the shipping box offered by the manufacturer. The OPQ selected for supplying the individual stores may equal the case pack quantity, but it could also be different, since retailers unpack or combine case packs in their DCs to create their own ship pack sizes (Kuhn and Sternbeck 2013; Wen et al. 2012). We use the term ship pack size as a synonym for OPQ. In several cases, manufacturers offer their products in different case pack sizes or offer different pack units within the packaging hierarchy of the product (pallet, layer, case pack, sub-packaging, sub-sub-packaging, single CU). Retailers then face the problem of selecting the right size of OPQ for their stores.

On average, more than 30 % of items sold in 2010 in 19 European countries are private label products (Private Label Manufacturer Association 2011). Retailers are able to influence secondary packaging design for this considerable sales volume and decide about case pack sizes that can be used as an OPQ without manipulating packaging units in the DCs. Moreover, grocery retailers are increasingly creating their own OPQs by unpacking (downsizing) and/or bundling supplier case packs (upsizing) so that the resulting OPQ better suits their specific requirements. Especially home and personal care retail chains generally do not use case packs for store delivery that are predefined by manufacturers. They unpack more than 60 % of SKUs listed in their DCs (Kuhn and Sternbeck 2013). This demonstrates that contrary to the common assumption that case pack sizes are exogenous for retailers, decision makers can largely influence the number of consumer units used as an OPQ for supplying the stores (Kuhn and Sternbeck 2013; Wen et al. 2012).

As a result, companies are increasingly concerned with the question of how to dimension OPQs on a tactical operations planning level. For example, German retailers have set up a working group organized by the association Global Standards One (GS1) Germany to explore procedures and solutions (GS1 Germany GmbH 2011). Some companies heavily invest in (semi-)automated unpacking lines in their DCs and/or negotiate with suppliers to receive the products unpacked in reusable boxes in order to have greater freedom in creating OPQs that fit retailers' needs better.

Currently, retail companies mostly solve the problem of how to dimension ship pack sizes based on intuition (e.g., average days of inventory) (Sternbeck and Kuhn 2014).

Waller et al. (2008) note that larger OPQs “increase the probability that some units will need to be stored in the backroom”, which results in additional handling costs. However, retail research lacks an approach to determine appropriate OPQs taking into account limited shelf space and backroom handling efforts. Therefore, the goal of this paper is to develop an approach to determine minimal-cost OPQs from an instore perspective, which can be used by retail decision makers to support their ship pack decisions. This paper is the first to focus on packaging sizes by applying a consistent shelf-back perspective with a focus on instore shelf stacking operations. Methodologically, the paper is based on inventory management theory.

The remainder of this paper is organized as follows. Section 2 first presents relevant literature. After that, in Sect. 3, we describe the problem considered in this article in more detail. We then discuss the research setting in Sect. 4, before addressing our approach to solving the decision problem in Sect. 5. An empirical example is presented in Sect. 6. Section 7 discusses the results, research contributions and further research avenues.

2 Literature review

In this section we review relevant literature related to instore logistics processes (Sect. 2.1), the problem of backroom usage (Sect. 2.2) and the role of packaging sizes and their interrelations (Sect. 2.3). We show that although some publications deal with the question of how packaging sizes affect instore operations, there is only very little academic insight into how these could be dimensioned from an instore retail perspective. This research gap serves as a starting point for our solution approach.

2.1 Instore logistics processes

In the recent past, authors have increasingly focused on instore logistics. Kotzab and Teller (2005), Kotzab et al. (2007) and Reiner et al. (2012) shed light on the “black-box” of instore operations by developing a generic explorative model of instore logistics processes and testing it empirically with simulation approaches based on data of the dairy assortment of an Austrian retail company. The model covers material flows within stores from the inbound ramp to the shelf as well as disposal and recycling. The authors state that the ultimate goal to achieve by configuring instore logistics processes is efficiency (Kotzab and Teller 2005). This implies offering the quantities of merchandise requested by customers at the lowest possible cost (Kotzab and Teller 2005). This global process model can be used as a framework to measure the efficiency of instore logistics systems or for intra- and cross-company comparisons (Trautrimis et al. 2010; Reiner et al. 2012).

More specifically, Curşeu et al. (2009) investigated the initial shelf stacking process with products from new deliveries. The authors demonstrate that reducing the number of order lines is accompanied by lower handling costs in the store due to fixed setup times and economies of scale. Larger case packs are identified as one

possibility for increasing efficiency. Of course, the positive effect mentioned is only feasible if enough shelf space is available, which was assumed to be the case in the study conducted by Curşeu et al. (2009).

2.2 Problem of overflow inventory and backroom use

In retail practice, a frequent problem is that merchandise delivered to stores does not fit onto the shelves at the time of initial shelf stocking from new DC pallets due to capacity restrictions (Kuhn and Sternbeck 2013). In this case, excess inventory—“overflow inventory” (Eroglu et al. 2013)—has to be stored in the backroom as an intermediate solution. In an empirical study, Kuhn and Sternbeck (2011) showed that handling activities resulting from overflow inventory are a major problem for retail logisticians. 54 % of retail experts interviewed claimed that leftovers and the corresponding handling processes are a key aspect that has to be considered in inventory planning and control.

Multiple authors consider temporary storage of products in the backroom of a store the cause of several interrelated problems. First, there are additional operational costs associated with manual handling of overflow inventory (Eroglu et al. 2011, 2013; Wen et al. 2012; Kuhn and Sternbeck 2013). Eroglu et al. (2013) incorporate the backroom effect into periodic review inventory systems with fixed pack sizes applied by retailers. From a cost minimization perspective, higher costs associated with handling efforts of temporarily storing products in the backroom can result in lower reorder points depending on the ratio introduced by the authors between backroom costs and backorder costs. Second, there is the problem that backroom storage complicates the process, making it difficult to keep inventory records accurate, with implications for the quality of automatically generated order proposals and the retailer’s profit (Raman et al. 2001a, b; DeHoratius and Raman 2008; DeHoratius and Ton 2009; Ton and Raman 2010). Third, the usage of backrooms impacts retail stockouts. The problems related to the movement of items from the backroom to the correct space on the shelf are identified as a fundamental cause of stockouts and phantom products, i.e., products that are physically in the store in storage areas but not on the sales floor (Ton and Raman 2010; Gruen et al. 2002; Ehrental and Stölzle 2013; Taylor and Fawcett 2001).

2.3 The role of packaging in instore logistics

Saghir and Jönson (2001) conclude from their studies that there is a lack of methods for evaluating packaging handling from a logistics viewpoint. In retail practice, the concept of shelf-ready packaging is frequently discussed, including suggestions for designing packaging units from a handling perspective. The concept recommends using packaging units that are easy to identify and grab, easy to open, easy to place on the shelf and easy to dispose of (Institute of Grocery Distribution 2005; Thonemann et al. 2005). Packaging *size* is considered to be a particularly fundamental instore efficiency driver as it influences the degree to which the backroom is utilized (Ferguson and Ketzenberg 2006; Ketzenberg and Ferguson 2008; Eroglu et al. 2011, 2013; Kuhn and Sternbeck 2013). Eroglu et al. (2011) state

that the amount of overflow inventory depends on the ratio between shelf space and packaging size. For a given shelf space, they show that smaller packaging sizes lead to a decrease in retail stockouts as more units fit on the shelf at the time of store delivery rather than storing them in the backroom followed by unreliable refilling processes (Eroglu et al. 2011). However, most authors treat the packaging sizes as dictated exogenously rather than providing approaches for calculating appropriate packaging sizes (e.g., Broekmeulen et al. 2007; Ferguson and Ketzenberg 2006; Ketzenberg and Ferguson 2008).

Ketzenberg et al. (2002) examine the benefits of unpacking case packs in retail DCs and supplying stores with individual CUs. However, the clear focus lies on the possible implications for category management rather than focusing on instore handling. The authors demonstrate that supplying stores with single CUs combined with adapting the inventory replenishment method applied leads to less space requirements. Case pack elimination therefore allows for two strategies in retail space management: either more SKUs or categories can be listed or less space is required for the current assortment—both of which impact profit and costs (Ketzenberg et al. 2002). The authors conclude that the benefits identified have to be weighed up with the additional costs.

