The Value of RFID Technology Enabled Information to Manage Perishables

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The value of RFID technology enabled information to manage perishables

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Abstract

We address the value of RFID technology enabled information to manage perishables in the context of a supplier that sells a random lifetime product subject to stochastic demand and lost sales. The product's lifetime is largely determined by the time and temperature history in the supply chain. We compare two information cases to a Base case in which the product's time and temperature history is unknown and therefore its shelf life is uncertain. In the first information case, the time and temperature history is known and therefore the remaining shelf life is also known at the time of receipt. The second information case builds on the first case such that the supplier now has visibility up the supply chain to know the remaining shelf life of inventory available for replenishment. We formulate these three different cases as Markov decision processes, introduce well performing heuristics of more practical relevance, and evaluate the value of information through an extensive simulation using representative, real world supply chain parameters.

Keywords: perishable inventory, value of information, RFID, simulation.

1 Introduction

We place our research in the context of the grocery industry. There appears to be both little doubt and little disagreement that efficient and effective management of perishables continues to be a priority in the grocery industry *and* that this area of management is ripe for improvement. Enter a simple search on the Internet or glance through a recent trade publication like *Supermarket News* or *Progressive Grocer* for quick and easy confirmation. Perishables not only represent a significant portion of supermarket sales, but serve as means for suppliers to distinguish themselves from competitors. Perhaps most importantly, the quality, variety, and availability of perishables have become the principal order winning criteria for consumers (Axtman, 2006; Tortola, 2005). Suppliers have responded by dramatically increasing the quantity and quality of their product offering in fresh items.

From an operational perspective, the growth in perishables creates additional challenges for suppliers. Waste and spoilage are rampant and on the rise (Boyer, 2006; Tortola, 2005). Spoilage is a significant component of total store shrink, with estimates indicating that shrink costs an average supermarket approximately $450,000 per year. While perishable departments account for only 30% of total store sales, they contribute 56% to total store shrink (The National Supermarket Research Group, 2003). These figures, however, do not address spoilage throughout the supply chain, with some estimates indicating that as much as 10% of all perishable goods (fresh produce and other food products) spoil in the supply chain (Roberti, 2005).

Clearly, the problem for suppliers is how to maintain product availability without spoilage. Adding to the problem is that a large majority of the fresh items, and therefore the most perishable items, have random lifetimes. These random lifetimes are largely the result of variability in the time it takes for the product to flow through the supply chain, as well as, the product's temperature history (along with other environmental factors like humidity, handling, and lighting). Since these factors are generally unknown and highly variable, there is considerable uncertainty with regard to the timing of product expiration. In turn, effective inventory management is challenging.

Recently, however, new technologies including RFID chips and data loggers, have been introduced to the marketplace that promise the ability to track the time and temperature history (TTH) of inventory as it moves through the supply chain so that a variety of benefits may be obtained. These include:

- accurate shelf life prediction,
- improved issuing policies from warehouses based on a first to expire first out (FEFO) policy, rather than a first in first out (FIFO) policy,
- improved stock rotation based on current quality of the product rather than sell by dates,
- identification of food safety issues and their correction,
- dynamic allocation of products based on shelf life so that soon to expire product is distributed locally while longer shelf life products can be distributed to more distant locations,
- lower supply uncertainty should enable improved replenishment decisions leading to higher profit.

Even so, the technology and its capability remains a largely untested promise since there has been limited diffusion of the technology. Indeed, there remains a lack of understanding among both academics and practitioners regarding the value of RFID technology to manage perishables or for that matter non-perishables as well. Several publications discuss the potential benefits of RFID (e.g., Gaukler and Siefert, 2007) for logistics, transportation, and warehousing through increased supply chain visibility. Increased visibility will enable increased efficiency, lower safety stocks, and provide the same or better service. Yet, there is little discussion on specifically how these benefits can be achieved nor are the benefits quantified. As Lee and Ozer (2007) state:

> *Most such claims are educated guesses at best and are not substantiated... there is a huge credibility gap of the value of* RFID, *and that a void exists in showing how the proclaimed values are arrived at, and how those values can be realized.*

We address the value of RFID technology enabled information (VOI) to manage perishables in the context of a supplier that sells a random lifetime product subject to stochastic demand and lost sales. We compare two information cases to a Base case in which the product's TTH is unknown. In the first information case (RFID case) the TTH is known and therefore the remaining shelf life is also known at the time of receipt. The second information case (Visibility case) builds on the RFID case such that the supplier has visibility up the supply chain to know the remaining shelf life of inventory available for replenishment.

We formulate these three different cases as Markov decision processes (MDPs), introduce well performing heuristics of more practical relevance, and evaluate the VOI through an extensive simulation using representative, real world supply chain parameters. The VOI is measured as the percentage reduction in average cost per period obtained with information, relative to the Base case. Results indicate that the VOI enabled through the RFID case is generally modest with an average of 4.0% across experiments, but runs as high as 14.3%. For the Visibility case, the VOI (relative to the RFID case) is considerably smaller with an average of 0.7% and a maximum of 5.5%. Hence a supplier can generate significant value from RFID without supply chain visibility and therefore without the additional investment needed for information sharing technology.

The rest of the paper is organized as follows. In Section 2 we position our research with respect to the literature and in Section 3 we define the model and formulate the respective cases as MDPs. Then, in section 4 we introduce and test heuristic policies since the MDPs are not practical and in Section 5 we report the results of an extensive simulation study. Finally, we conclude our study in Section 6 and discuss future research directions.

2 Literature review

Our research intersects several streams of literature that includes value of information, perishable inventory, cold chain management, food safety, temperature monitoring, RFID, and shelf life prediction. These streams cut across a wide array of disciplines that include agribusiness, computing technology, industrial engineering, technology management, food science, microbiology, and horticulture. From this perspective, our study represents a multidisciplinary contribution to the literature that uniquely ties together multiple fields of research. Broadly, however, we can classify the related literature into three streams: (1) perishable inventory management, (2) time and temperature monitoring, and (3) value of information. Below we provide an overview of each stream using representative examples from the literature and position our research with respect to them.

2.1 Perishable Inventory Management

A major distinction in the literature on perishable inventory systems is whether the product has a fixed or random lifetime. Much of the early work focuses on fixed lifetime problems under periodic review with seminal work by Nahmias (1975) and Fries (1975) who were the first to derive and evaluate optimal policies for perishable products with lifetimes greater than two periods. The often referenced literature review by Nahmias (1982) provides an excellent overview of this early work.

A preponderance of the work since then has shifted to the analysis of random lifetime models under the assumption of continuous review and continuous decay, the majority of which assume that the decay is exponential. Raafat (1991) provides a review of the seminal and early work in this area and it was later followed up by Goyal and Giri (2001). It is interesting to note that of the 372 contributions referenced by the three literature reviews, plus those published since then, we are aware of only one (Nahmias, 1977) that addresses a perishable product with random lifetime that is subject to random demand and managed under periodic review. These are the key assumptions of our model that make the research both novel and relevant to practice.

Moreover, since we address the VOI for a random lifetime product under periodic review in which information essentially makes the lifetime deterministic, our research intersects the two areas of fixed and random lifetimes. However, because we assume a periodic, discrete time model, the stochastic dynamic programming formulations of the fixed lifetime research are much more closely related. Indeed, Nahmias (1977) which is the most closely related study to our own is a direct extension of Nahmias (1975) which introduces the fixed lifetime case. He analyzes the problem of a random lifetime product with stochastic demand, no fixed order cost, backlogged demand, and where orders outdate in the same sequence that they enter stock. That is, an order in a later period will not expire prior to an order placed in an earlier period. Because of this latter assumption, FIFO issuing is optimal and he is able to prove certain properties, most notably convexity of the cost minimizing objective function with respect to the order quantity. Our analysis here differs considerably in that unsatisfied demand is lost, product may arrive already expired, and orders may not outdate in sequence. Since outdating may be out of sequence, information on the TTH through RFID enables FEFO issuing.

