

## **Lost Sales Inventory Models with Batch Ordering and Handling Costs**

T. Van Woensel, N. Erkip, A. Curseu, J.C. Fransoo

Beta Working Paper series 421

BETA publicatie	WP 421 (working paper)
ISBN	
ISSN	
NUR	804
Eindhoven	July 2013

# Lost Sales Inventory Models with Batch Ordering and Handling Costs

T. Van Woensel

School of Industrial Engineering  
Technische Universiteit Eindhoven  
P.O. Box 513, 5600 MB, Eindhoven  
The Netherlands

N. Erkip

Department of Industrial Engineering  
Bilkent University  
Ankara 06800, Turkey

A. Curşeu, J.C. Fransoo

School of Industrial Engineering  
Technische Universiteit Eindhoven  
P.O. Box 513, 5600 MB, Eindhoven  
The Netherlands

October 30, 2012

## Abstract

In this paper, we integrate inventory and handling into a single model for analysis and optimization of inventory replenishment decisions for a grocery retail store. We consider a retailer who periodically manages his inventory of a single item facing stochastic demand. The retailer may only order in multiples of a fixed batch size, the lead time is less than the review period length and all unmet demand is lost, which is a realistic situation for a large part of the assortment of grocery retailers. The replenishment cost includes both fixed and variable components, dependent on the number of batches and units in the order. This structure captures the shelf-stacking costs in retail stores. We investigate the optimal policy structure under the long-run average cost criterion. Our results show that it is worthwhile to explicitly take handling costs into account when making inventory decisions. We use parameter values typical for grocery retail environments. For an important subset of the retail assortment, we show that significant cost reductions exist by explicitly considering handling in the inventory policy.

*Keywords:* Retail inventory control, Handling, Lost sales, Periodic review, Fixed batch sizes

## 1 Introduction

The grocery retail inventory problem has several rich features (Broekmeulen et al., 2004). A store orders inventory on a periodic basis and receives replenishment according to a fixed schedule. Demand for products is stochastic and is typically lost if inventory is not available on the shelf. Orders are usually constrained to batches of fixed sizes (case packs). In this paper, we build upon the shelf-stacking insights of Curşeu et al. (2009) to investigate inventory replenishment decisions including merchandise handling. The handling of goods mainly represented the daily process of manually refilling the shelves in the store with products from new deliveries (i.e. shelf stacking), which is typically time consuming and costly.

The case we consider is a lost sales inventory system, with fixed ordering cost, quantized ordering quantity, the lead-time being less than review period, as well as additional handling cost. In the literature, to our knowledge, no study exists that analyses the optimal policy structure similar to the inventory problem discussed in this paper. Additional complexity caused by cost components related to handling costs, substantially complicates the analysis of the optimal solution structure.

We observed in the different in-company projects executed at various grocery retailers that in-store retail inventory management ignores handling costs. This is remarkable since Van Zelst et al. (2009) reported that the handling of goods in the store accounted for 75% of the total logistics store costs, while inventory accounted for the remaining 25% of total costs (see also Saghir and Jonson (2001) for similar insights on the importance of handling). Van Donselaar et al. (2010) discussed in their paper that retailers do not always follow order advices generated by an automated inventory replenishment system. These authors showed that store managers consistently modify automated order advices by advancing orders from peak to non-peak days. One important reason for doing so is to incorporate in-store handling costs, which were not considered in their standard inventory replenishment systems. Several other authors, not necessarily with a specific focus on inventory policy formulations, also emphasize the importance of handling and labor in retail operations (see e.g. Fisher et al. (2006), Fisher (2009), Randall et al. (2006), Roumiantsev and Netessine (2007)).

In this paper, we show that ignoring handling costs leads to serious cost increases. We show that depending upon the specific product (category), significant gains can be realized by considering handling costs in the objective function. These gains are especially pronounced for slow to medium moving products. Based on the dataset used in Curşeu et al. (2009), we find that around 25 – 30% of the SKUs match these specifications, showing the potential for using an inventory policy including handling costs. We also compare the optimal policy with the best  $(s, S, nq)$  and  $(s, Q, nq)$  policies <sup>1</sup> both with handling and without handling in the

---

<sup>1</sup>The  $(s, S, nq)$  policy's advice is as follows: whenever the inventory level at a review period is less than or equal to  $s$ , order the largest integer multiple  $n$  of  $q$  which results in an inventory position less than or equal

objective function. Interestingly, a large part of the potential gains of considering handling can also be used when utilizing the best  $(s, S, nq)$  policy but with a complete objective function (including handling).

Our paper makes a number of contributions to the existing literature. First, we study a stochastic lost sales system that combines important features as seen in practice: fixed batch sizes and inventory handling costs. We formulate the problem as a Markov decision process and explore the structure of the optimal policies. We formulate a number of propositions based on the observed structures. Secondly, we base our analysis and inventory models on the real-life field study as presented in Curşeu et al. (2009). We draw upon this field study to demonstrate the importance of considering merchandize handling. The field study also provides us with realistic numbers to incorporate in our numerical analysis. Last, we numerically illustrate the impact of handling cost components on the optimal policy and the associated long-run average cost. We investigate the impact of inventory handling costs on the structure of the optimal policies and the corresponding long-run average cost. Finally, we analyze the added value of including the handling costs into decision making.

The remainder of this paper is organized as follows. The next section gives a brief review of related literature. Section 2 gives a detailed discussion for the handling costs function used in this paper. A literature review on the relevant references within inventory management is given in Section 3. Section 4 formally introduces the problem and formulates the model using a Markov decision process. The optimal policy is illustrated in Section 5.1. Specifically, we illustrate the complexity of the optimal policies and identify some structural properties in Section 5.2. In Section 5.3, we investigate the added value of handling costs and compare our optimal policy to two policies well-known in the literature (and often employed in practice). Section 6 discusses the results for the real-life data obtained in Curşeu et al. (2009). Finally, we present our conclusions.

---

to  $S$ . For the  $(s, Q, nq)$  policy, one orders always  $Q$  if the inventory level at a review period is less than or equal to  $s$ ;  $Q$  is constrained to be an integer multiple  $n$  of  $q$ .

## 2 In-store handling costs

Curşeu et al. (2009) estimated the handling time per Stock Keeping Unit (SKU) required to execute the shelf-stacking operation depending on the number of batches and the number of consumer units stacked. The authors estimated the Total Stacking Time per SKU ( $TST$ ), based on a reduced set of underlying factors, given a specific inventory replenishment rule, assortment, shelf space and package.

Two grocery retail chains (denoted as A and B) agreed to participate in this study. Empirical data on the stacking process was collected using a motion and time study approach. Data from chain A are used to test the hypotheses, and data from chain B are used to validate the results. In four stores, (two for each supermarket chain) employees familiar with the operations, were videotaped during the shelf stacking process. The product subgroups were selected such that they: (1) contain both fast- and slow movers; (2) contain different case pack sizes; (3) contain SKUs for which sufficient shelf space is available to accommodate more than one case pack in a delivery; (4) contain items that are comparable in terms of the handling process and productivity. Finally, we note that the data collection period did not include days with peak or dropping demand, and the stores were consistent in their operations. The stacking of items on the shelves is observed and recorded for each SKU. Afterwards, the execution time of each individual sub-activity and the Total Stacking Time per order line ( $TST$ ) was registered using a computerized time registration tool, and results were entered into a database. Additional information necessary to identify the stacking process for each SKU was added as well, such as the SKU type, the number of case packs and case pack size per order line or the product category each SKU belongs to.

The final dataset contained 1048 observations, for chain A, across nine different product categories. The authors adopted two strategies for estimating the  $TST$  per order line and evaluating the relative impact of each factor identified (sequential vs. overall regression). The two approaches served two different practical purposes. On one hand, the sequential approach, allows one for a better insight into the details of the shelf-stacking process, iden-

tifying those sub-activities that are mostly affected by the number of items being handled (case packs and number of consumer units), and those for which the variation in workload is potentially affected by other factors. At the same time, the approach indicates which sub-activities contribute mostly to the total variation in the stacking time of a new order line. Using the overall regression strategy, the authors found enough support to conclude that a simple prediction model, depending only on the number of case packs and the number of consumer units, offers already a reliable estimate of the  $TST$ . Results from testing and validation show that the model is stable and it explains the  $TST$  to a large extent. Although the influence of case packs and number of consumer units on the shelf-stacking process may be implicitly recognized, it was demonstrated that both variables are relevant predictors for  $TST$ . For more details on this study, the reader is referred to Curşeu et al. (2009).

Based on the collected data, a predictive model is developed that allows estimating the total stacking time. The model is tested and validated using the collected real-life data and allows for evaluating the workload required for the shelf-stacking operations. The analysis lead to a general handling cost structure in which each replenishment is associated with costs of the following structure

$$c(nq) = \delta(nq)K + K_1n + K_2nq$$

where  $q$  is the fixed batch size, order quantities  $nq$  are nonnegative integers multiple of these  $q$  consumer units,  $K$  is the fixed cost incurred for each order,  $K_1$  is the variable cost per batch,  $K_2$  is the variable unit handling cost, and  $\delta(a)$  is a function with a value equaling one if  $a$  is strictly positive, and zero otherwise. Table 1 gives the observed sales characteristics (i.e. the average, minimum and maximum weekly demand) of the Chain A product categories used in Curşeu et al. (2009). The table also gives details for the rounded handling coefficients as estimated through the regression analysis. Ignoring the specific product category, i.e. for an arbitrary product, the parameters are estimated in Curşeu et al. (2009) to be  $K = 10, K_1 = 20, K_2 = 1$ . Note that since Curşeu et al. (2009) only were able to statistically significantly capture the effect of the product group on the fixed cost

$K$ , the variable costs ( $K_1$  and  $K_2$ ) are independent of the product category. Table 1 clearly shows the large spread in characteristics of the different product categories. Note that this is observed sales and not necessarily equal to actual demand as lost sales might have occurred (see also Huh et al., 2009b).

Table 1: Characteristics of the product categories used in Curşeu et al. (2009)

Category	# of products	Weekly observed sales			Casepacksize			Handling		
		Avg.	Min.	Max.	Avg.	Min.	Max.	$K$	$K_1$	$K_2$
Arbitrary product	1048	17.11	0.17	491.46	12	1	36	10	20	1
Baby food	31	5.91	0.51	29.31	10	3	16	18	20	1
Chocolate	168	13.66	2.10	64.22	17	6	33	10	20	1
Coffee	163	18.81	0.77	491.46	12	1	30	21	20	1
Coffee milk	56	42.20	1.74	243.24	16	6	30	25	20	1
Candy	248	13.21	2.08	52.34	16	6	36	12	20	1
Sugar	18	23.86	1.31	226.84	10	5	20	14	20	1
Canned Meat	47	17.89	1.35	122.56	13	6	24	16	20	1
Canned Fruit	32	11.47	0.78	47.32	12	8	24	6	20	1
Personal Care	285	4.45	0.17	55.45	8	3	24	4	20	1

In this study, we adapt our cost function to include  $c(nq)$ . Additionally, we make use of the data summarised in Table 1 for benchmark computations.

### 3 Literature Review

We give a brief review of the literature on periodic review lost sales inventory models with positive lead times and possibly batch (quantized) ordering. The complexity of optimal policies for lost sales inventory models contrasts with that of classical backorder models, which are known to have solutions of the  $(s, S)$  type, when only fixed ordering cost are considered. For a lost sales formulation, the optimal control policy will, in general, be neither of the  $(s, S)$  nor of the  $(s, Q)$  type, but will depend in a much more complex way on the physical stock at the time of placing an order.

The classical lost sales problem, originally formulated by Karlin and Scarf (1958), is known to be far less analytically tractable than the corresponding backorder problem. If the lead time is positive, the complete structure of the optimal ordering policy is unknown (Hadley and Within, 1963). In the presence of a positive setup cost, reorder-point policies of  $(s, S)$  type (Wagner, 1962) or  $(s, Q)$  type (Johansen and Hill, 2000) are considered in



a lost sales setting. Hill and Johansen (2006) presents numerical examples for detecting optimal policy structure; concluding that neither  $(s, S)$  nor  $(s, Q)$  is optimal and the optimal structure may look different depending on the inventory level. Chiang (2006, 2007) proposed a dynamic programming model for periodic-review systems in which a replenishment cycle consists of a number of small periods (each of identical but arbitrary length) and holding and shortage costs are charged based on the ending inventory of small periods, rather than ending inventory of replenishment cycles. Note that the way costs are charged becomes especially important when the review cycle is considered as a decision variable. Chiang (2006) considers the case with no fixed ordering cost, whereas Chiang (2007) concentrates on the case with a fixed ordering cost. Both papers analyze backorder and lost sales inventory models (under the assumptions of lead times shorter than the replenishment cycle length, but a multiple of known length of time period). Chiang (2006) provides some properties and structure, however Chiang (2007) provides mostly computational results. Other interesting papers are considering a number of structural properties and have different extensions (see e.g. Huh et al. (2009), Huh et al. (2011), Huh and Janakiraman (2010), Levi et al. (2008), Zipkin (2008a), Zipkin (2008b)) but are different than our consider environment, as they do not consider fixed ordering costs and have integer lead times. Li and Yu (2012) describe a unified lost sales inventory model that takes a number of issues into consideration: capacity constraints, two-ordering modes and supply capacity constraint. They show that, under quite general conditions, with few restrictions, the expected profit function is quasi-concave. The difference is, again, our lead-time structure, as well as we have discrete demand. Further details and additional issues regarding lost sales systems can be found in the recent review by Bijvank and Vis (2011).