To our knowledge, the only approach to determine optimal ship pack sizes from a supply chain perspective for the internal retail supply network—consisting of DCs, transportation and stores—is provided by Wen et al. (2012). The authors developed a cost-minimization model for the discrete selection of packaging units within the packaging hierarchy offered by suppliers, i.e., the selection between cases (supplier shipping box), inners (sub-packaging, when applicable) or eaches (CU). Seven cost components are included in the model derived: fixed store order costs, DC costs of replenishing the picking area, DC picking costs, store receiving costs, store extra handling costs of overflow inventory, and store and DC inventory costs. However, instore operations are only reflected in very general terms. Shelf capacity per SKU is set 25 % higher for all stores and products than the order-up-to level of the periodic review inventory policy applied, without taking planograms into account. Therefore, by far the biggest cost pool in bricks-and-mortar retailing is integrated only approximately.

Summarizing the literature reviewed in this section, there is a clear deficit in publications on how to dimension OPQs from a retail perspective. This realization from the literature reviewed in this section is the starting point for our analyses. This paper aims to contribute to existing literature by providing an approach to determine order packaging quantities from a store perspective of grocery retailers, i.e., assessing instore logistics effects as a fundamental basis for comprehensive solution approaches, including DC operations and transportation.

3 Problem description

This section focuses in greater detail on the midterm retail decision problem of selecting minimal-cost OPQs from an instore perspective, taking limited shelf space into account.

We consider a replenishment cycle system that is used by the majority of European grocery retailers for the dry grocery items including the home and personal care categories, which are replenished via retail DCs (Kuhn and Sternbeck 2013). Normally, these assortments represent the majority of items listed in a grocery store to which our approach is limited. A store may only order according to a specific order and delivery schedule. Derived from this schedule the inventory position IP is reviewed accordingly. If, at this time, it has dropped below the reorder level s , an order is created. The order size q is chosen in such a way that the inventory position reaches the reorder level or overshoots it as little as possible. The order quantities per SKU have to be an integer multiple of the OPQ selected. Retailers may choose supplier case packs as the OPQ. However, case packs may be broken up in retail DCs and combined again to create own OPQs.

Within such an inventory replenishment system, the OPQ selected has direct implications for instore performance measures. Firstly, the OPQ has a clear impact on instore inventory levels and therefore influences the amount of total inventory holding costs as with smaller OPQs, the average overshoot above the reorder level is reduced. For example, in the extreme case of applying an OPQ of one, the order size can generally be dimensioned such that IP is raised exactly to the reorder level. Secondly, related to instore inventory levels, the OPQ can have a direct impact on the degree to which new deliveries can be stacked directly onto the shelves without the need for temporarily storing products in the backroom. As noted above, instore handling processes associated with backroom operations are very costly. In contrast to inventory carrying costs, studies show that backroom handling activities are a major cost driver within the retail logistics chain (Eroglu et al. 2013; Kuhn and Sternbeck 2013). In this study we limit our analyses to an instore perspective.

Academic literature does not so far provide a store-oriented solution approach. This research therefore aims to provide first insights into this decision problem of bricks-and-mortar grocery retailers. The goal of this paper is to develop an approach to determine appropriate OPQs per SKU based on an instore operations perspective and capacitated shelf space. Against the backdrop of instore logistics processes and related cost structures, retailers need to assess instore effects of different pack sizes. This tactical model quantifies these effects and can thus be used by retailers to support their decisions (Hübner et al. 2013), defining their internal ship pack sizes, for example, and negotiating with manufacturers or allocating products to capacitated unpacking operations in their DCs.

4 Research setting

In this section we elaborate on the research setting, i.e., instore cost structures of grocery retailers (Sect. 4.1), the store inventory replenishment system applied (Sect. 4.2) with correspondent calculations of order levels and order sizes (Sect. 4.3), the total shelf capacity per SKU (Sect. 4.4), and the assumptions of our approach (Sect. 4.5).

4.1 Instore cost structures

Instore logistics cost structures are a decisive factor for designing processes and planning approaches. Cost structures applied in this research originate from interviews conducted with retailers, joint instore projects with grocery retailers and from literature (Curşeu et al. 2009; van Zelst et al. 2009). The cost components regarded in this study are listed in Table 1. We differentiate between costs for initial shelf stocking with products supplied directly from the retail DCs and restocking costs from the backroom where products were stored temporarily due to insufficient shelf space at the time of initial stocking.

The initial shelf stocking costs represent labor costs for stacking items from DC deliveries onto the shelves. These are characterized by fixed costs per stocking activity per ship pack delivered c_{fix}^{Fill} (i.e., picking up the ship pack, identifying the SKU, walking to the shelf, looking for the slot on the shelf) and variable costs c_{var}^{Fill} per CU (i.e., stacking the individual CUs on the shelf), resulting in non-linear cost structures (van Zelst et al. 2009). We assume the fixed costs to occur per OPQ delivered rather than per order line because it is likely that in the case of several ship packs per SKU per delivery, the ship packs may not be grouped together on the DC pallet. Moreover, shelf stocking is mostly performed by several store employees, which supports the assumption that fixed initial shelf stocking costs occur per ship pack.

The process of restocking the shelf from the backroom is reflected in variable restocking costs c_{var}^{Refill} per single CU that are derived from the time needed to perform this operation (labor costs). These variable costs per CU contain activity costs that arise in the initial shelf stocking process per entire ship pack. This is because there are only negligible bundling effects within the most companies' restocking processes. The unpacked CUs that are temporarily stored instore are often at different locations on roll-cages or on a top-tier shelf. Moreover, the process of restocking the shelf has to be carried out at high-frequent intervals as there is no IT-supported information about the fill level of the shelves. Consequently, it is likely that at the time of restocking, only single CUs fit onto the shelf while others stay on the roll cage or the top-tier shelf. The circumstances of

Table 1 Overview of cost components regarded

Cost component	Processes/costs reflected
Fixed initial shelf stocking costs per OPQ (c_{fix}^{Fill})	Picking up the <i>ship pack</i> , identifying the SKU, opening the box, walking to the shelf, looking for the slot on the shelf (labor costs)
Variable initial shelf stocking costs per CU (c_{var}^{Fill})	Stacking the individual CU on the shelf (labor costs)
Variable restocking costs per CU (c_{var}^{Refill})	Picking up a <i>CU</i> , identifying the SKU, walking to the shelf, looking for the slot, stacking the individual CU on the shelf (labor costs)
Inventory carrying costs in % on tied capital per year (c_{mvc})	Cost of capital tied in products or opportunity costs in the case of long due dates for payments (capital costs)

this concurrent restocking process imply representing the restocking processes by variable costs per CU (van den Berg et al. 1998).

Generally, our cost analyses show that variable restocking costs are higher than variable initial shelf stocking costs plus fixed costs per ship pack as restocking activities are principally carried out by highly-qualified store personnel in comparison to initial shelf stocking, which is often executed by low-cost workers. For example, a retail company reported in a joint project that compared with the current rate of stocking the shelf directly from new DC deliveries, handling operations to restock a CU from the backroom are roughly three times more expensive.

Moreover, we take inventory carrying costs into consideration as these are dependent on the OPQ selected (c^{InvC}). The inventory carrying costs integrated into our model comprise only the cost of the capital that is tied up in instore inventories, which represents frequently the largest component of inventory carrying costs (Coyle et al. 2003). We exclude further components as space costs as these are not dependent on the OPQ in this setting (Coyle et al. 2003). Inventory carrying costs can be interpreted as opportunity costs as the capital tied in inventory cannot be used for other projects (Silver et al. 1998; Coyle et al. 2003). We calculate inventory carrying costs by integrating the retail purchasing prices per SKU and the internal hurdle rate of return (Coyle et al. 2003).

4.2 Inventory replenishment system applied

The specific inventory replenishment system considered is a (R, s, nQ) policy in discrete time, following the notation of Silver et al. (1998). This policy is applied by the majority of retailers for the dry assortment. For example, this policy has been described by Hax and Candea (1984), Axsäter (2006), Broekmeulen and van Donselaar (2009), van Donselaar and Broekmeulen (2008), Tempelmeier (2011) and Tempelmeier and Fischer (2010). In general, periodic review systems are commonly used when items are ordered from the same (internal) supplier as is the case in grocery retailing since large parts of the assortment are supplied via retail DCs (Silver et al. 1998; Kuhn and Sternbeck 2013).