2.2 Time and Temperature Monitoring

Nunes et al. (2006) report that temperature is the characteristic of the distribution environment that has the greatest impact on the storage life and safety of fresh perishables. Effective temperature management is in fact the most important procedure for delaying product deterioration. The relation between shelf life (or Time before Expiration) and temperature is studied extensively, e.g. by Doyle (1995) and Taoukis et al. (1999).

There are a host of articles on temperature stability for perishable goods in cold chains that examine product deterioration in various chains and then optimize preservation activities using input/output analysis. See for example Bogataj et al. (2005) who explore the tradeoff between preservation cost and the reduction in product deterioration, as well as the impact of potential time delays. They analyze an n stage perishable supply chain and the state of the system is described by a set of first-order linear differential-delay equations.

One would think that temperature is one factor that can be easily and promptly controlled in the supply chain through refrigerated trucks and containers. Yet, a glance at the literature shows that even in temperature controlled environments, perishables are subject to time-temperature variability and that this has a direct impact on product shelf life. Rodriguez-Bermejo et al. (2007) and Moureh and Flick (2004) provide empirical measures of temperature variability for a set of containers. These studies show that there are significant temperature and air flow variance within a truck or container that affect the remaining shelf life of products such that even different units within the same transport vehicle will have different remaining shelf lives. As Koutsoumanis et al. (2005) state:

> *Since in practice significant deviations from specified conditions often*

occur, temperature monitoring and recording is a prerequisite for chain control and any logistics management system that aims on product quality optimization at the consumer's end.

There has been significant research in the use of time-temperature monitoring to predict shelf life of perishables. One very common approach is to describe the quality decay according to the law of Arrhenius for reaction kinetics. Taoukis et al. (1999) demonstrates the accuracy and reliability of a predictive model of shelf life for fish through time-temperature monitoring. Although the research stream that develops predictive models for shelf life does not address how the information should be used for inventory management. This latter research generally falls within the stream on the VOI.

2.3 Value of information

There are a few fairly recent contributions that provide literature reviews and taxonomies on the VOI. Sahin and Robinson (2002) and Huang et al. (2003) are representative examples and each provides a very broad overview of the literature and uses its own classification scheme. Ketzenberg et al. (2007), in addition to providing an extensive literature review, develops and tests a framework using the collective studies on the VOI in the literature. These literature reviews indicate that a preponderance of research in this area focuses on the value of demand information to improve supply chain performance. Bourland et al. (1996), Gavirneni et al. (1999), and Moinzadeh (2002) are representative examples.

There are a few papers that explore the value of supply information. Some of these consider cases where information such as available supplier capacity and lead-time is shared forward in the supply chain so that customers can reduce supply uncertainty, e.g. Van der Duyn Schouten et al. (1994). Another form of supply uncertainty arises in closed loop supply chains, where there may be uncertainty with regard to the quantity, quality, and timing of product returns. Ferrer and Ketzenberg (2004) evaluate the value of yield information in the context of remanufacturing. Ketzenberg et al. (2006) later extends the literature by examining the value of information to explain different sources of uncertainty that include demand, returns, as well as remanufacturing yield. They observe that no one type of information dominates in terms of value and that it can be quite substantial, even with imperfect information.

Product perishability represents another source of supply uncertainty. We are aware of only a few studies that address the VOI for a perishable product and most of these are studies that compare the performance of different issuing policies which are enabled by knowing a product's TTH and include Dada and Thiesse (2008), Koutsoumanis et al. (2005), and Taoukis et al. (1999). These contributions do not formulate the optimal replenishment policies nor introduce well performing heuristic policies of more practical relevance.

Ketzenberg and Ferguson (2008) is a more closely related study that evaluates the VOI in the context of a serial supply chain that supplies a product with a fixed lifetime and examines the case in which a retailer shares its demand and inventory information with a supplier and another case in which full information at both echelons is known to a centralized decision maker. Unlike the majority of contributions where the VOI and value of centralized control are often small in the context of non-perishable serial supply chains, they show significantly larger benefits due to the ability of the supplier to provide a fresher product.

In an earlier study, Ferguson and Ketzenberg (2006) examine the VOI for a retailer that sells a perishable product with a fixed lifetime, although the remaining lifetime may vary from replenishment to replenishment. On receipt the remaining lifetime of replenishment is known, corresponding closely with our own RFID information case. They evaluate the value of knowing the remaining lifetime of available replenishment prior to placing an order with a supplier. This information case corresponds closely with our Visibility case. The principal differences between their research and ours is that in our research a) product lifetimes are inherently random, b) product lifetimes are affected by the TTH of the product, c) there are no batch ordering restrictions on replenishment.

Collectively, we draw upon the three broadly defined streams of research: perishable inventory management, time and temperature history monitoring, and value of information to introduce and test new inventory policies that are then used in evaluating the VOI for a product with random lifetime. In the next section we introduce our model.

3 Model

The general setting involves a supplier that sells a single perishable product to retailers. The product lifetime is random, although it has a maximum shelf life of M periods. We assume the product has constant utility throughout its shelf life and once the product expires, it is discarded (outdated) at a cost per unit c. The operational decision of interest is the quantity of new product q_t to order in period t.

The order of events each period is (i) place replenishment order if necessary, (ii) realize demand, (iii) receive replenishment and (iv) outdate any expired units from inventory. Demand is discrete, stochastic, and stationary over time, with mean μ_d, probability mass function (pmf) $\phi(\cdot)$, coefficient of variation C_d, and let d_t denote its realization. Unsatisfied demand is lost and we assume a penalty p for each unit of lost sales. A holding cost h is assessed on ending inventory. To keep the problem tractable we assume a perfectly reliable source of supply (no shortages) and that any replenishment ordered in the beginning of a period arrives at the end of that same period.

Since the product is perishable, inventory may be composed of units with different shelf lives. We refer to the number of periods x elapsed since replenishment arrives as the inventory age class where $x = 0, 1, \ldots, M$ and the special case of age class 0 refers to newly arrived replenishment that has not yet been placed in inventory. Let $i_{x,t}$ denote the age class of beginning inventory with $\vec{i}_t = (i_{1,t}, i_{2,t}, \ldots, i_{M,t})$ and define $I_t = \sum_{x=1}^{M} i_{x,t}$.

We assume all units of the same age class (those units ordered and received together) expire at the same time, although the timing itself is random. Furthermore, it is possible for a product that has spent a short time in inventory to expire prior to a product that has spent a longer time in inventory. Note that even new replenishments q_t, which corresponds to age class 0, may arrive already expired, in which case they are immediately outdated. However, we assume that the supplier is credited in such cases so that there is no outdating cost applied to already expired product. All other units that expire incur an outdating cost c per unit. Let $g(x)$ denote the probability that all inventory in age class x expires at the end of a period. Given a maximum lifetime of M periods, then $g(M) = 1$. Next, we derive

$g(x)$ for all $0 \leq x \leq M-1$. Letting $\psi(x)$ and $\Psi(x)$ denote the pmf and cdf for the shelf life remaining, measured as the number of periods until the inventory is outdated, and assuming the shelf life of replenishment is i.i.d. over time, then

$$g(x) = \begin{cases} \psi(x) & x = 0 \\ \\ \frac{\psi(x)}{1-\Psi(x-1)} & x > 0 \cdot \end{cases}$$

For ease of exposition, let $z^+ \equiv max(z, 0)$. Finally, let $w_{x,t}$, $\vec{w}_t = (w_{0,t}, w_{1,t}, \ldots, w_{M,t})$, and $W_t = \sum_{x=0}^{M} w_{x,t}$ denote the realization of expired product where

$$w_{x,t} = \begin{cases} [i_{x,t} - (d_t - \sum_{j=x+1}^{M} i_{j,t})^+]^+ & 1 \leq x \leq M \\ \\ q_t & x > 0 \end{cases}$$

occurs with probability $g(x)$ and $w_{x,t} = 0$ occurs with probability $1 - g(x)$.

