European Journal of Operational Research 259 (2017) 84–99

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Production, Manufacturing and Logistics

Decision support for selecting the optimal product unpacking location in a retail supply chain

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ARTICLE INFO

Article history:
Received 1 September 2015
Accepted 28 September 2016
Available online 6 October 2016

Keywords:
Supply chain management
Inventory
Modern retail operations
Packaging
In-store logistics

ABSTRACT

The purpose of this research is to investigate the optimal product unpacking location in a bricks-and-mortar grocery retail supply chain. Retail companies increasingly are investing in unpacking operations at their distribution centres (DC). Given the opportunity to unpack at the DC requires a decision as to which products should be selected for unpacking at the DC and which should be shipped to stores in a case pack (CP) or outer pack provided by the supplier. The combined unpacking and unit size decision is evaluated by focusing on the relevant costs at the DC and in-store, i.e., picking in the DC, unpacking either in the DC or in the store, shelf stacking in the store and refilling from the backroom. For replenishing stores, an (R, s, nQ) inventory policy is considered when using the supplier CP and a (R, s, S) policy when the product is unpacked at the DC. Expressions are developed to quantify the relevant volumes and to calculate the corresponding costs on which the unpacking decision is based. A numerical example with empirical data from a European modern retailer demonstrates that unpacking a subset of the stock keeping units (SKUs) at the DC results in a significant cost reduction potential of 8% compared to no unpacking at the DC. The example shows that DC unpacking can generally be highly favorable for a large share of products.

1. Introduction

Retailers receive products or Stock Keeping Units (SKUs) in case packs (CPs), i.e., outer packs (secondary packaging), from their suppliers, but sell these products in consumer units (CUs), i.e., eaches (primary packaging), to their customers. A well-designed CP facilitates the handling of multiple CUs in the supply chain and protects the products during picking and transportation. However, the CP size also determines the minimum order quantity for the individual stores and consequently the number of store orders of a product per period submitted to the DC and the resulting in-store inventory level. The number of store orders per product and the inventory levels are not the only cost drivers that are influenced by CP sizes. If the inventory immediately after a delivery does not fit on the shelf space allocated, overflow inventory has to be stored elsewhere in a store, typically in the backroom, leading to additional costs (Eroglu, Williams, & Waller, 2013). Defining an optimal CP size is not an easy task since individual stores may differ greatly in terms of average sales and shelf space allocated for the same product.

As the CP frequently is considered to be too large, retailers unpack increasingly secondary packaging from manufacturers at their DCs to create pack sizes that better fit their needs. In an empirical investigation, Kuhn and Sternbeck (2013) show that full-line supermarket retailers in Austria, Germany and Switzerland unpack 8% of all SKUs listed in their DCs. Home and personal care retailers unpack as much as 63% of their SKUs to create appropriate order packaging quantities for their store deliveries. The present study therefore investigates whether a retailer gains any benefit from removing the secondary packaging upstream in the supply chain and then using reusable boxes for transportation instead of using the original manufacturer's CP as minimum transportation unit.

Throughout this paper, two possible alternatives are distinguished for grocery retailers that operate modern distribution channels. First, the retailer may decide to use also the supplier CP for store delivery or, second, the retailer may decide to unpack the CP in the DC and ship individual CUs to stores. To ensure adoption in practice, only the existing CP and the individual CU are considered, since both options can be implemented by retailers without requiring any CP negotiations with their suppliers. The

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http://dx.doi.org/10.1016/j.ejor.2016.09.054

unpacking decision relates directly to ordering decisions by the store, meaning that all stores of the retailer can order either integer multiples of the supplier CP or the CU.

This paper aims to shed light on these two unpacking alternatives and their consequences, and to support retail decision-makers by providing an evaluation and optimization model selecting the best unpacking point for each SKU. The relevant cost drivers along the internal retail supply chain that are dependent on the unpacking decision, are identified, quantified and subsequently included in a selection approach. As a result, the approach developed here shows the comparative effects of unpacking products either in a retail DC or, as done traditionally, in the stores on the different subsystems of the internal retail supply chain, with a special focus on costs. Although the problem of which unpacking alternative to choose is highly relevant for grocery retailers, scientific research on this topic is extremely rare.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on this decision problem. Section 3 introduces the research setting, describing the two, alternative supply chain configurations based on the unpacking locations and inventory policies applied. In addition, the relevant cost drivers are defined. Section 4 describes the evaluation and decision model and quantifies the relevant cost drivers. The evaluation and decision model is applied in a case study using empirical data provided by a major European retailer in Section 5. The results are presented and discussed in Section 6. Section 7 summarizes the main findings of the paper and discusses potential areas for future research.

2. Related literature

In this section, the relevant literature on product unpacking and CP size decisions in grocery retailing is reviewed.

To our knowledge, the question of which unpacking location is best in a retail network has not yet been addressed in the literature. Publications exist on the composition of packaging and the evaluation of packaging handling (e.g., with regard to opening the case packs), such as Gámez Albán, Soto Cardona, Mejía Argueta, and Sarmiento (2015) and Hellström and Saghir (2007). However, the identification of an appropriate location for unpacking operations in the supply chain is neglected.

Ketzenberg, Metters, and Vargas (2002) consider the case of supplying stores with individual CUs. The authors argue in favor of removing the CP constraint at the store completely by letting stores order in CUs only. They show that considerable benefits result from removing the CP constraint, but leave the consequences on cost to future research. However, other studies show that such an absolute strategy might not be optimal in general. In an empirical study, Kuhn and Sternbeck (2013) showed that CP size is considered to be a highly relevant, interdependent planning problem in a grocery retail chain that impacts warehouse operations as well as transportation and in-store logistics. The decision on CP sizes should therefore be considered on a strategic level, or at the very least on a tactical decision level (Hübner, Kuhn, & Sternbeck, 2013).

Only very few scientific approaches exist for calculating case pack sizes or minimum order quantities in a setting similar to the one studied in this paper. For example, De Souza, De Carvalho, and Brizon (2008) consider the related question of selecting container sizes in the automotive industry for feeding production lines. In the retail environment, Sternbeck (2015) provides a cost model for determining appropriate order packaging quantities from an in-store perspective, building on a periodic review, order point, order quantity inventory system. However, in-store costs are only one side of the coin and upstream logistics processes, such as DC picking, are not included in the analysis, although they play an important role for retailers when deciding on case pack sizes.

Wen, Graves, and Ren (2012) develop an approach for calculating CP sizes that considers all the relevant processes along the internal retail supply chain. The authors develop a cost model consisting of seven decision-relevant cost components, which represent the processes in the DC and in the stores that are dependent on CP size. The model results in the selection of a packaging unit for each SKU within the packaging hierarchy of the product, i.e., cases (supplier boxes), inners (sub-packaging) or eaches (CUs). Applying their model to a case example with real data reduces total costs by less than 0.5%. However, a few assumptions are made that do not reflect the reality of grocery retailers. For example, shelf space per SKU in each store is assumed to be 25% higher than the order-up-to-level. This shelf space assumption contradicts planogram analyses in reality and therefore neglects a significant amount of backroom activities and costs. Moreover, unpacking costs in the DC are included, while unpacking activities in the stores are not. The possible efficiency gains in the DC by standardizing the unpacking activity or even mechanizing it, which has the potential to reduce the unpacking cost compared to the store, is not taken into account yet.

Wensing, Sternbeck, and Kuhn (2016) also suggest a planning approach that quantifies the optimal CP size of a grocery retailer. They develop an inventory model that comprises multiple periods within a stationary cyclic model in order to cover demand distributions that vary within the store's business week and to consider an irregular weekly replenishment policy. Therefore, the model generalizes the periodic review reorder point (R, s, nQ) inventory policy to a cyclic version. Compared to the present study the authors neglect however the decision and the costs related to the unpacking location, either the DC or the store.

Generally, most publications on retail operations treat CP size as being exogenous (e.g., Broekmeulen, Fransoo, van Donselaar, & van Woensel, 2007; Eroglu, Williams, & Waller, 2011; Waller, Tangari, & Williams, 2008). An exogenous CP size is a legitimate assumption, since most CPs are designed and dimensioned by manufacturers and defined therefore externally from the retail perspective. Nevertheless, the influence of CP size is considered to be highly relevant. For example, Eroglu et al. (2013) integrate the backroom effect in the calibration of reorder levels to reach a cost minimum. The authors argue that the costs associated with handling overflow items lower the cost-optimal reorder level compared to the situation without overflows. They show that ignoring the costs of temporarily storing products in the backroom can lead to significant losses. The expected amount of overflow inventory calculated by the authors is also relevant for calculating store-optimal minimum order quantities. However, the assumption of continuous review inventory systems is usually not appropriate in the context of grocery retailing. Moreover, in-store activities are characterized by fixed costs, related to the number of store orders for a specific product (e.g., orientation and moving to the shelf), and variable stacking costs, related to the number of units stacked (e.g., putting the CUs on the shelf), resulting in nonlinear cost structures that are not integrated in the approach of Eroglu et al. (2013). On the other hand, if the available shelf space for a product is much larger than its CP size, the allocated shelf space might never be completely filled up, i.e., excess shelf space exists. van Donselaar, Gaur, van Woensel, Broekmeulen, and Fransoo (2010) show that local managers enlarge order quantities for products with excess shelf space reducing the number of store orders for a specific product and thus the effort for shelf stacking.

The literature review shows a lack of papers which pose the question of where to unpack CPs in the retail network, and the related question of how large the optimum picking unit should be. The goal of this paper is therefore to identify for each SKU the better of the two possible unpacking locations in the retail

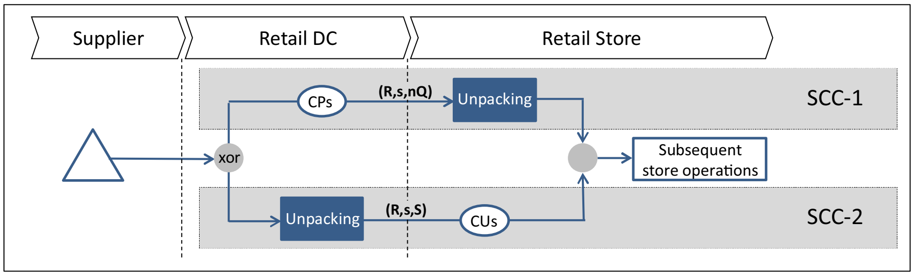

Fig. 1. Two unpacking alternatives: at the store or at the DC.

supply network, i.e., the DC or the store, and to consider the corresponding cost effects of the resulting picking unit size, i.e., CP or CU.

3. Research setting

In this section, the research context is outlined and the decision problem is described in greater detail in Subsection 3.1. Subsections 3.2 and 3.3 analyze the relevant processes and costs included in the study and describe the replenishment policies applied, respectively. Finally, Subsection 3.4 summarizes the decision-relevant cost drivers.

