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Abstract

So far the literature on inventory control for perishable products has mainly focused on (near-) optimal replenishment policies for a stylized environment, assuming no leadtime, no lot-sizing, stationary demand, a first in first out retrieval policy and/or product life time equal to two periods. This literature has given fundamental insight in the behavior and the complexity of inventory systems for perishable products. In practice, many grocery retailers have recently automated the inventory replenishment for non-perishable products. They recognize they may need a different replenishment logic for perishable products, which takes into account e.g. the age of the inventory in the system. Due to new information technologies like RFID, it now also becomes more economically feasible to register this type of information. This paper suggests a replenishment policy for perishable products which takes into account the age of inventories and which requires only very simple calculations. It will be shown that in an environment, which contains important features of the real-life retail environment, this new policy leads to substantial cost reductions compared with a base policy that does not take into account the age of inventories.

Keywords: Inventory, perishable, model, replenishment policy, simulation

1. Introduction

Worldwide sales at grocery retailers in 2006 easily exceeded $1,000 billion. Perishable products such as fresh produce, dairy and meat constitute more than a third of these sales [1]. Controlling the inventories of these perishable products is increasingly important. On the one hand, margins on non-perishable products are relatively small and decreasing. On the other hand, customers are asking for higher product variety in perishable product categories, leading to less predictable demand per product and to more outdating, and for new product categories with a short shelf life, such as fresh ready-to-eat meals.

Our paper originates from discussions with several European grocery retailers. Analyses of their data and interviews revealed the following characteristics of their perishable products: the products' remaining shelf life is short (1 to 30 days), demand within a week is non-stationary with high demand on Friday and Saturday, the customer can observe the expiration date of the items and is allowed to select the items, and inventory replenishment is done periodically and in small batches ([2], [3]). These retailers are using an Automated Store Ordering (ASO) system for the non-perishable products, which does not take into account detailed information about the age of the inventory. They wonder whether this type of ASO system can also be applied to the perishable products.

In addition, until recently, most of the literature on inventory replenishment policies for perishable products in a stochastic environment (see paragraph 2 for more details), has focused on policies which do not take into account detailed information about the age of the inventory. At the same time, new technology allows new ways of controlling the inventories. Technology like RFID will enable an efficient administration of both the quantity and the age of the inventory in the system. In this paper, we propose and evaluate a new inventory replenishment policy for perishable products, which takes into account this detailed information. We will do this for an environment that contains important features of the original problem setting, i.e., with stochastic demand, a weekly demand pattern, positive lead-times and with lot sizing. The literature mostly assumes a first in first out (FIFO) retrieval policy, while according to Silver et al. [4] and Cohen and Prastacos [5] customers typically prefer a last in first out (LIFO) retrieval in an environment where they can see the expiration date and where they are allowed to select the item. Therefore, we will evaluate the different replenishment policies for both the FIFO and the LIFO customer retrieval behavior.

2. Literature review

Excellent literature reviews on perishable inventory systems are done by Nahmias [6], Raafat [7] and Goyal and Giri [8]. Since 2001 most publications in this field deal with pricing and lot-sizing models (e.g. [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], and [23]) or with 2-echelon systems (e.g. [24], [25], [26], [27], [28], [29], [30], and [31]). The papers on pricing and lot-sizing models often assume a deterministic environment.

In this paper, we focus on a different environment: we study replenishment policies for a single echelon perishable inventory system with stochastic demand and a fixed lifetime. Although this type of system has been studied since Van Zyl [32], the number of publications since then is limited. Nahmias [33] and Fries [34] showed that for a perishable item with fixed lifetime equal to m periods, incurring outdating costs for units of inventory available in the system at the end of their lifetime, the optimal replenishment policy in general depends on a $(m-1)$-dimensional vector, which describes the age distribution of the inventory in the system. This makes the computation of optimal policies very complex for large values of m [6]. To deal with this complexity, authors typically have chosen either to simplify the system, e.g. by assuming $m=2$ periods (this case is discussed by [32], [35] and [36]) or to consider simple replenishment policies. The simplest and most studied policy is the critical number policy, in which a new order is generated if the inventory position in the system drops below a critical number. Several heuristics have been suggested for the determination of the critical number (see e.g. [37], [38], and [39]). All these papers assume the retrieval policy is first in first out (FIFO), the lead-time is zero, there is no lot sizing and the demand is stationary. Although the single critical number policy does not use any information about the age distribution of the inventory, [37], [38], and [39] have shown that this simple policy is close to optimal under the assumptions just mentioned.