In the (R, s, nQ) policy, the inventory position IP of a SKU is reviewed periodically according to the delivery schedule applied. The underlying demand model is also periodic. Thus, demand arrivals during the period are aggregated to one single-period demand (Tempelmeier and Fischer 2010, p. 6275). Data are gathered in each case at the beginning of a period. A replenishment order is only created if the inventory position IP_t of a SKU is below the reorder level s at review moment t . Given this situation, an OPQ or an integer multiple n of the OPQ is ordered to bring the inventory position back to or just above the reorder level s . That implies that just after an ordering decision, the inventory position is in the interval $[s; s + OPQ[$. We assume that store ordering is based on a static reorder level s , which is calculated such that weekly seasonality is taken into account to reach a target service level. Certainly, this approach can only be applied for SKUs exposed to stationary demand.

4.3 Calculating the reorder level and order quantity

Applying a (R, s, nQ) inventory replenishment system implies that an order is only created if at review moment t the inventory position IP_t is strictly below the reorder level s (Broekmeulen and van Donselaar 2009). As we assume lost sales in case of excess demand, the inventory position can be defined as the sum of the physical inventory in stock and the inventory on order resulting from orders placed earlier (Wensing 2011). As we further assume that new orders are only placed after delivery of the previous order, IP_t at the time of ordering is equivalent to the physical inventory in stock. This assumption reflects the situation of many retailers that offer short lead times in order to give store employees the chance to place orders without having to account for outstanding deliveries (Kuhn and Sternbeck 2011). We calculate the reorder level s in the same way as commercial automated store ordering (ASO) systems (see Broekmeulen and van Donselaar 2009):

$$s = DS + SS + \hat{x}^{L+R} \quad (1)$$

with DS being the display stock, SS the safety stock and \hat{x}^{L+R} the expected demand during lead time L and review period R (Broekmeulen and van Donselaar 2009). DS is regularly set for presentation purposes without being included in safety stock calculations, with the aim of selling more products by always displaying enough “product pressure”. However, from a service level perspective, DS naturally serves as additional safety stock resulting in higher service levels than calculated.

Whenever the inventory position at a review moment is below the reorder level, an order quantity has to be calculated. As the (R, s, nQ) inventory replenishment system equates to a stock minimization strategy, the order size corresponds to the possible minimum quantity to raise the inventory position up to the reorder level. However, this amount is dependent on the OPQ selected. This implies that the order size q corresponds to the minimum positive integer multiple of the OPQ to raise the inventory position IP_t at least to the reorder level s or above it. Therefore, the overshoot of the inventory position above the reorder level just after placing an order is strictly less than one OPQ with a maximum of $OPQ - 1$, otherwise an order would not have been necessary at this review moment. Therefore the order size q_t at review moment t can be calculated according to the following decision rule (van Donselaar and Broekmeulen 2008, p. 5):

$$q_t = \text{Max} \left\{ \left\lceil \frac{s - IP_t}{OPQ} \right\rceil \cdot OPQ, 0 \right\} \quad (2)$$

with $\left\lceil \frac{s - IP_t}{OPQ} \right\rceil$ being the integer number n_t of OPQs ordered at the review moment t .

4.4 Total shelf capacity

In our approach, shelf space allocated to a SKU plays a central role in calculating the OPQ. Shelf space is a scarce resource. For example, in 2009 German hypermarkets listed more than 50,000 SKUs on average—up 30 % compared to

2000 (EHI Retail Institute GmbH 2009). We assume that assortment decisions and shelf space allocation are a result of marketing planning and therefore given exogenously.

Total shelf capacity (gross shelf space) for SKU i in store j is denoted as S_{ij} . This results from the depth of the shelf in store j ($Depth_j^{\text{Shelf}}$), the depth of the single consumer unit ($Depth_i^{\text{SKU}}$), and the shelf space assigned to SKU i in store j (measured by the number of product facings PF_{ij} including product layers on the shelf when applied).

$$S_{ij} = \left[\frac{Depth_j^{\text{Shelf}}}{Depth_i^{\text{SKU}}} \right] \cdot PF_{ij} \quad (3)$$

Shelf capacity data can be obtained from commercial shelf planogram software incorporating physical shelf structures and product master data, e.g., Nielsen's Spaceman Suite. Such software is widely used by retailers, mainly for visualization purposes (Hübner and Kuhn 2012).

4.5 Assumptions

The description of the research setting results in the following assumptions on which our approach is based:

1. Assumptions concerning assortment and display on shelf

- The assortment in the stores is determined by exogenous marketing considerations
- Shelf space allocation is exclusively based on marketing considerations and therefore treated as given
- Individual CUs are displayed on the shelf
- Products considered belong to the dry grocery assortment, demand is assumed to be stationary
- It is assumed that the retailer sells products in his own name and for his own account

2. Basic conditions of store supply and operations

- Store delivery patterns from retail DCs are fixed exogenously
- Store delivery is assumed to be uncapacitated
- The backroom of a store is assumed to be uncapacitated and shelf supplies from the backroom are carried out on an ongoing basis.

3. Assumptions concerning inventory management

- Inventory replenishment is based on an (R, s, nQ) inventory policy
- Product demand is integrated by discrete empirical distributions that are estimated by sales data.

- Store delivery lead times from DCs are assumed to be deterministic
- Display stock DS for optical purposes only is static and given exogenously per SKU
- Safety stock SS is static and derived exogenously per SKU, usually from an automatic store ordering system
- There are no outstanding orders when an order is placed
- We assume that consumer demand that cannot be satisfied is lost

5 Approach to determine order packaging quantities

In this section we describe the cost-minimization model to evaluate and determine OPQs from an instore perspective. We use the notation as listed in Table 2.

The goal from an instore perspective is to minimize the three cost components considered over all stores j of a retail company. The calculation can be carried out for each SKU i independently as no interdependencies between SKUs are integrated into the model.

$$\text{Min } C^{\text{Total}} = \sum_{j \in J} (C_j^{\text{Fill}} + C_j^{\text{Refill}} + C_j^{\text{InvC}}) \quad (4)$$

For each SKU, we derive this cost minimum by enumerating the costs for each store j occurring per year associated with possible OPQs that may be selected. These costs are summed up for all stores. Finally, the OPQ (one size for all stores) with the lowest overall costs is chosen. In the following we describe the cost calculations for one SKU-store combination and leave out the indices i for the different SKUs and j for the specific stores for readability reasons.

5.1 Initial shelf stocking costs

Initial shelf stocking costs comprise fixed stocking costs per shelf stocking activity per OPQ delivered and variable costs per CU if it fits onto the shelf when initially stocking the shelf just after delivery. When an order is actually released at a review moment (i.e., $IP < s$), initial shelf stocking costs can be calculated by multiplying the expected number of OPQs per order ($E\{n\}$) with the fixed cost rate per OPQ ($c_{\text{fix}}^{\text{Fill}}$) plus the variable stocking costs that correspond to the expected number of products that directly fit onto the shelf ($E\{\#CU^{\text{direct}}\}$) multiplied by the variable cost rate for initially stocking one CU ($c_{\text{var}}^{\text{Fill}}$).

$$C^{\text{Fill}} = E\{\#Orders^{\text{year}}\} \cdot \left(E\{n\} \cdot c_{\text{fix}}^{\text{Fill}} + E\{\#CU^{\text{direct}}\} \cdot c_{\text{var}}^{\text{Fill}} \right) \quad (5)$$

In order to determine the value of initial shelf stocking costs per year, we need to consider the frequency of ordering which is dependent on the OPQ selected. By assuming stationary demand, we approximate the expected number of orders per year ($E\{\#Orders^{\text{year}}\}$) by dividing the demand per year (D^{year}) by the expected

