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Inventory control for returnable transport items in a closed-loop supply chain

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ABSTRACT

An inventory control model for returnable transport items (RTI) where the manager selects the optimal length for inspection, repair, and purchase cycles is described. Repaired and newly obtained RTI are used in combination to satisfy current production requirements. Uncertain returns are incorporated into the model by determining a satisfactory safety stock level to buffer the inventory of used and repairable containers. The minimum cost solution is obtained when inspection and repair runs begin simultaneously. Cycle times are a function of the expected return rate and repairable percentage, while variability in these random assumptions affects the required safety stock.

1. Introduction

Returnable transport items (RTI) are containers used multiple times by manufacturers to avoid the cost of purchasing new shipping material each time their product is distributed to a customer location (Twede and Clarke, 2004). RTI include such packaging types as kegs, pallets, roll cages, barrels, trolleys, and refillable liquid or gas containers (ISO, 2007). The investment in RTI can be necessitated by the need to reduce the costs in a supply chain versus employing one-way packaging items, and is also attractive for reducing environmental impacts (Kroon and Vrijens, 1995; Twede and Clarke, 2004; Hellström, 2009). While acknowledging the potential cost reduction through material savings associated with RTI, McKerrow (1996) also outlines additional benefits of reusable packaging that include improved handling and storage.

This paper proposes a model for determining inventory control policies for the inspection, repair, and purchase of RTI in a closed-loop supply chain (CLSC). Motivation for the system presented is the determination of inventory policies for a beverage manufacturer that utilizes returnable kegs. The product is delivered through distributors, who eventually collect and return the containers to the manufacturer. Returned kegs are processed and inspected to determine whether they can be repaired and reutilized for future shipments. The inspected containers are transferred to a repair station where parts are replaced as necessary and the kegs are cleaned and sanitized. Once the repair process is completed, the containers are added to an inventory of serviceable containers that are ready to be refilled. The workflow in the facility and the proximity of the inspection and repair functions is such that the containers can be continuously transferred between the inventory queues once each process is completed. Inspection and repair are performed on containers in batches, so the manufacturer

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must establish effective cycle lengths and corresponding lot sizes for these functions. Only a fraction of the containers are returned from distributors, so the company must also decide when to purchase new containers and set an order quantity.

This research contributes to the current models available to manufacturers for managing their collections of RTI. Decisions regarding the purchase, inspection, repair, and transportation of RTI affect the costs of distributing products to customers (Thoroe et al., 2009; Kim and Glock, 2014). Kelle and Silver (1989a,b) and Buchanan and Abad (1989) developed methods for forecasting RTI returns and determining optimal purchase quantities for replacement of lost containers. Witt (2000) notes that decisions affecting the ability of the company to recollect RTI quickly are also important because these determined the number of containers needed in a fleet. In a study of an engine manufacturer in Brazil, Silva et al. (2013) found that once logistics policies were established to reduce the time-to-return of reusable packaging to satisfactory levels, both positive economic and environmental impacts were realized. Accorsi et al. (2014) study both the environmental and economic effects of deploying a fleet of RTI in a food catering supply chain. They note that the reduced environmental impact is significant, but that the economic returns can be negative if the distribution system is not configured properly.

Managing the collection of RTI owned by a manufacturer can be aided by setting inventory control policies for processing used containers and returning them to the production system. The model in this paper seeks to minimize total expected inventory costs of the closed-loop RTI supply chain when the percentage of containers returned in each production lot and the percentage of repairable containers are random variables. The design of the system is similar in some respects to the method proposed by Kim and Glock (2014); however, the prior model is implemented in a single-supplier, single-retailer supply chain where containers are collected by the retailer and returned in a batch to the supplier. In the system proposed here, containers return to the manufacturing facility continuously.

This research makes the contribution of providing optimal inspection, repair, and purchase intervals for a CLSC under the following assumptions that are not simultaneously permitted in current methodology:

1. Containers are continuously returned by distributors to the manufacturer.
2. Both the return rate of RTI and the percentage of returned containers that are repairable are allowed to be random variables.
3. Returned containers travel through separate inspection and repair processes at finite rates.
4. Safety stock is established to buffer against uncertain container return and repairable container rates.