Finally, let $\eta(\vec{w}_t)$ denote the joint pmf for outdating across all age classes in a period.

3.1 Base Case Optimization

We formulate the replenishment problem as an MDP where the objective is to find the supplier's optimal reorder policy so that its average per period expected cost is minimized. The linkage between periods is captured through the one period transfer function of the supplier's age dependent inventory. Starting inventory $\vec{i}_t$ depends on the prior period's starting inventory $\vec{i}_{t-1}$, demand d_{t-1}, replenishment q_{t-1}, and outdating $\vec{w}_{t-1}$. Letting $\tau(i_{t-1}, d_{t-1}, q_{t-1}, w_{t-1})$ denote the one period transfer function, then $\vec{i}_t = \tau(i_{t-1}, d_{t-1}, q_{t-1}, w_{t-1})$ and assuming a FIFO issuing policy we have

$$i_{x,t} = \begin{cases} [i_{x-1,t-1} - (d_{t-1} - \sum_{j=x}^{M} i_{j,t-1})^+]^+ - w_{x,t-1} & 1 < x \leq M \\ \\ q_{t-1} - w_{0,t-1} & x = 1 \cdot \end{cases}$$

From here forward, we suppress the subscript t when the context is clear. Given the vector of starting inventory $\vec{i}$ and an order quantity q, the infinite horizon cost-to-go, if future periods behave optimally, is $f(\vec{i})$. As is the custom in average cost dynamic programming models, we use $\bar{c}$ to denote the equivalent average cost per period when an optimal policy is used. Let the superscript B represent the Base case which assumes that RFID information is not available. We can explicitly write the infinite horizon recursion as

$$f^B(\vec{i}) + \bar{c} = \min_{q \geq 0} p \sum_d (d - I)^+ \phi(d) + \tag{1}$$
$$\sum_d \sum_{\vec{w}|\vec{i}} [h(I + q - \max(d, W - w_0)^+ + c(W - w_0) + f^B(\tau(\vec{i}, d, q, \vec{w}))] \eta(\vec{w}) \phi(d) \cdot$$

The left hand side of equation (1) denotes an extremal equation that is defined by the state space which comprises the vector of age dependent starting inventory. The right hand side computes expected total cost which includes the penalty cost for lost sales, holding cost for ending inventory, the cost of outdated inventory, and future expected cost. Note that future expected cost is predicated on the realizations of both outdating and demand. The decision space for q is restricted to the set of non-negative integer values. Since the state and decision spaces are discrete and finite and the cost is bounded, there exists an optimal stationary policy that does not randomize (Putterman, 1994, pages 102-111).

3.2 RFID Case Optimization

With RFID the supplier knows the time–temperature history for replenishment and therefore the remaining shelf life as well. Hence, while there remains uncertainty with regard to the shelf life of available supply when an order is placed, there is no uncertainty regarding the timing of product expiration once replenishment is received. In this case, we change the interpretation of our state variable $\vec{i}$ to keep track of remaining shelf life, as opposed to the elapsed days on the shelf in the Base case. Formally, let i_x now denote the quantity of on-hand beginning inventory with a remaining shelf life of x periods where $1 \leq x \leq M$. The product is now issued on a FEFO basis. Letting a, $0 \leq a \leq M$ denote the remaining lifetime of replenishment in the current period, then the one period transfer function for starting inventory is now given by $\vec{i_t} = \tau(i_{t-1}, d_{t-1}, q_{t-1}, a_{t-1})$ where

$$i_{x,t} = \begin{cases} [i_{x+1,t-1} - (d_{t-1} - \sum_{j=1}^{x} i_{j,t-1})^+]^+ & x \neq a_{t-1} \\ \\ [i_{x+1,t-1} - (d_{t-1} - \sum_{j=1}^{x} i_{j,t-1})^+]^+ + q_{t-1} & x = a_{t-1} \cdot \end{cases}$$

Note that the only uncertainty with respect to product expiration is with regard to current period demand and replenishment. If $a = 0$, then $(i_1 - d)^+ + q$ units outdate, otherwise only $(i_1 - d)^+$ units outdate.

Just as in the Base case, we formulate the RFID replenishment problem as an MDP where the objective is to find the supplier's optimal reorder policy so that its average per period expected cost is minimized. Let the superscript R represent the RFID enabled information case. We can explicitly write the infinite horizon recursion as

$$f^R(\vec{i}) + \bar{c} = \min_{q \geq 0} p \sum_d (d - I)^+ \phi(d) + \tag{2}$$
$$\sum_d [h(I - \max(i_1, d)) + c(i_1 - d)^+] \phi(d) + \sum_d \sum_a f^R(\tau(\vec{i}, d, q, a)) \psi(a) \phi(d).$$

The state and decision spaces remain the same in equation (2) as they are in equation (1). The expectation of cost on the right hand side of the equation is now taken with respect to demand and the remaining shelf life of replenishment. Any inventory with a shelf life remaining of one period that are not used to satisfy demand expire and are outdated, as well as any newly arrived replenishment that have already expired ($a = 0$).

3.3 Visibility Case Optimization

In this case, the supplier has visibility into the inventory status of upstream supply so that it knows the remaining shelf life of replenishment a, prior to placing an order. Here, we expand the state space to include this additional information. Letting the superscript V denote the information case with visibility, the formulation for the infinite recursion is now

$$f^V(\vec{i}, a_t) + \bar{c} = \min_{q \geq 0} p \sum_d (d - I)^+ \phi(d) + \tag{3}$$
$$\sum_d [h(I - \max(i_1, d)) + c(i_1 - d)^+] \phi(d) + \sum_d \sum_{a_{t+1}} f^V(\tau(i, d, q, a_t), a_{t+1}) \psi(a_{t+1}) \phi(d).$$

The formulation of equation (3) follows the approach taken by Ferguson and Ketzenberg (2006) who also model a retailer that has visibility into the remaining shelf life of a replenishment order. Note that while a_t is known with respect to any order placed in the current period, this information is not known for subsequent periods. Hence, the state transition probability from state $(\vec{i}_t, a_t)$ to state $(\vec{i}_{t+1}, a_{t+1})$ is predicated on both $\psi(\cdot)$ and $\phi(\cdot)$ just as it is in the other cases.

4 Heuristics

In this section, we introduce and test the performance of heuristic policies. The policies introduced in the previous section are impractical to implement for many realistically sized problems given that the size of the state space expands exponentially with the age dependent vector of inventory. Hence, we provide heuristics that enable a broad evaluation on the VOI and that are more relevant to practice. Below, we first define our heuristic policies for each information case and then demonstrate their excellent performance relative to optimal policies. In Section 5, we proceed with an analysis on the VOI.