Table 2 Notation

Notation	
IP	Inventory position
IP_O	Inventory position at the time of ordering
s	Reorder level
q	Order size consisting of one or several OPQs
DS	Display stock
SS	Safety stock
L	Lead time
R	Review period
\bar{x}^L	Expected demand during lead time
\bar{x}^R	Expected demand during review period
S_{ij}	Shelf capacity for SKU i in store j
$Depth_j^{\text{Shelf}}$	Depth of the shelf in store j
$Depth_i^{\text{SKU}}$	Depth of the CU of SKU i
PF_{ij}	Number of product facings of SKU i in store j
C^{Total}	Total instore costs of the company per annum
C_j^{Fill}	Stocking costs in store j per annum
C_j^{Refill}	Restocking costs in store j per annum
C_j^{InvC}	Inventory carrying costs in store j per annum
$c_{\text{fix}}^{\text{Fill}}$	Fixed initial shelf stocking costs per OPQ
$c_{\text{var}}^{\text{Fill}}$	Variable initial shelf stocking costs per CU
$c_{\text{var}}^{\text{Refill}}$	Variable restocking costs per CU
c^{InvC}	Inventory carrying costs in % on tied capital per year
$E\{n\}$	Expected number of OPQs per order
$E\{\#CU^{\text{direct}}\}$	Expected number of CUs that fit directly onto the shelf at the time of delivery arrival
$E\{\#Orders^{\text{year}}\}$	Expected number of orders per year
$E\{q\}$	Expected order size in CUs
D^{year}	Demand per annum in CUs
D^{RP}	Demand in the review period in CUs
D^{LT}	Demand during lead time in CUs
U	Undershoot of the IP under s
PI_D	Physical inventory on hand instore at the time of delivery arrival
FSS	Free shelf space at the time of delivery arrival
PV	Product value of one CU

order size per order ($E\{q\}$). We restrict the calculations to OPQs that do not exceed the annual demand of the store with the lowest sales volume.

$$E\{\#Orders^{\text{year}}\} = \frac{D^{\text{year}}}{E\{q\}} \quad (6)$$

As a prerequisite for these calculations, the specific product volumes must be determined and charged with the relevant costs. First, we need the expected number of OPQs ordered when an order is actually released at a review moment ($E\{n\}$). The number of OPQs ordered is dependent on the undershoot of the inventory position below the reorder level s at the time of ordering. That is why we first approximate the distribution of the undershoot U^* . From this distribution the probabilities of the inventory position at the time of ordering $P(IP_O = ip_O)$ can be derived (see [Appendix A1](#)) that are needed to calculate the expected number of OPQs ordered when an order is placed:

$$E\{n\} = \sum_{ip_O=0}^{s-1} P\{IP_O = ip_O\} \cdot \left\lceil \frac{s - ip_O}{OPQ} \right\rceil \tag{7}$$

This value can be used to calculate the fixed stocking costs as well as –by multiplying with the OPQ– the expected order size ($E\{q\}$), i.e., the number of CUs ordered. However, in order to calculate the expected number of CUs that can be put directly onto the shelf during initial shelf stocking immediately after arrival of the store delivery ($E\{\#CU^{direct}\}$) we have to calculate free shelf space at the time of delivery (FSS):

$$FSS = Max(S - (IP_O + D^{LT}); 0) \tag{8}$$

At the time of delivery we can fill up the free shelf space available with CUs delivered up to the level until either the shelf is filled completely or the order size q is completely put onto the shelf. We therefore formulate:

$$E\{\#CU^{direct}\} = E\{Min(FSS; q)\} \tag{9}$$

As the order size q is stochastically dependent on the inventory position for OPQs smaller than s we convolve the probability distribution of the inventory position including its corresponding order sizes with the probability distribution of demand during lead time in order to derive the probability distribution of the amount of CUs delivered that fit onto the shelf. In other words, we calculate the order size q for every possible event based on IP_O . By adding every possible demand event during the lead time we calculate $Min(FSS; q)$ per event allowing us to generate the distribution of the number of CUs that can be stacked directly onto the shelf $P\{\#CU^{direct} = cu^d\}$ that serves as basis to calculate the expected number of CUs that can be put directly onto the shelf during initial shelf stocking ($E\{\#CU^{direct}\}$) (see [Appendix A2](#)).

5.2 Restocking costs from the backroom

Those CUs that cannot be put onto the shelf during the initial stocking activity immediately after the delivery has arrived in the store have to be stored temporarily in the backroom and restocked later when there is space available on the shelf due to customer purchases. Restocking activities are mostly carried out during the day by

high-qualified personnel at frequent intervals to guarantee customer service. As explained in Sect. 4.1, the resulting restocking costs are reflected by a variable cost rate per CU that has to be restocked (c_{var}^{Refill}). Consequently, the restocking costs per order can be calculated by multiplying the expected number of CUs that have to be restocked per order ($E\{\#CU^{Refill}\}$) with the cost rate. Multiplied by the number of orders per year we get the restock costs C^{Refill} per annum:

$$C^{Refill} = E\{\#Orders^{year}\} \cdot E\{\#CU^{Refill}\} \cdot c_{var}^{Refill} \quad (10)$$

The expected number of CUs per order that do not fit onto the shelf and have to be restocked ($E\{\#CU^{Refill}\}$) can be calculated analogous to the number of CUs that can be stacked directly. Having calculated one value, the corresponding value can be easily derived by subtraction from the expected value of the order size $E\{q\}$:

$$E\{\#CU^{Refill}\} = E\{q\} - E\{\#CU^{direct}\} \quad (11)$$

5.3 Inventory carrying costs

The third cost component considered is inventory carrying costs that are dependent on the OPQ selected. Inventory carrying costs in grocery retailing are comparatively low compared to handling costs due to the assortment structure with low purchasing prices for retailers that are reflected in low product values (PV). We approximate the OPQ-dependent inventory carrying costs per year by means of a simple calculation that is also applied in the basic EOQ model:

$$C^{InvC} = \frac{E\{q\}}{2} \cdot PV \cdot c^{InvC} \quad (12)$$

6 Empirical example

In this section, we describe the application of the cost model developed to a real industry case with data we obtained from a European retail company. First, we illustrate the setting of the case in Sect. 6.1 before we describe and analyse the results in Sect. 6.2.

6.1 Case description

An empirical case study with real industry data serves to demonstrate the cost calculations introduced in this paper. The case company referred to as DELTA in the following is a leading European home and personal care retail company operating roughly 3,000 company-owned stores in several European countries. All stores belong to the same retail format and are largely similar with regard to their assortments and the categories listed. However, store managers are able to decide about product (de-)listings and the number of product facings on the shelf.

We focus on the German market for which the calculations are carried out. DELTA operates 8 DCs in Germany. While the picking systems in the regional DCs

are adjusted to supplier case picking, DELTA has implemented automated unpacking processes in its central DC to manipulate industry case packs in order to supply the stores with OPQs that fit their specific requirements. Therefore the company has the infrastructure that is necessary to provide retail-designed ship pack sizes for the stores.

We obtained data for one food subcategory consisting of 39 items that are characterized as non-perishables due to expiration dates that imply very long shelf lives. For each SKU-store combination, we received the relevant data to calculate the OPQ as described in Sect. 5. The only modification we made in this case study was to assume a lead time of one day to comply with the requirement that there are no outstanding orders when an order is released.

As the company operates according to the everyday-low-price-principle without price promotions, the time series are free of promotional effects. The inventory replenishment calculus incorporated in the ASO system is based on an (R, s, nQ) inventory policy. Generally, store managers are able to manually override the order volumes suggested to guarantee high customer service if they have additional information about relevant factors that are not included in the ASO system, e.g., weather conditions. However, analyses of DELTA show that less than 2 % of all order lines are adjusted manually. Shelf filling and restocking is completely executed by own personnel. The SKUs selected are known to have very high restocking rates. The retailer's operations managers are therefore interested in the potential of consciously dimensioning the OPQ from an instore perspective. As the company intends to choose one OPQ per SKU for all stores, we calculated the costs in this case example for all 1,180 German stores. We calculated the costs for all potential OPQs containing between 1 and 35 CUs for each SKU and store, resulting in roughly 1.6 million data records.

6.2 Case results

Applying the cost model described allows us to calculate the costs for each potential OPQ, for each store and each SKU, and to select the minimal-cost OPQs that can subsequently be aggregated to company-wide cost curves per SKU to derive a global instore cost minimum.