The next section reviews relevant research in the area of management of RTI and remanufactured inventory. Section 3 defines the CLSC model that will be utilized to determine RTI inventory policies for the manufacturer. Section 4 shows the calculation of the optimal inventory control parameters and presents a safety stock model needed to buffer against uncertain returns and an uncertain percentage of repairable containers. Section 5 provides analysis of the solution and managerial implications. Section 6 provides a case study that applies the model to decisions made by a beverage manufacturer. Section 7 concludes the paper by discussing limitations and future research.

2. Literature review

The prior work that is most closely aligned with this paper is a collection of studies that offer methods for jointly determining optimal policies for remanufacturing used inventory while also purchasing or producing new items, with both sources of inventory (or RTI) used to satisfy demand. Relevant work is summarized in Table 1 with further explanation below. The work reviewed here includes methodology for systems with deterministic, stationary demand where either repair or remanufacturing is required to return RTI to serviceable condition. A review by Guide and Van Wassenhove (2009) cites other applications that develop inventory policies other under sets of assumptions.

The work of Schrady (1967) first considered joint optimal repair and purchase lot sizes for repairable inventory items. Replenishment of inventory through either repair or purchase is assumed to occur instantaneously. This is referred to as an "infinite" purchase rate and repair rate in Table 1. The terms repair and recovery are both used in this stream of research to mean the process by which used inventory is repaired to reusable condition after it is returned to the manufacturer.

The solution developed by Schrady (1967) was extended by Nahmias and Rivera (1979) to consider fixed storage capacity for repaired and purchased items, with repairs occurring at a finite, non-instantaneous rate. Mabini et al. (1992) presents a variation on a model for determining repair and purchase lot sizes by incorporating returns of multiple types of items that share a finite repair capacity. Teunter (2001) presents a deterministic model to calculate optimal manufacturing and recovery batch sizes for reusable inventory items where recovery and production rates are assumed to be infinite. Batches of recovered items are alternated with newly produced items, or vice versa. Thoroe et al. (2009) study the effect of improving the return rate of RTI through RFID tracking on a model with similar characteristics to that of Teunter (2001). Richter (1996a,b) also solves a repair and production lot sizing with alternating new and used batches of inventory items, but includes a disposal option for items that cannot be repaired.

Koh et al. (2002) extended the model of Nahmias and Rivera (1979) to consider the case where the demand rate exceeds the repair rate. The policies developed are of two types. The first alternates one lot of recovered items with multiple purchase lots of new products. The second alternates one lot of new inventory with multiple batches of recovered items. Teunter (2004) incorporates finite and infinite production and recovery rates into a model designed to calculate optimal production

Table 1
Previous research on optimal repair and purchase lot sizes for returnable transport and inventory items.

Reference	Return flow	Return rate	Percent repairable (recoverable)	Purchase (or production) rate	Inspection rate	Repair (or recovery) rate	Container usage	Safety stock
Schrady (1967)	Continuous	Constant	Constant (100%)	Infinite	N/A	Infinite	Alternate new/used	N/A
Nahmias and Rivera (1979)	Continuous	Constant	Constant (100%)	Infinite	N/A	Finite	Alternate new/used	N/A
Mabini et al. (1992)	Continuous (multiple item)	Constant	Constant (100%)	Infinite	N/A	Finite	Alternate new/used	N/A
Richter (1996a,b)	Continuous	Constant	Constant (fraction)	Infinite	N/A	Infinite	Alternate new/used	N/A
Teunter (2001)	Continuous	Constant	Constant (100%)	Infinite	N/A	Infinite	Alternate new/used	N/A
Koh et al. (2002)	Continuous	Constant	Constant (100%)	Infinite	N/A	Finite (< or > demand rate)	Alternate new/used	N/A
Teunter (2004)	Continuous	Constant	Constant (100%)	Finite	N/A	Finite	Alternate new/used	N/A
Tang and Grubbström (2005)	Continuous	Constant	Constant (100%)	Infinite (with stochastic lead time)	N/A	Infinite (with stochastic lead time)	Alternate new/used	N/A
Thoroe et al. (2009)	Continuous	Constant	Constant (100%)	Infinite	N/A	Infinite	Alternate new/used	N/A
Kim et al. (2014)	Batch (single-supplier, single-retailer)	Constant (random return time)	Constant (100%)	N/A	N/A	Infinite	N/A	N/A
Kim and Glock (2014)	Batch (single-supplier, single-retailer)	Random	Constant (fraction)	Infinite	Infinite	Infinite	Alternate new/used	N/A
Current paper	Continuous	Random	Random (fraction)	Infinite	Finite	Finite	Simultaneous mixture of new/used	Yes