In the replenishment policy we suggest in this paper, we take into account the full age distribution of the inventory. Earlier, Nahmias [40], Tekin [41] and Haijema et al. [42] have shown that the performance of the system can be improved by taking into account partial information about the age of the inventory in the system at the moment the replenishment decision is made. Nahmias [40] approximated the original problem with a heuristic that takes into account detailed age information about newer inventory and aggregated information about older inventory. Tekin [41] introduced a (Q, r, T)-policy, in which a replenishment order of size Q is placed either when the inventory drops to r, or when T units of time have elapsed since the last instance at which the inventory level hit Q, whichever occurs first. Haijema et al. [42] take into account age-information by using two critical numbers in their replenishment policy: one for the total inventory and one for the young inventory. They also distinguish two demand classes: demand for young items and demand for items of any age. Their replenishment policy is a double-level order-up-to rule with one level for young inventory and the other level for the total inventory. Our paper differs from these three papers in two ways. First, our replenishment policy takes into account all information about the age distribution and secondly, the assumptions on the retrieval policy and the inventory system are different. The paper of Nahmias [40] assumes FIFO-retrieval, no lot sizing and no week pattern. In his numerical experiments, Nahmias [40] only finds very small improvements compared to the approximate single critical number policy. The paper of Tekin [41] assumes FIFO-retrieval, no week pattern, continuous review and they assume that the aging of items in a replenishment batch only starts after all units of the previous replenishment batch are exhausted either by demand or through decay; in other words, aging of a replenishment batch starts when it is unpacked for consumption. The paper from Haijema et al. [42] deals with inventory control for blood platelets and therefore they assume that the supplier instead of the customer controls the retrieval of the inventory. They assume FIFO is applied to meet the demand for items of any age and a wider range of retrieval options (including both FIFO and LIFO) for the demand for young items. They assume there are no lot-sizing restrictions.

The literature on LIFO perishable inventory systems is very scarce. Cohen and Prastacos [5] deal with the effect of FIFO versus LIFO retrieval policies on both the system performance and ordering decisions. Their analysis is restricted to $m = 2$. They derive approximations for the critical number for LIFO systems and compare these with the values for FIFO systems. The critical numbers turned out to be rather insensitive to the type of retrieval policy although the optimal expected costs were significantly higher for LIFO. Nahmias [6] mentions that this result suggests that simple approximations for FIFO systems could also be used effectively in LIFO systems. Since Cohen and Prastacos [5] did not investigate replenishment policies other than critical number policies, our paper has added value in showing whether or not an age based replenishment policy leads to improved performance in a LIFO system.

3. Model assumptions and notation

To compare different replenishment policies, we used a discrete event simulation model of the retail process of perishable products at a single store. We used the following assumptions and notation:

- We study a single perishable product with fixed lifetime of m days; the lifetime is defined here as the remaining lifetime for goods when they arrive in the store (in general an agreement on the lifetime is made with the supplier who prints an expiration date on the item taking into account the lead-time from supplier to the store);
- Demand is probabilistic with a seasonal demand pattern week during the week. The weekly demand has mean μ and variance σ^2, with f_d the fraction of the week demand for weekday d. We modeled the demand for each weekday d with a Gamma distribution (cf. Burgin [43]), with mean $\mu_d = f_d \cdot \mu$ and variance $\sigma_d^2 = f_d \cdot \sigma^2$;
- The inventory is controlled with a periodic review system with review period $R = 1$ day, i.e., daily ordering;
- The inventory in the store at the start of day t consists of one or more batches. A batch is defined here as a set of items available in the store, which all have the same remaining shelf life (i.e. the same age). The amount of items available in the store at the start of day t having r days remaining shelf life is equal to B_{tr};
- Replenishment orders arrive with a fixed lead-time $L = 1$ day. We assume that the supplier has ample stock;
- Replenishment quantities are limited to multiples of an exogenous determined case pack size Q, i.e., predetermined lot sizes;
- Upon delivery of the replenishment order, all the items are placed on the shelf. We assume that the shelf has ample capacity;
- Customers retrieve items with positive remaining shelf life from the batches on the shelf, depending on their demand and preference regarding remaining shelf life, with W_{tr} the amount retrieved with remaining shelf life r at day t. Outdating O_t is the retrieval by store clerks of items with 1 day remaining shelf life at the end of day t, since these items can not be sold the next day;