3.1. Decision problem

Two alternative supply chain configurations (SCC) are considered for each SKU, depending on where in the supply chain the product is unpacked, i.e., the secondary packaging of a product is removed (see Fig. 1).

SCC-1: The secondary packaging serves as a picking unit in the DC and is not removed until shelf-stacking takes place, i.e., after delivery of the product to the store. From a store perspective, all upstream handling is performed using the original CP from the supplier.

SCC-2: The secondary packaging is removed in the retail DC and the product is stored in temporary bins. During order picking in the DC, the products are picked from these bins with the CU as picking unit and transferred to reusable boxes for shipment to stores.

In this setting, the decision where to unpack the product is inextricably linked with the decision which picking unit to use in the DC. In the case where no unpacking at the DC takes place (SCC-1), the assumption is made that the supplier CP is always used as the picking unit. In the case of unpacking a product in the DC (SCC-2), the assumption is that individual CUs are used as picking unit. Combinations of CPs and CUs in one order are not allowed as retailers mostly apply only one unit per SKU in their distribution system, in order to avoid the need for multiple storage locations per SKU.

3.2. Processes and costs

Whether SCC-1 or SCC-2 is favorable for a specific SKU depends on several effects that occur as the product moves through the supply chain. In the setting studied, the individual CUs are made available to customers without any boxes on the shelf. This assumption implies that the secondary packaging has to be removed, no later than a product is stacked on the shelf. Assuming a given supplier CP, the expected number of supplier CPs that has to be unpacked per period is therefore independent on the unpacking location. Differences in unpacking costs exist clearly between the store and the DC environment. The DC is characterized by more standardized processes and technical support compared to the store.

There are several processes which depend on the size of the picking unit. This is why volume effects arising from the picking unit and the selected dispatch rule must be assessed and properly incorporated in decision-making. The relevant processes in the retail supply chain are illustrated in Fig. 2.

At the DC, the picking unit determines the number of picks for a given output volume and has therefore a major influence on DC costs, since in general picking costs account for more than half of total warehouse expenses (Rouwenhorst et al., 2000; de Koster, Le-Duc, & Roodbergen, 2007).

Store orders are sent to the DC. An order for a specific SKU is in general denoted as “order line” since a store order consists of several printed lines or positions, one for each specific SKU ordered, independently of the number of units ordered of this SKU.

DC picking costs consist of a fixed portion per order line (i.e., orientation time, movement of the order picker to the location of the product in the DC) and a variable portion per individual pick (i.e., grabbing the individual unit and placing it on the loading carrier for store delivery). This explains why total picking costs depend on the expected number of order lines and the expected number of units picked. Depending on the type of SCC selected, the picking unit can be the supplier CP or the individual CU. Retailers operate often different picking systems depending on the size of the picking units. For example, flow racks for small, unpacked products, or highly automated small-part picking systems. These include frequently pick-by-light picking and occasionally automatic supply of the parts to the picker, particularly if product variety is very large. These (small) products are usually packed into reusable boxes that circulate between the DC and the stores. For the picking of larger cartons and boxes, manual systems that are based on the worker-to-parts principle (e.g., block storage, pallet rack systems) are still most common, although the share of automatic picking is on the rise (e.g., automatic tray building and palletizing). Different picking systems for different picking unit sizes are naturally associated with different cost structures that must be reflected in any decision-making, as illustrated in Fig. 3. Due to the higher SKU density in a small parts system compared to a carton pick area, the fixed order line costs are relatively lower in a small parts system. Because this paper focuses on a single product situation, the effects of order batching procedures in the retail DC are not included.

The impact on transportation is assumed to be small enough to be omitted from further analysis, since transportation costs are mainly driven by the fixed costs resulting from the chosen delivery schedule, given that the sales volume in CU stays the same. Minor differences do exist of course in packaging density, depending on the use of the CP or CU as the picking unit, with a possible effect on the necessary freight space. In the single product case under study, only a very limited effect on transportation costs could be observed.

Store operations are the most complex operational subsystem in the internal retail supply chain. The standard in-store process

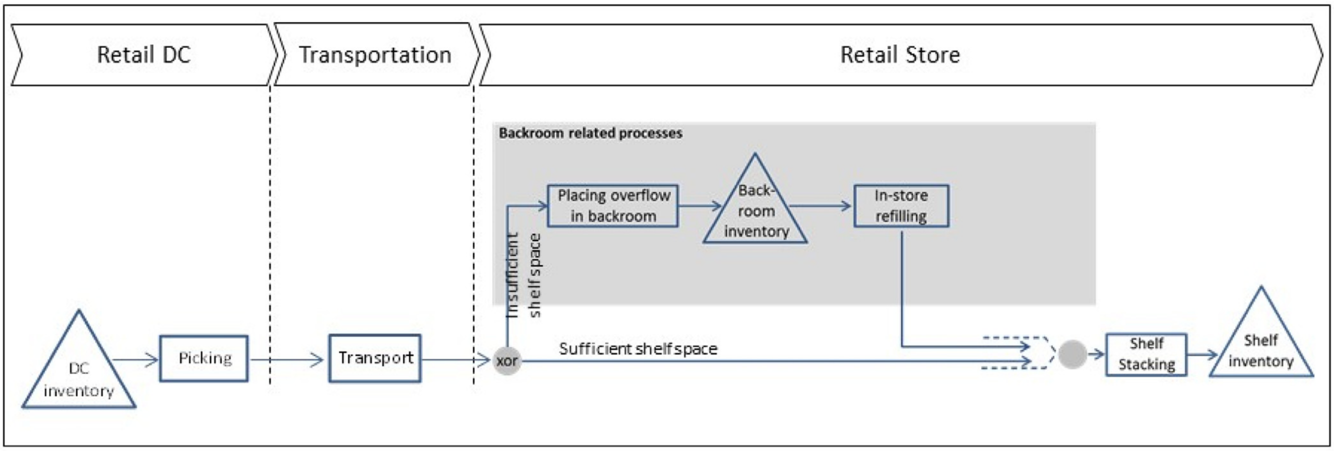

Fig. 2. Internal retail supply chain from DC to shelf.

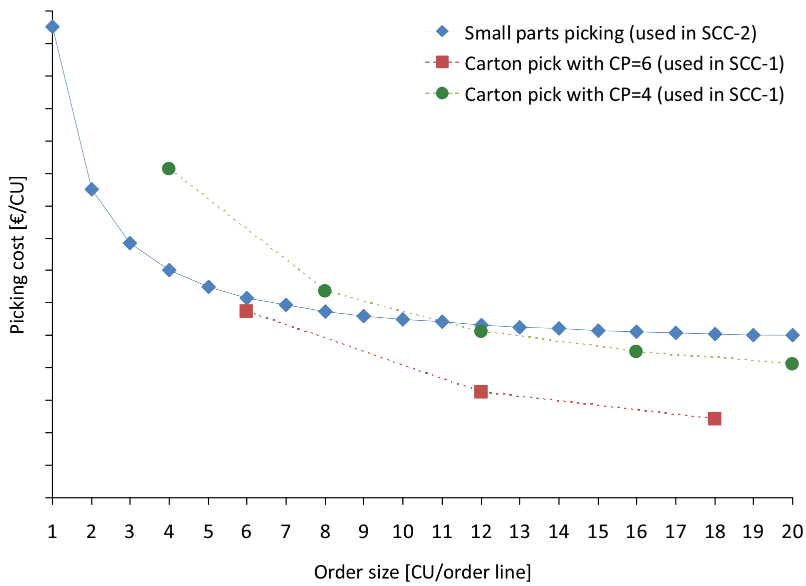

Fig. 3. Example of a cost comparison between two carton picking systems and a small-parts picking system, using the cost factors from Table 4. Note that for carton picking, the order size is measured in CUs, based on the number of CUs per CP.

in modern retail markets is mostly designed as follows: after a product delivery from the DC on pallets or in roll cages, products are either carried directly in front of the shelf or are kept in specific areas of the backroom until shelf stacking starts. During the shelf stacking process, products are unpacked if they are delivered in CPs, and put on the shelf. If the shelf space for an SKU is insufficient for accommodating all the products delivered, they have to be carried to the backroom, stored in the backroom and restocked later when free shelf space becomes available after consumer purchases. Such temporary storage in the backroom of the store is costly (Broekmeulen et al., 2007; Sternbeck, 2015). On the one hand, the store management is interested in frequent restocking, since the shelf is the preferred location for inventory in the store (Hariga, Al-Ahmari, & Mohamed, 2007). On the other hand, enabling combined restocks of several SKUs by establishing a schedule for in-store replenishments reduces the in-store replenishment cost. Generally, a retailer prefers to refill shelves from the backroom outside store hours in order to avoid the disruption for customers and regular staff and due to higher stocking efficiency. Scheduling the in-store replenishments just before the shelf stacking of every (potential) DC delivery has the additional benefit that the store clerks assigned already to shelf stacking can take over the refilling tasks from the backroom. It also ensures First In First Out rotation of the stock. Berg van den, Sharp, Gademann, and Pochet (1998) make also a distinction between replenishments during idle and busy periods in a warehouse. Fig. 4 illustrates the relationship between deliveries from the DC and the moment of in-store replenishment for the case that these activities are tightly synchronized. In the case that pallets or roll cages are regularly placed in the backroom before shelf stacking starts later, this will be reflected accordingly in the lead time and the pallets or roll cages are treated as stock in transit.

The fixed frequency of in-store replenishments during a review period gives an internal review period for the inventory policy that controls the inventory on the shelf in situations with backroom inventory. An SKU gets a restock in CUs when the inventory on the shelf drops below the shelf space, which acts as the order-up-to level. The probability of having backroom inventory together with the demand during the internal review period determine the expected number of in-store replenishments $E[NIR]$.