The incorporation of a batch size that is a multiple of fixed amount is hardly taken into account in lost sales inventory control models. The above mentioned policies can be extended to the batch ordering policy variants:  $(s, S, nq)$  and  $(s, Q, nq)$ . Veinott (1965) points out that  $(R, nQ)$  policies are not optimal in general if a fixed cost is taken into

consideration and he proposes a two parameter policy instead. Zheng and Chen (1992) provide an efficient heuristic to compute the best  $R$  and  $Q$  parameters and later on, Hill (2006) uses this heuristic in the analysis and optimization of an  $(s, S, q)$  policy, where  $s$  and  $S$  are assumed to be multiples of  $q$ . The structure of the optimal policy for lost sales systems with batch ordering remains an open question (Veinott, 1965; Hill and Johansen, 2006). A recent result of Huh et al. (2009) shows that, when there are no setup costs, the order-up-to policies are asymptotically optimal as the penalty cost becomes large compared to the holding cost and the lead time is an integral multiple of the review period length.

Given a fixed batch size  $q$ , our specific handling cost structure described in the previous section can be rewritten as  $c(nq) = \delta(nq)K + k_q n$ , with  $k_q = K_1 + K_2 q$ . This model can be motivated as a special case in an inventory control setting in which the order quantities are not necessarily restricted to multiples of the batch size, and we interpret  $K$  as the fixed administrative cost incurred for each order, and  $k_q$  as the fixed cost charged per batch (irrespective of being fully or partially filled). In a recent study, Caliskan-Demirag et al. (2012) describe and study several variants of stochastic periodic-review inventory systems with quantity-dependent fixed costs, including batch-dependent fixed costs.

## 4 The Mathematical Model

We use Markov Decision Processes to model the inventory system and to explore the structure of the optimal policy. The main notation used throughout this paper is given in Table 2. We assume the period demand to be a known, nonnegative discrete random variable and the demand process is i.i.d. stationary. The lead time is fixed and shorter than the review period length. The review cycle length  $R$  is exogenous to the model and set as the time unit.

Figure 1 depicts the sequence of events in each period.

More specifically, at the beginning of each review period, the inventory on-hand  $X_t$  is observed and an order  $a_t$  is placed, which will arrive  $L$  time units later (but within the same

Table 2: Notation used in this paper

$R$	Review period
$L$	Lead time ( $0 \leq L \leq R$ )
$t$	Period index, $t = 0, 1, 2, \dots$
$X_t$	Inventory on hand at the beginning of period $t = 0, 1, 2, \dots$
$a_t$	Quantity ordered in period $t = 0, 1, 2, \dots$
$D_L$	Demand during lead time (i.e. the demand occurring between the start of a period and the time the order $a_t$ is received)
$D_{R-L}$	Demand after the receipt of the orders (and until the end of the period)
$D_R$	Total demand during a review period, $D_R = D_L + D_{R-L}$
$q$	Fixed (exogenously determined) batch size, $q = 1, 2, \dots$
$K$	Fixed cost per order
$K_1$	Handling cost per batch
$K_2$	Handling cost per unit
$h$	Holding cost per unit of inventory (charged at the end of the period)
$p$	Penalty cost for each unit of sales lost during a period (charged at the end of the period)
$s$	Reorder level
$I_{Max}$	Maximum stock level

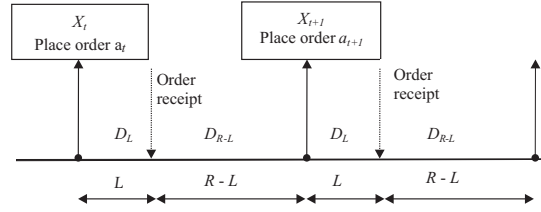


Figure 1: Sequence of events

review cycle). The order  $a_t$  is restricted to be a nonnegative integer, multiple of the fixed batch size  $q$ , i.e.  $a_t \in \{0, q, 2q, \dots\}$ . Next, the stochastic demand  $D_L$  is realized and satisfied with on-hand inventory (if possible); unsatisfied demand is lost. Then, the order placed at the beginning of the period arrives and afterwards stochastic demand  $D_{R-L}$  continues to occur, up until the beginning of the next ordering moment. All demand occurring in this time period not directly satisfied is again assumed to be lost. The random variables  $D_L$  and  $D_{R-L}$  are stochastically independent. In practice, independency is not necessarily guaranteed, but this assumption is needed for obtaining a tractable model that can be analyzed.

The decision epoch is the beginning of each review period and the inventory on-hand at the beginning of a review moment characterizes the system state, with state space  $SS = \{0, 1, 2, \dots\}$ . At each review moment a decision is made regarding the ordering quantity, which is limited to the set  $A(i) = \{0, q, 2q, \dots\}$ , for every  $i \in SS$ . Due to assumption  $L \leq R$ , the expected transition times from one decision epoch to the next are deterministic and equal  $R$ . The evolution of on-hand inventory from one decision epoch to the next is given by the

following recursive relation:

$$X_{t+1} = ((X_t - D_L)^+ + a_t - D_{R-L})^+, \quad t = 0, 1, 2, \dots,$$

where  $(x)^+ = \max\{0, x\}$  for any  $x \in \mathbb{R}$ .

The probability  $p_{ij}(a_i)$  of a transition from state  $i$  at one decision epoch to state  $j$  at the next epoch, given decision  $a_i$  at the first decision epoch is defined as:

$$p_{ij}(a_i) = \mathbf{P}(j = ((i - D_L)^+ + a_i - D_{R-L})^+), \quad i, j = 0, 1, \dots, \quad a_i = 0, q, 2q, \dots,$$

and is given by:

$$p_{i0}(0) = \mathbf{P}(D_R \geq i), \quad i = 1, 2, \dots,$$

$$p_{ij}(0) = \mathbf{P}(D_R = i - j), \quad i = 0, 1, \dots, \quad j = 1, 2, \dots, i,$$

$$p_{00}(0) = 1,$$

when there is no order, and when the order amounts to  $a_i = n_i q > 0$  by:

$$\begin{aligned} p_{i0}(a_i) &= \sum_{k=0}^{i-1} \mathbf{P}(D_L = k) \mathbf{P}(D_{R-L} \geq i + a_i - k) + \mathbf{P}(D_L \geq i) \mathbf{P}(D_{R-L} \geq a_i), \quad i = 1, 2, \dots, \\ p_{ij}(a_i) &= \sum_{k=0}^{i-1} \mathbf{P}(D_L = k) \mathbf{P}(D_{R-L} = i + a_i - j - k) + \mathbf{P}(D_L \geq i) \mathbf{P}(D_{R-L} = a_i - j), \quad i = 1, 2, \dots, \\ &\quad j = 1, 2, \dots, a_i, \\ p_{ij}(a_i) &= \sum_{k=0}^{i+a_i-j} \mathbf{P}(D_L = k) \mathbf{P}(D_{R-L} = i + a_i - j - k), \quad i = 1, 2, \dots, \quad j = a_i + 1, \dots, a_i + i, \\ p_{00}(a_0) &= \mathbf{P}(D_{R-L} \geq a_0), \\ p_{0j}(a_0) &= \mathbf{P}(D_{R-L} = a_0 - j), \quad j = 1, 2, \dots, a_0, \\ p_{ij}(a_i) &= 0, \quad \text{otherwise.} \end{aligned}$$

The total expected cost from one decision epoch to the next (i.e., the one-period transition

cost), given that we are in state  $i$  and order  $a_i = n_i q$ , is defined as:

$$c_i(a_i) = c_i^r(a_i) + c_i^h(a_i) + c_i^p(a_i), \quad a_i \in A(i), \quad i \in SS, \quad (1)$$

where the expected replenishment cost  $c_i^r$  and the expected holding  $c_i^h$  and penalty costs  $c_i^p$  are given by:

$$\begin{aligned} c_i^r(0) &= 0, \\ c_i^r(a_i) &= K + K_1 a_i / q + K_2 a_i \quad a_i = n_i q > 0 \end{aligned} \quad (2)$$

and

$$\begin{aligned} c_i^h(0) + c_i^p(0) &= h\mathbb{E}[(i - D_R)^+] + p\mathbb{E}[(i - D_R)^-], \\ c_i^h(a_i) + c_i^p(a_i) &= h\mathbb{E}[(i - D_L)^+ + a_i - D_{R-L})^+] \\ &\quad + p\left\{\mathbb{E}[(D_L - i)^+] + \mathbb{E}[(D_{R-L} - a_i - (i - D_L)^+)^+]\right\} \\ &= h\left\{\sum_{k=0}^{i-1} \mathbb{P}(D_L = k)\mathbb{E}[(i - k + a_i - D_{R-L})^+] + \mathbb{P}(D_L \geq i)\mathbb{E}[(a_i - D_{R-L})^+]\right\} \\ &\quad + p\left\{\mathbb{E}[(D_L - i)^+] + \sum_{k=0}^{i-1} \mathbb{P}(D_L = k)\mathbb{E}[(D_{R-L} - a_i - i + k)^+]\right\} \\ &\quad + p\mathbb{P}(D_L \geq i)\mathbb{E}[(D_{R-L} - a_i)^+], \end{aligned}$$

for  $a_i > 0$ , respectively, where  $(x)^- = \max\{0, -x\} = -\min\{0, x\}$  for any  $x \in \mathbb{R}$ .

From (1) and (2), we derive the total one-period transition cost as follows:

$$\begin{aligned} c_i(0) &= h\mathbb{E}[(i - D_R)^+] + p\mathbb{E}[(i - D_R)^-], \\ c_i(a_i) &= K + K_1 a_i / q + K_2 a_i \\ &\quad + h\mathbb{E}[(i - D_L)^+ + a_i - D_{R-L})^+] \\ &\quad + p\left\{\mathbb{E}[(D_L - i)^+] + \mathbb{E}[(D_{R-L} - a_i - (i - D_L)^+)^+]\right\}, \quad a_i = n_i q > 0. \end{aligned} \quad (3)$$

We aim to determine the inventory policy  $U^*$ , solving the following optimization problem:

$$\min_U C(U) = \frac{1}{R} \sum_{i \in SS} \pi_i c_i(a_i) \stackrel{R=1}{=} \sum_{i \in SS} \pi_i c_i(a_i),$$

where  $C(U)$  denotes the long-run expected average cost under policy  $U$ , and  $(\pi_i)_{i \in SS}$  represents the steady-state distribution of the inventory on hand (provided it exists).

Note that  $C(U)$  is generally a very complex function of  $U$  and the steady-state distribution may not be determined in closed form. For the exact conditions that guarantee the existence of an average-cost optimal policy see, e.g., Puterman (1994), or Cavazos-Catena and Senott (1992). If an optimal policy exists, then there exist relative values  $(v_i)_{i \in SS}$  and the long-run average cost  $g$ , such that they satisfy the average-cost optimality equations:

$$v_i = \min_{a \in A(i)} \{c_i(a) - g + \sum_{j \in SS} p_{ij}(a)v_j\}, \quad i \in SS. \quad (4)$$

Unique relative values  $(v_i)_{i \in SS}$  are obtained if we provide an initial condition, such as  $v_0 = 0$ . In order to solve the optimality equations and determine an optimal policy, it is common to use an algorithm such as policy iteration or value iteration (Puterman, 1994).

## 5 Structure of the optimal policy

For the lost-sales problem introduced in Section 4, there is no apparent analytic solution of a simple form. To calculate the optimal stationary policy under the long-run average cost criterion, we numerically solved the average cost optimality equations of the inventory system using the standard relative value iteration algorithm with  $\epsilon = 10^{-12}$  (see, e.g., Puterman, 1994 or Bertsekas, 1995). The state space was truncated to a size sufficiently large to ensure finding a global optimum. The computational time increases with the state space size due to the generation of all needed transition probabilities. In our numerical computations, the state space is truncated to a size sufficiently large to ensure we find a global optimum.

The state space size increases with the mean demand per period. The truncated state space is determined by testing larger and larger sizes until the results are insensitive to the increments. We observed that the computational time increases with the state space, which indicates the size of the system of equations to be solved in the policy evaluation step. The most time consuming part is the generation of transition probabilities in each step. For any given policy, we evaluate numerically the long run average cost by solving the average-cost optimality equations. The best policy within a given policy class is determined by exhaustive search over its defining parameters.

We first illustrate the structure of the optimal policy, then we develop some structural insights based on the optimal policy.

## 5.1 Illustrations of the optimal policy

As an illustration, Figure 2 depicts the optimal policies for three different lead times  $L$  (right side) and the effect of the batch sizes,  $q = 1$  vs.  $q = 6$  vs.  $q = 12$  (left side). The top row in Figure 2 assumes  $\lambda = 20, h = 1, p = 50, K = 10, K_1 = 20, K_2 = 1, q = 1, L = 0.5$  in the base case. The bottom row in Figure 2 assumes  $\lambda = 10, h = 1, p = 50, K = 10, K_1 = 20, K_2 = 1, q = 1, L = 0.5$  in the base case.