- When the inventory on the shelf is insufficient to satisfy the demand, the excess demand is lost;
- In the replenishment policies we apply the same safety stock SS for each weekday;

The timing of events during a day in the model is: after opening the store, inventory decreases due to customers' demand, after closing the store outdated inventory is removed, remaining inventory is counted, and performance measures such as the service level are calculated, goods arrive and are stacked on the shelves, and finally the orders are placed.

4. Replenishment policies

The new replenishment policy, to be introduced in this paper, is called the EAR policy. It will be compared with a base policy. This base policy is essentially the same policy that is used by some grocery retailers to replenish non-perishable products. Moreover, if the lot size is equal to one and there is no week pattern, this base policy is equal to the single critical number policy, often studied in the literature on inventory systems for perishable products. Both the base policy and the EAR policy will be described in detail below.

Following the notation of Silver [4], the base policy is a (R, s, nQ) policy. In this policy, a replenishment order is created only when the inventory position at a periodic review moment is strictly below the dynamic reorder level s_t. In that case a number of case packs (n_t), each with size Q, is ordered which is necessary to bring the inventory position back to or just above the reorder level s_t. Note that the inventory position is the sum of the inventory on hand in the store and the inventory in transit. Further, the reorder level s_t is dynamic, since it has to deal with the weekly seasonality of demand. Following common practice as discussed in Silver [4], we set the reorder level as follows:

$$s_t = SS + \sum_{i=t+1}^{t+L+R} \hat{D}_i \tag{1}$$

with SS the safety stock and $\sum_{i=t+1}^{t+L+R} \hat{D}_i$ the expected demand during lead-time plus review period. Finally, the value of n_t is chosen such that the inventory position just after a replenishment decision is at or above s_t, but strictly less than $s_t + Q$. If we define IP_t^B as the inventory position at day t just before an order is placed, then n_t is determined as follows:

$$\text{if} \quad IP_t^B < s_t \quad \text{then} \quad n_t = \left\lceil \frac{s_t - IP_t^B}{Q} \right\rceil \tag{2}$$

In the EAR policy, the inventory position is first corrected for the estimated amount of outdating and an order is placed if this revised inventory position drops below the reorder level s_t.

$$IP_t^B - \sum_{i=t+1}^{t+L} O_i < s_t \tag{3}$$

The estimated amount of outdating is determined via recursive equations, using the age distribution of the inventory. To derive these equations, we first note that the amount of outdating, which is the retrieval by store clerks of products with one day remaining shelf life at the end of a day, depends on which items from which batches are chosen by the customers to satisfy their demand. Therefore, we will derive recursive equations for both FIFO and LIFO retrieval.

In the case of FIFO retrieval, we have the following recursive expressions at each day t. The retrieval is the maximum of the remaining batch size and the unsatisfied demand from older batches on the shelf, i.e., for $r = 1, \ldots, m$

$$W_{tr} = Max\left\{ B_{tr}, D_t - \sum_{i=1}^{r-1} W_{ti} \right\} \tag{4}$$

In the case of LIFO retrieval, the amount of retrieval from a batch on day t is the maximum of the remaining batch size and the unsatisfied demand from fresher batches on the shelf, i.e., for $r = m, m-1, \ldots, 1$

$$W_{tr} = Max\left\{ B_{tr}, D_t - \sum_{i=r+1}^{m-L} W_{ti} \right\} \tag{5}$$

At the end of each day, an inventory replenishment decision is made which determines $B_{t+L+R,m}$. After each day, the batches are updated to account for aging, retrieval and outdating, i.e., for $r = 2, \ldots, m$

$$B_{t+1,r-1} = B_{tr} - W_{tr} \tag{6}$$

And for the batch with 1 day remaining shelf life

$$O_t = B_{t,1} - W_{t,1} \tag{7}$$

The recursive equations above are the basis for calculating the estimated outdating quantities, which are needed in the EAR policy, as shown in formula (3). We estimate these outdating quantities by calculating for consecutive periods i (ranging from $i = t+1$ to $i = t+L$) the retrieval, the remaining batches and the outdating in period i using (4)-(7) under the assumption that in period i demand is equal to the expected demand. This implies the following procedure, starting with $i = t+1$:

1. Determine the estimated retrieval in period i using (4) or (5) and by assuming demand in period i was equal to the expected demand.
2. Determine the estimated remaining batches available for the next period and the estimated outdating in period i using (6) and (7) and by assuming the retrieval in period i is equal to the estimated retrieval as determined in Step 1.
3. While $i < t+L$ do $i := i+1$ and continue with Step 1, otherwise stop.

5. Simulation experiments

In order to compare the performance of the replenishment policies, we measured the long-term average costs. The costs incurred during a period t are given by:

$$C_t = C_Q \cdot Q_t + C_Z \cdot Z_t + C_K \cdot K_t + C_H \cdot H_t \tag{13}$$

with Q_t the amount of units ordered, Z_t the amount of units outdated, K_t the lost sales in units and H_t the average inventory in period t.

We did a factorial experiment in which we tested several levels for each of the eight input parameters. The experimental setup is given in Table 1. The parameters for the product lifetime, average demand, coefficient of variation and lot-sizes are based on parameters reported in [41], [38], and [2]. The purchasing costs and outdating costs are similar to the values used by Nandakumar [38]. To determine the lost sales costs we used the result that for the classical newsboy problem (a 1-period problem for a perishable item) the service level should be equal to the underage cost divided by the sum of the overage cost and the underage cost. In our case, the underage costs are equal to the lost sales costs, while the overage costs are equal to the purchasing plus the outdating costs. We used this result to find lost sales cost parameters which are likely to lead to relatively low lost sales fractions, in line with the design of experiments of

Tekin [41]. Thus, in our experiments we use the lost sales costs C_K which follow from solving the equation $CR_K = C_K / (C_K + C_Z + C_Q)$, in which the lost sales cost ratio CR_K is set equal to one minus the lost sales fractions used by Tekin [41]. The values for the remaining input parameters were as follows: week length of 7 days with week pattern $\{f_d\} = \{0.12, 0.13, 0.13, 0.16, 0.18, 0.18, 0.10\}$ (taken from [4]), review period $R = 1$ day, and lead-time $L = 1$ day.

Following Law and Kelton [44], the reported values for the simulation are the averages from at least 10 replications. In each replication, the first 50 weeks were the warming-up periods and statistics are recorded for the last 1000 weeks. We replicated until a 95 % confidence interval was reached for the customer service level $P_2 \pm 0.002$. P_2 is the percentage of demand delivered from stock, also known as the fill rate.

We ran each of the 69120 simulation experiments for the following four scenarios:

I. Base (R, s, nQ) policy with FIFO retrieval;
II. EAR policy with FIFO retrieval;
III. Base (R, s, nQ) policy with LIFO retrieval;
IV. EAR policy with FIFO retrieval.

In all four scenario's we determined for each parameter setting the optimal safety stock level SS, which minimized the average simulated costs.

Insert Table 1 here.

6. Results and Discussion

The performance on average cost of the optimal EAR policy, *C(EAR)*, compared to the average cost of the optimal base policy, *C(Base)*, is measured by

$$\Delta_C = 100 \frac{C(Base) - C(EAR)}{C(Base)}$$

The performance of the EAR policy will be described separately for the inventory system with FIFO retrieval and the system with LIFO retrieval.

FIFO retrieval

Insert Table 2 here.

Table 2 shows the relative performance of the EAR policy under FIFO retrieval. It gives the minimum, the average and the maximum average cost reduction of the optimal EAR policy compared to the base policy for a subset of all 69120 experiments, in which one input parameter was kept constant at a certain level.