When the shelf space in combination with the frequency of in-store replenishments is too low to guarantee a sufficient fill rate, the store manager has to increase the frequency of in-store replenishments to guarantee a sufficient fill rate during the internal review period. For SKUs with a high demand uncertainty and very small shelf space allocated compared to the demand during

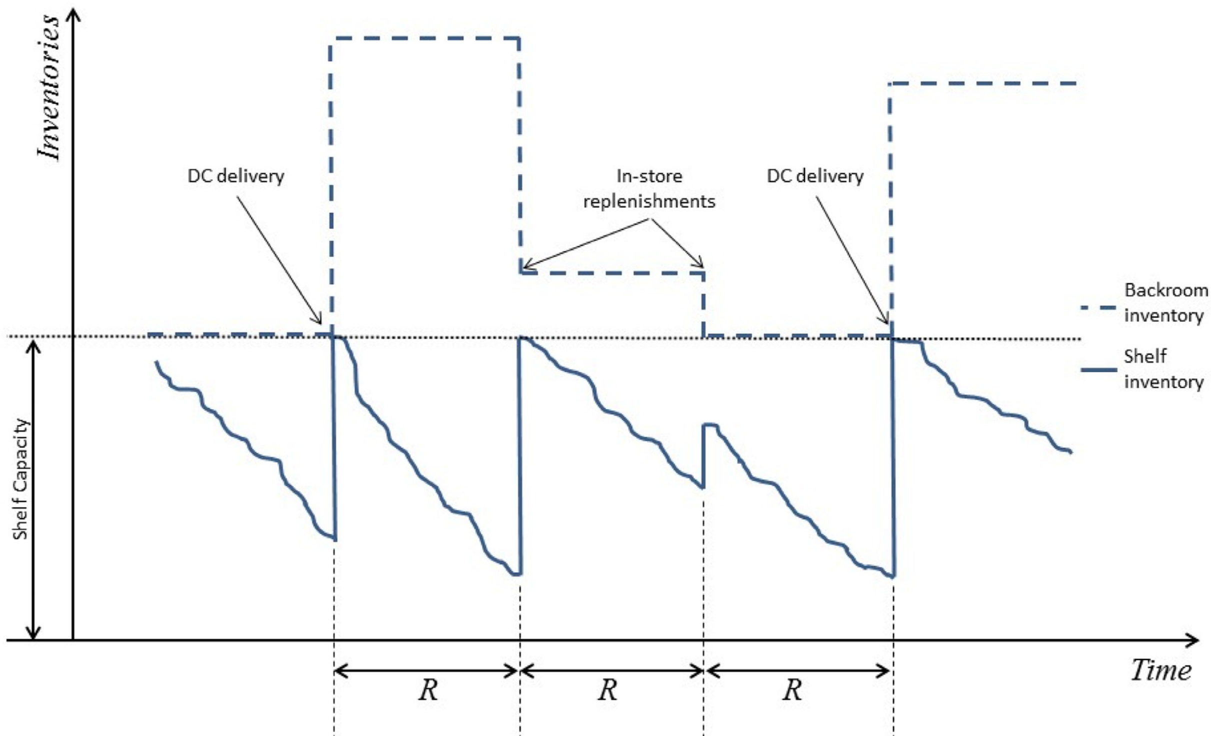

Fig. 4. The relationship between shelf and backroom inventory with a single periodic in-store replenishment from the backroom per review period R. The in-store replenishments are synchronized with the potential delivery moments of the DC, such that in-store replenishments always precede shelf stacking of the new stock.

the internal review period, just in time replenishments based on a continuous review of inventory on the shelf are needed. Otherwise, the frequency of scheduled in-store replenishments becomes impractical. For these situations, models based on continuous review and a space restriction, such as described by Hariga (2010) and Eroglu et al. (2013) are more suitable and these SKUs are not further considered in this research setting.

Note that the presented approach supports rather modern retail channels with retail-operated DCs and stores with backroom areas and well-defined planograms for the merchandize in developed or middle-income countries. The effect of overflow inventory is largely absent in traditional stores in emerging markets (e.g., Gámez Albán et al., 2015). However, this study mainly relates to the European grocery retail market including discounters and full-line supermarkets. The stores of those retailers include generally a backroom area.

3.3. Store replenishment policies

The amount of overflow inventory in the backroom and the frequency of in-store replenishments depend on store specific characteristics, such as the mean and variance of the SKU demand and the allocated shelf space for the SKU in the planogram, but also on the type of replenishment policy and the associated parameters. The delivery schedule from the DC, which is used to combine order lines for individual SKUs in store orders to coordinate transportation, determines a periodic review inventory policy with a given review period and lead-time. The picking unit gives a lower bound on the minimal order quantity (MOQ) and the incremental order quantity (IOQ). The minimal order quantity sets a lower limit on the order size that a store can order. The incremental order quantity determines the step size in which the order size can be increased, often to facilitate efficient handling in the supply chain. A higher MOQ reduces the expected number of order lines by increasing the time between orders. Without unpacking at the DC, the CP is used as picking unit and the size of the CP is both the MOQ and the IOQ. Unpacking at the DC results in the CU as picking unit, which could be too low to use as MOQ, since this would result in a high number of order lines. With stores that differ in demand and shelf space, a CP with a fixed size for all stores is less flexible than using the CU together with a store-specific MOQ and/or IOQ to reduce the number of order lines. A periodic review inventory policy with a review period R and fixed CP size Q is in general reflected in practice by an (R, s, nQ) inventory policy. Note that s is the reorder level that is used to trigger an order at a review moment and n indicates that the order size must be an integer multiple of the value Q. For situations with periodic review, a store-specific MOQ and $IOQ=1$, the (R, s, S) inventory policy applies. In such an inventory system, the order-up-to level S is determined by $S=s-1+MOQ$. An alternative inventory policy in the situation with the CU as picking unit would be the (R, s, nQ) inventory policy, but now with a store-specific $Q=MOQ$ and $IOQ=MOQ$. Note that setting IOQ equal to MOQ is more restrictive than allowing that $IOQ=1$. In this research setting, no additional cost benefit from setting $IOQ=MOQ$ is assumed since the handling along the supply chain is not considered to be dependent on the IOQ. But in the case that the automated store replenishment system used by the retailer only supports the (R, s, nQ) logic, this alternative becomes interesting. Based on these assumptions, the replenishment policy for SCC-1 is (R, s, nQ) with the supplier CP as MOQ and IOQ, and the replenishment policy for SCC-2 is (R, s, S) with a store specific MOQ and $IOQ=1$. A more in-depth discussion on the advantages and disadvantages of the different replenishment policies is given in Section 4.

3.4. Summarizing the decision-relevant cost drivers

Together with the inventory policy chosen, the MOQ and IOQ influence (1) overall store inventory carrying, (2) shelf stacking, (3) backroom storage as well as (4) in-store shelf refilling from the

Table 1
Cost types considered in the decision model, based on Gámez Albán et al. (2015) and Wen et al. (2012), and complemented by the authors.

Cost type	Cost driver(s)
DC picking costs	Expected number of order lines ($= E[OL]$)
	Expected number of supplier CPs or CUs picked (depending on configuration)
DC unpacking costs	Expected number of supplier CPs unpacked at the DC
Store inventory costs (capital costs)	Expected inventory on-hand in the store (shelf plus backroom) ($= E[I^{OH}]$)
Backorder penalty costs	Expected amount of backorders
Store unpacking cost	Expected number of supplier CPs unpacked in the store
Store shelf stacking costs	Expected number of order lines ($= E[OL]$)
Store backroom storage costs (space costs)	Expected inventory on-hand in the backroom ($= E[I^{BR}]$)
Store refilling costs from backroom	Expected number of in-store replenishments from the backroom ($= E[NIR]$)

backroom. First, the *MOQ* and *IOQ* influence the expected overall inventory on-hand in the store (shelf and backroom) $E[I^{OH}]$, and therefore also the capital tied up in the store, since order sizes and therefore order frequencies depend on these parameters. Note that the storage cost for inventory on the shelf (space costs) is sunk, since the planogram, i.e., shelf space allocation, is out of scope in this research. Second, the size of a CP or *MOQ* affects shelf stacking, which is characterized by fixed costs per order line and variable costs per CU delivered (van Zelst, van Donselaar, van Woensel, Broekmeulen, & Fransoo, 2009). Because the expected number of order lines $E[OL]$ depends significantly on the CP or *MOQ* size, shelf stacking is affected by the unpacking decision. Third, the size of the *MOQ* and *IOQ* impact the degree to which items delivered fit onto the shelf at the time of delivery since shelf space allocated in the planogram is restricted. The unpacking decision determines the degree of freedom in setting the *MOQ* and *IOQ* and therefore influences the expected inventory on-hand in the backroom $E[I^{BR}]$. As the *MOQ* and/or *IOQ* increase, the probability increases that shelf space will be insufficient for accommodating all the products delivered. On the other hand, a small *MOQ* in the presence of abundant shelf space results in overly frequent shelf-stacking activities, associated with fixed stacking costs per order line. Note that unpacking is considered separately and not included in shelf-stacking costs. For the products stored temporarily in the backroom, backroom storage costs are assumed based on the expected backroom inventory $E[I^{BR}]$. These costs are based on the shortage of backroom space and the low level of organization in the backroom. Fourth, because the amount of overflow inventory depends on *MOQ* and *IOQ*, the processes associated with refilling the shelf from the backroom must also be taken into account when planning an appropriate unpacking location. Table 1 gives an overview of the cost types in the research setting.

4. Model

This section describes the model for selecting the optimal unpacking location in an internal retail supply chain. The notation (Table 2) and assumptions are introduced first (Subsection 4.1), followed by derivation of expressions for several cost drivers for the respective order policies (Subsection 4.2), these being required to formulate the overall optimization model (Subsection 4.3).

4.1. Main assumptions and notation

A single product situation is modelled, in which the decision on the unpacking location and possibly the decision on the store-specific *MOQ* is independent of decisions concerning other products in the supply chain. When a retailer offers a product in different sizes to the customers in the stores (primary packaging), these product variants are considered as separate SKUs. The assumption is made that the retailer displays and sells the products generally in CUs only, and that all products are delivered to the retail DC in multiples of a secondary packaging, i.e., a CP of a fixed size. A further assumption is that the decisions do not influence shipment sizes from the manufacturer to the retail DC. An ample supply of external CPs and no capacity restrictions for the unpacking operations at the DC or the store are assumed. Each stage in the supply chain receives only one size from the preceding stage, i.e., they receive either CPs or CUs as picking units, and not a mix of both during the planning horizon.

The backroom area is assumed being sufficiently large to accommodate the complete DC delivery until the shelf stacking process starts if DC deliveries and shelf stacking are not tightly synchronized. Moreover, the backroom is assumed to be uncapacitated for the temporary storage of 'overflow inventory' when the DC delivery does not entirely fit onto the shelves.

The fixed review period for the stores is determined by the delivery schedule of the DC. A delivery schedule defines the intervals, i.e., the time between delivery, with which a store receives deliveries from the warehouse (Holzapfel, Hübner, Kuhn, & Sternbeck, 2016; Sternbeck & Kuhn, 2014). Delivery intervals of equal length are assumed. The lead-time for the store consists of the lead-time from the DC plus the time between delivery and the start of the shelf stacking. Due to the uninterrupted delivery to the shelves in the stores, the lead-time is considered to be deterministic.

Only the two SCCs mentioned in the research setting are considered. In SCC-1, denoted by the index $m=1$, the store orders from the retail DC in multiples of the CP size Q using the (R, s, nQ) policy, with review period R and reorder level s. In SCC-2, denoted by the index $m=2$, the store orders using the (R, s, S) policy, which results in replenishment quantities that are greater than or equal to a *MOQ*.