and repair lot sizes. Tang and Grubbström (2005) assume remanufacturing and new production replenished inventory items instantaneously after a stochastic lead time. Kim et al. (2014) is a model of a single-supplier, single-retailer supply chain where RTI are employed to ship a perishable product whose value deteriorates over time. All containers are assumed to return to the supplier in one shipment with a random return time.

Kim and Glock (2014) designed a model for inventory control in a closed-loop supply chain that implements RTI. The manufacturer selects control parameters for the inventory system to minimize expected total inventory costs, which are the sum of fixed, variable, and holding costs associated with inspecting, repairing, and purchasing containers. The control parameters are the length of time between container purchases and the number of repair and inspection lots per cycle. The authors describe the potential of RFID tracking to reduce the variability in the return rate distribution, thus improving inventory policies and reducing costs.

Of articles reviewed in this section, the structure of the Kim and Glock (2014) model is the one that is most similar to the one presented in this paper. There are some important differences. Kim and Glock (2014) model a single-supplier, single-retailer supply chain where RTI return to the supplier in batches, whereas this paper assumes RTI return to the facility continuously via multiple distributors. Both papers assume the proportion of containers returned is random, while here we also assume the proportion returned that can be repaired is random. Kim and Glock (2014) assume repaired containers are added to serviceable inventory at an infinite rate, whereas the current paper assumes containers are added at a finite rate as they are repaired. Demand in the new model is fulfilled via a simultaneous combination of newly purchased and repaired containers, as opposed to alternating batches of repaired and purchased RTI. This paper discusses holding safety stock to buffer against uncertainty in returns and the proportion of RTI that can be repaired. Some of the differences are also noted in Table 1.

3. Closed-loop supply chain model

3.1. Overview

The closed-loop supply chain model considered in this paper is shown in Fig. 1. During a specified time period, a company utilizes production lots with a quantity of d containers each to package its product. Only a fraction αd of these containers are returned, with $(1-\alpha)d$ being the fraction lost. Upon return, the αd RTI are added to the inventory of used containers. The inventory buckets are denoted by ovals in Fig. 1.

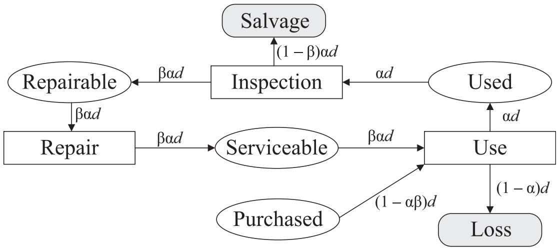

Fig. 1. Flow of containers in the closed-loop supply chain.

The RTI in used inventory are subjected to an inspection, upon which a fraction of these $\beta\alpha d$ are deemed to be reusable. These are added to the inventory of repairable containers. A quantity $(1-\beta)\alpha d$ containers are not reusable but can be sold for a salvage value. Once repaired, the $\beta\alpha d$ containers are added to the inventory of serviceable containers. New containers in the amount $(1-\alpha\beta)d$ are held in the purchased container inventory and added to the serviceable containers to meet production requirements. The parameters α and β are referred to as the *return rate* and *percent repairable* and are random variables with different realizations in each production lot. In this paper, we assume that $0 \leqslant \alpha \leqslant 1$ and $0 \leqslant \beta \leqslant 1$.

The model in Fig. 1 has some similarities to the one proposed by Kim and Glock (2014), most notably the existence of inventory stations for used, repairable, and serviceable RTI. One exception is the separation of production-ready containers into inventories of serviceable and purchased units; other differences are present in the assumptions used to model the inventory level as noted in Table 1 and mentioned in the last section.

Table 2 contains a definition of the notation used for the closed-loop supply chain model throughout the paper. Most of the notation has been retained from Kim and Glock (2014).