With FIFO retrieval the EAR policy outperforms the base policy in 96% of the experiments. The EAR policy leads on average to 4.0% lower costs, with a minimum of -1.4% and a maximum of 20.7%. The EAR policy gives the largest improvements for short product lifetimes ($m \leq 5$), high coefficients of variation and high outdating costs. As expected the improvement from the EAR policy, which has been designed to prevent unnecessary outdating, is relatively high for small product lifetimes or high outdating costs, since in these cases the prevention of outdating is relatively important (either because there is a lot of outdating or outdating is expensive). The EAR policy performs relatively well for situations with high coefficients of variation due to the fact that if demand is relatively uncertain, some periods will have no or very low demand. After these periods the system has high inventory levels of old items. The base policy does not take this information on the age distribution into account, while the EAR policy recognizes this and adjusts the replenishment decision accordingly.

LIFO retrieval

Insert Table 3 here.

In Table 3, the relative performance of the EAR policy is shown under LIFO retrieval. With LIFO retrieval the EAR policy outperforms the base policy in more than 99% of the experiments. We see substantial larger benefits under LIFO compared to FIFO. The average cost reduction over all 69120 experiments is 16.6% under LIFO compared to 4.0% under FIFO. For products with a short lifetime the difference is even larger; for $m = 2$ the average cost reduction due to the

EAR policy is 31.0% under LIFO compared with 7.0% under FIFO. Under LIFO the largest improvements (up to 60%) are for products with a short product lifetime, a low coefficient of variation and a high lost sales cost ratio. The EAR policy performs well when the lost sales cost ratio is high, since then the amount of safety stock is high and as a result the amount of outdating is large. On the other hand, if the demand is relatively uncertain in a system with LIFO retrieval, the EAR policy may occasionally become a victim of its own prophecy: if the EAR policy estimates that part of the old inventory will be outdated, it will order additional inventory. If then demand in the periods until arrival of the new inventory is less than or equal to the estimated demand and if demand in the next periods after arrival of the new inventory turns out to be higher than estimated, this latter demand will first be satisfied (due to the LIFO retrieval) from the new inventory and as a result more old inventory will be outdated then would have been the case if no additional inventory was ordered.

Apart from costs, we also considered the effects of different systems and policies on the average inventory and the freshness of products offered to consumers. Under both FIFO and LIFO retrieval, the average inventory increases when using the EAR policy compared to the base policy (with 1.9% for FIFO and 9.6% for LIFO). For perishable products, outdating is much more important than inventory holding cost, but the improvements of the EAR policy over the base policy decrease slightly with increasing holding cost.

The effect of using the EAR policy compared to the base policy on the freshness for the customers is relatively small (on average 2% fresher products under FIFO and on average 0.0% under LIFO). The EAR policy orders on average earlier than the base policy, but still keeps the products on the shelf until they are outdated. Under LIFO retrieval, the customer gets products that are on average 30% fresher than under FIFO retrieval regardless of the policy used. This results for the retailer using the EAR policy in a cost increase of on average 23%. This is down from an average cost increase of 33% under the base policy.

7. Managerial insights and future research

One main insight from this research is that taking into account the age distribution in the replenishment decision for perishable items often gives a large cost reduction. In order to implement such a policy, a more detailed registration is needed. This can be achieved by modern information technology (using RFID and/or bar coding) or visual inspection. The cost difference between the EAR policy and the base policy can be used by management as an indication for the budget for the implementation of this additional registration.

On the other hand, it turned out that under FIFO retrieval the cost benefit of the EAR policy is substantially smaller. This indicates that if the costs for the registration of full age information are high, managers may opt for an alternative scenario to prevent high costs in an environment in which customers are inclined to use LIFO retrieval: they may try to change the retrieval behavior in the direction of FIFO. This can be achieved by giving price discounts to customers for products with low remaining lifetime or by keeping only items of one age on the shelves and the remainder of the inventory in the backroom. The latter solution requires a considerable amount of labor, since it requires continuous monitoring of all perishable items in order to prevent out-of-stock situations and frequent replenishment from the backroom to the shelves. The cost difference between the replenishment policies under FIFO and LIFO can serve as a budget for the price discounts or the additional labor costs.

An advantage of the EAR policy is its simplicity: to determine the estimated outdating quantities, only very simple calculations are needed. Also it is relatively easy to explain the logic behind the EAR policy to people in the stores who are responsible for managing the inventory of perishable products. Moreover, only one parameter (the safety stock) needs to be optimized per product. This makes the parameter setting relatively easy, especially when the parameters are set manually by local inventory managers.