The structure of the heuristic policies is predicated on a balance between simplicity and performance. Since a retailer can place an order each day, without batch ordering restrictions or a fixed order cost, and doing so with an effective one period lead-time, our heuristics represent myopic policies where the order decision rests *principally* on whether sufficient stock exists in the current period that will carry over and minimize the next period's expected penalty and holding costs (if so, the decision is delayed to the next period). We use the term *principally* because there are two additional costs to be considered. The first relates to the cost of product outdating and the second relates to receiving replenishment that has already expired. The latter cost requires the supplier to carry inventory as a hedge for such occurrences, so long as it is cost effective to do so. We begin by defining the Base case heuristic.

4.1 Base Case Heuristic

The Base case heuristic comprises four cost components:

1. the cost of holding additional inventory purchased in the current period used to satisfy demand in the next period,
2. next period expected penalty and holding cost,

3. next period expected outdating cost, and

4. the penalty cost for unsatisfied demand should a replenishment arrive expired.

The objective is to make a replenishment decision that minimizes the sum of these four cost components. The first cost component is slightly complicated by the possibility of receiving already expired product. The corresponding holding cost expression is given by $h(q - w_0)$. The second cost component is captured by the one period loss function $L(\vec{i})$ where

$$L(\vec{i}) = p \sum_{d} (d - I)^{+} \phi(d) + h \sum_{d} \sum_{\vec{w}|\vec{i}} (I - \max(d, W))^{+} \eta(\vec{w}) \phi(d) \cdot$$

The third component, denoted by $O(\vec{i})$, is simply a one period expectation of product outdating cost, given starting inventory $\vec{i}$ where

$$O(\vec{i}) = c \sum_{d} \sum_{\vec{w}|\vec{i}} (W - w_0) \eta(\vec{w}) \phi(d) \cdot$$

While current period purchases may have an impact on the cost of product outdating beyond the one period, to account for it would be onerous.

The final cost component is designed to accommodate the realization of receiving already expired product in a period. In this case, demand can only be met with carried over inventory. The expected one period penalty costs that arise strictly from satisfying demand from carried over inventory are denoted by $P(I)$ where

$$P(I) = p \sum_{d} (d - I)^{+} \phi(d) \cdot$$

If no useable replenishment arrives in the current period, then next period penalty costs are predicated on carried over inventory from the current period and that quantity is dependent upon current period demand and product outdating. Let $N(\vec{i})$ denote the expected penalty costs that arise in the next period, given starting inventory of $\vec{i}$ and no current period replenishment, so that

$$N(\vec{i}) = \sum_{d} \sum_{\vec{w}|\vec{i}} P(I - \max(d, W))^{+} \eta(\vec{w}) \phi(d) \cdot \tag{4}$$

Now, this last cost component occurs only a fraction of the time, corresponding to the fraction of periods in which already expired product arrives. Hence, we do not fully load the cost associated with equation (4) into our heuristic's cost minimizing objective function. Instead, we weight the expression by a constant factor α, $0 \leq \alpha \leq 1$. Although α is unknown, it can readily be found through a simple numerical search between its bounds. Letting the superscript HB denote the base case heuristic, the cost minimizing objective function is given by $f^{HB}(\vec{i})$ where

$$f^{HB}(\vec{i}) + \bar{c} = \min_{q \geq 0} \sum_{\vec{w}|\vec{i}} h(q - w_0)\phi(d)\eta(\vec{w}) + \tag{5}$$
$$\sum_{d} \sum_{\vec{w}|\vec{i}} (L(\tau(\vec{i}, d, q, \vec{w})) + O(\tau(\vec{i}, d, q, \vec{w})) + \alpha N(\tau(\vec{i}, d, q, \vec{w}))\eta(\vec{w})\phi(d) \cdot$$

Note that the four terms on the right hand side of equation (5) correspond to each of the four cost components that have been defined and that the expectation of these costs is taken with respect to both demand and outdating. Each of the two information heuristics conform to the same structure as the Base case heuristic, although minor changes are made to accommodate the additional information available in each case, as we describe below.

4.2 RFID Case Heuristic

With RFID enabled information, the remaining shelf life of replenishment is known and this information is incorporated into the heuristic. In essence, the timing of product expiration is no longer uncertain, once replenishment is received. Product outdating only remains stochastic with respect to the uncertainty of demand. Each of the four cost components introduced with the Base case heuristic require modifications. First, the holding cost on replenishment carried into the next period is now given by $h \times j(q, a)$ where

$$j(q, a) = \begin{cases} q & a > 0 \\ \\ 0 & a = 0 \cdot \end{cases}$$

The one period loss function is also changed. Here we have

$$L(\vec{i}) = p \sum_{d} (d - I)^{+} \phi(d) + h \sum_{d} (I - \max(d, i_1))^{+} \phi(d) \cdot$$

Since the timing of product expiration is no longer stochastic, the outdating cost expression is greatly simplified. Moreover, because inventory is issued on a

FEFO basis and the expiration date is known on receipt, any replenishment decision will no longer impact the outdating of on-hand inventory. Here our expectation of the outdating cost $O(\vec{i})$ becomes

$$O(q+i_a,a) = c\sum_{d=0}^{q+i_a-1}(q+i_a-d)^+\phi_a(d)$$

where $\phi_a(d)$ denotes the a-fold convolution of demand.

Finally, the expectation for the next period penalty cost given that demand can only be met with carried over inventory is simplified to become

$$N(\vec{i}) = \sum_d P(I-\max(d,i_1))^+\phi(d)\cdot$$

Now, letting the superscript HR denote the RFID case heuristic policy, the objective function is given by $f^{HR}(\vec{i})$ where

$$\begin{aligned} f^{HR}(\vec{i})+\bar{c} = \min_{q\geq 0}\sum_a h\times j(q,a)\phi(d)\psi(a)+ \\ \sum_d\sum_a(L(\tau(\vec{i},d,q,a))+O(\tau(\vec{i},d,q,a))+\alpha N(\tau(\vec{i},d,q,a))\phi(d)\psi(a)\cdot \end{aligned} \tag{6}$$

4.3 Visibility Case Heuristic

In essence, the Visibility case heuristic is a simple, direct extension of the RFID case. Here, there is now no uncertainty with respect to the remaining lifetime of replenishment in the current period. The only remaining uncertainties lie with demand and the remaining lifetime of replenishment in future periods. Letting the superscript HV denote the Visibility case heuristic, the objective function is given by $f^{HV}(\vec{i},a)$ where

$$\begin{aligned} f^{HV}(\vec{i},a)+\bar{c} = \min_{q\geq 0} h\times j(q,a)\phi(d)+ \\ \sum_d(L(\tau(\vec{i},d,q,a))+O(\tau(\vec{i},d,q,a))+\alpha N(\tau(\vec{i},d,q,a))\phi(d)\cdot \end{aligned} \tag{7}$$

Note that in equation (7), since the remaining shelf life of replenishment is known for the current period, it is moved to the state space on the left hand side of the equation and its expectation on the right hand side has been removed (as compared to equation (6)). There are no other differences between equations (7) and (6).

4.4 Validation of heuristic performance

We test the heuristics by comparing their performance to optimality for a variety of scenarios. Demand $\phi(\cdot)$ corresponds to a truncated negative binomial distribution with mean demand of five and a maximum value of 50 (the insignificant probabilities for values exceeding 50 are nevertheless redistributed proportionately within the truncated limit of the distribution), see Agrawal and Smith (1996) regarding the advantages of assuming negative binomial distributions for demand. For our computational study, we evaluate maximum product lifetimes of $M \in (2, 3, 4)$, although the realized lifetime varies according to $\psi(\cdot)$. We explore both uniform and bell shaped distributions. In the case of uniformly distributed lifetimes, $\psi(x) = 1/(M + 1)$ for all x. For bell shaped distributions, we use the distributions specified in Table 1 for each M.