Generally, when  $q > 1$ , the optimal order quantity is a stepwise decreasing function of on-hand inventory, and the step size equals  $q$ . Note that the structure of the optimal solution differs from an  $(s, S, nq)$  policy, as for this policy, for low levels of inventory on-hand, the advice is to still order the same quantity, multiple of  $q$ . The optimal order quantity as a function of on-hand inventory exhibits no clear structure. It is observed that there exists a reorder point ( $s = \max\{i \in SS | a_i > 0\}$ ) below which it is always optimal to place an order and beyond which it is never optimal to order. Thus,  $s$  plays the role of a reorder level in a general inventory policy. A similar observation was made by Hill and Johansen (2006), both for a continuous review setting, as well as periodic review setting for the lost sales system without handling costs. Moreover, as illustrated in Figure 2 bottom row, we

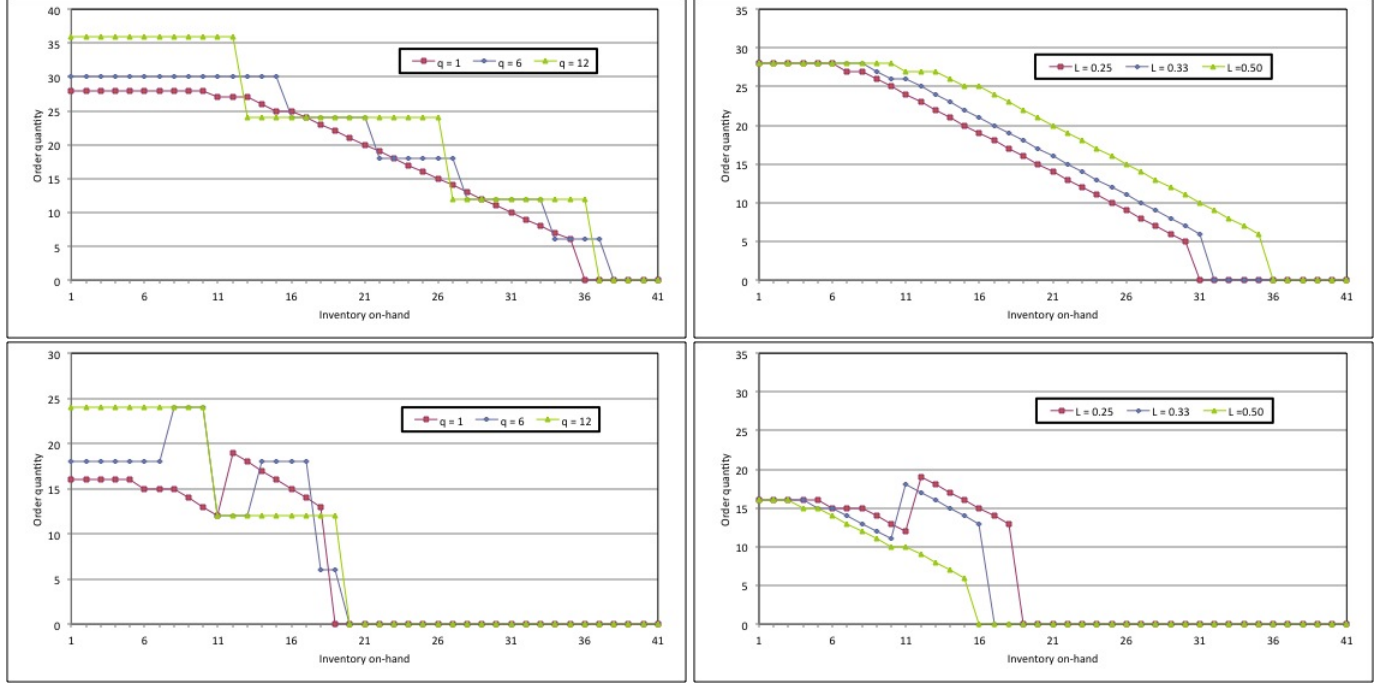


Figure 2: Optimal order quantity as a function of inventory on-hand

find similar peculiar non-monotonic behavior of our policy as observed earlier by Hill and Johansen (2006) and Jansen (1998). A complete and detailed sensitivity analysis for a broad set of parameter values can be found in Appendix A.

## 5.2 Structural insights from the optimal policy

Observe from Figure 2 that the advice is either to order a fixed amount  $Q$  (and thus act like an  $(s, Q)$  policy), for low levels of stock on-hand; or, for high levels of inventory, order enough to reach a target stock level  $S$  (and act like an  $(s, S)$  policy). Outside these regions however, the optimal policy structure remains unclear. This observation also suggests that a policy combining the logic of both  $(s, Q)$  and  $(s, S)$  policies might perform close to optimal. The proposed policy is a structured way of taking into consideration the observations made earlier in this paper, as well as Hill and Johansen (2006) and Chiang (2007). Both Hill and Johansen (2006) and Chiang (2007) computationally came up with similar structures. However the environment we consider has handling cost compared to both papers.



Note that there is sufficient complexity to the periodic cost function for making a proof of the optimal policy structure for the entire state space analytically challenging. However, based on the numerical insights for the optimal policy, we present next three propositions. Proposition C.1 discusses an upper threshold for the state variable, i.e. an inventory level above which we will never order. Proposition C.2 discusses the instances where we never order at all. Lastly, Proposition C.3 presents a sufficient condition that gives the existence of a lower threshold for the state variable, i.e. an inventory level below which we will always order. The proofs for the different propositions are given in Appendix C. Note that these results can be utilised to have a more efficient search procedure for the optimal solution of an instance.

**Proposition 5.1.** *There exists a state  $i_u$  such that for  $i \geq i_u$  the optimal decision is not to order.*

**Proposition 5.2.** *There exists a set of parameter values for which we would not operate the lost sales inventory system under consideration, i.e. we will never order.*

Next, we identify a condition that guarantees a threshold value for the initial inventory level below which it is always optimal to order.

**Proposition 5.3.** *If*

$$\begin{aligned} (h + p)E[D_R] &\geq K + K_1 a_{R-L}^{NV}/q + K_2 a_{R-L}^{NV} + hE[(a_{R-L}^{NV} - D_{R-L})^+] \\ &+ pE[(D_{R-L} - a_{R-L}^{NV})^+] + pE[D_L] + hE[D_R]. \end{aligned}$$

*is satisfied, then there exists a state  $i$  for which it is optimal to order. Here  $a_{R-L}^{NV}$  is the optimal order-up-to-level for a news vendor problem with Poisson demand over  $R - L$  time units.*

### 5.3 Ignoring retail handling costs in the optimal policy

Retail handling costs, although acknowledged in practice, are not taken into account when making inventory replenishment decisions. We study the extra costs of using a suboptimal policy (i.e. ignoring the handling costs). We first compute the optimal policy and its optimal average cost under the assumption of no handling costs. Then, we evaluate this policy with the lost sales model considering handling costs to obtain the corresponding average cost. Finally, we compare the results against the true optimal cost, associated to the optimal policy determined while taking the handling costs into account. The percentage difference in costs for not explicitly considering handling,  $\xi$ , is calculated as follows.

$$\xi = 100 \times \frac{C_{(K,K_1,K_2)}(U_{(0,0,0)}) - C_{(K,K_1,K_2)}^*}{C_{(K,K_1,K_2)}^* - (K_1/q + K_2) \cdot \lambda} \quad (5)$$

where  $U_{(0,0,0)}$  denotes the optimal policy assuming no handling costs ( $K = K_1 = K_2 = 0$ ),  $C_{(K,K_1,K_2)}(U)$  is the average cost of the original model with cost components  $K, K_1$  and  $K_2$  corresponding to policy  $U$ , and  $C_{(K,K_1,K_2)}^*$  represents the true minimum average cost, which is re-scaled to better reflect policy-related costs. Table 3 gives the average error averaged over different  $q$  values ( $q \in \{1, 3, 6, 9, 12\}$ ).

Table 3: Cost of ignoring handling  $\xi$

$L = 0.25$							
$K$	$\lambda = 0.1$	$\lambda = 1$	$\lambda = 5$	$\lambda = 10$	$\lambda = 15$	$\lambda = 20$	Average
5	1.15%	4.80%	1.81%	0.37%	0.28%	0.36%	1.46%
10	1.72%	10.42%	8.22%	1.14%	0.42%	0.36%	3.71%
15	3.62%	16.70%	15.45%	7.66%	1.26%	0.41%	7.51%
20	5.21%	22.12%	22.50%	14.11%	6.51%	1.07%	11.92%
25	6.57%	27.18%	29.54%	20.28%	12.40%	5.35%	16.89%
$L = 0.33$							
$K$	$\lambda = 0.1$	$\lambda = 1$	$\lambda = 5$	$\lambda = 10$	$\lambda = 15$	$\lambda = 20$	Average
5	1.19%	4.56%	1.77%	0.36%	0.47%	0.42%	1.46%
10	1.77%	10.30%	7.89%	1.16%	0.56%	0.41%	3.68%
15	3.64%	16.17%	14.81%	7.46%	1.35%	0.45%	7.31%
20	5.21%	21.58%	21.91%	13.69%	6.54%	1.11%	11.67%
25	6.56%	26.53%	29.05%	19.76%	12.19%	5.28%	16.56%
$L = 0.50$							
$K$	$\lambda = 0.1$	$\lambda = 1$	$\lambda = 5$	$\lambda = 10$	$\lambda = 15$	$\lambda = 20$	Average
5	1.26%	4.01%	1.90%	0.45%	0.39%	0.38%	1.40%
10	1.88%	10.26%	7.69%	1.31%	0.50%	0.38%	3.67%
15	3.69%	15.91%	14.21%	7.23%	1.28%	0.43%	7.12%
20	5.22%	20.98%	21.01%	13.12%	6.20%	1.07%	11.27%
25	6.53%	25.84%	27.90%	18.93%	11.49%	5.05%	15.95%
Average	3.68%	15.82%	15.04%	8.47%	4.12%	1.50%	8.11%

Note:  $h = 1, K_1 = 20, K_2 = 1, p = 50$

The results in Table 3 show that the cost impact of ignoring the handling costs may be significant. Two effects are pronounced. First, for slow to medium moving products

(i.e.  $\lambda \in \{1, 5, 10\}$ ), the error made is high. Fast movers and extreme slow movers are less affected by ignoring the handling aspects in the inventory policy. Secondly, increasing  $K$  values lead to a larger error. Intuitively, the fixed ordering cost,  $K$ , affects the total costs more substantially when ignored. From a broad retail assortment point of view, many products in the categories referred to in Table 1 are affected by this significant cost of ignoring the handling operations in the inventory ordering process.

## 6 Detailed results for the data from Curşeu et al. (2009)

In this section, we return to the dataset available from Curşeu et al. (2009). For the different product categories presented in Table 1, we generated the optimal policy for the average demand  $\lambda$  and the average casepack size  $q$ . The results are reported in Table 4. Next to characterizing the optimal policy, we give the percentage error made if a retailer would use the best  $(s, S, nq)$  or  $(s, Q, nq)$  policy including handling in the cost function. Additionally, we also show in the last two columns the same two policies but excluding the handling component in the cost function when identifying the best policy. The policy obtained as such (i.e. excluding handling costs) is then evaluated in the full objective function (including handling). Finally, note that this table does not represent a complete parametric design (which is available in Appendix D).

Based on the results presented in Table 4, we make the following observations:

- In a number of cases, extending the objective function with a handling cost component for the  $(s, S, nq)$  or  $(s, Q, nq)$  policy leads to errors less than 1%. This is an important observation, since using an extended standard policy is more straightforward from a practice point of view. In this case, retailers can use the same inventory logic but only need to adapt their cost functions used, which is a small effort compared to implementing a completely new policy.
- There are product categories where ignoring handling has a large effect on the costs.