In Fig. 1, the discrete cost points for one SKU-store combination of the case example have been connected to cost curves for illustration purposes. Raising the OPQ leads to decreasing initial shelf stocking costs and increasing restocking and inventory carrying costs. Due to the degressive shape of the number of orders per year with an increasing OPQ, we also notice degressively decreasing initial shelf stocking volumes accompanied by degressively increasing restocking volumes (see Fig. 2). Charging these restocking volumes with the variable restocking costs results in the restocking cost curve. However, calculating the costs for all stores of a company may mean the resulting cost curves look different, with a cost minimum at a different OPQ (see Fig. 3).

The overall results of the cost calculations exhibit significant potential (see Table 3). By comparing the minimal-cost OPQ calculated with the OPQ currently used by the retailer, we can identify a cost reduction potential of 9.4 % of instore logistics

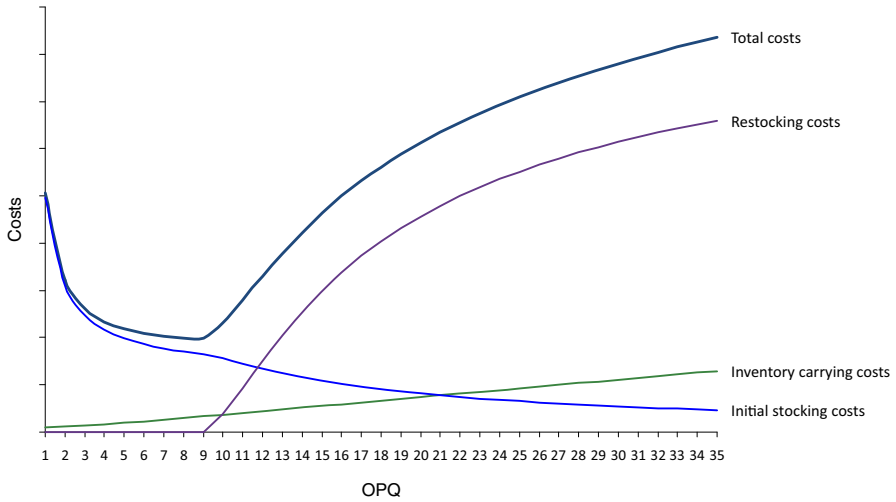


Fig. 1 Example of resulting cost curves for one SKU-store combination

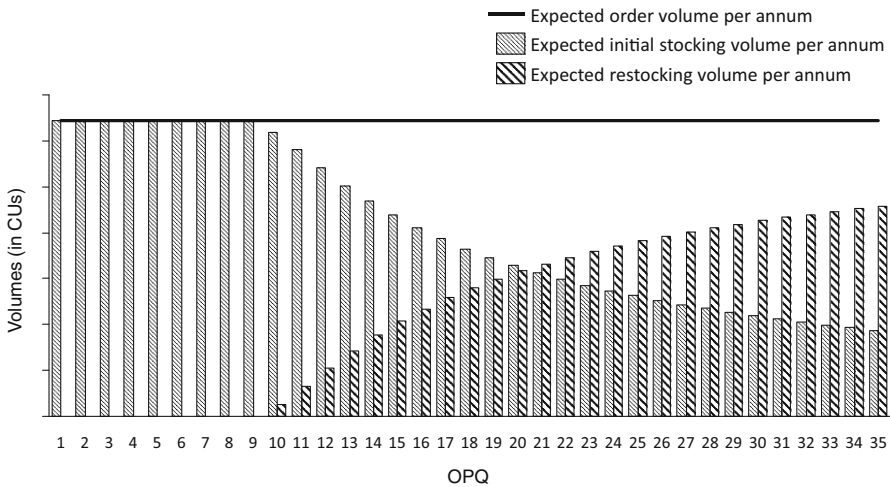


Fig. 2 Example of expected volumes for the SKU-store combination considered in Fig. 1

costs, which is the biggest cost pool in bricks-and-mortar retailing. Assuming that other categories are structurally identical, that would correspond to tens of millions of euros per annum for the retailer investigated.

From the 39 SKUs included in this analysis, the minimal-cost solutions would require 35 reductions in the ship pack size and 3 enlargements. Currently the ship pack size of one SKU corresponds to the cost minimum. The aim of reducing the OPQ is to be able to place more CUs on the shelf during initial shelf stocking and reduce restocking expenses. However, the 3 enlargements are not a result of ample shelf space. In these cases, shelf space is so scarce that most of the CUs have to be

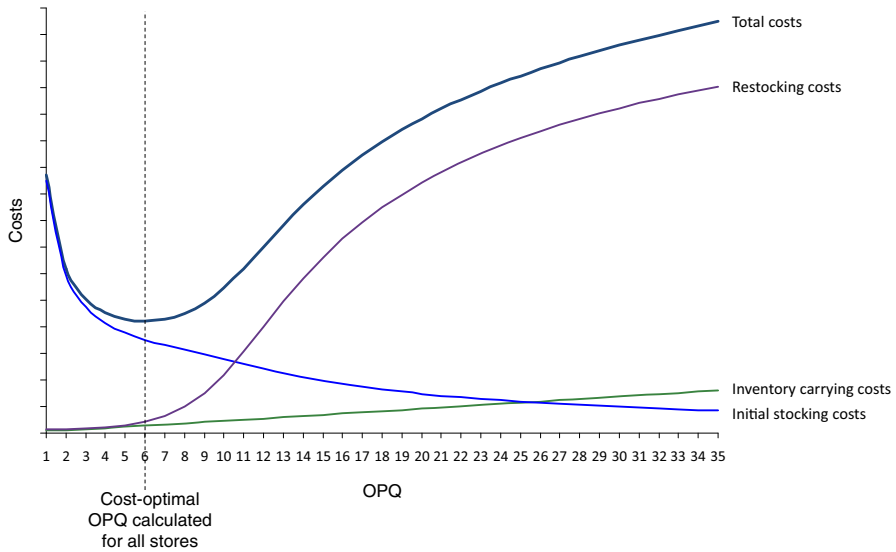


Fig. 3 Cost curves of SKU from Fig. 1, now calculated for all stores of a company

restocked anyway. In cases where a large number of CUs have to be restocked even with small OPQs, larger OPQs save at least fixed initial stocking costs.

Applying the optimal solution would result in an increase in the volume that can be placed on the shelf during initial stocking of 32 % per year. The volume that has to be restocked would in turn be reduced by 20 %. As we calculate with variable restocking costs, these would be reduced accordingly by 20 %. Due to the considerable size reductions in the optimal solutions, the inventory carrying costs are reduced by 45 % in average over all 39 SKUs. Smaller ship pack sizes imply more OPQs being shipped to the store resulting in higher fixed stocking costs. Additionally, with more CUs on average that can be stacked onto the shelf during initial shelf stocking, the variable stocking costs increase as well. On average over the subcategory investigated, initial shelf stocking costs increase in the optimal solutions by slightly more than 60 %.

Hypothetically, if every store was supplied with its minimal-cost OPQ, total instore costs could be reduced by 13.8 %. In 68.8 % of the SKU-store combinations, a smaller OPQ than the ship pack currently used would be optimal; in 26.9 % of cases the current size is smaller than the optimum and in 4.3 % of all combinations regarded the current size corresponds to the instore cost minimum. Figure 4 compares the global optimal OPQ derived by cost analysis over all stores with the distributions of the store-individual minimal-cost OPQs. Contrary to the commonly used box whisker plots, the horizontal lines printed in bold represent in this case the minimal-cost OPQ for all stores. The boxes indicate the central part of the data distributions of store-individual minimal-cost OPQs from the lower to upper quartile. The lines extending from the boxes show the range of the store-individual minimal-cost OPQs per SKU. The chart demonstrates that in some cases the global