The holding cost is fixed at one across all experiments and we consider a set of experiments that comprise a factorial design for all combinations of the following parameter values: $c \in (0, 1, 2, 4)$, $p \in (7.5, 15, 25)$, and $C_d \in (0.45, 0.55, 0.65)$.

We do not propose the values chosen for our test are relevant to practice. Rather the selection of values is chosen to test the robustness of the heuristics over widely varying operating cost environments. Moreover, our choice of parameter values for testing is constrained by the computational feasibility of the MDPs, our principal motivation for developing the heuristics in the first place.

M	$\psi(0)$	$\psi(1)$	$\psi(2)$	$\psi(3)$	$\psi(4)$
2	0.25	0.75	0.25		
3	0.17	0.33	0.33	0.17	
4	0.1	0.2	0.4	0.2	0.1

Table 1: Bell shaped age distribution

We duplicate the factorial design for each M and $\psi(\cdot)$. Hence, there are a total of 216 experiments in our test. For each experiment and heuristic policy, we conduct an exhaustive search for the value of α that minimizes the corresponding objective function, but limit precision to 0.01. We use value iteration to compute the average expected cost for the respective optimal and heuristic policies. We measure the performance of each heuristic policy as the percentage difference in expected cost, relative to the corresponding optimal policy.

Overall, the heuristics are extremely well performing. The Base case heuristic achieves, on average, an expected cost that is 0.1% of optimal and the worst case cost is 0.8% of optimal. The RFID case and Visibility case heuristics demonstrate similar performance with average expected costs that are, respectively, 0.3% of optimal and 0.7% of optimal, with worst case costs being 1.4% and 2.5% of optimal. In a second test, we compare the VOI achieved with the heuristics to that of the optimal policies. The VOI is measured as the % improvement in expected cost achieved with information. With two information cases, there are three different measures for the VOI: the RFID case relative to the Base case, the Visibility case, relative to the RFID case, and the Visibility case relative to the Base case. Let π_B, π_R, and π_V respectively denote the average expected cost for the Base, RFID, and Visibility cases. Then for each corresponding measure of VOI (B/R, R/V, B/V) we have

$$\text{VOI(B/R)} = \frac{\pi_B - \pi_R}{\pi_B} \quad \text{VOI(R/V)} = \frac{\pi_R - \pi_V}{\pi_R} \quad \text{VOI(B/V)} = \frac{\pi_B - \pi_V}{\pi_B}.$$

We compare the VOI between heuristic and optimal policies in Table 2 across percentiles of the test cases which are ordered from lowest to highest VOI. For example, at the 0.50 (median) percentile, the heuristic VOI for the RFID case relative to the Base case is 4.3% and the corresponding optimal VOI is 4.4%. Note that across all percentiles, the heuristic VOI is ordered very closely to the optimal VOI.

In addition, a thorough comparison of the heuristic VOI to the optimal VOI, across all parametric settings, demonstrates the same qualitative relationships. From the basis of these tests and comparisons, we consider the heuristic policies to be well suited for our purposes and provide in the next section an extensive evaluation of the VOI using simulation.

5 Simulation Study

In this section, we report on a simulation study that evaluates the VOI using the heuristic policies defined in Section 4. We first detail the simulation procedures and experimental design, then report our principal results and general observations. We

	Heuristic VOI			Optimal VOI		
Percentile	B/R	R/V	B/V	B/R	R/V	B/V
0.0	0.0%	0.0 %	1.4%	0.6 %	0.0%	1.5%
0.05	1.0%	0.3%	2.3%	1.1%	0.4%	2.6%
0.10	1.2%	0.6%	2.7%	1.4%	0.6%	3.1%
0.25	1.7%	1.1%	3.8%	1.8%	1.4%	4.2%
0.50	4.3%	2.0%	6.6%	4.4%	2.6%	7.0%
0.75	6.9%	3.4%	9.5%	7.0%	4.0%	10.3%
0.90	9.3%	5.0%	12.1%	9.4%	5.5%	12.7%
0.95	10.0%	5.7%	13.5%	10.7%	6.5%	14.5%
1.00	12.7%	7.8%	19.6%	12.6%	7.7%	19.4%

Table 2: Comparison of heuristic and optimal VOI

conclude with a sensitivity analysis as well as a cost assessment of supply chain time and temperature changes.

5.1 Simulation model and procedures

Most supply chains that support and facilitate the distribution of perishable products are broadly split into two parts. The first part, referred to here as the ambient chain, involves all the processing, handling, and transportation of product prior to entering the cool chain which is the second part of the supply chain. The ambient chain is not temperature controlled, while the cool chain is temperature controlled. Common examples are agricultural products, like fruit and vegetables that enter the ambient chain at the time of harvest, which then wait to be transported to a distribution point, where they are loaded onto refrigerated trucks headed to market. Temperature control, at "cool" temperatures inhibits the growth of microbiological agents that cause product decay and hence extends product shelf life. Effective and efficient supply chain practices are designed to minimize product exposure in the ambient chain, but generally such time cannot be eliminated altogether. Even in the cool chain, temperature control is not absolute; numerous scientific studies (e.g., Koutsoumanis et al., 2005) have demonstrated variations in temperature such that even product within the same vessel (e.g. refrigerated truck, container, etc.) may have different remaining shelf lives once they make it to market.

Time and temperature variability, in both ambient and cool chains, impacts product freshness and the corresponding uncertainty regarding product exposure makes shelf life prediction challenging. The promise of time-temperature monitoring through RFID and similar technologies, is accurate prediction through knowledge of the complete time and temperature history. The method for translating such histories into accurate shelf life predictions remains to be defined here. In the scientific literature there are several models (Tijskens and Polderdijk, 1996), most predicated on the Arrhenious law dating back to Chang (1981). An altogether different model has been developed specifically for fresh fish through years of research at CSIRO, Division of Food research, Hobart, Australia (Doyle, 1995). Because of its simplicity and demonstrated accuracy for a large number of fish species (Ronsivalli and Charm, 1975; Bremner, 1984; Bremner et al., 1987), we adopt this predictive model for our study and describe it below. We note that virtually any other model in which shelf life prediction is based on the time temperature history of a product may be substituted in its stead.

Shelf life prediction of fresh fish is based on a simple formula that accurately predicts the growth rate of spoilage bacteria and deterioration rate of muscle food between temperatures of $-2°C$ and $20°C$ ($28.4°F$ and $68°F$) (Olley and Ratkowsky, 1973; Ratkowsky et al., 1982, 1983). The model links the spoilage rate r to a given temperature τ, relative to the spoilage rate at $0°C$ (on ice) and is given by

$$r = (0.1\tau + 1)^2 \cdot \tag{8}$$

If fish is stored at $0°C$, then r is 1. Suppose however that $\tau = 4$. Then $r = (0.1(4) + 1)^2 = 1.96$. Therefore, the rate of spoilage for fish stored at $4°C$ is nearly twice that of fish stored at $0°C$. Thus, if the total shelf life of a species of fish held in ice from the time of catching is known, and the complete time temperature history is known, then the remaining shelf life can be readily calculated. As an example consider a shipment of fish stored on a boat at $10°C$ for one day and then enters the cool chain for three days at $2°C$. If the maximum shelf life on ice is 10 days (e.g. king salmon, sablefish) then the remaining shelf life is $10 - (0.1(10) + 1)^2 - (0.1(2) + 1)^2 = 4.6$ days. Since we assume that partial days are infeasible, all shelf life values are rounded down to the nearest integer.