Retailers who want to make their ASO system for non-perishable items applicable to perishable items will have to take into account that not only additional information on the age of the inventory is needed. Due to the outdating costs for perishable items, the retailer may aim for a lower service level for perishables compared to non-perishables, resulting in a larger percentage of demand that is not registered due to out-of-stock situations. As a result, the demand forecasting may become more difficult. See Tan and Karabati [45] for a further discussion on the resulting complications and ways to counter those. For low service levels, the impact of the lost sales in the perishable inventory system may become more and more prominent and an adaptation of the EAR policy may be needed, in which the inventory position is not only corrected for estimated outdating, but also for estimated retrieval quantities. This is an area for future research.

Other areas for future research are the impact on the performance of the EAR policy when the leadtimes are increased (e.g. due to the implementation of cross docking at the retailers' DC), the amplitude of the weekly demand pattern are increased or decreased or when the delivery frequency is changed.

8. Conclusions

With the advent of RFID technology, the EAR policy becomes a practical solution for a retailer that manages a large assortment of perishable products. Currently, the store managers have to spend considerably amounts of time to manually decide on order quantities or to correct the order advice from an automated store ordering system for this product segment. Using the complete age vector of the inventory, the EAR policy can lead to substantial cost reductions for a retailer selling perishable products. The cost reductions are especially large (up to 60%) for products with a short lifetime, when customer retrieval is Last In First Out, the coefficient of variation of demand is low and when the retailer aims for a high product availability.

References

[1] ACNielsen, What's hot around the globe, insights on growth in food & beverages, Executive News report, http://www2.acnielsen.com/reports/documents/2006WhatsHotFoodBev.pdf, 2006.

[2] Donselaar K van, Woensel T van, Broekmeulen R, Fransoo J. Inventory control of perishables in supermarkets. International Journal of Production Economics 2006;104:462-472.

[3] Kahn BE, Schmittlein DC. Shopping trip behavior: an empirical investigation. Marketing Letters 1989;1(1):55-69.

[4] Silver EA, Pyke DF, Peterson R. Inventory Management and Production Planning and Scheduling (third ed.). Chichester: Wiley, 1998.

[5] Cohen, MA, Prastacos, GP. Critical number ordering policy for LIFO perishable inventory systems. Computers & Operations Research 1981:8(3):185-195.

[6] Nahmias S. Perishable inventory theory: a review. Operations Research 1982;30:680-708.

[7] Raafat F. Survey of literature on continuously deteriorating inventory models. Journal of the Operational Research Society 1991;42:27-37.

[8] Goyal SK, Giri BC. Recent trends in modeling of deteriorating inventory. European Journal of Operational Research 2001;134:1-16.

[9] Ferguson M, Jayaraman V, Souza GC. Note: An application of the EOQ model with nonlinear holding cost to inventory management of perishables. European Journal of Operational Research 2007;180(1):485-490.

[10] Li J, Cheng TC, Wang S. Analysis of postponement strategy for perishable items by EOQ-based models. International Journal of Production Economics 2007;107(1):31-38.

[11] Dye CY. Joint pricing and ordering policy for a deteriorating inventory with partial backlogging. Omega 2007;35(2):184-189.

[12] Teng JT, Ouyang LY, Chen LH. A comparison between two pricing and lot-sizing models with partial backlogging and deteriorated items. International Journal of Production Economics 2007;105(1):190-203.

[13] Ouyang LY, Wu KS, Yang CT. A study on an inventory model for non- instantaneous deteriorating items with permissible delay in payments. Computers & Industrial Engineering 2006;51(4):637-651.

[14] Chang CT, Goyal SK, Teng JT. On "An EOQ model for perishable items under stock-dependent selling rate and time-dependent partial backlogging" by Dye and Ouyang. European Journal of Operational Research 2006;174(2):923-929.

[15] Perakis G, Sood A. Competitive Multi-period Pricing for Perishable Products: A Robust Optimization Approach. Mathematical Programming 2006;107(1-2):295-335.

[16] Feng Y, Xiao B. Integration of pricing and capacity allocation for perishable products. European Journal of Operational Research 2006;168(1):17-34.

[17] Li MZF. A model of pricing perishable inventories using two restrictions, with an application to airline pricing. Journal of Revenue and Pricing Management 2006;4(4):329-343.