Table 3 Results of empirical case study calculated over all 1,180 stores

SKU ID	Cost optimal OPQs calculated						OPQs currently applied						Comparison		
	Instore costoptimal OPQ			Costs			OPQ currently applied			Costs			Volumes	Costs	
	Initial stocking volume (CUs, in %)	Restocking volume (CUs, in %)	Inventory carrying costs (in %)	Initial stocking costs (in %)	Restocking costs (in %)	OPQ currently applied	Initial stocking volume (CUs, in %)	Restocking volume (CUs, in %)	Inventory carrying costs (in %)	Initial stocking costs (in %)	Restocking costs (in %)	Change of initial stocking volume (%)	Change of restocking volume (%)	Change of overall instore costs (%)	
1	2	83	17	9	59	32	12	25	75	22	6	71	231	-77	-49.8
2	12	99	1	6	87	6	16	97	3	8	78	14	2	-56	-4.5
3	11	98	2	5	85	9	16	96	4	7	72	21	3	-58	-7.3
4	12	99	1	7	87	6	16	98	2	9	79	12	1	-52	-3.5
5	10	97	3	4	83	13	16	94	6	6	66	28	4	-59	-9.8
6	11	99	1	6	87	7	16	97	3	8	76	16	2	-57	-4.7
7	4	29	71	0	16	83	6	23	77	0	11	88	28	-8	-2.6
8	3	41	59	1	24	75	12	13	87	2	5	93	214	-32	-16.6
9	2	72	28	1	50	48	12	21	79	4	7	89	246	-64	-34.1
10	3	52	48	1	29	70	12	17	83	3	6	91	213	-42	-24.7
11	2	85	15	2	67	31	12	25	75	5	8	87	244	-80	-45.6
12	2	55	45	1	37	61	6	30	70	3	13	85	83	-36	-11.3
13	5	22	78	0	12	88	12	12	88	0	5	94	83	-11	-4.1
14	4	41	59	0	20	80	12	23	77	0	8	92	85	-24	-9.8
15	3	70	30	1	43	57	12	30	70	1	9	89	135	-57	-32.4
16	3	26	74	1	18	81	6	14	86	2	9	89	82	-14	-4.5
17	3	27	73	2	19	80	6	15	85	3	9	88	78	-14	-5.0
18	2	67	33	2	46	52	6	31	69	3	13	83	113	-52	-23.2
19	3	25	75	1	18	81	6	15	85	1	9	90	68	-12	-2.6
20	9	5	95	1	5	94	12	4	96	1	4	95	29	-1	-0.2
21	4	66	34	1	36	64	6	59	41	1	26	73	13	-18	-5.8

Table 3 continued

SKU ID	Cost optimal OPQs calculated						OPQs currently applied						Comparison		
	Instore costoptimal OPQ			Costs			Volumes currently applied			Costs			Volumes		Costs change of overall instore costs (%)
	Initial stocking volume (CUs, in %)	Restocking volume (CUs, in %)	Inventory carrying costs (in %)	Initial stocking costs (in %)	Restocking costs (in %)	OPQs currently applied	Initial stocking volume (CUs, in %)	Restocking volume (CUs, in %)	Inventory carrying costs (in %)	Initial stocking costs (in %)	Restocking costs (in %)	Change of initial stocking volume (%)	Change of restocking volume (%)		
22	3	28	72	1	19	80	6	17	83	1	10	89	67	-14	-3.9
23	3	35	65	1	21	78	6	21	79	2	11	88	65	-17	-6.5
24	2	50	50	1	34	65	6	25	75	2	12	87	101	-33	-10.7
25	3	29	71	1	19	79	6	18	82	2	10	88	63	-14	-4.2
26	3	33	67	2	21	78	6	20	80	3	10	87	68	-17	-6.7
27	4	32	68	1	17	82	6	27	73	1	12	87	18	-7	-1.2
28	4	18	82	0	13	87	6	13	87	0	9	91	31	-5	-0.4
29	14	2	98	1	3	96	6	4	96	0	7	93	-49	2	-1.4
30	10	97	3	4	83	12	12	96	4	5	77	18	2	-33	-2.7
31	4	17	83	2	13	86	6	13	87	2	9	89	35	-5	-1.0
32	3	89	11	8	65	27	12	35	65	14	10	76	153	-84	-53.8
33	6	98	2	7	83	10	6	98	2	7	83	10	0	0	0.0
34	3	33	67	2	20	77	8	12	88	5	7	88	187	-24	-13.4
35	27	100	0	9	91	0	30	100	0	10	90	0	0	0	-0.1
36	13	1	99	2	3	95	6	2	98	1	7	92	-46	1	-1.4
37	9	3	97	2	5	93	6	4	96	1	7	92	-26	1	-0.6
38	5	95	5	6	75	18	12	73	27	9	30	62	31	-81	-38.0
39	5	90	10	4	65	31	12	64	36	6	24	71	41	-73	-38.8
Average	5.9	50.4	49.6	1.5	23.7	74.8	9.9	38.1	61.9	2.4	13.3	84.3	32	-20	-9.4

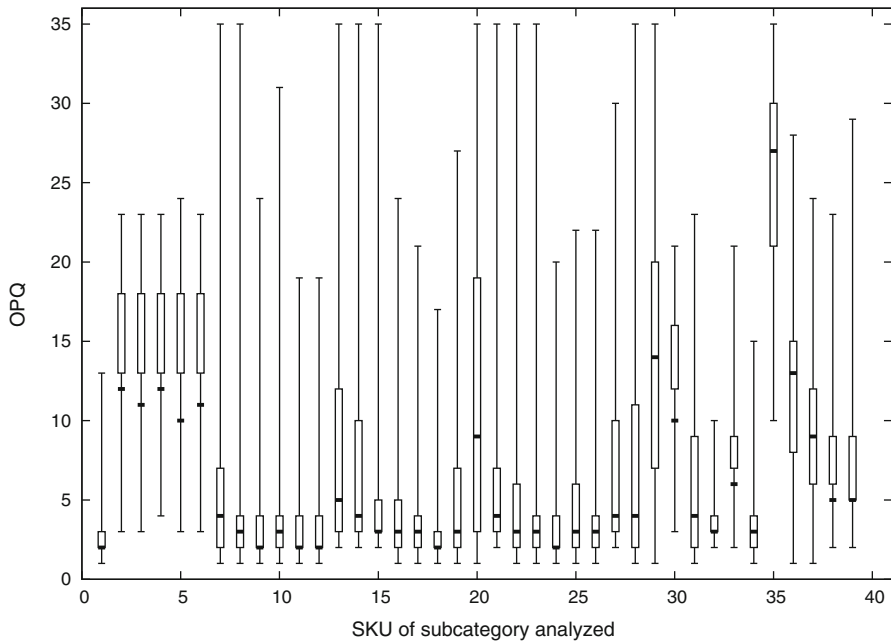


Fig. 4 Modified *box whisker* plot to compare the minimal-cost OPQ calculated for all stores per SKU (*horizontal lines printed in bold*) with the distributions of the minimal-cost OPQs calculated individually per store and SKU

minimal-cost OPQ is smaller than the lower quartile of the optimal OPQs calculated per individual store. This is due to the cost structure, according to which restocking is significantly more expensive than initially stocking the shelf after delivery. Although most of the stores would prefer larger OPQs to be able to realize greater fixed cost degression, this cannot compensate for expensive restocking processes at a limited number of stores.

Besides this focus on operational costs, further dependencies have to be taken into account. With an increasing rate of direct stocking and decreasing restocking activities from the backroom, there is a temporal shift of labor time required in the store. This implies that employee scheduling has to be adjusted, and different store workforce structures could even be beneficial. Store employees learned to store excess stock in the backroom to be certain of being able to fulfil consumer demand. From this perspective it is important that operational benefits resulting from smaller OPQs are not hindered by differing ordering behavior.

This empirical example conducted with real retail data demonstrates that selecting the OPQ from an instore logistics point of view offers significant potential to free up time currently spent on shelf stocking and restocking. Even if the cost reductions identified in this empirical case study cannot be realized to this extent due to upstream processes, packaging-related aspects and others, the potential seems to be comparatively high in a very competitive and labor-intensive environment that is far from being automated.

7 Discussion and conclusions

In this ultimate section we discuss the cost model developed in this paper and its first application in an empirical case study. We highlight the findings and its implications for both theory and retail practice (Sect. 7.1), and discuss the limitations and further research opportunities (Sect. 7.2).