As far as store demand is concerned, stationary demand for the product from a discrete demand distribution is assumed. The probability mass function $P[D(\tau, \tau+T)=d]$ for the demand during a period of length T can be obtained by the method of Adan, van Eenige, and Resing (1995) using the first two moments of the demand, μ_T and σ_T, or directly by using the empirical distribution.

4.2. Calculation of cost drivers

In the next step, expressions are developed to calculate all the relevant cost drivers described in Section 3 and listed in Table 1. These cost drivers depend on the inventory policy used by the store in a given SCC.

Assuming the SCC-1 strategy ($m=1$), then (R, s, nQ) is the relevant policy (see Silver, Pyke, & Peterson, 1998). At periodic review moment τ, a replenishment order of size OS_τ with n_τ CPs (each of size Q) is only created if the inventory position, which is the sum of inventory on hand in the store and inventory in transit, is strictly below reorder level s. The value of n_τ is chosen such that the inventory position just after a replenishment decision is at or above s, but strictly less than $s+Q$. If IP_τ^- is defined as the inventory position at review moment τ just before an order is

Table 2
Notation.

Symbol	Description
β	Fill rate
BO	Backorders
C_m^{TRC}	Total relevant costs for an SKU in supply chain configuration m
C^{DSFix}	Fixed direct stacking costs in the store
C^{BR}	Backroom storage costs
C^{IR}	Costs of an in-store replenishment order line from the backroom
$C_m^{OPDCFix}$	Fixed order picking costs in the DC in supply chain configuration m
$C_m^{OPDC\_CP}$	Variable order picking costs per CP in the DC in supply chain configuration m
$C_m^{OPDC\_CU}$	Variable order picking cost per CU in the DC in supply chain configuration m
C_m^{UNPACK}	Variable unpacking costs per external CP in supply chain configuration m
$D(\tau,\ \tau+T)$	Demand between τ and $\tau+T$ (period of length T)
F	Frequency per review period of the in-store replenishments from the backroom
h	Holding cost parameter related to review period R
I^{BR}	Inventory on hand in the backroom
I^{OH}	Inventory on hand in the store (shelf plus backroom)
IP	Inventory position
IOQ	Incremental order quantity
L	Lead-time
m	Index for the supply chain configuration (SCC), $m=1$ denotes SCC-1 and $m=2$ denotes SCC-2
MOQ	Minimum order quantity (**decision variable**)
NIR	Number of in-store replenishment order lines from the backroom
OL	Number of order lines in store delivery from DC
OS	Order size
p	Backorder penalty costs
Q	CP size, externally defined by the supplier
R	Review period for the store orders
s	Reorder level (**decision variable**)
S	Order-up-to level
V	Shelf capacity
w	Index for the store, $w \varepsilon W$
W	Set of retail chain's stores, $W \varepsilon$ {1, 2, ..., w, …, $\|W\|$}
$\mu_T,\ \sigma_T$	Mean and standard deviation of the demand during a period of length T
ρ	In-store replenishment moment
τ	Periodic review moment

placed, then n_τ is determined as follows:

$$OS_\tau^{RsnQ} = n_\tau \cdot Q = \frac{s - IP_\tau^-}{Q} \cdot Q \quad \text{if} \cdot IP_\tau^- < s \tag{1}$$

Note that x rounds up x to the nearest integer.

In a backordering system with discrete demand, the inventory position after ordering IP_τ^+ is known to be uniformly distributed between $[s,\ \cdots,\ s-1+Q]$ (Hadley & Whitin, 1963). This result, however, does not hold for lost sales systems. Following common practice as discussed in Silver et al. (1998), the reorder level is set as follows:

$$s = SS + E[D(\tau, \tau + R + L)] \tag{2}$$

In (2), SS is the safety stock and $E[D(\tau,\ \tau+R+L)]$ the expected demand during review period R plus lead time L. Note that the parameter s is set specifically for store and product in SCC-1.

With the SCC-2 strategy ($m=2$), replenishment follows the (R, s, S) policy, with R being the review period, s the reorder level and S the order-up-to level. As with the (R, s, nQ) policy, an order is placed when the IP is strictly below the reorder level. The order size is determined as follows:

$$OS_\tau^{RsS} = S - IP_\tau^- \quad \text{if} \cdot IP_\tau^- < s \tag{3}$$

Note that there is no CP restriction in this situation. In this case, however, the difference between the order-up-to and reorder levels determines the expected number of order lines that drive picking and shelf-stacking costs. The (R, s, S) policy is interesting in the case of positive fixed ordering costs and replenishment in CUs (after unpacking), because the inventory position is always raised exactly up to the maximum inventory level given by S. The minimum order quantity MOQ is defined as the difference between the order-up-to level and the reorder level: $MOQ=S-s+1$. It is guaranteed that this amount at least is ordered with every order.

In a backordering system with discrete demand, the distribution of the inventory position after ordering IP_τ^+, which is between $[s,\ \cdots,\ s-1+MOQ]$, can be determined recursively based on renewal theory using the procedure described by Zheng and Federgruen (1991). Note, the parameters s and S are set specifically for store and product.

Looking at the different phases of the order cycle, first $\tau+L$ is defined, which is the moment a potential delivery arrives at the stock point and is added to the inventory on hand. Note that the delivery is potential, because not every review period results in an order being placed. The lowest inventory on hand occurs after $\tau+R+L$, which is the end of a potential delivery cycle, immediately before a potential delivery arrives at the stock point.

The variable representing the difference between IP_τ^+ and the reorder level minus 1 is denoted by Δ and has the range $[1,\ \cdots,\ U]$. For the (R, s, nQ) policy and assuming backorders, Δ is uniformly distributed between 1 and the incremental order quantity, which is in SCC-1 the CP size Q ($U=Q$). For the (R, s, S) policy, the procedure developed by Zheng and Federgruen (1991) can be applied to determine the distribution of Δ, with $U=MOQ$.

For the classical single-item, single-echelon inventory system under standard assumptions (independent demands, backordering, a fixed ordering cost, convex holding and backordering costs), the (R, s, S) policy is known to be the optimal policy for minimizing the long-run average costs (Veinott, 1966 and Zheng & Federgruen, 1991). When considering service constraints, the (R, s, S) policy is not necessarily the optimum policy (Axsäter, 2006, par. 6.2.2). In a grocery retailing environment the lost-sales case and not the backordering case is relevant. In the case of high fill rates or relatively high backorder penalty costs, the lost-sales case can be approximated by assuming an inventory policy with backordering. In the numerical study, the result obtained by the backordering approximation will be compared to the result of a simulation of a lost sales system to get an indication of the approximation error.

Based on the concept of the potential delivery cycle, expressions are developed for several cost drivers for the (R, s, nQ) and (R, s, S) policies under discrete demand. The cost drivers are exact for the backordering scenario and approximate for the lost sales scenario. The following cost drivers are used in the presented decision model: expected inventory on-hand $E[I^{OH}]$, fill rate β, expected number of order lines $E[OL]$, expected backroom inventory $E[I^{BR}]$ and expected number of in-store replenishment order lines $E[NIR]$.

The expected inventory on hand $E[I^{OH}]$ after a potential delivery cycle is determined by the IP_τ^+ minus the demand during the review period plus the lead time.

$$\begin{aligned}
E\left[I^{OH}(\tau+R+L)\right] &= E\left[\left(IP_\tau^+ - D(\tau,\tau+R+L)\right)^+\right] \\
&= E\left[(s-1+\Delta-D(\tau,\tau+R+L))^+\right] \\
&= \sum_{i=1}^{U} P[\Delta=i]\cdot E\left[(s-1+i-D(\tau,\tau+R+L))^+\right] \\
&= \sum_{i=1}^{U} P[\Delta=i]\cdot \sum_{d=0}^{\infty}(s-1+i-d)^+\cdot P[D(\tau,\tau+R+L)=d] \\
&= \sum_{i=1}^{U} P[\Delta=i]\cdot \sum_{d=0}^{s-1+i}(s-1+i-d)\cdot P[D(\tau,\tau+R+L)=d]
\end{aligned} \tag{4}$$

Note that $(x)^+$ is equal to max{0, x}.

According to Axsäter (2006, par 5.12), the fill rate β for a periodic review system is defined by the additional backorders occurring during a review period divided by the expected demand during the review period.

$$\begin{aligned}
\beta &= 1-\frac{E[BO(\tau+R+L)]-E[BO(\tau+L)]}{E[D(\tau+L,\tau+R+L)]} \\
&= \frac{E\left[I^{OH}(\tau+L)\right]-E\left[I^{OH}(\tau+R+L)\right]}{E[D(\tau+L,\tau+R+L)]}
\end{aligned} \tag{5}$$

The expected number of order lines $E[OL]$ at a review period τ is

$$\begin{aligned}
E[OL] &= P\left[IP_\tau^+ - D(\tau,\tau+R) < s\right] \\
&= P[s-1+\Delta-D(\tau,\tau+R)\le s-1] \\
&= P[D(\tau,\tau+R)\ge \Delta]
\end{aligned} \tag{6}$$

The probability of having overflow inventory on hand in the backroom P_{BR} just after a potential delivery and after direct stacking is equal to the probability that the IP just after a potential order moment minus the demand during the lead time is greater than the shelf capacity V, i.e.,:

$$P_{BR} = P\left[IP_\tau^+ - D(\tau,\tau+L) > V\right] = P[s-1+\Delta-D(\tau,\tau+L) > V] \tag{7}$$

Note that the backroom is never needed to store the product when the allocated shelf space V is greater than or equal to the maximum inventory on hand, which in turn is equal to $s-1+Q$ for the (R, s, nQ) policy and S for the (R, s, S) policy. Based on the expression for overflow inventory, the resulting expected backroom inventory $E[I^{BR}]$ immediately after a potential delivery is:

$$E\left[I^{BR}\right] = E\left[(s-1+\Delta-D(\tau,\tau+L)-V)^+\right] \tag{8}$$

The fixed frequency F determines the number of potential in-store replenishments per review period. If positive demand has occurred between two consecutive in-store replenishment moments $\rho-1$ and ρ (with an internal review period R/F), and inventory is still available in the backroom, an in-store replenishment order line results, which is added to the trip from the backroom to the shelf. The expected number of in-store replenishment order lines $E[NIR]$ per review period is then as follows:

$$\begin{aligned}
E[NIR] = \sum_{\rho=1}^{F} & P\left[D\left(\tau+L+(\rho-1)\cdot\frac{R}{F},\tau+L+\rho\cdot\frac{R}{F}\right)>0\right] \\
&\cdot P\left[IP_\tau^+ - D\left(\tau,\tau+L+(\rho-1)\cdot\frac{R}{F}\right)>V\right]
\end{aligned} \tag{9}$$

Note that if the shelf space is too small to guarantee the target fill rate with only in-store replenishments at the end of each internal review period, additional refilling operations are necessary during the internal review periods and Eq. (9) gives only a lower bound on $E[NIR]$.