Table 2
Notation used for the closed-loop supply chain model.

Parameters	
d	Demand per unit of time
α	Fraction of containers returned after usage, $0 \leqslant \alpha \leqslant 1$
$E[\alpha]$	Expected value of return rate
$f_\alpha(\alpha)$	Probability density function (PDF) of return rate
β	Fraction of repairable containers from returned containers, $0 \leqslant \beta \leqslant 1$
$E[\beta]$	Expected value of fraction of repairable containers
$f_\beta(\beta)$	Probability density function (PDF) of repairable fraction
C_I	Fixed inspection cost per inspection lot
C_R	Fixed repair cost per repair lot
C_P	Fixed ordering cost per order for new containers
c_i	Variable inspection cost per inspected container
c_r	Variable repair cost per repaired container
c_p	Purchase cost for a new container
s	Salvage value of a non-repairable container
h_u	Annual holding cost for a used container
h_r	Annual holding cost for a repairable container
h_s	Annual holding cost for a serviceable container
h_p	Annual holding cost for a purchased container
i	Inspection rate per unit of time
r	Repair rate per unit of time
w	Working periods per year
D	Annual production demand, $w \cdot d$
Decision variables	
T_I	Length of an inspection run
T_P	Time between new container purchases
Definitions	
T_R	Length of a repair run, $T_I\beta i/r$
ETC	Expected total cost
TC	Total cost
FC	Fixed cost
VC	Variable cost
HC	Inventory holding cost
IUC	Inventory of used containers
IRC	Inventory of repairable containers
ISC	Inventory of serviceable containers
IPC	Inventory of purchased containers

3.2. Inventory models

In the model proposed here, inspection and repair occur at a constant rate per unit of time, and inspection and repair runs begin simultaneously. The number of containers processed in an inspection run is $Q_I = iT_I$, and the length of a repair run is the time required to process the repairable portion of those units in the repair station, $T_R = E[\beta]Q_I/r = E[\beta]iT_I/r$. Thus, the length of a repair run, T_R, is a function of the length of an inspection run, T_I. The inspection rate is greater than the repair rate, $i > r$. The install and repair rates are central to modeling the inventory level over time.

The inventory levels over time in the four buckets are displayed graphically in Fig. 2 and are described in the following sub-sections. Relaxation of the restriction that inspection and repair begin simultaneously will be discussed later in the paper.

3.2.1. Inventory of used containers

Due to the continuous nature of the process, the used containers are collected in the IUC until the maximum inventory level is reached, then an inspection run of length T_I begins. With iT_I containers processed each inspection run, the fraction of a year elapsed in each run is $iT_I/E[\alpha]D$. Thus, the idle time between inspection runs in units of time and the expected units accumulating in the IUC over that time are

$$\begin{aligned} &\text{Idle Time} = T_{idle} = w\frac{iT_I}{E[\alpha]D} - T_I; \\ &\text{Exp. Max. Inventory} = E\left[\left(w \cdot \frac{iT_I}{\alpha D} - T_I\right)\alpha d\right] = E[T_I(i - \alpha d)]. \end{aligned} \tag{1}$$

Inventory decreases at a rate of $i - E[\alpha]d$ containers per day while inspection is running and accumulates at a rate of $E[\alpha]d$ containers per day when inspection is idle. This is shown graphically in the top panel of Fig. 2.

3.2.2. Inventory of repairable containers

Inspection and repair begin simultaneously. The number of units processed in a repair run is $T_I E[\beta]i = rT_R$. During the inspection run the units accumulate in the IRC at a rate of $E[\beta]i - r$. Once the maximum inventory of $E[T_I(\beta i - r)]$ is reached, the IRC decreases at a rate of r per unit of time, which takes $E[T_I(\beta i - r)]/r$ time periods. The annual repair days and annual percentage of time repair is active are

$$\text{Annual Repair Days} = \frac{E[\beta]E[\alpha]D}{r}; \quad \text{Active Repair Percentage} = \frac{E[\beta]E[\alpha]D}{wr}.$$

The IRC inventory level over time is displayed in the second panel of Fig. 2.