Table 4: Optimal policy for the product categories as reported in Curşeu et al. (2009)

	$\lambda$	$q$	$K$	$L$	Optimal Policy			Handling		No handling	
					$s$	$I_{max}$	$C^*$	$(s, S, nq)$	$(s, Q, nq)$	$(s, S, nq)$	$(s, Q, nq)$
Arbitrary product	17.11	12	10	0.5	30	44	78.4119	0.20%	12.53%	0.64%	12.53%
				0.33	27	41	74.9735	0.19%	5.45%	0.39%	5.45%
				0.25	25	39	73.2901	0.20%	6.12%	0.69%	6.12%
Baby food	5.91	10	18	0.5	11	29	39.7233	0.00%	0.81%	6.15%	6.46%
				0.33	10	28	38.4331	0.00%	0.64%	6.67%	7.01%
				0.25	9	27	37.7752	0.00%	0.84%	6.56%	6.92%
Chocolate	13.66	17	10	0.5	25	43	59.8172	0.00%	0.39%	0.04%	0.39%
				0.33	22	41	57.0048	0.00%	0.67%	0.06%	0.67%
				0.25	21	40	55.7162	0.00%	0.77%	0.06%	0.77%
Coffee	18.81	12	21	0.5	31	59	94.5068	0.00%	1.96%	3.11%	2.04%
				0.33	27	56	90.5513	0.00%	2.76%	3.72%	2.76%
				0.25	26	54	88.7614	0.00%	2.99%	3.87%	2.99%
Coffee milk	42.20	16	25	0.5	69	89	163.4191	0.00%	11.67%	0.01%	11.67%
				0.33	62	81	155.3126	0.00%	27.88%	0.00%	27.88%
				0.25	58	78	151.4613	0.00%	19.53%	0.00%	19.53%
Candy	13.21	16	12	0.5	23	42	53.3841	0.00%	0.70%	0.23%	0.70%
				0.33	21	39	54.5734	0.00%	0.55%	0.14%	0.55%
				0.25	20	38	53.3841	0.00%	0.70%	0.23%	0.70%
Sugar	23.86	10	14	0.5	40	52	113.7879	0.13%	19.73%	0.14%	19.73%
				0.33	35	48	109.068	0.03%	26.65%	0.03%	26.65%
				0.25	33	46	106.8054	0.00%	17.39%	0.01%	17.39%
Canned Meat	17.89	13	16	0.5	31	58	85.2725	0.12%	0.62%	0.83%	0.62%
				0.33	27	55	81.636	0.11%	0.91%	0.88%	1.03%
				0.25	26	53	79.9394	0.10%	0.95%	0.84%	0.95%
Canned Fruit	11.47	12	6	0.5	21	34	54.5348	0.00%	9.77%	0.22%	18.74%
				0.33	18	31	52.0773	0.00%	11.14%	0.69%	22.76%
				0.25	17	30	50.9219	0.00%	11.91%	0.46%	11.91%
Personal Care	4.45	8	4	0.5	8	16	28.3628	0.08%	0.00%	0.08%	0.00%
				0.33	7	15	27.3204	0.08%	0.00%	0.08%	0.00%
				0.25	7	15	26.8417	0.08%	0.00%	0.08%	0.00%

Note:  $h = 1, K_1 = 20, K_2 = 1, p = 50$ . Percentage errors computed based on the normalized costs

A detailed analysis of the different scenarios (the full table is given in Appendix D) reveals that settings where  $\lambda \in \{10, 15\}$ ,  $L \in \{0.33, 0.50\}$ ,  $K \in \{5, 10\}$ ,  $p \in \{10, 25\}$  and  $q \in \{1, 6, 12\}$  gives improvements of over 1% when comparing the optimal policy with the best  $(s, S, nq)$  policy.

- It is clear that the  $(s, Q, nq)$  policy may lead to a significant optimality gap, even when explicitly considering the handling costs in the policy. Interestingly, the  $(s, S, nq)$  policy performs remarkably well with a maximum optimality gap of less than 1% (considering handling in the cost function).
- The results show that for a significant part of the retail assortment, especially the slow to medium moving products, significant costs reductions can be expected. Note that a 1% cost reduction directly translates into important higher margins, which are already very slim.

We observed in our experiments (Appendix D) that the cost  $C(s, Q, S)$  is relatively flat around the optimal  $s$  and  $Q$  values, respectively and more sensitive to changes in  $S$ . Similar to Hill and Johansen (2006), we observe the occurrence of local minima in the cost

function. In view of these numerical results, we may expect that the  $(s, S, nq)$  policies are also asymptotically optimal (see also Huh et al., 2009), as  $p$  gets large and  $K > 0$ . Regarding the solution space, we observed that, in nearly all cases, the order-up-to levels and the reorder points are nearly identical for both the optimal policy and the  $(s, S, nq)$  policies (the occasional differences are small). Apparently, the average cost  $C(s, Q, S)$  is less sensitive to changes in the values of parameter  $Q$ . These insights could be exploited in the derivation of easily computable policy parameters, which is left for future research.

## 7 Conclusions and Future Research

We studied a single-location, single-item periodic-review lost-sales inventory control problem with the following features: there are stochastic customer demands, lead time is less than the review period length, there is a fixed (predetermined) batch size for ordering and orders are restricted to integers multiples of the batch size. Furthermore, we assume a replenishment cost structure that includes a fixed cost, as well as linear components depending on the number of batches, and the number of units in a replenishment order. Our motivation and data comes from the retail environment, but the analysis is appropriate for systems in which there is a fixed unit-size and there are economies of scale in the replenishment component. Using Markov decision processes, we explore the structure of the optimal policies and investigate, in particular, the impact of handling costs on the optimal policy and the long-run average cost.

Our results show that it is worthwhile to explicitly take handling costs into account when making inventory decisions. We have used parameter values that are typical for grocery retail environments, where decision models typically abstain from including these costs. Using an  $(s, S, nq)$  policy rather than the often used in practice  $(s, Q, nq)$  policy seems from a cost perspective more plausible. A detailed ABC analysis of the product portfolio is important in using the obtained results. The results showed that for a significant part of the retail

assortment, especially the slow to medium moving products, higher reductions are expected. Moreover, a 1% cost reduction directly translates into important higher margins.

Future research could involve a number of directions. In many contexts there is also consideration of a minimum stock presentation, i.e., retailers do not want the stock on the shelf to go below some positive number of units, e.g. because of its marketing impact on the visual impression given to customers. The incorporation of this minimum stock level is an interesting path for future research.

## References

- Bertsekas, D. 1995. *Dynamic programming and optimal control*, Vol. 2. Athena Scientific.
- Barnes, R.M. 1968. *Motion and time study design and measurement of work*, John Wiley & Son. New York.
- M. Bijvank and I. F. A. Vis. 2011. Lost-sales inventory theory: A review. *EJOR*. article in press, doi:10.1016/j.ejor.2011.02.004.
- Broekmeulen R., K. van Donselaar, J. Fransoo, T. van Woensel. 2004. Excess shelf space in retail stores: an analytical model and empirical assessment. BETA working paper 109, Technische Universiteit Eindhoven, Eindhoven, The Netherlands.
- Cavazos-Catena R., L.I., Senott. 1992. Comparing recent assumptions for the existence of average optimal stationary policies. *Oper. Res. Lett.* **11** 33-37.
- Chiang, C. 2006. Optimal ordering policies for periodic-review systems with replenishment cycles. *Eur. J. Oper. Res.* **170** 44-56.
- Chiang, C. 2007. Optimal ordering policies for periodic-review systems with a refined intra-cycle time scale. *Eur. J. Oper. Res.* **177** 872-881.

- Curşeu, A., T. van Woensel, J.C. Fransoo, K.H. van Donselaar, R.A.C.M. Broekmeulen. 2009. Modelling handling operations in grocery retail stores: an empirical analysis. *J. Oper. Res. Soc.* **60**(2) 200-214.
- Caliskan-Demirag, O., Chen, Y., Yang, Y. 2012. Ordering Policies for Periodic-Review Inventory Systems with Quantity-Dependent Fixed Costs, *Operations Research*, doi: 10.1287/opre.1110.1033.
- Fisher, M.L., J. Krishnan and S. Netessine (2006), Retail Store Execution: An Empirical Study, Knowledge@Wharton, Wharton School Working Paper.
- Fisher, M.L. (2009), OR FORUM Rocket Science Retailing: The 2006 Philip McCord Morse Lecture, *Operations Research*, vol. 57, no. 3, 527-540.
- Hadley, G., T.M. Whitin. 1963. *Analysis of Inventory Systems*. Prentice-Hall, Englewood Cliffs, NJ.
- Hill, R.M. 2006, Inventory control with indivisible units of stock transfer. *Eur. J. Oper. Res.* **175** 593-601.
- Hill, R.M., S.G. Johansen. 2006. Optimal and near-optimal policies for lost sales inventory models with at most one replenishment order outstanding. *Eur. J. Oper. Res.* **169**(1) 111-132.
- Huh, W.T., G. Janakiraman, J.A. Muckstadt, P. Rusmevichientong. 2009a. Asymptotic optimality of order-up-to policies in lost sales inventory systems. *Management Sci.* **55** 404-420.
- Huh, W.T., G. Janakiraman, J.A. Muckstadt, P. Rusmevichientong. 2009b. An adaptive algorithm for finding the optimal base-stock policy in lost sales inventory system with censored demand. *Mathematics of Operations Research* **34** 2 397-416.

- Huh, W.T., G. Janakiraman, M. Nagarajan. 2011. Average Cost single stage Inventory Models: An Analysis using vanishing discount approach. *Operations Research* **59**, 143-155.
- Huh, W.T. and G. Janakiraman. 2010. On the Optimal Policy Structure in Serial Inventory Systems with Lost Sales. *Operations Research* **58**, 486-491.
- Janakiraman, G., J.A. Muckstadt. 2001. Analytic results for a periodic review inventory control problem with lost sales. Technical report 1283, School of Operations Research and Industrial Engineering, Cornell University, Ithaca, NY.
- Janakiraman, G., J.A. Muckstadt. 2004. Inventory control in directed networks: a note on linear costs. *Oper. Res.* **52**(3) 491 - 495.
- Jansen, J.B., 1998. Service and inventory models subject to a delay-limit (published PhD thesis), CentER for Economic Research, Tilburg University, The Netherlands.
- Johansen, S.G., R.M. Hill. 2000. The  $(r, Q)$  control of a periodic-review inventory system with continuous demand and lost sales. *Internat. J. Production Econom.* **68** 279-286.
- Karlin, S., H. Scarf. 1958. Inventory models of the Arrow-Harris-Marschak type with time lag. K.J. Arrow, S. Karlin, H. Scarf, eds. *Studies in the mathematical theory of inventory and production*. Stanford University Press, Stanford, CA.
- Levi, R., G. Janakiraman, M. Nagarajan. 2008. A 2-Approximation algorithm for stochastic inventory control models with lost sales. *Math. Oper. Res.* **33**(2) 351-374.
- Li Q. and P. Yu. 2012. Technical Note: On the Quasiconcavity of Lost Sales Inventory Models with Fixed Costs. *Operations Research* **60**, 286-291
- Puterman, M.L. 1994. *Markov Decision Processes*. John Wiley and Sons Inc., Wiley, New York, NY.



- Randall T., S. Netessine and N. Rudi (2006), An Empirical Examination of the Decision to Invest in Fulfillment Capabilities: A Study of Internet Retailers, *Management Science*, vol. 52, no. 4, 567-580.
- Roumiantsev S. and S. Netessine (2007), What can be learned from classical inventory models: a cross-industry exploratory investigation, *MSOM*, Vol. 9, No. 4, 409-429.
- Saghir M., G. Jonson 2001. Packaging handling evaluation methods in the grocery retail industry. *Packag. Technol. Sci.* **14** 21-29.
- Van Donselaar, K.H., V. Gaur, T. van Woensel, R.A.C.M. Broekmeulen, J.C. Fransoo. 2010. Ordering behavior in retail stores and implications for automated replenishment. *Management Sci* **56** 766-784.
- Van Zelst, S., K. van Donselaar, T. Van Woensel, R.A.C.M. Broekmeulen and J.C. Fransoo. 2009. A Model for shelf stacking in grocery retail stores: potential for efficiency improvement. *Internat. J. Production Econom.* **121** 620-632.
- Veinott, A. 1965. The optimal inventory policy for batch ordering. *Oper. Res.* **13** 424-432.
- Wagner, H. M. 1962. *Statistical Management of Inventory Systems*, Wiley, New York.
- Zheng, Y.-S., F. Chen. 1992. Inventory policies with quantized ordering. *Naval Res. Logist.* **39** 285-305.
- Zipkin, P. 2008a. Old and new methods for lost-sales inventory systems. *Oper. Res.* **56**(5) 1256-1263.
- Zipkin, P. 2008b. On the structure of lost-sales inventory models. *Oper. Res.* **56**(4) 937-944.

## A Sensitivity Analysis

We discuss the sensitivity of the optimal policy and its associated average cost to the relevant system parameters. In the absence of simple-structured policies, it is difficult to evaluate the impact of changes in the problem parameters on the optimal solution. Therefore, we use the reorder point ( $s = \max\{i \in SS | a_i > 0\}$ ) and the maximum stock level ( $I_{max} = \max\{i + a_i | 0 \leq i \leq s\}$ ) as main operational indicators.

### Sensitivity on $\lambda, L, K$ and $q$

Table 5 provides a representative set of our results, where  $p = 50, L \in \{0.25, 0.33, 0.5\}, \lambda \in \{0.1, 1, 5, 15, 25, 50\}, K \in \{5, 10, 15, 20, 25\}, q \in \{1, 3, 6, 12, 18, 36\}$ .