7.1 Findings and implications

Motivated by a clear lack of research on the question of how to size OPQs from an instore perspective, this article is a first in-depth analysis of the dormant efficiency potential in connection with correctly dimensioned OPQs that seems to be largely untapped in retail research and practice. However, companies and industry associations increasingly care about ship pack sizes, and are heavily investing in highly automated DCs to unpack and repack products with the aim of achieving sizes that suit their needs. This requires solution methods to determine minimal-cost OPQs. We developed a model to derive minimal-cost OPQs from an instore operations perspective. By applying the model to an industry case with real retail data, we showed that instore costs could be reduced by 9.4 % with an appropriate OPQ that is used for all stores of the company investigated. This result indicates that adapting OPQs to company-specific situations can unleash instore cost potential up to the high single-digit percentage range.

This article contributes to existing literature by firstly providing decision support for this highly relevant question for retailers operating in such an environment. It becomes evident that the OPQ is a crucial lever to use the limited resources in the store, especially shelf space allocated, as efficiently as possible. The model provided is based on a highly differentiated instore cost structure to determine OPQs from an instore perspective, integrating shelf space restrictions. We provide evidence that dimensioning the OPQ is a substantial efficiency driver in instore logistics.

Of course, the resulting cost curves are heavily dependent on the cost parameters included. With the variable restocking costs being higher than the fixed initial stocking costs per OPQ plus the variable stocking costs for one CU, the model strives for higher initial stocking rates, maximizing the usage of shelf space allocated as long as it is not restricted by the underlying basic economic order quantity model without consideration of restocking (EOQ). With the minimal shelf space available at the time of order arrival in the store $Max(S - (s + 1); 0)$, a lower bound (LB) can be derived for the minimal-cost OPQ at the store level: $LB = Min(Max(S - (s + 1); 1); [EOQ])$. There are two factors that prevent OPQs from getting too large: restricted shelf space with the corresponding restocking costs, and inventory carrying costs. Assuming unlimited shelf space, the OPQ calculated in the model is only restricted by inventory carrying costs. According to the basic EOQ model, the minimal-cost OPQ is then determined by fixed initial stocking costs and inventory carrying costs (see Fig. 5). The OPQ that corresponds to the $[EOQ]$ without considering restocking therefore serves as upper bound (UB) for the minimal-cost solution at the store level ($UB = [EOQ]$). The restriction of inventory carrying costs is also relevant in the case of severe underfacing

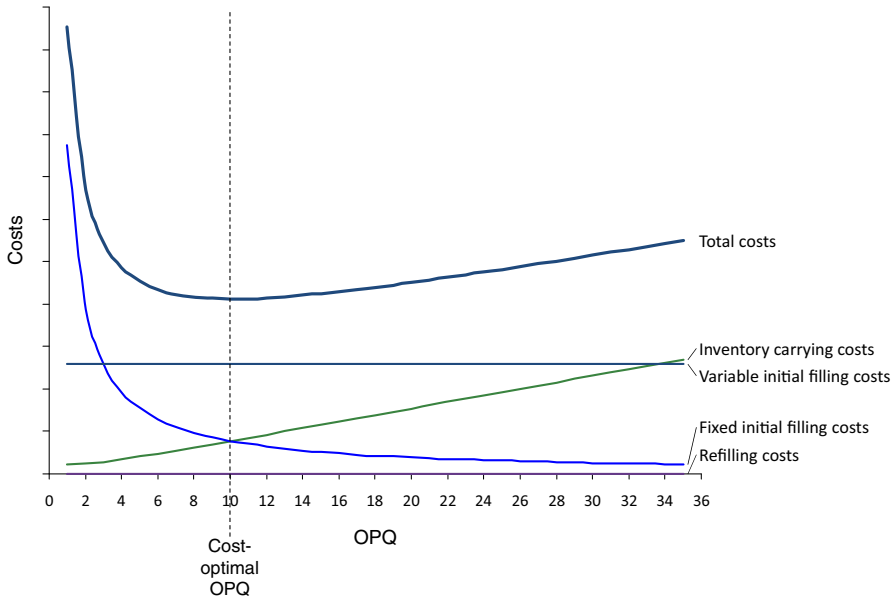


Fig. 5 Example of cost curves under the assumption of unlimited shelf space

accompanied by very high probabilities that all products delivered have to be restocked. In this case, the model aims for large OPQs as well in order to avoid fixed initial stocking costs, restricted only by inventory-carrying costs.

Figure 6 demonstrates the effects of both shelf space restriction and inventory carrying costs for different levels of total shelf capacity assigned to one SKU-store combination that is used as an example throughout this article. On the left side of the chart, where shelf space assigned corresponds to only 1 or 2 CUs, the probability that all CUs have to be restocked is very high resulting in the situation described above with the minimal-cost OPQ corresponding to the result of the basic economic order quantity model. When the assigned shelf space is 16 CUs or more, shelf capacity is no longer the restriction applied by the model due to inventory carrying costs being higher than fixed initial shelf stocking costs. An additional order is cheaper than the cost of capital that is tied due to larger OPQs. However, with shelf space of between 3 and 16 CUs, the minimal-cost OPQ and the resulting total costs are highly dependent on the assigned shelf space. With the cost rates applied and with increasing shelf space, the minimal-cost OPQ first gets smaller until a certain point accompanied by decreasing restocking volumes. The costs associated with fewer CUs that have to be restocked compensate for more orders with higher fixed initial stocking costs. From a certain point onwards, in this example at total shelf capacity of 9 units, the shelf space assigned is sufficient to carry out the inventory policy without having to restock any CUs at any time. Of course, in this situation as shelf space increases, the minimal-cost OPQ also raises until inventory costs restrict a further enlargement. From that point on, total costs will of course remain constant. The decrease in total instore costs with increasing shelf space is naturally dependent

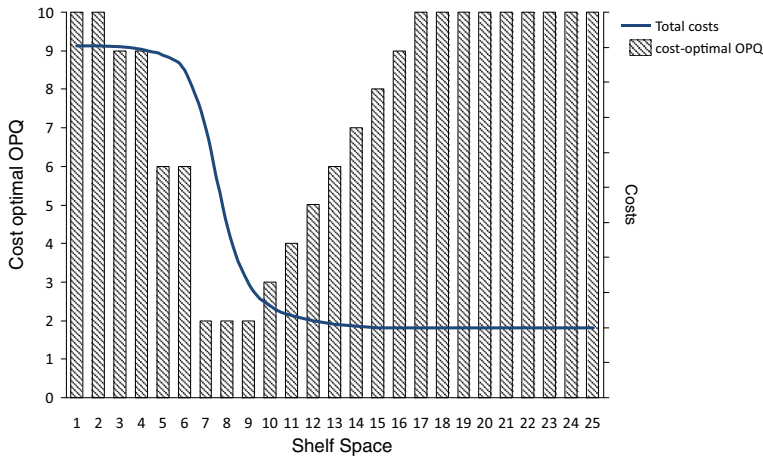


Fig. 6 Example of the dependence of total in-store costs on shelf space assigned

on the distributions of undershoot and demand during lead time. However, this example demonstrates the value of shelf space for bricks-and-mortar retailers. In practice, category managers are often not aware of the logistics implications of planograms, which mainly incorporate marketing aspects. Therefore, this research also provides vital input for category management as the adaption of shelf space is one potential approach besides dimensioning OPQs.

Against the backdrop of these analyses, it is of particular relevance for retailers to assess the robustness of the minimal-cost OPQs calculated. The robustness of the minimal-cost solution is dependent on the shape of the total cost curve around the minimum. These shapes are very different for the SKUs considered in the case example. We identify rather flatter curves and greater robustness of the minimal-cost OPQ for products with ample and very scarce shelf space, i.e., where the difference between S and $s - 1$ is high or negative. In these cases, the minimal-cost OPQ tends to be higher and covers more sales than where the difference between S and $s - 1$ is a small positive value, generally resulting in smaller minimal-cost OPQs. A deviation from minimal-cost OPQs that are large in comparison has minor effects around the cost minimum as an even larger ship pack will increase restocking costs for a comparatively small percentage of items delivered, and a reduction in the ship pack quantity would result in an increase in orders at a comparatively low rate. However, the effects are vice versa for SKUs with comparatively small minimal-cost OPQs. An enlargement quickly leads to a significant proportion of items that have to be restocked, and a further reduction in the ship pack size results in significant increases in the number of orders required. This means the smaller the minimal-cost OPQ calculated, the lower the robustness of the solution, which again emphasizes the relevance of shelf space as a very valuable resource in the retail trade. With this differentiation in mind, Fig. 7 shows the mean percentage change in total costs per SKU, including the effects in all stores from the case example.