3.2.3. Inventory of serviceable containers

During the period of time T_R that repair is active each cycle, the ISC increases by $E[r - \beta\alpha d]$ containers per unit of time. Once repair is idle, inventory decreases by a rate of $E[\beta\alpha d]$ units per period. This is shown in the third panel of Fig. 2. The expected maximum inventory level is $E[T_R(r - \beta\alpha d)]$.

3.2.4. Inventory of purchased containers

The inventory of purchased containers over time is shown graphically in the bottom panel of Fig. 2. The time between purchases T_P establishes the quantity of containers purchased each cycle of $Q_P = E[T_P(1 - \alpha\beta)d]$ and this is the maximum inventory level. Inventory decreases at a rate of $(1 - E[\alpha]E[\beta])d$ each time period. Of course, it is possible that repairable returns in a particular cycle could average less than $E[\alpha]E[\beta]d$ per unit of time. In the model considered in this paper, we will account for this by holding a safety stock of used containers in the IUC and IRC.

3.3. Cost model

The total inventory-related costs for the fleet of RTI are $TC = FC + VC + HC$, with the components defined as follows:

$$FC = \frac{\alpha D}{iT_I} \cdot (C_I + C_R) + \frac{w}{T_P} \cdot C_P$$

$$VC = \alpha D(c_i - s + \beta(s + c_r - c_p)) + Dc_p$$

$$HC = \frac{T_I}{2}\left((i - \alpha d) \cdot h_u + \frac{\beta\alpha D}{wr} \cdot (\beta i - r) \cdot h_r + \frac{\beta i(r - \beta\alpha d)}{r} \cdot h_s\right) + \frac{T_P(1 - \beta\alpha)d}{2} \cdot h_p$$

The fixed costs are incurred once for each cycle in each inventory bucket, with the exception of the serviceable containers. Variable costs are based on the number of containers processed in each bucket, while holding costs are determined by the average inventory level at each stage. In the IRC bucket, the average inventory is multiplied by the percentage of time during