4.3. Optimization model

For a given SKU, the relevant cost drivers can be determined for each store $w\in W$ and SCC m using the expressions introduced and assuming backordering. The decision-relevant average total cost for an SKU under SCC m during a review period is:

$$\begin{aligned}
C_m^{TRC} = \sum_{w} & h\cdot\ E\left[I^{OH}\right]_{wm} + p\cdot(1-\beta_{wm})\cdot\mu_R + \left(C_m^{OPDCFix}+C^{DSFix}\right) \\
&\cdot E[OL]_{wm} + C^{BR}\cdot E\left[I^{BR}\right]_{wm} + C^{IR}\cdot E[NIR]_{wm} \\
&+\left(\frac{1}{Q}\left(C_m^{UNPACK}+C_m^{OPDC_CP}\right)+C_m^{OPDC_CU}\right)\cdot\mu_R
\end{aligned} \tag{10}$$

To find the optimal costs for configuration SCC-1 with unpacking at the store ($m=1$), the optimization procedure searches for the reorder level s^* that minimizes the cost function in Eq. (10). In configuration SCC-2, where the CP is unpacked at the retail DC ($m=2$), the procedure searches for the combination of MOQ and reorder level s^* that minimizes the cost function by full enumeration. In the latter case, the procedure starts with MOQ=1 and subsequently increases the MOQ until a predefined upper bound for it is reached. For each MOQ considered, the procedure searches for the corresponding optimal reorder level. The problem requires an exhaustive search, since the cost function has multiple local minima, due to the integer nature of the reorder level. Without a restriction on the number of SKUs in the various picking systems, the optimal configuration for an SKU is the SCC with the lowest costs.

An alternative, service-constrained optimization model is based on finding the reorder level $\hat{s}$ that minimizes C_{wm}^{TRC}, subject to the constraint that $\beta_{wm}\ge\hat{\beta}$, with $\hat{\beta}$ being the target fill rate. If a service-level constraint exists, the penalty cost p is set to zero in Eq. (10).

The decision model was implemented in Microsoft Access 2013 and all cost driver expressions were coded in Visual Basic for Applications. Optimizing the reorder level for a single SKU and a given MOQ or Q requires an average of 1.6 milliseconds on a desktop PC with an Intel Core i5-3570 CPU.

5. Numerical study

In this section, the model is applied to a hypothetical environment that reflects real-life conditions. In the study, empirical secondary data is used, obtained from a large European retail company (referred to in the following as DELTA). However, since costs could not be disclosed, cost factors available in the literature are applied, mainly from van Zelst et al. (2009) and Huntjens (2008). This procedure leads to an artificial company with documented cost factors that can be reproduced in future research projects.

DELTA is a major European home and personal care retail company. The company operates over 1500 stores in Germany that are supplied with the whole assortment of roughly 13,000 SKUs from two types of DCs.

Table 3
Descriptive store statistics.

Store	Fraction of these stores in the chain	Sales [CU/day]			Shelf space [CU]	Number of SKUs
		Min	Average	Max	Average	
1	0.16	0.05	1.23	9.73	13.38	1255
2	0.24	0.03	0.65	4.60	13.29	1251
3	0.11	0.01	0.65	6.99	13.01	1195
4	0.11	0.06	1.18	13.81	15.38	1277
5	0.38	0.02	0.72	4.29	13.31	1202

The first DC type is characterized by a conventional carton pick process, in which supplier CPs are packed onto pallets which are transported to the stores. This DC corresponds to configuration SCC-1. Picking is carried out manually. Because the picking unit sizes are greater when using the CP instead of the CU, there is only one provisioning layer from which CPs are picked, this resulting in longer travel distances and times per stop compared to intralogistics systems with several provisioning layers. In this type of DC, DELTA cannot modify the supplier CP and uses CP sizes as the general picking and distribution unit to supply the stores. The second type of DC is one in which small pieces, sub-packages or single CUs are picked into reusable boxes which are distributed to the stores. This DC more or less matches configuration SCC-2. The corresponding unpacking activities are also part of the intralogistics system. Highly automated unpacking lines are in place for unpacking supplier CPs, so that a smaller packaging unit can be selected as the picking and distribution unit. The pick-by-light picking system is adapted to the picking unit sizes with specified working areas and several layers from which the picker grabs the products. This reduces remarkably travel distances, resulting in less time per stop and pick compared to a conventional case picking system.

We obtained data from DELTA on three product categories (cleaning agents, hair care products and organic food) in five typical stores, ranging from small to large, based on the sales in CU over all categories carried in the store. These stores can order daily, i.e., a review period corresponds to one sales day, but to facilitate work at the DC, the lead-time is four days, a reasonable concept since the retail format operates according to the everyday-low-price principle. A constant lead time of $L=4$ and a review period of $R=1$ are assumed. The company aims for a target fill rate of 99%.

Of the 1279 SKUs in the data set, 1135 are in the assortment of all five stores and 20 are only sold in one store. The data set of 6180 store-SKU combinations includes one year of demand data (mean and variance of daily sales from May 2012 until April 2013), CP sizes and shelf capacities. From the 6180 store-SKU combinations, 80% are fitted with a mixed negative binomial distribution, 13% with a mixed geometric distribution, and 7% with a mixed binomial distribution according to the method of Adan et al. (1995). The average CP from the supplier contained 10.87 CUs on average with a minimum of 2 and a maximum of 216. The actual CP sizes and CUs used for store orders contained 8.46 CUs on average, with a minimum of 1 and a maximum of 35. This lower range is a result from using the supplier's sub-packaging (inner) for 74 SKUs. The supplier CP was completely unpacked for only 8 SKUs. The original supplier CP was used in all other 1197 instances. Table 3 shows descriptive statistics on daily sales, available shelf space for the SKUs and assortment size per store.

There are 58 store-SKU combinations requiring more than one in-store replenishment from backroom storage per review period due to limited shelf space and high average daily sales or variance in the daily sales. A single in-store replenishment per review period, assumed in this numerical study, would therefore be insufficient for supporting an in-store target fill rate of 99%. These store-SKU combinations, which make up 2% of sales, are excluded in the remainder of the analysis as we propose to apply continuous review of these few products according to the models provided for example by Hariga (2010) and Eroglu et al. (2013) or to increase the frequency of in-store replenishments.

Since we are unable to disclose DELTA's actual cost data, the cost data in this numerical study draws on empirical data compiled by Huntjens (2008) from a comparable retailer in the Netherlands and therefore reflects the Dutch environment. The assumption is made that all products have the same holding cost $h=0.25$ €/(CU and year), based on an average product value of 2.5 €/CU and an inventory carrying charge of 10% per year. The penalty cost p is derived from the holding cost using the newsvendor equation, based on the target fill rate β of 0.99 and a lead-time of 4 days, resulting in 0.275 €/CU. An average wage of 18 €/h is assumed for the distribution centre and 9 €/h for the temporary shelf stackers. In reference to the study of van Zelst et al. (2009), the fixed time per order line in the store is 12 seconds, resulting in an average order line cost in the store for direct shelf stacking C^{DSFix} of 0.03 €/OL. In a conventional order picking system for CPs, the time per stop for an SKU is assumed to be 6 seconds on average according to the motion and time study by Huntjens (2008), which results in an average order line cost in the DC $C_1^{OPDCFix}$ of 0.03 €/OL. In a pick-by-light order picking system for CUs, the time per stop for an SKU is only 2 seconds, resulting in $C_2^{OPDCFix}$ of 0.01 €/OL. The grabbing times in the DC are 4.5 seconds per CP in the conventional picking area and 1.5 seconds per CU in the small-parts area, resulting in $C_1^{OPDC\_CP} = 0.0225$ €/CP ($C_2^{OPDC\_CP} = 0$) and $C_2^{OPDC\_CU} = 0.0075$ €/CU ($C_1^{OPDC\_CU} = 0$). According to van Zelst et al. (2009), unpacking in the store during shelf-stacking takes an average of 10 seconds per CP, resulting in $C_1^{UNPACK} = 0.025$ €/CP. By using an automated unpacking system in the DC, the unpacking cost there are $C_2^{UNPACK} = 0.015$ €/CP. The time per SKU needed for an in-store replenishment order line from the backroom is assumed to be the same as for an order line during direct stacking, since in both situations only the time without unpacking is considered, resulting in $C^{IR}=C^{DSFix} = 0.03$ €/OL. The backroom storage costs C^{BR} is set to 0.1 €/(CU and year) to account for the storage operations needed to keep the storage area tidy and accessible. Table 4 summarizes the cost factors.

6. Results and discussion

This section presents and discusses the results of the numerical study applied. Scenario A shows the current situation at DELTA and four additional scenarios are calculated:

- A *Current situation at DELTA (one size for all stores):* All stores receive products in the units currently applied by DELTA, either in the supplier CP or in the units created in the DC (using inners or CUs) and unpacking is done during shelf stacking (for CPs and inners).
- B *SCC-1 (CPs for all stores and all products):* All stores receive exclusively all products in supplier CPs of size Q and unpacking is done during shelf stacking. Store orders are based on a (R, s, nQ) policy.
- C *SCC-2 (CUs for all stores and all products):* All stores receive exclusively all products unpacked from the DC in CUs and store

Table 4
Cost data for the numerical study.

Cost type	SCC-1	SCC-2
Fixed DC picking cost	$C_1^{OPDCFix} = 0.03$ [€/OL]	$C_2^{OPDCFix} = 0.01$ [€/OL]
Variable DC picking cost	$C_1^{OPDC\_CP} = 0.0225$ [€/CP]	$C_2^{OPDC\_CU} = 0.0075$ [€/CU]
Unpacking cost	$C_1^{UNPACK} = 0.025$ [€/CP]	$C_2^{UNPACK} = 0.015$ [€/CP]
Inventory cost	$h = 0.25$ [€/CU.year]	
Penalty cost	$p = 0.275$ [€/CU]	
Fixed store shelf-stacking cost	$C^{DSFix} = 0.03$ [€/OL]	
In-store replenishment cost	$C^{IR} = 0.03$ [€/OL]	

orders are based on a (R, s, S) policy with a store-specific MOQ and IOQ = 1.

D *Optimal solution (per product one picking unit for all stores)*: All stores receive a product either by configuration 1 (SCC-1, $m = 1$) or configuration 2 (SCC-2, $m = 2$), depending on which configuration achieves minimum costs for all stores.

E *Lower bound (LB) (optimal picking unit per product per store):* Each store receives a product either by configuration 1 (SCC-1, $m = 1$) or configuration 2 (SCC-2, $m = 2$), depending on which configuration is cost-optimal for that specific store-product combination. This scenario requires that in the DC, a product can either be picked in CPs or CUs, and therefore represents a lower bound on the achievable total cost value.