[18] Shah BJ, Shah NH, Shah YK. EOQ model for time-dependent deterioration rate with a temporary price discount. Pacific Journal of Operational Research. 2005;22(4):479-485.
[19] Chande A, Dhekane S, Hemachandra N, Rangaraj N, Perishable inventory management and dynamic pricing using RFID technology, Sadhana 2005;30, Parts 2 & 3, 445–462.
[20] Anjos MF, Cheng RCH, Currie CSM. Optimal pricing policies for perishable products. European Journal of Operational Research 2005;166(1):246-254.
[21] Williams CL, Patuwo BE. Analysis of the effect of various unit costs on the optimal incoming quantity in a perishable inventory model. European Journal of Operational Research 2004;156(1):140-147
[22] Elmaghraby W, Keskinocak P. Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. Management Science 2003;49(10):1287-1309.
[23] Chu P, Chung KJ, Lan SP. Economic order quantity of deteriorating items under permissible delay in payments. Computers & Operations Research 1998;25(10):817-824.
[24] Wee HM, Jong JF, Jiang JC. A note on a single-vendor and multiple-buyers production-inventory policy for a deteriorating item. European Journal of Operational Research 2007;180(3):1130-1134.
[25] Zanoni S, Zavanella L. Single-vendor single-buyer with integrated transport-inventory system: Models and heuristics in the case of perishable goods. Computers & Industrial Engineering 2007;52(1):107-123.
[26] Ketzenberg ME, Ferguson M. Managing Slow Moving Perishables in the Grocery Industry. Working paper Georgia Institute of Technology, Atlanta, USA 2007:1-28.
[27] Ferguson M, Ketzenberg ME. Information Sharing to Improve Retail Product Freshness of Perishables. Production and Operations Management 2006;15(1):57-73.
[28] Kanchanasuntorn K, Techanitisawad A. An approximate periodic model for fixed-life perishable products in a two-echelon inventory-distribution system. International Journal of Production Economics 2006;100(1):101-115.
[29] Huq F, Asnani S, Jones V, Cutright K. Modeling the influence of multiple expiration dates on revenue generation in the supply chain. International Journal of Physical Distribution & Logistics Management 2005;35(3/4):152-160.
[30] Sarker BR, Jamal AMM, Wang S. Supply chain models for perishable products under inflation and permissible delay in payment. Computers & Operations Research 2000;27(1):59-75.
[31] Abdel-Malek, Layek L, Ziegler H. Age Dependent Perishability in Two-Echelon Serial Inventory Systems. Computers & Operations Research 1988;15(3):227-238.
[32] Van Zyl G. Inventory control for perishable commodities. Unpublished PhD dissertation, University of North-Carolina, Chapel Hill, NC, 1964.
[33] Nahmias S. Optimal ordering policies for perishable inventory – II. Operations Research 1975;23(4):735-749.
[34] Fries BE. Optimal ordering policy for a perishable commodity with fixed lifetime. Operations Research 1975;23(1):46-61.
[35] Nahmias S, Pierskalla WP. Optimal ordering policies for a product that perishes in two periods subject to stochastic demand. Naval Research Logistics Quarterly 1973;20:207-229.
[36] Cohen MA. Analysis of single critical number ordering policies for perishable inventories. Operations Research 1976;24(4):726-741.

[37] Nahmias S. Myopic approximations for the perishable inventory problem. Management Science 1976;22(9):1002-1008.
[38] Nandakumar P, Morton TE. Near myopic heuristics for the fixed-life perishability problem. Management Science 1993;39(12): 1490-1498.
[39] Cooper WL. Path-wise properties and performance bounds for a perishable inventory system. Operations Research 2001;49(3):455-466.
[40] Nahmias S. Higher order approximations for the perishable inventory problem. Operations Research 1977;25(4):630-640.
[41] Tekin E, Gürler Ü, Berk E. Age-based vs. stock level control policies for a perishable inventory system. European Journal of Operational Research 2001;134:309-329.
[42] Haijema R, Wal J van der, Dijk NM van. Blood platelet production: Optimization by dynamic programming and simulation. Computers & Operations Research 2007; 34(3):760-779.
[43] Burgin TA. The Gamma distribution and inventory control. Operational Research Quarterly 1975;26: 507.
[44] Law AM, Kelton WD. Simulation modeling and analysis (third ed.). Boston: McGraw-Hill, 2000.
[45] Tan B, Karabati S. Can the desired service level be achieved when the demand and lost sales are unobserved? IIE Transactions 2004;36(4):345-358.