To evaluate the VOI, we simulate the transportation of fresh fish in a two part supply chain (ambient and cool) to derive the remaining shelf life of product available for purchase by the supplier. Further, we assume that both time and temperature are normally distributed random variables in *each* part of the supply chain and we generate age distributions $\psi(\cdot)$ through 1,500 simulations (realizations of the random variables). That is, we estimate $\psi(\cdot)$ with the resulting 1,500 realization of product shelf life and these are then subsequently used in an inventory simulation from which performance of the Base, RFID, and Visibility cases can be compared.

We developed a simulation program using the PASCAL programming language to simulate the inventory performance for each information case. Each experiment is simulated for 2,100 periods and replicated 30 times. The first 100 periods of each replication are set aside as the simulation warm-up period so that statistics are calculated for 2,000 periods in each replication. The warm-up period was chosen for convenience, yet larger than the number of days necessary for the system to exhibit steady-state behavior. In each replication, the random number streams across all experiments are identical in order to reduce the sampling error. The estimated standard error for the expected average period cost, using each heuristic, averages 0.6% of its mean value, and has a maximum error of 1.6%. Thus, we are over 99% confident that the true VOI in each experiment falls within 5.3% of the reported value.

We conducted another test of the simulation program by duplicating the set of experiments used to test the heuristics. In Table 3 we compare the simulated VOI to the optimal VOI, just as we compared the heuristic VOI to the optimal VOI in Table 2. Considering that the simulated VOI is obtained using the heuristics and the optimal VOI is obtained exactly using the MDPs, the comparisons in Table 3 demonstrate that the simulation provides very accurate assessments for each measure of the VOI.

5.2 Experimental design

The study comprises a base set of 27 experiments that is replicated to explore model sensitivity to additional parameters values. The base set of experiments corresponds to a factorial design of the following parameter values: $c \in (0, 2, 4)$,

	Simulated VOI			Optimal VOI		
Percentile	B/R	R/V	B/V	B/R	R/V	B/V
0.00	0.4%	0.0%	0.9%	0.6%	0.0%	1.5%
0.05	0.8%	0.3%	1.9%	1.1%	0.4%	2.6%
0.10	0.9%	0.6%	2.6%	1.4%	0.6%	3.1%
0.25	1.2%	1.2%	4.1%	1.8%	1.4%	4.2%
0.50	4.8%	2.3%	7.2%	4.4%	2.6%	7.0%
0.75	8.1%	3.4%	10.6%	7.0%	4.0%	10.3%
0.90	10.9%	4.6%	12.9%	9.4%	5.5%	12.7%
0.95	12.0%	5.3%	14.6%	10.7%	6.5%	14.5%
1.00	14.1%	7.0%	19.7%	12.6%	7.7%	19.4%

Table 3: Comparison of heuristic and optimal VOI

$p \in (7.5, 15, 30)$, and $C_d \in (0.45, 0.65, 0.85)$. Across experiments, $\mu_d = 5$ and $h = 1.0$. The maximum product shelf life is 10 days and the supply chain time (in hours) and temperature (in centigrade) parameters are specified in Table 4.

	Time		Temperature	
	Mean	Std. Deviation	Mean	Std. Deviation
Ambient Chain	18	3	10	3
Cool Chain	36	6	2	1

Table 4: Supply chain time and temperature settings

The selected parameter values for time, temperature, and shelf life are commonly observed in supply chains and thus allow an assessment of the VOI relevant to practice. The cost parameters are designed to provide a range over which we can identify the determinants and sensitivity of the VOI. We further explore model sensitivity with regard to the time and temperature parameters using a one-at-a-time approach. That is, the full set of 27 base experiments is replicated, except one parameter (value) is changed. The additional values we explore are specified in Table 5. In total, there are 891 numerical examples through which we evaluate the VOI.

	Time		Temperature	
	Mean	Std. Deviation	Mean	Std. Deviation
Ambient Chain	10,14,22,26	1,2,4,5	8,9,10,11,12	1,2,4,5
Cool Chain	20,28,44,52	2,4,6,8,10	0,1,3,4	0.25, 0.5, 1.5, 2.0

Table 5: Additional experimental time and temperature parameter values

5.3 General observations and results

In Table 6, we report the VOI for each type of information at given percentiles of the 891 experiments. For example, the 0.50 percentile denotes the median values. From this table, two observations emerge: 1) RFID information can be quite valuable and supply chain visibility provides marginal incremental value, and 2) the range of VOI shows demonstrable sensitivity to model parameters that depend largely on system behavior as we discuss for each case below.

	Value of Information		
Percentile	B/R	R/V	B/V
0.00	-0.4%	-0.2%	- 0.1%
0.05	0.6%	0.0%	0.8%
0.10	1.2%	0.1%	1.5%
0.25	2.3%	0.4%	3.1%
0.50	4.0%	0.7%	5.1%
0.75	6.8%	1.6%	8.2%
0.90	9.7 %	2.7%	11.2%
0.95	11.3%	3.5%	12.8%
1.00	14.3%	5.5%	17.6%

Table 6: Summary of results

In general, information reduces uncertainty with respect to product outdating such that more inventory can be held to satisfy a higher level of demand, while simultaneously decreasing spoilage. Relative to the Base case, we find that, on average, lost sales decreases 12.4%, as outdating decreases 12.6% in the RFID case. In the Visibility case, the improvements are smaller since they are incremental to the RFID case. On average, lost sales decrease another 3.9% and unit outdating another 5.0%. Overall, the largest cost reductions occur when lost sales are significantly reduced. Consider that when the VOI is greater than the average of 4.8% across experiments, lost sales are reduced by an average of 20.2% compared to 7.0% when the VOI is less than the average. Comparatively, the relationship of VOI with respect to outdating is the reverse. That is, when the VOI is high, outdating is reduced by a lower amount (10.8%) than when the VOI is low (13.8%).

Overall, there is a pronounced concave relationship between the VOI and the product shelf life at the supplier. While the maximum product lifetime is 10 days for our experiments, the product shelf life varies from zero to seven days, depending on the time and temperature conditions in the supply chain. The VOI is largest at intermediate values (moderate perishability) of product shelf life. In Figure 1, we illustrate this relationship, showing the VOI as a function of the mean effective shelf life (life remaining after receipt) at the supplier. We have inserted polynomial fitted trend lines to highlight the relationship. This relationship is best understood in the context of extreme examples. With extremely short product lifetimes of a day or less, information provides little value since it will not meaningfully change the supplier's behavior. That is, the lifetime is always short, so there is also very little uncertainty with respect to product outdating. At the other extreme, with long product lifetimes, the product essentially becomes non-perishable and outdating is eliminated - even without information. Hence, there is also no uncertainty with regard to the timing of spoilage and the value of information is insignificant. We extend our evaluation on the VOI through a sensitivity analysis in the next paragraph.

5.4 Sensitivity Analysis

Table 7 summarizes our sensitivity analysis for parameters other than supply chain time and temperature, and shows that the VOI increases with respect to the CV of demand, penalty cost, and outdating cost.

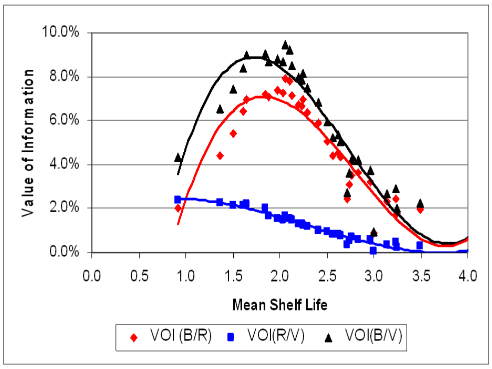

Figure 1: VOI as a function of mean lifetime (left) and lifetime coefficient

The relationship between cost and the VOI is intuitive. Higher system costs correspond to a higher cost of product perishability and hence information that reduces the uncertainty with respect to spoilage is valuable. The relationship between the VOI and Demand CV is less clear. Higher demand uncertainty also leads to higher system costs. Information used in this context will also reduce uncertainty, but only with respect to spoilage. As demand uncertainty increases, the proportion of total uncertainty represented by spoilage decreases and hence information will only reduce a smaller proportion of total cost.