Clearly, the results in Table 5 are in agreement with expectations. We observe that the batch size  $q$  mostly affects  $I_{max}$ , which increases, in general, as  $q$  increases (other parameters being equal). Numerical results suggest that, in general,  $s$  increases with  $L$ , and  $I_{max}$  also increase with  $L$  and  $q$  (and there is little interaction between  $L$  and  $q$ ). Additionally,  $s$  decreases with  $K$ , while  $I_{max}$  increases with  $K$  and  $q$ . Furthermore, regarding the sensitivity of the average cost to changes in problem parameters, our numerical studies suggest that the optimal long-run average cost is increasing in  $L$  and  $K$  (all other things being equal). Note that similar monotonic results (w.r.t.  $L$ ) of the average cost (as well as the infinite horizon discounted costs) are claimed by Zipkin (2008) for the lost sales model with lead times which are integers multiple of the review period length. Note that previous research (Janakiraman and Muckstadt, 2004) shows that linear purchase costs ( $K_2$ ) can be assumed to be zero without loss of generality, for general distribution and assembly systems with lost sales and/or backorders, when lead times are integers. Janakiraman and Muckstadt (2001) extend the result to a lost sales model with lead times which are a fraction of the review period length (see Lemma B.1 in Appendix B). The result states that the finite horizon, discounted cost problem with no setup cost and a positive unit purchasing cost can be

Table 5: Sensitivity analysis on  $L, \lambda, K, q$ 

$L = 0.25$																			
$K$	$q$	$\lambda = 0.1$			$\lambda = 1$			$\lambda = 5$			$\lambda = 10$			$\lambda = 15$			$\lambda = 20$		
		$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$
5	1	0	1	3.68	2	5	26.12	8	13	116.8	15	19	225.86	23	27	333.87	30	34	441.62
	6	0	6	4.02	2	8	10.15	9	17	34.2	16	24	60.61	24	31	85.42	31	39	109.91
	12	-	-	4.98	1	13	10.62	8	20	26.4	16	29	44.90	23	36	61.95	30	43	78.17
	18	-	-	4.98	1	19	12.63	8	26	25.5	15	33	40.48	23	41	55.03	30	48	68.95
	36	-	-	4.98	0	36	20.56	6	42	30.0	14	50	41.25	21	57	52.20	28	64	63.15
10	1	0	2	4.11	1	6	27.30	7	16	119.3	14	20	230.79	22	27	338.87	29	34	446.62
	6	0	6	4.10	2	8	10.98	8	20	36.8	15	30	65.09	23	31	90.40	30	39	114.91
	12	-	-	4.98	1	13	11.03	8	20	28.5	15	30	48.69	22	36	66.65	29	43	83.14
	18	-	-	4.98	1	19	12.91	8	26	26.9	15	33	43.25	22	42	58.97	29	49	73.58
	36	-	-	4.98	0	36	20.69	6	42	30.7	14	50	42.63	21	57	54.27	28	64	65.92
15	1	0	2	4.35	1	7	28.10	7	18	121.3	14	29	233.43	21	27	343.85	28	34	451.62
	6	0	6	4.18	2	8	11.80	8	22	38.7	15	32	67.83	22	43	95.26	29	39	119.91
	12	-	-	4.98	1	13	11.44	8	24	30.6	15	36	51.66	22	46	70.91	29	55	88.08
	18	-	-	4.98	1	19	13.18	8	26	28.2	15	33	46.01	22	44	62.80	29	49	78.18
	36	-	-	4.98	0	36	20.83	6	42	31.4	14	50	44.02	21	57	56.35	28	64	68.69
20	1	0	2	4.58	1	8	28.83	7	20	123.0	14	30	235.88	20	41	346.89	27	34	456.62
	6	0	6	4.26	2	8	12.62	8	23	40.5	15	34	70.23	22	45	98.18	28	39	124.90
	12	-	-	4.98	1	13	11.85	8	27	32.5	15	38	54.00	22	48	73.65	28	57	92.02
	18	-	-	4.98	1	19	13.46	8	26	29.6	15	41	48.69	22	51	66.11	28	61	82.39
	36	-	-	4.98	0	36	20.97	6	42	32.1	14	50	45.40	21	57	58.43	28	64	71.46
25	1	0	2	4.82	1	8	29.48	7	22	124.5	13	31	238.18	20	42	349.43	27	54	459.97
	6	0	6	4.34	2	8	13.45	7	25	42.0	15	35	72.52	21	45	100.73	28	57	128.07
	12	-	-	4.98	1	13	12.25	8	28	34.2	15	39	56.09	21	49	76.20	28	59	95.29
	18	-	-	4.98	1	19	13.73	8	26	31.0	15	43	50.99	21	54	68.59	28	64	85.12
	36	-	-	4.98	0	36	21.10	6	42	32.8	14	50	46.79	21	57	60.50	28	64	74.23
$L = 0.33$																			
$K$	$q$	$\lambda = 0.1$			$\lambda = 1$			$\lambda = 5$			$\lambda = 10$			$\lambda = 15$			$\lambda = 20$		
		$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$
5	1	0	1	3.70	2	5	26.24	8	14	117.36	16	20	226.87	24	28	335.35	32	36	443.52
	6	0	6	4.02	2	8	10.27	9	17	34.69	17	25	61.64	25	32	86.95	33	40	111.84
	12	-	-	4.98	1	13	10.80	9	21	27.01	17	30	45.91	24	37	63.45	32	45	80.07
	18	-	-	4.98	1	19	12.76	8	26	25.95	16	34	41.48	24	42	56.42	31	50	70.84
	36	-	-	4.98	0	36	20.70	7	43	30.49	15	51	42.23	22	58	53.62	30	66	65.02
10	1	0	2	4.12	2	6	27.41	8	17	119.81	15	28	231.79	23	28	340.35	30	36	448.52
	6	0	6	4.11	2	8	11.09	9	20	37.34	16	31	66.11	24	33	91.93	32	40	116.84
	12	-	-	4.98	1	13	11.20	9	21	29.08	16	31	49.69	24	38	68.12	31	45	85.03
	18	-	-	4.98	1	19	13.03	8	26	27.33	16	34	44.25	24	43	60.41	31	51	75.49
	36	-	-	4.98	0	36	20.83	7	43	31.18	15	51	43.62	22	58	55.70	30	66	67.79
15	1	0	2	4.36	1	7	28.28	8	19	121.84	15	30	234.41	22	28	345.34	29	36	453.52
	6	0	6	4.19	2	8	11.91	8	22	39.27	16	33	68.83	23	45	96.73	31	40	121.83
	12	-	-	4.98	1	13	11.61	9	25	31.15	16	37	52.66	23	47	72.35	31	57	89.97
	18	-	-	4.98	1	19	13.31	8	26	28.71	16	34	47.01	23	45	64.28	30	51	80.08
	36	-	-	4.98	0	36	20.97	7	43	31.87	15	51	45.00	22	58	57.77	30	66	70.56
20	1	0	2	4.59	1	8	28.98	7	21	123.56	15	31	236.86	22	43	348.31	29	36	458.51
	6	0	6	4.27	2	8	12.73	8	24	40.98	16	35	71.24	23	46	99.61	30	40	126.83
	12	-	-	4.98	1	13	12.02	8	27	33.08	16	39	55.00	23	49	75.07	30	59	93.91
	18	-	-	4.98	1	19	13.58	8	26	30.09	16	42	49.69	23	53	67.53	30	63	84.26
	36	-	-	4.98	0	36	21.11	7	43	32.56	15	51	46.39	22	58	59.85	30	66	73.33
25	1	0	2	4.82	1	9	29.63	7	22	125.04	14	32	239.13	21	43	350.84	28	55	461.80
	6	0	6	4.35	2	8	13.56	8	25	42.50	15	36	73.50	23	47	102.17	30	59	129.94
	12	-	-	4.98	1	13	12.42	8	29	34.67	15	40	57.06	23	51	77.62	30	61	97.17
	18	-	-	4.98	1	19	13.85	8	26	31.47	16	44	52.00	23	55	70.02	30	66	87.00
	36	-	-	4.98	0	36	21.24	7	43	33.25	15	51	47.77	22	58	61.92	30	66	76.10
$L = 0.50$																			
$K$	$q$	$\lambda = 0.1$			$\lambda = 1$			$\lambda = 5$			$\lambda = 10$			$\lambda = 15$			$\lambda = 20$		
		$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$
5	1	0	1	3.73	2	6	26.55	10	15	118.50	18	22	229.01	27	31	338.44	35	40	447.53
	6	0	6	4.04	2	8	10.56	10	18	35.89	19	27	63.79	28	36	90.08	37	44	115.91
	12	-	-	4.98	2	14	11.09	10	22	28.16	19	31	48.03	27	40	66.57	36	49	84.08
	18	-	-	4.98	1	19	13.06	9	27	27.08	18	36	43.60	27	45	59.43	35	54	74.85
	36	-	-	4.98	1	37	20.89	8	44	31.57	17	53	44.30	25	61	56.62	34	70	68.99
10	1	0	2	4.14	2	7	27.63	9	18	120.93	17	30	233.86	26	31	343.43	34	40	452.53
	6	0	6	4.12	2	8	11.38	10	21	38.48	18	34	68.26	27	36	95.05	36	44	120.91
	12	-	-	4.98	2	14	11.50	10	22	30.23	18	33	51.84	27	41	71.23	35	49	89.04
	18	-	-	4.98	1	19	13.33	9	27	28.46	18	36	46.36	27	46	63.46	35	55	79.52
	36	-	-	4.98	1	37	21.02	8	44	32.26	17	53	45.68	25	61	58.70	34	70	71.76
15	1	0	2	4.38	2	8	28.53	9	20	122.94	17	32	236.48	25	31	348.42	33	40	457.53
	6	0	6	4.20	2	8	12.20	10	23	40.44	18	35	70.95	26	48	99.82	35	44	125.91
	12	-	-	4.98	2	14	11.91	10	26	32.29	18	39	54.78	26	50	75.42	34	61	93.97
	18	-	-	4.98	1	19	13.60	9	27	29.84	18	36	49.13	26	48	67.32	34	55	84.08
	36	-	-	4.98	1	37	21.16	8	44	32.95	17	53	47.07	25	61	60.77	34	70	74.53
20	1	0	2	4.61	2	8	29.30	8	22	124.66	17	33	238.92	25	46	351.31	32	40	462.53
	6	0	6	4.29	2	8	13.02	9	25	42.12	18	37	73.34	26	49	102.66	34	44	130.90
	12	-	-	4.98	2	14	12.32	10	28	34.23	18	41	57.10	26	52	78.12	34	63	97.91
	18	-	-	4.98	1	19	13.87	9	27	31.22	18	44	51.80	26	56	70.56	34	67	88.24
	36	-	-	4.98	1	37	21.30	8	44	33.64	17	53	48.45	25	61				

transformed into a finite horizon problem with zero unit purchase cost. We deduce that for any value of  $q$ , the optimal policy for a problem with parameters  $(K_1, K_2, h, p, q)$  and  $K = 0$  is the same as the optimal policy for a problem with parameters  $(0, 0, h, p - K_1/q - K_2, q)$ , and on the long-run, the average cost difference between the former and the latter model is given by  $(K_1/q + K_2) * \lambda$ , a term independent of the policy (see Proposition B.2 in Appendix B). Therefore, when  $q$  is exogenous, the batch ( $K_1$ ) and unit ( $K_2$ ) handling costs can be assumed to be zero without loss of generality, for determining the optimal policy, provided the penalty cost transformation  $p(q) := p - K_1/q - K_2$ .

## Sensitivity on $p, \lambda$ and $L$

In the above scenarios, the penalty cost is quite high ( $p = 50$ ) compared to the holding costs, resulting in high service levels. With a very high service level, shortages are rare events, and the lost sales model could be approximated by a backorder one. Table 6 shows the performance with regards to different values of the lost sales penalty cost  $p$ , together with  $\lambda$  and  $L$ . Clearly, if the penalty is too low (i.e.  $p = 5$ ) the policy is to not order anything and take the lost sales costs completely. Higher penalties for very low demand ( $\lambda = 0.1$ ) also do not lead to changes in this policy behavior. On the other hand, for higher levels of demand ( $\lambda \geq 1$ ) it becomes more efficient from a cost point of view to order positive amounts of inventory. Remember, that in the previous Table 5, we set  $p = 50$  which resulted in policies where also positive orders are seen for low values of  $\lambda$ , but only if  $q$  is small enough ( $q \leq 6$ ).