Table 1: Input parameters for the simulation experiment.

Input parameter	Levels
Product lifetime m	$\{2, 3, 4, 5, 10, 15\}$
Mean week demand μ	$\{14, 21, 28, 35\}$
Coefficient of variation $CV = \sigma/\mu$	$\{0.25, 0.50, 1.0\}$
Case pack size Q	$\{1, 2, 4, 6\}$
Lost sales cost ratio CR_K	$\{0.90, 0.95, 0.98, 0.99, 0.995\}$
Outdating cost C_Z	$\{0, 2, 5, 10, 15, 20\}$
Purchasing cost C_Q	$\{1, 2, 5, 10\}$
Holding cost C_H	$\{0, 1\}$

Table 2: Cost comparison of the base and the EAR policy under FIFO retrieval.

Parameter	Level	Min	Avg	Max
Product lifetime	2	-0,23	6,97	20,70
	3	0,48	5,91	17,09
	4	0,16	4,90	16,93
	5	-0,63	4,27	14,18
	10	-1,39	1,25	4,39
	15	-0,57	0,66	2,67
Mean week demand	14	-1,38	4,16	20,70
	21	-1,39	4,00	17,97
	28	-0,25	4,00	15,45
	35	-0,32	3,81	14,69
Coefficient of variation	0,25	-1,39	2,81	20,70
	0,5	-1,38	4,11	12,65
	1	0,43	5,06	9,35
Case pack size	1	-0,27	3,67	9,35
	2	-0,42	3,77	11,51
	4	-0,57	4,15	20,70
	6	-1,39	4,39	17,97
Purchasing cost	1	-1,39	4,31	20,70
	2	-1,30	4,14	20,23
	5	-1,14	3,87	19,14
	10	-0,99	3,66	17,96
Outdating cost	0	-0,60	3,12	14,45
	2	-0,99	3,64	18,36
	5	-1,18	3,98	19,61
	10	-1,30	4,26	20,29
	15	-1,35	4,43	20,56
	20	-1,39	4,53	20,70
Lost sales cost ratio	0,90	-0,11	3,24	16,23
	0,95	-0,63	3,75	15,45
	0,98	-0,06	4,16	14,78
	0,99	-0,42	4,26	17,09
	0,995	-1,39	4,57	20,70
Holding cost	0	-1,39	4,05	20,65
	1	-1,24	3,94	20,70

Table 3: Cost comparison of the base and the EAR policy under LIFO retrieval.

Parameter	Level	Min	Avg	Max
Product lifetime	2	5,82	30,95	60,45
	3	4,07	22,79	48,30
	4	4,06	17,96	43,83
	5	3,34	14,77	37,45
	10	-0,83	7,30	31,06
	15	0,42	5,95	23,66
Mean week demand	14	0,68	16,56	59,60
	21	0,14	16,59	60,31
	28	0,48	16,88	59,83
	35	-0,83	16,44	60,45
Coefficient of variation	0,25	0,42	19,84	60,45
	0,5	0,71	17,24	54,18
	1	-0,83	12,78	39,83
Case pack size	1	-0,36	16,70	60,31
	2	-0,56	16,66	59,86
	4	-0,83	16,65	59,70
	6	-0,27	16,46	60,45
Purchasing cost	1	-0,83	17,71	60,45
	2	-0,82	17,14	59,94
	5	-0,80	16,18	58,69
	10	-0,76	15,45	57,22
Outdating cost	0	-0,64	13,57	50,87
	2	-0,76	15,45	57,22
	5	-0,80	16,62	59,06
	10	-0,82	17,57	59,94
	15	-0,83	18,08	60,27
	20	-0,83	18,42	60,45
Lost sales cost ratio	0,90	0,42	8,05	29,52
	0,95	1,20	12,00	34,28
	0,98	1,20	17,05	45,41
	0,99	1,35	21,04	53,15
	0,995	-0,83	24,95	60,45
Holding cost	0	-0,83	16,71	60,45
	1	-0,70	16,52	60,40