The remaining parameters relate to supply chain time and temperature. It is clear from equation (8) and our general knowledge of spoilage that product shelf life decreases with respect to both the time that a product resides in the supply chain as well as the temperature. Similarly, variability in both time and temperature also decrease expected shelf life. Further, our analysis shows that the VOI depends largely on shelf life itself and that it is most valuable at moderate levels of perishability (intermediate values of shelf life). Hence, there is little to conclude directly between the time temperature parameters and the VOI directly. Even so, in Figure 2, we characterize the relationship between mean shelf life and average period total cost that arises from our simulations.

As we would expect, the relationship between cost and shelf life is not linear, but rather costs increase at an increasing rate as the mean shelf life decreases. We can further quantify the relationship by performing a simple linear regression, after taking the natural logarithms of both independent and dependent variables and

Parameter	Value	Value of Information B/R	R/V	B/V
	0.45	5.7%	1.4%	7.0%
Demand CV	0.65	4.7%	1.1%	5.8%
	0.85	3.9%	0.9%	4.8%
	7.5	2.6%	1.0%	3.6%
Penalty Cost	15	4.6%	1.1%	5.7%
	30	7.3%	1.2%	8.4%
	0	4.5%	0.5%	5.0%
Outdating Cost	2	4.8%	1.0%	5.8%
	4	5.1%	1.9%	6.8%

Table 7: Sensitivity analysis

thereby fit the model:

$$ln(cost) = b_0 + b_1 ln(\text{shelflife}) \tag{9}$$

The resulting line fit is very good with an R^2 of 0.934, with $b_0 = 3.439$ and $b_1 = -0.638$. Hence, if we can quantify the relationships between the supply chain time and temperature variables and shelf life, we can also extend our analysis by estimating the relationship between time and temperature and cost. Doing so will allow us to evaluate the cost impact of changes in supply chain time and

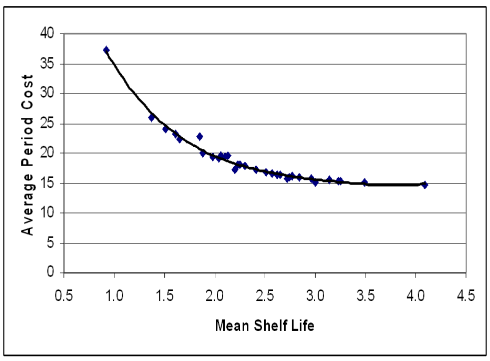

Figure 2: Relationship between shelf life and average cost in the base case

temperature. To extend our analysis in this direction, we ran an additional set of 512 time and temperature simulations, corresponding to a factorial design of the values presented in Table 8 along with values of 8 and 10 for the maximum shelf life.

	Time		Temperature	
	Mean	Std. Deviation	Mean	Std. Deviation
Ambient Chain	14,18	1,2	8,10	1,2
Cool Chain	32, 40	1, 2	0,2	0.5, 1

Table 8: Shelf life simulation parameters

The results of the 512 simulations were then used in a model to estimate the relationship between mean shelf life and the time, temperature, and maximum lifetime parameters:

$$\begin{aligned} \text{Shelflife} = b_0 + b_1\text{ATempM} + b_2\text{ATempS} + b_3\text{ATimeM} + b_4\text{ATimeS} \\ + b_5\text{CTempM} + b_6\text{CTempS} + b_7\text{CTimeM} + b_8\text{CTimeS} + b_9\text{MaxLife} \end{aligned} \tag{10}$$

In equation (10) we use a variable naming convention where the prefix A denotes 'Ambient', the prefix C denotes 'Cool', the suffix M denotes 'Mean' and the suffix S denotes 'Standard Deviation.' Hence, the variable name ATempS refers to the standard deviation of the ambient chain temperature. We fit the model expressed in equation (10) using least-squares regression and obtain an excellent fit as indicated by an R^2 of 0.996 with estimated coefficients as reported in Table 9.

The estimated models expressed in equations (9) and (10) can jointly be used to evaluate the cost impact of changes in the supply chain time and temperature variables. As a managerial tool, such estimates provide a means for assessing the benefit from making supply chain improvements such as reducing temperature variability or lead times. For example, an investment in cooling technology may enable a more consistent temperature thereby reducing the standard deviation of the temperature in the cool chain. Taking this example further, consider a supply chain where supply chain time and temperature variables are as presented in Table 4. Then the estimated mean shelf life for the supplier is 2.62 days with an average

Variable	Coefficient	Standard Error	t Stat	P-value
Intercept	3.095	0.06	51.5	0.0000
ATempM	-0.292	0.00	-90.1	0.0000
ATempS	-0.241	0.01	-37.2	0.0000
ATimeM	-0.172	0.00	-106.0	0.0000
ATimeS	-0.131	0.01	-20.2	0.0000
CTempM	-0.361	0.00	-111.5	0.0000
CTempS	-0.303	0.01	-23.4	0.0000
CTimeM	-0.057	0.00	-70.8	0.0000
CTimeS	-0.045	0.01	-7.0	0.0000
MaxLife	1.000	0.00	308.8	0.0000

Table 9: Estimates for the coefficients in equation (10)

daily cost of $16.87. Supposing the standard deviation of the cool chain temperature can be reduced from 1.0 to 0.5, the estimated mean shelf life would then increase to 2.77 and average daily cost would reduce to $16.28 - a 3.5% cost reduction. In comparison, the results from our simulation experiments show a 4.0% cost reduction between the two scenarios.

6 Conclusions

Our research addresses the VOI for the use of a product's TTH to explain shelf life uncertainty and thereby improve inventory management. Key assumptions of our model include random lifetime, periodic review, and lost sales. As in previous studies (e.g., Taoukis et al., 1999), we find that the TTH can significantly affect product shelf life and thereby generate considerable uncertainty in the management of perishables. Consequently, information that explains the TTH as a product flows through the supply chain can be quite valuable.

Using examples of fresh fish (e.g. salmon and cod), we find that the VOI is quite sensitive to environmental and parametric settings, ranging upwards to 14.3% with a mean of 4.0% in the RFID case and ranging upwards to 17.6% in the Visibility case, with a mean of 5.5%. The highest value is generated by decreasing spoilage and simultaneously increasing product availability and thereby service levels. Intuitively, these cases correspond to operating environments with high outdating and penalty costs. Interestingly, we find that the VOI decreases with respect to increasing demand variability and therefore demand uncertainty. We note that in Ferguson and Ketzenberg (2006) the VOI increases with demand uncertainty for fixed lifetime perishables. As discussed in Ketzenberg et al. (2007), there are conflicting results reported on the relationship between demand uncertainty and the VOI. Clearly, more research is needed to better understand the determinants of this relationship.

We find that the incremental value provided by supply chain visibility is generally quite small, averaging just 0.7%. Hence, it seems difficult to justify the additional investment in information sharing technology that would enable information sharing for many products. Of course, while our results are indicative of the VOI for some representative fresh fish supply chains, model sensitivity demonstrates that the VOI will be specific to a supply chain and the products that flow through it. We also extended our analysis into the relationship between a supply chain's time and temperature parameters to cost and developed a model for assessing potential cost reduction due to improvements in lead time and temperature control. In this way, it is also possible to compare the value of these type of investments to that of RFID technology.