## B On Unit vs. Batch Costs

**Lemma B.1.** (*Janakiraman and Muckstadt 2001, Lemma 1*) *For all valid sets of cost parameters  $(c'; h'; p')$  (i.e.  $(\alpha(p' - h') \geq c')$ ) there exists another set of cost parameters  $(0; h; p)$*

Table 6: Sensitivity analysis on  $p$ 

$L = 0.25$															
$\lambda = 0.1$				$\lambda = 1$				$\lambda = 5$				$\lambda = 10$			
$p$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$
5	-	-	0.56	-	-	5.00	-	-	25.00	-	-	50.00	-	-	100.00
15	-	-	1.54	0	6	9.89	5	17	34.54	12	27	62.14	18	28	87.22
25	-	-	2.52	1	7	10.33	7	19	35.63	14	29	63.59	21	29	88.78
40	-	-	4.00	2	8	10.87	8	19	36.43	15	30	64.63	22	31	89.94
$L = 0.33$															
$\lambda = 0.1$				$\lambda = 1$				$\lambda = 5$				$\lambda = 10$			
$p$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$
5	-	-	0.56	-	-	5.00	-	-	25.00	-	-	50.00	-	-	100.00
15	-	-	1.54	0	6	10.02	6	18	34.98	13	28	63.05	20	29	88.55
25	-	-	2.52	1	7	10.47	7	19	36.14	14	30	64.57	22	31	90.21
40	-	-	4.00	2	8	10.96	8	20	36.96	16	31	65.64	23	32	91.39
$L = 0.50$															
$\lambda = 0.1$				$\lambda = 1$				$\lambda = 5$				$\lambda = 10$			
$p$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$	$s$	$I_{max}$	$C^*$
5	-	-	0.56	-	-	5.00	-	-	25.00	-	-	50.00	-	-	100.00
15	-	-	1.54	1	7	10.19	7	19	36.01	14	30	64.99	22	32	91.45
25	-	-	2.52	1	7	10.79	8	20	37.23	16	32	66.60	25	34	93.22
40	-	-	4.00	2	8	11.19	9	21	38.10	18	33	67.75	26	35	94.48

Note:  $h = 1, q = 6, K = 10, K_1 = 20, K_2 = 1$  and  $s = I_{max} = -$  refers to a do-not-order-policy with an average cost equal to  $p \cdot \lambda$ .

with  $h = h' + c'(1 - \alpha)/\alpha$  and  $p = p' - c$  such that

$$f_n^{(c'; h'; p')}(x_n, q_n) = f_n^{(0; h; p)}(x_n, q_n) + \zeta,$$

where  $f_n^{(c; h; p)}(x_n, q_n)$  denotes the minimum expected sum of all discounted future costs (with discount factor  $\alpha$  and cost parameters  $c, h$  and  $p$ ) and  $\zeta$  is a term independent of the policy, if we start period  $n$  with  $x_n$  units of inventory on hand and we order  $q_n$  units.

For the proof, we refer the reader to Janakiraman and Muckstadt (2001). In view of this result, we derive the following result for the infinite horizon, average cost model with batch ordering and no setup cost.

**Proposition B.2.** *Consider the inventory system introduced in Section 4 and assume there is no setup cost. For any given batch size  $q$ , and all sets of cost parameters  $(K_1, K_2, h, p)$  such that  $p - h \geq K_1/q + K_2$ , the parameter transformation*

$$(K_1, K_2, h, p, q) \mapsto (0, 0, h, p - K_1/q - K_2, q)$$

leads to the following cost transformation:

$$C_{(K_1, K_2, h, p, q)}^* = C_{(0, 0, h, p - K_1/q - K_2, q)}^* + (K_1/q + K_2) \cdot \lambda,$$

where  $C_{(K_1, K_2, h, p, q)}^*$  denotes the minimum long-run average cost corresponding to parameters  $(K_1, K_2, h, p, q)$  and  $\lambda$  denotes the average demand per review period.

*Proof.* For every fixed value of the batch size  $q$ , we can rewrite the replenishment cost as follows

$$c^r(nq) = \delta(nq)K + K_1n + K_2nq = \delta(nq)K + (K_1/q + K_2)nq = \delta(nq)K + c(q)nq,$$

where  $c(q) = K_1/q + K_2$  is the per unit purchasing cost (given  $q$ ). Then, since  $K = 0$ , we apply Lemma B.1 and a limiting argument and deduce:

$$C_{(K_1, K_2, h, p, q)}^* = C_{(0, 0, h, p - c(q), q)}^* + \zeta. \quad (6)$$

Next, assume that the problem parameters are such that the optimal policy corresponding to  $(0, 0, h, p - c(q); q)$  is to never order, in which case the minimum average cost equals  $C_{(0, 0, h, p - c(q), q)}^* = (p - c(q)) \cdot \lambda = (p - K_1/q - K_2) \cdot \lambda$ . It follows that the optimal policy for the problem with parameters  $(K_1, K_2, h, p, q)$  is also the policy of never ordering and the corresponding minimum average cost equals  $C_{(K_1, K_2, h, p, q)}^* = p \cdot \lambda$ . Replacing the average costs in (6) it follows that:

$$p \cdot \lambda = (p - c(q)) \cdot \lambda + \zeta,$$

and thus

$$\zeta = c(q) \cdot \lambda = (K_1/q + K_2) \cdot \lambda$$

## C Proofs for the different propositions

**Proposition C.1.** *There exists a state  $i_u$  such that for  $i \geq i_u$  the optimal decision is not to order.*

*Proof.* Consider the one-period transition cost  $c_i(a_i)$  defined in Equation (3), and let  $\underline{c}_i(a_i)$

be a lower bound for  $c_i(a_i)$  when  $a_i$  units are ordered. A possible  $\underline{c}_i(a_i)$  can be obtained when we eliminate certain terms in Equation (3).

To simplify notation, let

$$\begin{aligned}\theta(i) &= ((i - D_L)^+ + a_i - D_{R-L})^+ \\ \theta_1(i) &= (D_L - i)^+ + (D_{R-L} - a_i - (i - D_L)^+)^+.\end{aligned}$$

Then, using the identity  $(x - y)^+ = x - y + (x - y)^+$ , we obtain

$$\begin{aligned}\theta(i) &= (i - D_L + (D_L - i)^+ + a_i - D_{R-L})^+ = (i + a_i - D_R + (D_L - i)^+)^+, \\ \theta_1(i) &= (D_L - i)^+ + D_{R-L} - a_i - (i - D_L)^+ + ((i - D_L)^+ - D_{R-L} + a_i)^+ \\ &= D_L - i + D_{R-L} - a_i + ((i - D_L)^+ + a_i - D_{R-L})^+ \\ &= D_R - i - a_i + ((i - D_L)^+ + a_i - D_{R-L})^+ \\ &= D_R - i - a_i + \theta(i).\end{aligned}$$

Next, observe that

$$\begin{aligned}\theta(i) &\geq (i + a_i - D_R)^+, \\ \theta_1(i) &\geq D_R - i - a_i + (i + a_i - D_R)^+ = (D_R - i - a_i)^+.\end{aligned}$$

Therefore, we obtain the following lower bounds for the expected one-period holding and penalty costs:

$$\begin{aligned}c_i^h(a_i) &= h\mathbf{E} [((i - D_L)^+ + a_i - D_{R-L})^+] \geq h\mathbf{E} [(i + a_i - D_R)^+], \\ c_i^p(a_i) &= p\{\mathbf{E} [(D_L - i)^+] + \mathbf{E} [(D_{R-L} - a_i - (i - D_L)^+)^+]\} \geq p\mathbf{E} [(D_R - i - a_i)^+].\end{aligned}$$

Now, we define  $\underline{c}_i(a_i)$  as

$$\underline{c}_i(a_i) = \delta(a_i)K + h\mathbf{E}[(i + a_i - D_R)^+] + p\mathbf{E}[(D_R - i - a_i)^+]$$

to obtain a lower bound for the one-period transition cost  $c_i(a_i)$ . Note that  $\underline{c}_i(a_i)$  has a newsvendor structure, except for the fixed cost  $K$ .

Let  $a_R^{NV}$  be the optimal order quantity when  $i$  is not considered. Hence, the optimal solution for  $\underline{c}_i(a_i)$  would be

$$a_i^* = \begin{cases} a_R^{NV} - i, & \text{if } i \leq a_R^{NV} \\ 0, & \text{otherwise.} \end{cases}$$

Note that with this ordering policy  $\underline{c}_i(a_i^*) \geq c_i(0)$ , for  $i \geq a_R^{NV}$ . Hence,  $i_u = a_R^{NV}$ .

□

**Proposition C.2.** *There exists a set of parameter values for which we would not operate the lost sales inventory system under consideration, i.e. we will never order.*

*Proof.* No formal proof is necessary as one can set  $K$  arbitrarily large in Equation (3) to satisfy this proposition. □

Next, we identify a condition that guarantees a threshold value for the initial inventory level below which it is always optimal to order.

**Proposition C.3.** *If*

$$\begin{aligned} (h + p)E[D_R] &\geq K + K_1 a_{R-L}^{NV}/q + K_2 a_{R-L}^{NV} + h\mathbf{E}[(a_{R-L}^{NV} - D_{R-L})^+] \\ &+ p\mathbf{E}[(D_{R-L} - a_{R-L}^{NV})^+] + p\mathbf{E}[D_L] + h\mathbf{E}[D_R]. \end{aligned}$$

*is satisfied, then there exists a state  $i$  for which it is optimal to order. Here  $a_{R-L}^{NV}$  is the optimal order-up-to-level for a news vendor problem with Poisson demand over  $R - L$  time units.*



*Proof.* Consider Equation (3) for  $a_i = 0$  and observe that

$$\begin{aligned} c_i(0) &= h\mathbf{E}[(i - D_R)^+] + p\mathbf{E}[(D_R - i)^+] \\ &= (h + p)\mathbf{E}[(D_R - i)^+] + hi - h\mathbf{E}[D_R], \end{aligned}$$

using the identity  $(x - y)^+ = x - y + (y - x)^+$ . Using Equation (3) for  $a_i > 0$  and defining  $\bar{c}'_i(a_i)$  to be an upper bound for  $c_i(a_i)$ , we obtain the following:

$$\begin{aligned} \bar{c}'_i(a_i) &= K + K_1 a_i / q + K_2 a_i + h\mathbf{E}[(i + a_i - D_{R-L})^+] \\ &\quad + p\mathbf{E}[(D_{R-L} - a_i - i)^+] + p\mathbf{E}[D_L]. \end{aligned}$$

Assuming that we always carry the initial  $i$  units and satisfy the demand from the incoming order only, we obtain another upper bound for  $c_i(a_i)$ , denoted as  $\bar{c}_i(a_i)$ :

$$\begin{aligned} \bar{c}_i(a_i) &= K + K_1 a_i / q + K_2 a_i + hi + h\mathbf{E}[(a_i - D_{R-L})^+] \\ &\quad + p\mathbf{E}[(D_{R-L} - a_i)^+] + p\mathbf{E}[D_L]. \end{aligned}$$

Hence, any non-optimal solution for the upper bound will still be an upper bound for the original problem. Similarly to Proposition C.1, define  $a_{R-L}^{NV}$ . Hence,

$$\bar{c}_i(a_{R-L}^{NV}) \geq \bar{c}_i(a_i^*).$$

As a result,

$$\begin{aligned} \bar{c}_i(a_{R-L}^{NV}) &\leq K + K_1 a_{R-L}^{NV} / q + K_2 a_{R-L}^{NV} + hi + h\mathbf{E}[(a_{R-L}^{NV} - D_{R-L})^+] \\ &\quad + p\mathbf{E}[(D_{R-L} - a_{R-L}^{NV})^+] + p\mathbf{E}[D_L]. \end{aligned}$$

Now, writing  $c_i(0)$  and  $\bar{c}_i(a_{R-L}^{NV})$  together, we want  $c_i(0) \geq \bar{c}_i(a_{R-L}^{NV})$  or

$$\begin{aligned} (h+p)\mathbf{E}[(D_R - i)^+] + hi - h\mathbf{E}[D_R] &\geq K + K_1 a_{R-L}^{NV}/q + K_2 a_{R-L}^{NV} \\ &+ hi + h\mathbf{E}[(a_{R-L}^{NV} - D_{R-L})^+] \\ &+ p\mathbf{E}[(D_{R-L} - a_{R-L}^{NV})^+] + p\mathbf{E}[D_L]. \end{aligned}$$

Eliminating  $hi$  terms,

$$\begin{aligned} (h+p)\mathbf{E}[(D_R - i)^+] &\geq K + K_1 a_{R-L}^{NV}/q + K_2 a_{R-L}^{NV} + h\mathbf{E}[(a_{R-L}^{NV} - D_{R-L})^+] \\ &+ p\mathbf{E}[(D_{R-L} - a_{R-L}^{NV})^+] + p\mathbf{E}[D_L] + h\mathbf{E}[D_R]. \end{aligned}$$

Note that the righthand side is constant in  $i$  and the lefthand side is decreasing with  $i$ . The existence condition given in the statement of the proposition is the case when  $i = 0$ . Hence, if the condition is satisfied, the largest  $i$  satisfying this condition is  $i_L$ , a lower bound for inventory level  $i$  where it is optimal to order.  $\square$

## D Comparing with $(s, S, nq)$ and $(s, Q, nq)$ policies

We now report on the computational results on the performance of the best  $(s, S, nq)$  and the best  $(s, Q, nq)$  policies, compared to the optimal policy. This is an important analysis, since many retailers employ these policies. The key question to be answered is then whether by extending the cost function to include handling, these standard policies get closer in performance compared to the optimal policy. For any policy, we use a dynamic programming formulation (similar to (4) in Section 4) in order to determine the long-run average cost of the policy. In this case, for any state  $i \in SS$ , instead of minimizing over all possible order quantities, the order quantity is determined by the logic of the specific policy (either the  $(s, S, nq)$  or the  $(s, Q, nq)$  policy). We then solve the resulting system of equations to determine the long-run average cost  $C(s, Q, S)$ . To obtain the best policy, we exhaustively

search over a sufficiently large feasible region to ensure finding a global optimum. Note that all policies have a cost function including handling (which is not done in retail practice).