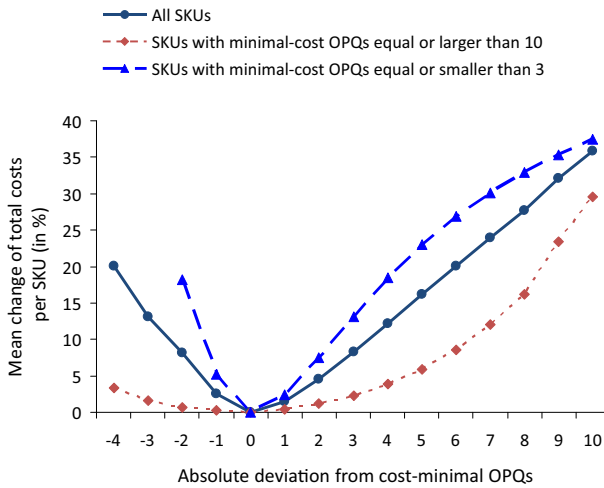


Fig. 7 Mean robustness of the minimal-cost OPQs calculated in the case example (one for all stores)

7.2 Limitations and areas for further research

The model developed and applied in this paper is definitely not exhaustive, resulting in the need for more research on the topic in future. Potential issues for further improvement are the instore cost structures included and the very important aspect of incorporating this research into a supply chain model. The significant cost reduction potential identified in the case study in this paper serves as a promising starting point for both researchers and practitioners to further address the question of how to dimension OPQs.

The instore costs integrated in the cost model reflect the processes as these are frequently configured in grocery retailing (Kuhn and Sternbeck 2013; van Zelst et al. 2009). However, as the volumes charged with the cost rates are calculated, the approach can easily be adopted to different instore cost structures. The determination of the specific cost rates is a difficult task in practice. Time and motion studies can help to identify the times that are needed to perform the relevant handling processes. The internal hurdle rate as a basis for calculating inventory carrying costs can potentially be determined by calculating the weighted average cost of capital. The variable restocking costs used in this paper are justified by high restocking frequencies and an overwhelming majority of slow-moving SKUs. However, this might be different for discount and small convenience stores with high selling rates per SKU, and may be subject to adaptation and further research. Restocking could also be interpreted as a periodic review inventory system within the delivery system from retail DCs with periods smaller than the corresponding periods derived from store deliveries. This could be one prospective approach for also integrating fixed restocking costs distributed over the number of CUs that fit onto the shelf at the time of restocking.

Perhaps the most important need for further research is the integration of instore logistics cost effects investigated in this paper into supply chain models comprising transportation and warehousing and possibly even packing operations at the supplier. Clearly, instore operations are mirrored in the retail DCs. When smaller OPQs are supplied to the stores, this naturally results in higher unpacking and picking costs in the DCs, or different cost structures at the manufacturers. Applying a supply chain perspective is inevitable in order to find an appropriate solution for the whole company or even for the supply chain segment, including the supplier. Instore logistics effects investigated in this paper play an important role in such a model due to the high proportion of instore costs, which could justify a shelf-back approach. In this context, further research could also address the question under what circumstances it would be favorable for retailers to offer more than one ship pack size per SKU, and allocate stores to the specific pack sizes on a fixed or dynamic basis. This would also be dependent on the divergence of store-specific requirements. As instore logistics costs represent the largest operational cost pool of bricks-and-mortar retailers, the store operations model developed is a fundamental basis for further approaches.

Acknowledgments We are deeply grateful to the European retailer for providing detailed data material and the comments received from research colleagues after presenting the topic at the 2012 European Conference of Operational Research in Vilnius, Lithuania. This paper benefited from discussions with Heinrich Kuhn, Andreas Holzapfel and Andreas Popp. We very much appreciate the comments and suggestions received from an associate editor and two anonymous reviewers, which significantly improved this paper. Furthermore, we would also like to acknowledge the financial support provided by the German retail and FMCG foundations “Goldener Zuckerhut” and “Erich Kellerhals”.

Appendix

A1: Calculation of the undershoot and corresponding inventory position at the time of ordering

By assuming that the undershoot and the relevant demand in the review period (D^{RP}) are stochastically independent (Tempelmeier 2011), we derive the discrete probability distribution of the undershoot with the help of the following approximate calculation with resulting probabilities that represent a non-increasing function of u (Tempelmeier 2011):

$$P\{U = u + 1\} = \frac{1 - P\{D^{RP} \leq u\}}{E\{D^{RP}\}} \quad (13)$$

with u in the interval $[0, 1, \dots, d^{RP, max} - 1]$ resulting in probabilities of an undershoot when an order is released in the interval $[1, 2, \dots, d^{RP, max}]$. As we assume lost sales when customer demand faces empty shelves, the undershoot cannot be larger than the order level s . However, the probabilities of larger undershoots should not be ignored. That is why we modify the resulting undershoot distributions by placing the mass, which is larger than s , right on s . We denote the resulting distribution as U^*

with u^* in the interval $[1, 2, \dots, s]$, which is now characterized by the following expression:

$$\sum_{u=1}^s P \{U^* = u^*\} = 1 \tag{14}$$

With this probability distribution of the undershoot we can easily calculate the probabilities of the inventory position $P(IP_O = ip_O)$ at the time of ordering:

$$IP_O = s - U^* \tag{15}$$

$$P \{IP_O = s - u^*\} = P \{U^* = u^*\}; \quad u^* = [1, 2, \dots, s] \tag{16}$$

A2: Calculation of the distribution of the number of CUs that can be stacked directly onto the shelf

The distribution of the number of CUs that can be stacked directly onto the shelf $P\{\#CU^{direct} = cu^d\}$ is calculated as follows:

$$\begin{aligned} P\{\#CU^{direct} = cu^d\} &= \sum_{\substack{Min(Max(S - (ip_O + d^{LT}); 0); \\ q(ip_O)) = cu^d}} P\{Min(Max(S - (ip_O + d^{LT}); 0); q(ip_O))\} \end{aligned} \tag{17}$$

with cu^d in the interval $[Min(Max(S - (s - 1); 0); OPQ), \dots, Min(\lceil \frac{s}{OPQ} \rceil \cdot OPQ; S)]$. This distribution serves as a basis to calculate the expected number of CUs that can be put directly onto the shelf during initial shelf stocking ($E\{\#CU^{direct}\}$).

For the cost calculations of OPQs that are greater than or equal to the order level s , calculation (17) –which continues to be valid– can be simplified as the order size q is independent of the undershoot because in every possible case only one OPQ will be ordered ($q = OPQ$). For these instances, we can simply convolve the probability distributions of U and D^{LT} and base all further calculations on the resulting distribution of physical inventory in stock instore (PI_D) at the time when the order consisting of one OPQ arrives in the store (Tempelmeier 2011):

$$P\{PI_D = s - pi_D\} = \sum_{u^* + d^{LT} = pi_D} P \{U^* = u^*, D^{LT} = d^{LT}\} \tag{18}$$

Again, the resulting probability distribution of PI_D has to be modified analogous to the undershoot distribution by cutting the distribution for values greater than s and placing the correspondent mass right on s . This is necessary, because the physical inventory cannot be further reduced. We denote the resulting distribution as PI_D^* with pi_D^* in the interval $[0, 1, \dots, s - 1]$, which is characterized by the following expression:

$$\sum_{p_{iD}=0}^{s-1} P\{PI_D^* = p_{iD}^*\} = 1 \quad (19)$$

In the case of $OPQ \geq s$, the probability distribution of the CUs that can be stacked directly after delivery can be calculated as follows:

$$\begin{aligned} P\{\#CU^{direct} = cu^d\} \\ = \sum_{Min(Max(S - p_{iD}^*; 0); OPQ)}^{Max(S - p_{iD}^*; 0); OPQ} P\{Min(Max(S - p_{iD}^*; 0); OPQ)\} \text{ for } OPQ \geq s \end{aligned} \quad (20)$$

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