Both the pure SCC-1 (B) and pure SCC-2 (C) configurations are covered here to get better insight into the optimal solution (D) and its relation to these exclusive scenarios without any differentiation across SKUs. The pure SCC-1 configuration is mainly applied by modern retail channels of large hyper or supermarkets, while the pure SCC-2 configuration is sometimes found in traditional stores, often in emerging markets. Please note, when applying the pure SCC-2 to retail distribution systems of traditional stores in emerging markets the picking cost structure will be different as assumed in the present study. In emerging markets – even for a SCC-2 configuration – manual systems are generally common, since labour cost are still too low to merit investments in labor saving automated systems (Bartholdi & Hackman, 2016, page 189). In addition the supply chain would favor inners instead of eaches for better handling and protection of products.

Furthermore, the situation where an SKU can be picked at the DC either in CPs or in CUs is considered (E), which probably requires multiple storage locations at the DC. In this case, each store-SKU combination is assigned exclusively to one SCC (no combination of CPs and CUs for one store-SKU combination) and each store receives the product in the configuration that results in minimal costs for the individual store. Scenario E therefore represents a lower bound on the minimal costs achievable.

In the following, first cost effects are considered as the presented models aim to minimize overall relevant costs with regard to the product unpacking decision (Subsection 6.1). Second, structural considerations of the results follow (Subsection 6.2). Third, selected sensitivity analyses are carried out to assess the robustness of the results obtained (Subsection 6.3). Fourth, alternative approaches are assessed, which might be of high relevance for retail decision makers (Subsection 6.4).

6.1. Cost considerations of the results

First of all, the focus of this numerical study is on total costs and the individual cost drivers as cost minimization is the objective of the models applied. The results are calculated as the daily costs for all SKUs considered for an average store (weighted average over the five stores included in the analysis, using the fraction of the store in the chain as weight factor). Table 5 shows the results. The search space for the optimal MOQ is limited to

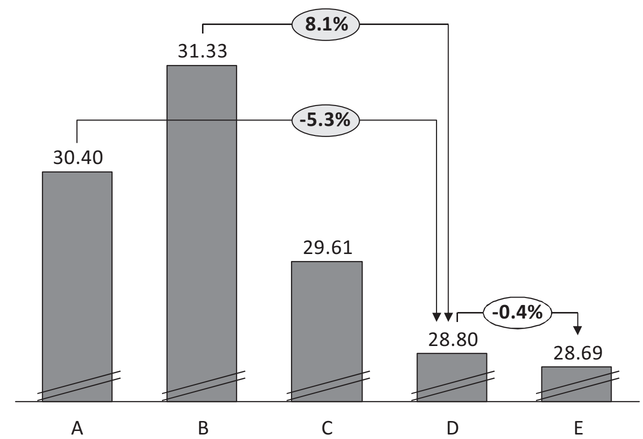

Fig. 5. Overall costs per scenario (daily costs for all SKUs for an average store).

150 units, which is well above the optimal values for scenarios C, D, and E determined given the maximum values as shown in the last row of Table 5.

Quality of the approximation: To check the effect of the backordering assumption on the approximation of the investigated lost sales system, a simulation study was executed to recalculate the cost drivers and the total costs in a lost sales environment. For each of the 12,244 experiments, at least 10 replications were executed, each consisting of 350 warming up periods, followed by 7000 periods in which the statistics are recorded. The simulation was replicated until an absolute precision for the fill rate β of $\pm$ 0.002 was reached with 95% confidence. The average relative approximation error (=100% * (simulation value − approximation value)/simulation value) of the total costs was 0.02% and the standard deviation was 2.75%. The larger errors were mainly caused by situations in which the in-store replenishment frequency of once per review period was insufficient in combination with the available shelf space. This indicates a high quality of the approximations applied for our setting.

Overall cost effects: In the optimal solution (D), the overall costs are reduced by 5.3% compared to the current situation (A) and by 8.1% compared to pure SCC-1 (B), which is the standard configuration for many grocery retail companies. The overall costs of the optimal solution (D) are very close to the lower bound (E), with a cost difference of less than 0.4% (see Fig. 5). This implies, at least in this case, that major cost reductions can be achieved even when differentiation between stores is not allowed and an SKU is delivered to all stores in the same mode, either in CPs or in CUs.

Comparison of SCC-1 (B) and Optimal (D): SCC-1 is the standard configuration for many modern grocery retailers (often applied exclusively). The exclusive SCC-1 scenario (B) was compared with the optimal solution (D) in greater detail. Fig. 6 shows that in absolute terms, the holding, backroom, and unpacking costs account for the largest cost reductions, while the picking costs in the DC increase.

Table 5
Results of the scenario analysis with cost-optimal service. All costs are in €/day for an average store for all SKUs considered.

	Current (A)	SCC-1 (B)	SCC-2 (C)	Optimal (D)	LB (E)
Holding costs	6.88	7.80	6.54	6.75	6.70
Penalty costs	2.99	2.98	2.90	2.92	2.89
Picking costs at DC	6.74	6.48	8.74	7.10	7.11
Unpacking costs	3.23	3.11	1.86	2.23	2.23
Stacking costs store	3.83	3.69	3.72	3.55	3.59
Backroom costs	6.73	7.27	5.85	6.25	6.16
Total	30.40	31.33	29.61	28.80	28.69
Average Q or MOQ	8.46	10.87	7.09	7.84	7.31
Maximum Q or MOQ	35	216	26	30	36

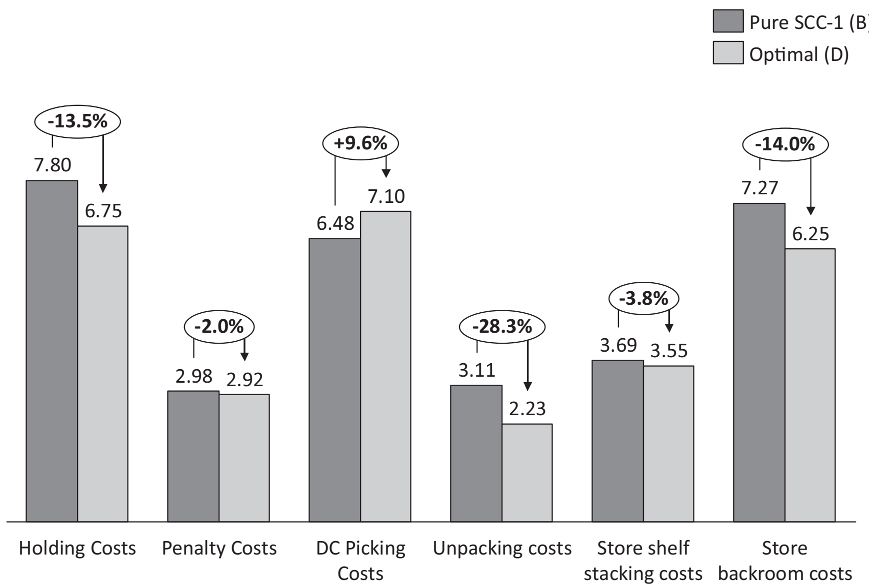

Fig. 6. Detailed cost comparison between the standard configuration SCC-1 (B) and the optimal solution (D).

Inventory carrying costs: The largest absolute cost effect (€1.05, i.e., 13.5%) results from inventory holding in the stores. Unpacking CPs and creating smaller MOQs results in an increasing delivery frequency per SKU with less average capital tied up in in-store inventories. In scenario D for SKUs unpacked in the DC and which exhibit a smaller MOQ than their corresponding CP, the number of order lines increases by 38% on average.

Unpacking costs: Selection of the unpacking location has a major impact on unpacking costs. As expected, unpacking costs are significantly lower when a large proportion of unpacking is performed at the DC, where unpacking operations can be standardized to a higher degree than in the stores. In the SCC-2 scenario (C), unpacking costs are 46% below the unpacking costs in the SCC-1 scenario (B).

Backroom costs: Considering all cost components, the backroom costs are very decision-relevant. Of the total backroom costs, less than 10% is due to backroom storage costs (space costs). The main factor behind the backroom costs is the number of in-store replenishments (refilling costs). In the optimal solution, there are 13.6% fewer in-store replenishments compared to the current situation. Since the number of in-store replenishments is limited to 1 trip per review period in the numerical study (for 99% of the store-SKU combinations in the dataset), increasing the backroom inventory (by increasing MOQ) beyond a certain level has no further effect on backroom handling costs.

Shelf-stacking costs: The effect of changing the SCC on shelf-stacking costs is the fourth largest. The results are driven by the effect that using CP instead of CUs reduces the average number of order lines and therefore shelf-stacking occurs less often. Consequently, shelf-stacking costs make up a larger proportion in the SCC-2 (C) than in the SCC-1 (B) scenario. Fig. 7 shows the proportional costs per scenario.

Service constraint approach: The entire analysis for the model was repeated with a service constraint instead of a cost-minimization approach. The results are shown in Table 6. The optimal solution shows lower overall costs than in Table 5 due to the absence of penalty costs. The reduction in total costs compared to the cost-optimized service model was not proportional to the reduction of the penalty cost in that scenario, but remained higher. Due to replacing the penalty cost with a service constraint, the other costs drivers are no longer balanced against out-of-stock based on penalty costs, resulting in relatively higher costs for holding, picking, and backroom.

6.2. Structural considerations of the results

Proportion of SCCs and CP sizes: Shifting the focus from the cost perspective to the structure of the optimal solution, it is evident that significant volumes are unpacked in the DC in the optimal scenario D. Compared to SCC-1 (B), 912 SKUs (71%) are changed to SCC-2 in the optimal solution (D), while 367 (29%) remain under SCC-1. In Scenario E, 72% of the store-SKU combinations are allocated to SCC-2 and unpacked in the DC, while 28% are assigned to SCC-1 and picked in CPs (see Fig. 8). One quarter of the SKUs considered is supplied in CPs as well as in CUs while 75% is distributed to all stores in an identical picking unit.