Table 7: Performance of the optimal policy compared to the best  $(s, S, nq)$  and the best  $(s, Q, nq)$  policies

$(s, S, nq)$				$(s, Q, nq)$		
$\lambda$	Avg	Min	Max	Avg	Min	Max
0.1	0.00%	0.00%	0.00%	37.63%	24.94%	50.32%
1	0.00%	0.00%	0.00%	1.33%	0.00%	10.88%
5	0.02%	0.00%	0.28%	0.29%	0.00%	4.75%
10	0.09%	0.00%	1.43%	0.91%	0.00%	8.91%
15	0.13%	0.00%	1.44%	2.81%	0.00%	15.37%
20	0.30%	0.00%	1.70%	6.31%	0.00%	20.52%
$q$	Avg	Min	Max	Avg	Min	Max
1	0.30%	0.00%	1.39%	4.84%	0.01%	50.32%
6	0.18%	0.00%	1.44%	4.14%	0.00%	24.94%
12	0.15%	0.00%	1.70%	2.73%	0.00%	13.27%
18	0.01%	0.00%	0.39%	2.06%	0.00%	20.52%
36	0.00%	0.00%	0.00%	0.23%	0.00%	2.27%
$K$	Avg	Min	Max	Avg	Min	Max
5	0.12%	0.00%	1.44%	6.04%	0.00%	50.32%
10	0.09%	0.00%	1.17%	2.23%	0.00%	14.12%
15	0.12%	0.00%	0.83%	1.15%	0.00%	7.66%
20	0.17%	0.00%	1.70%	0.88%	0.00%	4.08%
25	0.06%	0.00%	0.80%	0.80%	0.00%	3.99%
$p$	Avg	Min	Max	Avg	Min	Max
10	0.17%	0.00%	1.70%	1.85%	0.00%	18.83%
25	0.11%	0.00%	1.70%	2.03%	0.00%	20.52%
50	0.03%	0.00%	0.54%	5.48%	0.00%	50.32%
$L$	Avg	Min	Max	Avg	Min	Max
0.25	0.10%	0.00%	1.70%	2.08%	0.00%	20.52%
0.33	0.11%	0.00%	1.70%	3.11%	0.00%	50.32%
0.5	0.13%	0.00%	1.04%	1.68%	0.00%	9.45%
Overall	0.11%	0.00%	1.70%	2.59%	0.00%	50.32%

Note:  $h = 1, K_1 = 20, K_2 = 1$ . Percentage errors computed based on the normalized costs, i.e. total average costs  $-(K_1/q + K_2) \cdot \lambda$

Table 7 summarizes the results of our experiments. Results for the best  $(s, S, nq)$  and  $(s, Q, nq)$  policy are stated as percentage increase in average costs from the cost of the optimal policy. In computing the percentage errors, all average costs are first normalized by subtracting from the total costs the constant  $(K_1/q + K_2) \cdot \lambda$ . The main observation from Table 7 is that, on average, the best  $(s, S, nq)$  policy is performing relatively close to optimal, while the  $(s, Q, nq)$  heuristic is remarkably worse. The best  $(s, S, nq)$  policy, with an average error of 0.09%, deteriorates slightly. An important reason for the small optimality gap between these heuristics is the flatness of the cost curves  $C(s, Q, S)$  around the optimal  $Q$  value.

Nr.	Year	Title	Author(s)
421	2013	Lost Sales Inventory Models with Batch Ordering and Handling Costs	T. Van Woensel, N. Erkip, A. Curseu, J.C. Fransoo
420	2013	Response speed and the bullwhip	Maximiliano Udenio, Jan C. Fransoo, Eleni Vatamidou, Nico Dellaert
419	2013	Anticipatory Routing of Police Helicopters	Rick van Urk, Martijn R.K. Mes, Erwin W. Hans
418	2013	Supply Chain Finance: research challenges ahead	Kasper van der Vliet, Matthew J. Reindorp, Jan C. Fransoo
417	2013	Improving the Performance of Sorter Systems by Scheduling Inbound Containers	S.W.A. Haneyah, J.M.J. Schutten, K. Fikse
416	2013	Regional logistics land allocation policies: Stimulating spatial concentration of logistics firms	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
415	2013	The development of measures of process harmonization	Heidi L. Romero, Remco M. Dijkman, Paul W.P.J. Grefen, Arjan van Weele
414	2013	BASE/X. Business Agility through Cross-Organizational Service Engineering. The Business and Service Design Approach developed in the CoProFind Project	Paul Grefen, Egon Lüftenegger, Eric van der Linden, Caren Weisleder
413	2013	The Time-Dependent Vehicle Routing Problem with Soft Time Windows and Stochastic Travel Times	Duygu Tas, Nico Dellaert, Tom van Woensel, Ton de Kok
412	2013	Clearing the Sky - Understanding SLA Elements in Cloud Computing	Marco Comuzzi, Guus Jacobs, Paul Grefen
411	2013	Approximations for the waiting time distribution in an M/G/c priority queue	A. Al Hanbali, E.M. Alvarez, M.C. van der Heijden
410	2013	To co-locate or not? Location decisions and logistics concentration areas	Frank P. van den Heuvel, Karel H. van Donselaar, Rob A.C.M. Broekmeulen, Jan C. Fransoo, Peter W. de Langen
409	2013	The Time-Dependent Pollution-Routing Problem	Anna Franceschetti, Dorothée Honhon, Tom van Woensel, Tolga Bektas, Gilbert Laporte
408	2013	Scheduling the scheduling task: A time management perspective on scheduling	J.A. Larco, V. Wiers, J. Fransoo
407	2013	Clustering Clinical Departments for Wards to Achieve a Prespecified Blocking Probability	J. Theresia van Essen, Mark van Houdenhoven, Johann L. Hurink
406	2013	MyPHRMachines: Personal Health Desktops in the Cloud	Pieter Van Gorp, Marco Comuzzi
405	2013	Maximising the Value of Supply Chain Finance	Kasper van der Vliet, Matthew J. Reindorp, Jan C. Fransoo
404	2013	Reaching 50 million nanostores: retail distribution in emerging megacities	Edgar E. Blanco, Jan C. Fransoo
403	2013	A Vehicle Routing Problem with Flexible Time Windows	Duygu Tas, Ola Jabali, Tom van Woensel
402	2013	The Service Dominant Business Model: A Service Focused Conceptualization	Egon Lüftenegger, Marco Comuzzi, Paul Grefen, Caren Weisleder
401	2013	Relationship between freight accessibility and logistics employment in US counties	Frank P. van den Heuvel, Liliana Rivera, Karel H. van Donselaar, Ad de Jong, Yossi Sheffi, Peter W. de Langen, Jan C. Fransoo
400	2012	A Condition-Based Maintenance Policy for Multi-Component Systems with a High Maintenance Setup Cost	Qiushi Zhu, Hao Peng, Geert-Jan van Houtum
399	2012	A flexible iterative improvement heuristic to support creation of feasible shift rosters in self-rostering	E. van der Veen, J.L. Hurink, J.M.J. Schutten, S.T. Uijland

Nr.	Year	Title	Author(s)
398	2012	Scheduled Service Network Design with Synchronization and Transshipment Constraints for Intermodal Container Transportation Networks	K. Sharypova, T.G. Crainic, T. van Woensel, J.C. Fransoo
397	2012	Destocking, the bullwhip effect, and the credit crisis: empirical modeling of supply chain dynamics	Maximiliano Udenio, Jan C. Fransoo, Robert Peels
396	2012	Vehicle routing with restricted loading capacities	J. Gromicho, J.J. van Hoorn, A.L. Kok, J.M.J. Schutten
395	2012	Service differentiation through selective lateral transshipments	E.M. Alvarez, M.C. van der Heijden, I.M.H. Vliegen, W.H.M. Zijm
394	2012	A Generalized Simulation Model of an Integrated Emergency Post	Martijn Mes, Manon Bruens
393	2012	Business Process Technology and the Cloud: defining a Business Process Cloud Platform	Vassil Stoitsev, Paul Grefen
392	2012	Vehicle Routing with Soft Time Windows and Stochastic Travel Times: A Column Generation and Branch-and-Price Solution Approach	D. Tas, M. Gendreau, N. Dellaert, T. van Woensel, A.G. de Kok
391	2012	Improve OR-Schedule to Reduce Number of Required Beds	J. Theresia van Essen, Joël M. Bosch, Erwin W. Hans, Mark van Houdenhoven, Johann L. Hurink
390	2012	How does development lead time affect performance over the ramp-up lifecycle? Evidence from the consumer electronics industry	Andreas Pufall, Jan C. Fransoo, Ad de Jong, A.G. (Ton) de Kok
389	2012	The Impact of Product Complexity on Ramp-Up Performance	Andreas Pufall, Jan C. Fransoo, Ad de Jong, A.G. (Ton) de Kok
388	2012	Co-location synergies: specialized versus diverse logistics concentration areas	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
387	2012	Proximity matters: Synergies through co-location of logistics establishments	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
386	2012	Spatial concentration and location dynamics in logistics: the case of a Dutch province	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
385	2012	FNet: An Index for Advanced Business Process Querying	Zhiqiang Yan, Remco Dijkman, Paul Grefen
384	2012	Defining Various Pathway Terms	W.R. Dalinghaus, P.M.E. Van Gorp
383	2012	The Service Dominant Strategy Canvas: Defining and Visualizing a Service Dominant Strategy through the Traditional Strategic Lens	Egon Lüftenegger, Paul Grefen, Caren Weisleder
382	2012	A Stochastic Variable Size Bin Packing Problem with Time Constraints	Stefano Fazi, Tom van Woensel, Jan C. Fransoo
381	2012	Coordination and Analysis of Barge Container Hinterland Networks	K. Sharypova, T. van Woensel, J.C. Fransoo
380	2012	Proximity matters: Synergies through co-location of logistics establishments	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
379	2012	A literature review in process harmonization: a conceptual framework	Heidi Romero, Remco Dijkman, Paul Grefen, Arjan van Weele
378	2012	A Generic Material Flow Control Model for Two Different Industries	S.W.A. Haneyah, J.M.J. Schutten, P.C. Schuur, W.H.M. Zijm
377	2012	Dynamic demand fulfillment in spare parts networks with multiple customer classes	H.G.H. Tiemessen, M. Fleischmann, G.J. van Houtum, J.A.E.E. van Nunen, E. Pratsini
376	2012	Paper has been replaced by wp 417	K. Fikse, S.W.A. Haneyah, J.M.J. Schutten
375	2012	Strategies for dynamic appointment making by container terminals	Albert Douma, Martijn Mes

Nr.	Year	Title	Author(s)
374	2012	MyPHRMachines: Lifelong Personal Health Records in the Cloud	Pieter van Gorp, Marco Comuzzi
373	2012	Service differentiation in spare parts supply through dedicated stocks	E.M. Alvarez, M.C. van der Heijden, W.H.M. Zijm
372	2012	Spare parts inventory pooling: how to share the benefits?	Frank Karsten, Rob Basten
371	2012	Condition based spare parts supply	X. Lin, R.J.I. Basten, A.A. Kranenburg, G.J. van Houtum
370	2012	Using Simulation to Assess the Opportunities of Dynamic Waste Collection	Martijn Mes
369	2012	Aggregate overhaul and supply chain planning for rotables	J. Arts, S.D. Flapper, K. Vernooij
368	2012	Operating Room Rescheduling	J.T. van Essen, J.L. Hurink, W. Hartholt, B.J. van den Akker
367	2011	Switching Transport Modes to Meet Voluntary Carbon Emission Targets	Kristel M.R. Hoen, Tarkan Tan, Jan C. Fransoo, Geert-Jan van Houtum
366	2011	On two-echelon inventory systems with Poisson demand and lost sales	Elisa Alvarez, Matthieu van der Heijden
365	2011	Minimizing the Waiting Time for Emergency Surgery	J.T. van Essen, E.W. Hans, J.L. Hurink, A. Oversberg
364	2012	Vehicle Routing Problem with Stochastic Travel Times Including Soft Time Windows and Service Costs	Duygu Tas, Nico Dellaert, Tom van Woensel, Ton de Kok
363	2011	A New Approximate Evaluation Method for Two-Echelon Inventory Systems with Emergency Shipments	Erhun Özkan, Geert-Jan van Houtum, Yasemin Serin
362	2011	Approximating Multi-Objective Time-Dependent Optimization Problems	Said Dabia, El-Ghazali Talbi, Tom Van Woensel, Ton de Kok
361	2011	Branch and Cut and Price for the Time Dependent Vehicle Routing Problem with Time Windows	Said Dabia, Stefan Röpkke, Tom Van Woensel, Ton de Kok
360	2011	Analysis of an Assemble-to-Order System with Different Review Periods	A.G. Karaarslan, G.P. Kiesmüller, A.G. de Kok
359	2011	Interval Availability Analysis of a Two-Echelon, Multi-Item System	Ahmad Al Hanbali, Matthieu van der Heijden
358	2011	Carbon-Optimal and Carbon-Neutral Supply Chains	Felipe Caro, Charles J. Corbett, Tarkan Tan, Rob Zuidwijk
357	2011	Generic Planning and Control of Automated Material Handling Systems: Practical Requirements Versus Existing Theory	Sameh Haneyah, Henk Zijm, Marco Schutten, Peter Schuur
356	2011	Last time buy decisions for products sold under warranty	Matthieu van der Heijden, Bermawi Iskandar
355	2011	Spatial concentration and location dynamics in logistics: the case of a Dutch province	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
354	2011	Identification of Employment Concentration Areas	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
353	2011	BPMN 2.0 Execution Semantics Formalized as Graph Rewrite Rules: extended version	Pieter van Gorp, Remco Dijkman
352	2011	Resource pooling and cost allocation among independent service providers	Frank Karsten, Marco Slikker, Geert-Jan van Houtum
351	2011	A Framework for Business Innovation Directions	E. Lüftenegger, S. Angelov, P. Grefen
350	2011	The Road to a Business Process Architecture: An Overview of Approaches and their Use	Remco Dijkman, Irene Vanderfeesten, Hajo A. Reijers
349	2011	Effect of carbon emission regulations on transport mode selection under stochastic demand	K.M.R. Hoen, T. Tan, J.C. Fransoo, G.J. van Houtum