Naturally, there are several avenues for future research. The most promising, we believe, is a field study that demonstrates the VOI through actual implementation of RFID technology for TTH monitoring. While there have been some pilot studies for managing perishables with RFID (e.g., Kärkkäinen, 2003), none involve TTH monitoring. Other areas for future research involve model extensions to include batch ordering and assessing information accuracy. We also note that our research is directed at the VOI for a single location, not the entire supply chain. Nor do we address other uses for TTH monitoring such as dynamic allocation of product based on shelf life so that soon to expire product is distributed locally while longer shelf life products can be distributed to more distant locations.

References

Agrawal, N., S. Smith. 1996. Estimating negative binomial demand for retail inventory management with unobserveable lost sales. Naval Research Logistics, 43(6), 839–861.

Axtman, B. 2006. Ripe opportunities. Progressive Grocer, 85(4), 76–80.

Bogataj, M., L. Bogataj, R. Vodopivec. 2005. Stability of perishable goods in cold logistic chains. International Journal of Production Economics, 93-94, 345–356.

Bourland, K.E., S.G. Powell, D.F. Pyke. 1996. Exploiting timely demand information to reduce inventories. European Journal of Operational Research, 92, 239–253.

Boyer, M. 2006. Lost in SKUs. Progressive Grocer, 93–94, 118–121.

Bremner, A. 1984. Quality an attitude of mind. Australian fishing industry today and tomorrow, pages 244–269. Springer Berlin, Tasmania.

Bremner, H.A., J. Olley, A.M.A. Vail. 1987. Seafood Quality Determination, Chapter Estimating Time-Temperature effects by a rapid systematic sensory method, 413–436. Elsevier, Amsterdam.

Chang, R. 1981. Physical chemistry with applications to biological systems. Macmillan Publishing Co., New York.

Dada, A., F. Thiesse . 2008. Sensor applications in the supply chain: the example of quality-based issuing of perishables. In Floerkemeier, C., Langheinrich, M., Fleish, E., Mattern, F., Sarma, S. (editors), The Internet of Things, Volume 4952. Springer Berlin, Zurich.

Doyle, J.P. 1995. Seafood shelf life as a function of temperature. Alaska Sea Grant Marine Advisory Program, 30, 1–5.

Ferguson, M., M. Ketzenberg. 2006. Sharing information to improve retail product freshness of perishables. Production and Operations Management, 15(1), 57–73.

Ferrer, G., M. Ketzenberg. 2004. Value of information in remanufacturing complex products. IIE Transactions, 36(3), 265–278.

Fries, B. 1975. Optimal order policy for a perishable commodity with inventory deterioration. Operations Research, 23, 46–61.

Gaukler, G., R. Siefert. 2007. Trends in Supply Chain Design and Management: Technologies and Methodologies, Chapter Applications of RFID in Supply Chains. Springer-Verlag, London.

Gavirneni, S., R. Kapuscinski, S. Tayur. 1999. Value of information in capacitated supply chains. Management Science, 45(1), 16–24.

Goyal, S., Giri, B. 2001. Recent trends in modeling of deteriorating inventory. European Journal of Operational Research, 134, 1–16.

Huang, G., J. Lau, K. Mak. 2003. The impacts of sharing production infomration on supply chain dynamics: a review of the literature. International Journal of Production Research, 41(7), 1483–1518.

Kärkkäinen, M. 2003. Increasing efficiency in the supply chain for short shelf life goods using RFID tagging. Journal of Retail and Distribution Management, 31(10), 529–536.

Ketzenberg, M., M. Ferguson. 2008. Managing slow moving perishables in the grocery industry. Production and Operations Management, 17(5), 513–521.

Ketzenberg, M., E. Rosenzweig, A. Marucheck, R. Metters. 2007. A framework for the value of information in inventory replenishment. European Journal of Operational Resarch, 183(3), 1230–1250.

Ketzenberg, M., E. van der Laan, R.H. Teunter. 2006. Value of information in closed loop supply chains. Production and Operations Management, 15(3), 393–406.

Koutsoumanis, K., P.S. Taoukis, G.J.E. Nychas. 2005. Development of a safety monitoring and assurance system for chilled food product. International Journal of Food Microbiology, 100, 253–260.

Lee, H., O. Ozer. 2007. Unlocking the value of rfid. Production and Operations Management, 16(1), 40–64.

Moinzadeh, K. 2002. A multi–echelon inventory system with information exchange. Management Science, 48(3), 414–426.

Moureh, J., D. Flick. 2004. Airflow pattern and temperature distribution in a typical refrigerated truck configuration loaded with pallets. International Journal of Refrigeration, 27, 464–474.

Nahmias, S. 1975. Optimal ordering policies for perishable inventory – ii. Operations Research, 23(4), 735–749.

Nahmias, S. 1977. On ordering inventory when both demand and lifetime are random. Management Science, 24(1), 82–90.

Nahmias, S. 1982. Perishable inventory theory: A review. Operations Research, 30(4), 680–707.

Nunes, M.C.N., J.P. Emond, K.V. Chau, M. Rauth, S. Dea, W. Pelletier. 2006. Effects of in-store conditions on the quality of fresh fruit and vegetables. Research report to public super markets, University of Florida.

Olley, J., D.A. Ratkowsky 1973. Temperature function integration and its importance in the storage and distribution of fresh foods above the freezing point. Journal of Food Technology in Australia, 25(2), 66–73.

Putterman, M. 1994. Markov Decision Processes: Discrete Stochastic Dynamic Programming. John Wiley & Sons, Inc.

Raafat, F. 1991. Survey of literature on continuously deteriorating inventories. Journal of the Operational Research Society, 42(1), 27–37.

Ratkowsky, D.A., R.K. Lowry, T.A. Mc Meekin, A.N. Stokes, R.E. Chandler. 1983. Model for bacterial culture growth rate throughout the entire biokinetic temperature range. Journal of Bacteriology, 154(3), 1222–1226.

Ratkowsky, D.A., J. Olley, T.A. Mc Meekin, A. Ball. 1982. Relationship between temperature and growth rate of bacteria cultures. Journal of Bacteriology, 149(1), 1–5.

Roberti, M. 2005. RFID will help keep perishables fresh. RFID Journal. URL www.rfidjournal.com/article/articleview/1775/1/1.

Rodriguez-Bermejo, J.P., J.I. Barriero, L. Ruiz-Garcia. 2007. Thermal study of a transport container. Journal of Food Engineering, 80, 517–527.

Ronsivalli, L.J., S.E. Charm. 1975. Spoilage and shelf life prediction of refrigerated fish. Marine Fisheries Review, 37(4), 32–34.

Sahin, F., E.P. Robinson. 2002. Flow coordination and information sharing in supply chains: review, implications, and directions for future research. Decision Sciences, 33(4), 1–32.

Taoukis, P.S., K. Koutsoumanis, G.J.E. Nychas. 1999. Use of time-temperature integrators and predictive modelling for shelf life control of chilled fish under dynamic storage conditions. International Journal of Food Microbiology, 53, 21–31.

The National Supermarket Research Group 2003. 2003 national supermarket shrink survey. URL www.retailcontrol.com.

Tijskens, L.M.M., J.J. Polderdijk. 1996. A generic model for keeping quality of vegetable produce during storage and distribution. Agricultural systems, 51(4), 431–452.

Tortola, J. 2005. Loss leader. Progressive Grocer, 84(7), 14–15.

Van der Duyn Schouten, F., M. van Eijs, R. Heuts. 1994. The value of supplier information to improve management of a retailer's inventory. Decision Science, 25(1), 1–14.

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