The small parts picking system at the DC favors generally order sizes of less than 7 CUs compared to the CP picking system. Given

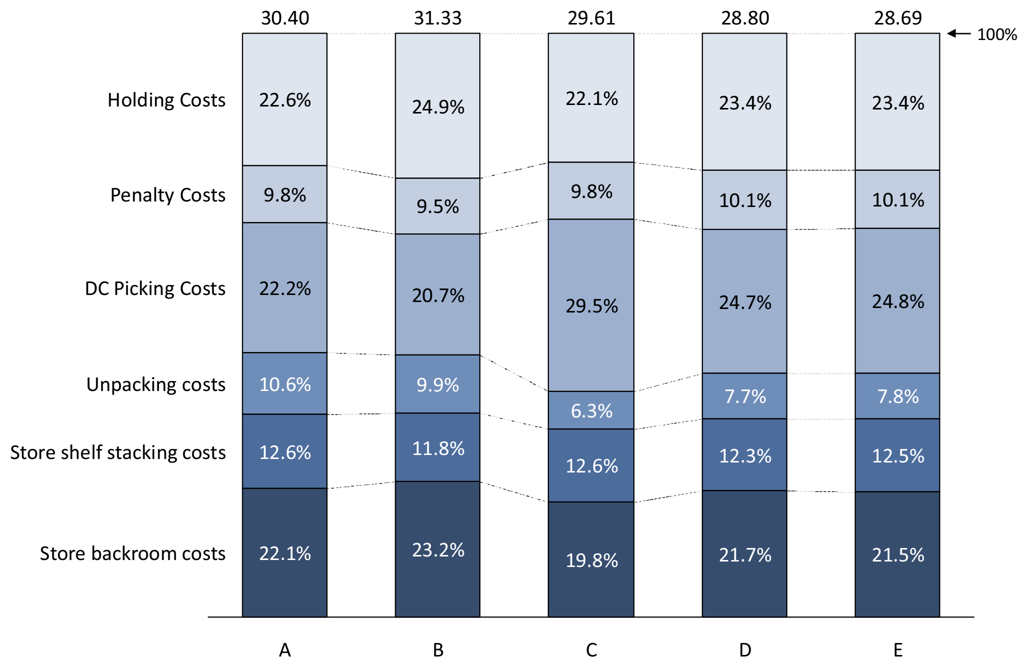

Fig. 7. Proportional costs of the scenarios.

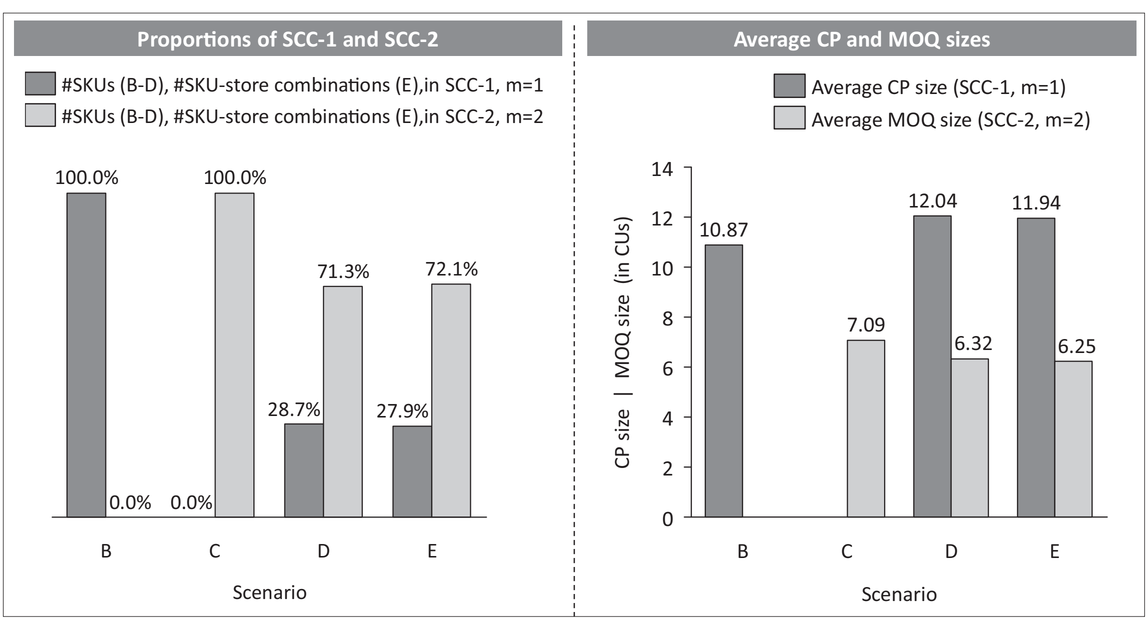

Fig. 8. Proportions of SCC-1 and SCC-2 and average CP and MOQ sizes.

Table 6
Results of the scenario analysis with a service constraint of 99%. All costs are in €/day for an average store for all SKUs considered.

	Current (A)	SCC-1 (B)	SCC-2 (C)	Opt (D)	LB (E)
Holding costs	7.36	8.28	6.77	7.02	6.97
Picking costs at DC	6.74	6.48	8.71	7.25	7.20
Unpacking costs	3.23	3.11	1.86	2.16	2.18
Stacking costs store	3.83	3.69	3.63	3.52	3.54
Backroom costs	7.85	8.37	6.67	7.01	6.94
Total	29.01	29.94	27.64	26.95	26.84

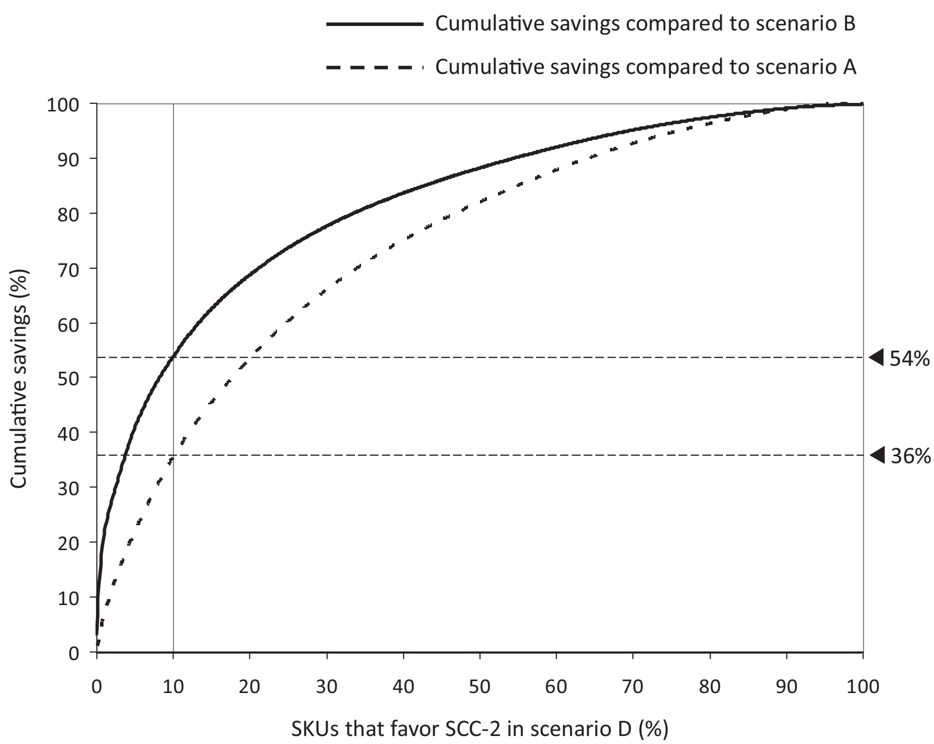

Fig. 9. Cumulative savings for switching from SCC-1 to SCC-2.

the large range of MOQs in the results for SCC-2, SCC-2 seems to be unsuitable for all SKUs. In the optimal solution (D), the average CP size of the SKUs that remain in SCC-1 is 12.04, while the average MOQ in SCC-2 is 6.32. The relatively low MOQ in the optimal solution confirms the observation that SCC-2 is particularly interesting for SKUs that can efficiently be supplied in relatively small order sizes. In tendency, other things being equal, the larger the necessary order sizes resulting from customer demand rather than from the picking unit size, the smaller the relative impact on those costs that are influenced by CP or MOQ size, e.g., when in-store replenishments cannot be avoided in any configuration.

In 70.8% of all store-SKU-combinations that favor SCC-2 in the optimal scenario (D) the resulting MOQ is smaller than the corresponding case pack – as expected. However, in 29.2% the MOQ is larger than the corresponding CP. This is in our setting the result of two effects. First, if there is ample shelf space, the available shelf space is used completely and order lines are reduced by breaking down CPs and enlarging corresponding MOQs. Second, the effect arises for products with high sales, which have to be refilled from the backroom once per review period in any configuration. This situation also drives order line reduction by increasing the MOQ compared to the corresponding CP.

Favorable products for SCC-2: The large savings reported in this study can only be realized by switching SKUs to a small parts picking system at the retail DC. These systems require considerable investments and companies might be reluctant to invest in these systems. Fig. 9 shows that 10% of the SKUs with the highest savings for all stores when allocated to SCC-2 in scenario D already contribute to 54% of the savings for product unpacking at the DC compared to scenario B (no unpacking at all). Compared with the specific situation of DELTA (scenario A), unpacking just the most favorable 10% results in savings as high as 36%.

As expected, the greatest savings tend to result from SKUs with large CP sizes compared to the available shelf space. The 10% most favorable SKUs for switching to SCC-2 are especially SKUs whose CP size significantly exceeds the allocated shelf capacity, often by a multiple thereof. The most favorable products for unpacking result in a MOQ in SCC-2 that is much smaller than the original CP size and often are significantly below the shelf capacity. These favorable 10% are not just slow-moving articles. On average, mean sales of these first 10% of SKUs are 35% higher than the average sales of all products. This higher than average sales also explains the great impact on total costs. Store deliveries with the corresponding smaller order sizes in SCC-2 and higher frequencies are expected to fit on the shelf completely. In short, the most attractive SKUs for SCC-2 are products with the highest possible sales and comparatively very large CPs, which get MOQs (with corresponding order sizes) that fit on the shelf completely at the point of delivery.

6.3. Sensitivity analyses

As not all SKUs are carried in all stores, the analysis was repeated with the data set limited to only those 1135 SKUs that are in the assortment of all five stores. The cost reduction of the optimal solution compared to the current situation in this case is 5.4%, which is only slightly higher because the leverage effect over more stores is larger. The percentage of SKUs assigned to SCC-2 remains at 71%.

To assess the robustness of the optimal solution (D), a sensitivity analysis was carried out for the cost-optimal service model based on the main parameters defined for this case example: product value, DC unpacking costs, store labour costs and picking time per CU in the small parts DC. The results of these sensitivity analyses are shown in Fig. 10. It is evident that a change in product values or store labour cost factors has a comparatively major impact on total costs and a minor impact on SKU assignment. Therefore, small cost changes do not significantly change the assignment decision.