Nr.	Year	Title	Author(s)
348	2011	An improved MIP-based combinatorial approach for a multi-skill workforce scheduling problem	Murat Firat, Cor Hurkens
347	2011	An approximate approach for the joint problem of level of repair analysis and spare parts stocking	R.J.I. Basten, M.C. van der Heijden, J.M.J. Schutten
346	2011	Joint optimization of level of repair analysis and spare parts stocks	R.J.I. Basten, M.C. van der Heijden, J.M.J. Schutten
345	2011	Inventory control with manufacturing lead time flexibility	Ton G. de Kok
344	2011	Analysis of resource pooling games via a new extension of the Erlang loss function	Frank Karsten, Marco Slikker, Geert-Jan van Houtum
343	2011	Vehicle refueling with limited resources	Murat Firat, C.A.J. Hurkens, Gerhard J. Woeginger
342	2011	Optimal Inventory Policies with Non-stationary Supply Disruptions and Advance Supply Information	Bilge Atasoy, Refik Güllü, Tarkan Tan
341	2011	Redundancy Optimization for Critical Components in High-Availability Capital Goods	Kurtulus Baris Öner, Alan Scheller-Wolf, Geert-Jan van Houtum
340	2011	Making Decision Process Knowledge Explicit Using the Product Data Model	Razvan Petrusel, Irene Vanderfeesten, Cristina Claudia Dolean, Daniel Mican
339	2010	Analysis of a two-echelon inventory system with two supply modes	Joachim Arts, Gudrun Kiesmüller
338	2010	Analysis of the dial-a-ride problem of Hunsaker and Savelsbergh	Murat Firat, Gerhard J. Woeginger
335	2010	Attaining stability in multi-skill workforce scheduling	Murat Firat, Cor Hurkens
334	2010	Flexible Heuristics Miner (FHM)	A.J.M.M. Weijters, J.T.S. Ribeiro
333	2010	An exact approach for relating recovering surgical patient workload to the master surgical schedule	P.T. Vanberkel, R.J. Boucherie, E.W. Hans, J.L. Hurink, W.A.M. van Lent, W.H. van Harten
332	2010	Efficiency evaluation for pooling resources in health care	Peter T. Vanberkel, Richard J. Boucherie, Erwin W. Hans, Johann L. Hurink, Nelly Litvak
331	2010	The Effect of Workload Constraints in Mathematical Programming Models for Production Planning	M.M. Jansen, A.G. de Kok, I.J.B.F. Adan
330	2010	Using pipeline information in a multi-echelon spare parts inventory system	Christian Howard, Ingrid Reijnen, Johan Marklund, Tarkan Tan
329	2010	Reducing costs of repairable spare parts supply systems via dynamic scheduling	H.G.H. Tiemessen, G.J. van Houtum
328	2010	Identification of Employment Concentration and Specialization Areas: Theory and Application	Frank P. van den Heuvel, Peter W. de Langen, Karel H. van Donselaar, Jan C. Fransoo
327	2010	A combinatorial approach to multi-skill workforce scheduling	M. Firat, C. Hurkens
326	2010	Stability in multi-skill workforce scheduling	M. Firat, C. Hurkens, A. Laugier
325	2010	Maintenance spare parts planning and control: A framework for control and agenda for future research	M.A. Driessen, J.J. Arts, G.J. van Houtum, W.D. Rustenburg, B. Huisman
324	2010	Near-optimal heuristics to set base stock levels in a two-echelon distribution network	R.J.I. Basten, G.J. van Houtum
323	2010	Inventory reduction in spare part networks by selective throughput time reduction	M.C. van der Heijden, E.M. Alvarez, J.M.J. Schutten
322	2010	The selective use of emergency shipments for service-contract differentiation	E.M. Alvarez, M.C. van der Heijden, W.H.M. Zijm
321	2010	Heuristics for Multi-Item Two-Echelon Spare Parts Inventory Control Problem with Batch Ordering in the Central Warehouse	Engin Topan, Z. Pelin Bayindir, Tarkan Tan
320	2010	Preventing or escaping the suppression mechanism: intervention conditions	Bob Walrave, Kim E. van Oorschot, A. Georges L. Romme

Nr.	Year	Title	Author(s)
319	2010	Hospital admission planning to optimize major resources utilization under uncertainty	Nico Dellaert, Jilly Jeunet
318	2010	Minimal Protocol Adaptors for Interacting Services	R. Seguel, R. Eshuis, P. Grefen
317	2010	Teaching Retail Operations in Business and Engineering Schools	Tom Van Woensel, Marshall L. Fisher, Jan C. Fransoo
316	2010	Design for Availability: Creating Value for Manufacturers and Customers	Lydie P.M. Smets, Geert-Jan van Houtum, Fred Langerak
315	2010	Transforming Process Models: executable rewrite rules versus a formalized Java program	Pieter van Gorp, Rik Eshuis
314	2010	Working paper 314 is no longer available	----
313	2010	A Dynamic Programming Approach to Multi-Objective Time-Dependent Capacitated Single Vehicle Routing Problems with Time Windows	S. Dabia, T. van Woensel, A.G. de Kok
312	2010	Tales of a So(u)rcerer: Optimal Sourcing Decisions Under Alternative Capacitated Suppliers and General Cost Structures	Osman Alp, Tarkan Tan
311	2010	In-store replenishment procedures for perishable inventory in a retail environment with handling costs and storage constraints	R.A.C.M. Broekmeulen, C.H.M. Bakx
310	2010	The state of the art of innovation-driven business models in the financial services industry	E. Lüftenegger, S. Angelov, E. van der Linden, P. Grefen
309	2010	Design of Complex Architectures Using a Three Dimension Approach: the CrossWork Case	R. Seguel, P. Grefen, R. Eshuis
308	2010	Effect of carbon emission regulations on transport mode selection in supply chains	K.M.R. Hoen, T. Tan, J.C. Fransoo, G.J. van Houtum
307	2010	Interaction between intelligent agent strategies for real-time transportation planning	Martijn Mes, Matthieu van der Heijden, Peter Schuur
306	2010	Internal Slackening Scoring Methods	Marco Slikker, Peter Borm, René van den Brink
305	2010	Vehicle Routing with Traffic Congestion and Drivers' Driving and Working Rules	A.L. Kok, E.W. Hans, J.M.J. Schutten, W.H.M. Zijm
304	2010	Practical extensions to the level of repair analysis	R.J.I. Basten, M.C. van der Heijden, J.M.J. Schutten
303	2010	Ocean Container Transport: An Underestimated and Critical Link in Global Supply Chain Performance	Jan C. Fransoo, Chung-Yee Lee
302	2010	Capacity reservation and utilization for a manufacturer with uncertain capacity and demand	Y. Boulaksil; J.C. Fransoo; T. Tan
300	2009	Spare parts inventory pooling games	F.J.P. Karsten; M. Slikker; G.J. van Houtum
299	2009	Capacity flexibility allocation in an outsourced supply chain with reservation	Y. Boulaksil, M. Grunow, J.C. Fransoo
298	2010	An optimal approach for the joint problem of level of repair analysis and spare parts stocking	R.J.I. Basten, M.C. van der Heijden, J.M.J. Schutten
297	2009	Responding to the Lehman Wave: Sales Forecasting and Supply Management during the Credit Crisis	Robert Peels, Maximiliano Udenio, Jan C. Fransoo, Marcel Wolfs, Tom Hendrikx
296	2009	An exact approach for relating recovering surgical patient workload to the master surgical schedule	Peter T. Vanberkel, Richard J. Boucherie, Erwin W. Hans, Johann L. Hurink, Wineke A.M. van Lent, Wim H. van Harten
295	2009	An iterative method for the simultaneous optimization of repair decisions and spare parts stocks	R.J.I. Basten, M.C. van der Heijden, J.M.J. Schutten
294	2009	Fujaba hits the Wall(-e)	Pieter van Gorp, Ruben Jubeh, Bernhard Grusie, Anne Keller
293	2009	Implementation of a Healthcare Process in Four Different Workflow Systems	R.S. Mans, W.M.P. van der Aalst, N.C. Russell, P.J.M. Bakker



Nr.	Year	Title	Author(s)
292	2009	Business Process Model Repositories - Framework and Survey	Zhiqiang Yan, Remco Dijkman, Paul Grefen
291	2009	Efficient Optimization of the Dual-Index Policy Using Markov Chains	Joachim Arts, Marcel van Vuuren, Gudrun Kiesmuller
290	2009	Hierarchical Knowledge-Gradient for Sequential Sampling	Martijn R.K. Mes; Warren B. Powell; Peter I. Frazier
289	2009	Analyzing combined vehicle routing and break scheduling from a distributed decision making perspective	C.M. Meyer; A.L. Kok; H. Kopfer; J.M.J. Schutten
288	2010	Lead time anticipation in Supply Chain Operations Planning	Michiel Jansen; Ton G. de Kok; Jan C. Fransoo
287	2009	Inventory Models with Lateral Transshipments: A Review	Colin Paterson; Gudrun Kiesmuller; Ruud Teunter; Kevin Glazebrook
286	2009	Efficiency evaluation for pooling resources in health care	P.T. Vanberkel; R.J. Boucherie; E.W. Hans; J.L. Hurink; N. Litvak
285	2009	A Survey of Health Care Models that Encompass Multiple Departments	P.T. Vanberkel; R.J. Boucherie; E.W. Hans; J.L. Hurink; N. Litvak
284	2009	Supporting Process Control in Business Collaborations	S. Angelov; K. Vidyasankar; J. Vonk; P. Grefen
283	2009	Inventory Control with Partial Batch Ordering	O. Alp; W.T. Huh; T. Tan
282	2009	Translating Safe Petri Nets to Statecharts in a Structure-Preserving Way	R. Eshuis
281	2009	The link between product data model and process model	J.J.C.L. Vogelaar; H.A. Reijers
280	2009	Inventory planning for spare parts networks with delivery time requirements	I.C. Reijnen; T. Tan; G.J. van Houtum
279	2009	Co-Evolution of Demand and Supply under Competition	B. Vermeulen; A.G. de Kok
278	2010	Toward Meso-level Product-Market Network Indices for Strategic Product Selection and (Re)Design Guidelines over the Product Life-Cycle	B. Vermeulen, A.G. de Kok
277	2009	An Efficient Method to Construct Minimal Protocol Adaptors	R. Seguel, R. Eshuis, P. Grefen
276	2009	Coordinating Supply Chains: a Bilevel Programming Approach	Ton G. de Kok, Gabriella Muratore
275	2009	Inventory redistribution for fashion products under demand parameter update	G.P. Kiesmuller, S. Minner
274	2009	Comparing Markov chains: Combining aggregation and precedence relations applied to sets of states	A. Busic, I.M.H. Vliegen, A. Scheller-Wolf
273	2009	Separate tools or tool kits: an exploratory study of engineers' preferences	I.M.H. Vliegen, P.A.M. Kleingeld, G.J. van Houtum
272	2009	An Exact Solution Procedure for Multi-Item Two-Echelon Spare Parts Inventory Control Problem with Batch Ordering	
271	2009	Distributed Decision Making in Combined Vehicle Routing and Break Scheduling	C.M. Meyer, H. Kopfer, A.L. Kok, M. Schutten
270	2009	Dynamic Programming Algorithm for the Vehicle Routing Problem with Time Windows and EC Social Legislation	A.L. Kok, C.M. Meyer, H. Kopfer, J.M.J. Schutten
269	2009	Similarity of Business Process Models: Metrics and Evaluation	Remco Dijkman, Marlon Dumas, Boudewijn van Dongen, Reina Kaarik, Jan Mendling
267	2009	Vehicle routing under time-dependent travel times: the impact of congestion avoidance	A.L. Kok, E.W. Hans, J.M.J. Schutten
266	2009	Restricted dynamic programming: a flexible framework for solving realistic VRPs	J. Gromicho; J.J. van Hoorn; A.L. Kok; J.M.J. Schutten;

Nr.	Year	Title	Author(s)
-----	------	-------	-----------

Working Papers published before 2009 see: <http://beta.ieis.tue.nl>