In contrast, a change in DC unpacking costs, and even more significantly in the picking time required per CU, impacts SKU assignment considerably, but has a relatively minor effect on total costs. In these situations, a task shift between the DC and

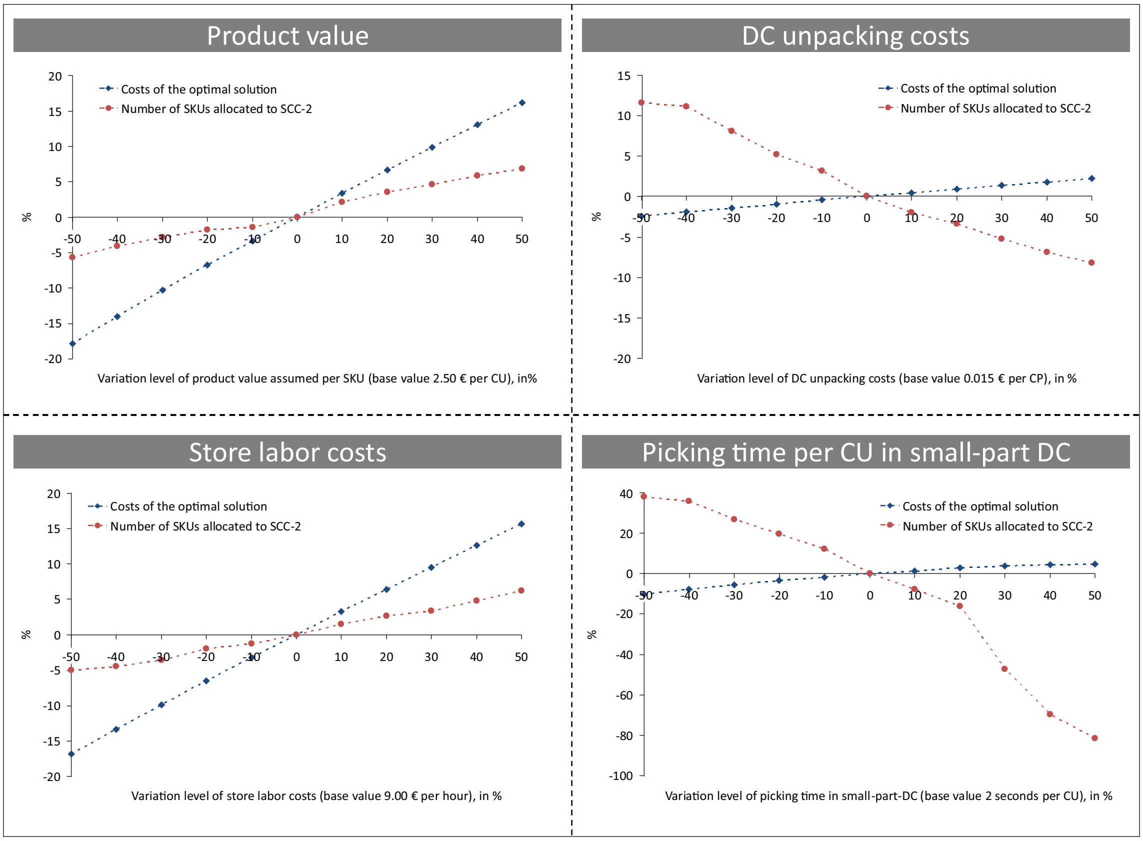

Fig. 10. Sensitivity analysis.

store takes place. For example, due to rising picking costs in the small parts area, unpacking advantages in the DC decrease. Therefore, with rising picking costs, an increasing number of SKUs are unpacked at the store (SCC-1) since the costs of the store domain, especially additional backroom handling, are lower than the costs of the DC domain, i.e., the combination of DC unpacking and picking, resulting in fewer SKUs being assigned to SCC-2 and vice versa. This result can also be explained by the fact mentioned above that few SKUs account for large proportions of the savings in unpacking and many SKUs show only minor effects, meaning they are likely to switch back to SCC-1 in the event of rising DC costs. The greater insensitivity of SKU assignment on store labour compared to picking is, among other aspects, a result of the considerably lower base cost level assumed in this study and the tight shelf-space restrictions: Even the possibility of MOQ sizing per store will frequently not eliminate backroom handling, since shelf capacity is too small to guarantee the service aspired. However, overall, the optimal solution can be characterized as being stable, at least in the parameter range of ±20%.

6.4. Assessment of alternative approaches

In this subsection, two alternative approaches are assessed that might be also relevant for retail decision makers, i.e., the application of the (R, s, nQ) policy also for unpacked products that are picked and transported in CUs and the case, in which suppliers already provide ideally suited CP sizes.

DC unpacking, but application of the (R, s, nQ) *policy:* Most retailers like DELTA use an automatic store ordering system that is based on the (R, s, nQ) policy instead of (R, s, S). For these retailers, it is interesting to identify the loss in efficiency which they must take into account when adhering also to this policy in an SCC-2 setting. In this situation, the optimal, store-specific MOQ is calculated and this value is used for store ordering decisions based on the (R, s, nQ) policy, $Q=MOQ$. The difference in cost when (R, s, nQ) instead of (R, s, S) is applied store-specifically under SCC-2 is only 0.3% for all SKUs. Note that the number of SKUs using SCC-2 in the optimal solution then drops from 912 to 894 SKUs. This is in line with the findings of Zheng and Chen (1992), who show that the cost improvement of an (R, s, S) policy over an (R, s, nQ) policy is relatively small. For retail operations managers, this means they can gain most of the positive effects of DC unpacking without switching to a different replenishment doctrine.

Effect of optimized supplier CP sizes: An alternative approach for obtaining positive findings would be to convince suppliers to supply DELTA with a newly designed CP (of size Q^*), which is optimal for the current set of stores (one size for all stores). To obtain an initial impression, this scenario is examined without including design restrictions on the new CP (e.g., weight, dimensions) or the costs to the supplier of offering this specific CP. For the retailer, it would mean that the DC is supplied with cost-optimal CPs, all SKUs are assigned to SCC-1 and unpacking is performed entirely on the store level. This alternative solution would require changing the CP size for 1101 SKUs compared to SCC-1 (B) and for 1095 SKUs compared to the current situation (A). In this scenario, with total costs of €29.49, a cost reduction of 5.9% is achieved compared to SCC-1 with the existing CP sizes (B), which falls between the current situation (A) and the optimal solution (D). This result is in line with the results reported by Wensing et al. (2016). However, when compared to the cost reduction of 8.1% between SCC-1 with current CP sizes (B) and the optimal solution (D), the difference is remarkable. It arises from the fact that DC unpacking makes it possible to adjust and apply the MOQ specifically for each store.

7. Conclusion and areas for future research

In this paper, a novel approach is presented for identifying the optimal product unpacking location in a classical bricks-and-mortar retail supply chain, i.e., either the DC or store, this being the standard configuration for many modern retail companies. Based on the (R, s, nQ) and (R, s, S) ordering policies, expressions for specific cost drivers are developed and applied, which are decision-relevant for evaluating and optimizing the effect on cost of supplying stores using an external supplier CP (SCC-1) or, if unpacked in the DC, a store-specific MOQ (SCC-2). Using these expressions, this research shows that unpacking the CP provided by the supplier in the retail DC can lead to considerable savings. These savings are a result of fewer backroom operations and the shifting of inefficient manual operations from the store to the technically supported operations in the DC.

The developed comprehensive model integrates all decision-relevant processes along the internal retail supply chain from the DC to the shelf. The objective function of the optimization approach comprises seven relevant cost components: DC picking costs, unpacking costs (either in DC or store), store inventory holding costs, store shelf-stacking costs, backroom storage costs, in-store replenishment costs from the backroom and, when applying the cost-optimal service model, penalty costs. With these costs and associated processes, the model reflects the practical necessity of balancing requirements at both the DC and the stores, which is a major concern of retail operations officers (Kuhn & Sternbeck, 2013). The model takes several aspects specific to retail into account, which are necessary for getting a clear picture of the interdependencies and achieving applicability in the real world. These aspects are, for example, different picking costs depending on the picking system used, limited shelf space derived store-specifically from planograms, backroom operations, and in-store replenishment processes. A comprehensive analysis of the process interdependencies through close cooperation with a major retail company was therefore a relevant preparatory task for ensuring the integration of practical requirements.

The applicability of the suggested approaches is demonstrated by an extensive numerical study, which is based in part on empirical data from a large, European home and personal care retail company. Compared to the standard configuration of using the supplier CP as the picking unit in the DC, the optimal solution generated by the model saves 8.1% of total relevant costs. Transferred to DELTA's current situation, applying the model reduces total relevant costs by 5.3%, or the equivalent of several million euros a year. Of course, DC unpacking and picking capacities have to be available to realize these savings. However, the numerical example demonstrates that unpacking the most favorable 10% of the SKUs already achieves over half of the potential savings compared to using the CP exclusively. Identifying those products which best fill up available capacities requires an analytical model. The model presented in this paper can be directly applied to answer this question. The method is user-friendly because it is relatively easy to implement, can be solved fast, and is based on data that is accessible in practice.

In summary, we agree with Ketzenberg et al. (2002) that breaking up bulk deliveries at the DC has a positive impact on the operations of a retail supply chain. However, contrary to their findings, this research found that the MOQ must be set higher than one in all cases due to the significant order line costs, even with a dedicated small parts picking system at the DC. This modelling and solution approach contributes to further improving the balance between operations at the DC and the stores, and therefore to achieving comprehensive retail efficiency.

This study considers the unpacking decision from a comprehensive retail supply chain perspective and therefore also serves as starting point for future research:

(a) The current design of the model assigns exclusively each SKU or store-SKU combination to exactly one SCC. However, there are some indications that a combination of the approaches could be beneficial, at least in some cases. This would imply that store orders per SKU could be composed of CPs and CUs simultaneously. Future research could examine the underlying cost potential.

(b) The developed expressions are only used to evaluate two SCCs. In future research, these expressions could provide a basis for answering other related questions. For example, because shelf capacities are highly relevant for retail productivity, the unpacking decision is closely related to the field of category management and assortment selection. The number of listed products impacts the use of available shelf space and influences the degree of freedom in shelf-space planning (see Hariga et al., 2007). In particular, the combining of planogramming with the DC unpacking decision may offer additional potential.

(c) Currently, this approach is designed as a tactical model based on stationary product demand data. In practice, however, demand is often non-stationary and it may be beneficial to plan unpacking operations in advance based on forecasting and product lifecycle data. Non-stationary demand would modify the optimization problem since it requires the integration of dynamic aspects.

(d) The model, although designed to answer tactical questions, could be modified to support long-term retail investment decisions. One promising possibility would be to adapt our approach to help answer the strategic question of whether to invest in unpacking and small parts picking systems, and if so, to what extent a company should build up its capacities.

(e) In future research, the model may be relevant not only to retailers, but also to cooperation projects between retailers and the manufacturers responsible for dimensioning CPs, particularly in the private-label segment. Intercompany processes could be integrated into the approach to determine whether DC unpacking or resizing of the supplier CP is the best alternative. This cooperation could be accompanied by a corresponding model for determining how to share the costs and benefits between business partners. Moreover, the model could be expanded to assess the introduction of reusable boxes that circulate between supplier and retailer and carry products unpacked, meaning that they conserve energy and resources by eliminating packaging along the entire process chain.

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