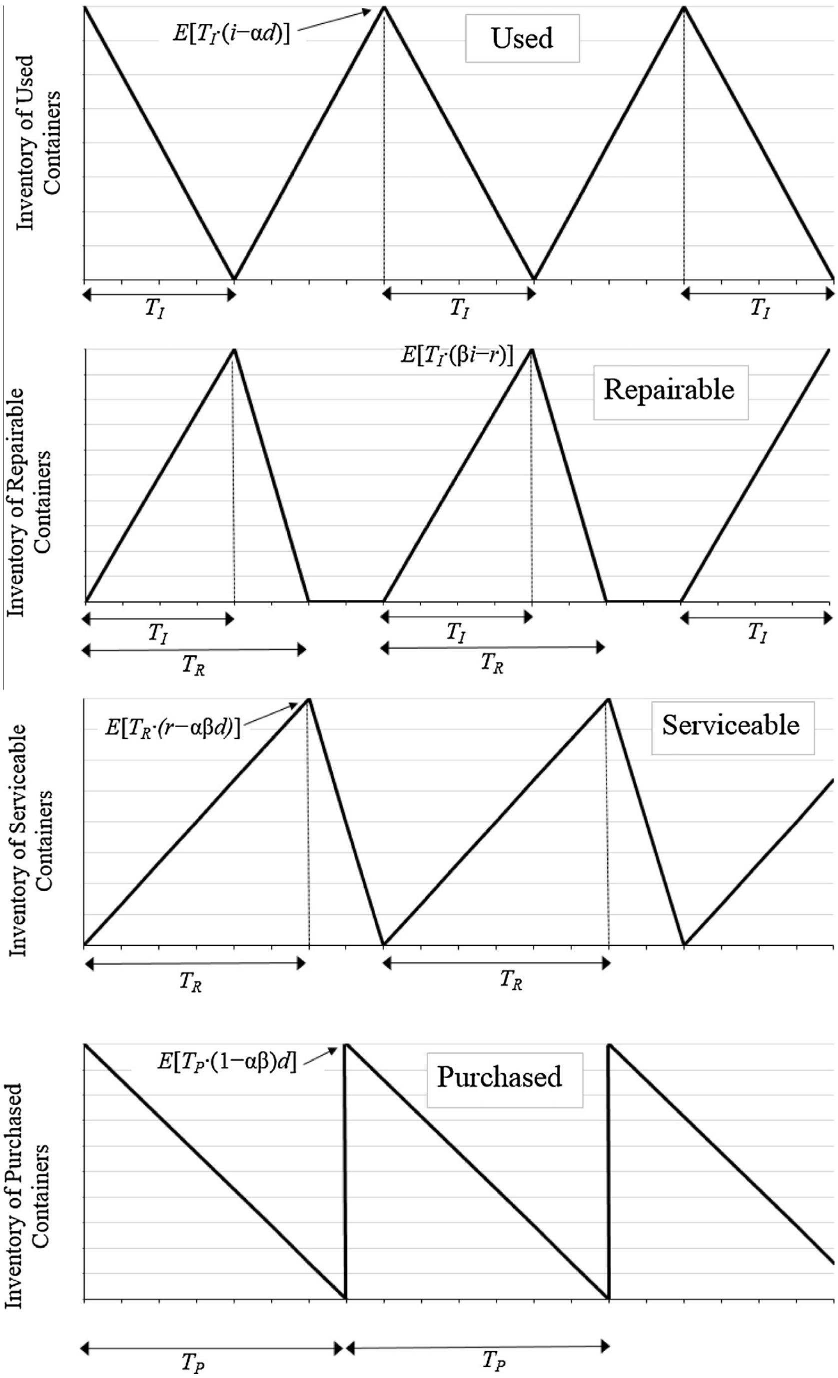

Fig. 2. Inventory levels in the four stages of the closed-loop supply chain.

the year that repair is active (and thus inventory is non-zero). The variable cost in the used bucket is offset by a salvage value obtained for the $E[(1-\beta)\alpha D]$ containers per year that do not pass inspection. The details of the calculation of these costs by category on an annual basis are shown in Table 3.

4. Control parameters

This section describes the inventory policies that will be used to operate the CLSC and manage the fleet of RTI. The total costs considered are the sum of all the cost terms detailed in Table 3, and the manufacturers objective is to minimize the expected value of these costs by choosing optimal values for its decision variables.

Table 3
Annual inventory costs.

Inventory bucket	Fixed costs	Variable costs	Holding costs
Used	$\frac{\alpha D}{iT_I}\cdot C_I$	$\alpha Dc_i-(1-\beta)\alpha Ds$	$\frac{T_I(i-\alpha d)}{2}\cdot h_u$
Repairable	$\frac{\alpha D}{iT_I}\cdot C_R$	$\beta\alpha Dc_r$	$\frac{\beta\alpha D}{wr}\cdot\frac{T_I(\beta i-r)}{2}\cdot h_r$
Serviceable	–	–	$\frac{T_I\beta i(r-\beta\alpha d)}{2r}\cdot h_s$
Purchased	$\frac{w}{T_P}\cdot C_P$	$(1-\beta\alpha)Dc_p$	$\frac{T_P(1-\beta\alpha)d}{2}\cdot h_p$

4.1. Length of inspection run and time between purchases

The manufacturer selects its inventory control parameters to minimize expected total cost as follows:

$$\begin{aligned}(T_I^*,T_P^*)&=\underset{(T_I,T_P)}{\text{ArgMin}}\int_0^1\left(\int_0^1 f_\alpha(\alpha)\cdot f_\beta(\beta)\cdot TC(\alpha,\beta,T_I,T_P)\,d\alpha\right)d\beta\\(T_I^*,T_P^*)&=\underset{(T_I,T_P)}{\text{ArgMin}}\;ETC[T_I,T_P].\end{aligned}\tag{2}$$

Examining the terms in the cost function reveals that the decision variables T_I and T_P do not appear simultaneously in any additive term. Thus, we can solve for the optimal values of both T_I and T_P as a function of the parameters in the problem. To determine the optimal value T_I^*, we solve $\partial ETC[T_I,T_P]/\partial T_I=0$ to obtain

$$T_I^*=\sqrt{\frac{2(C_I+C_R)D\cdot E[\alpha]\cdot wr}{Dh_r iE[\alpha](iE[\beta^2]r)+h_s i^2w(E[\beta]r-dE[\alpha]E[\beta^2])+h_u irw(i-dE[\alpha])}}.\tag{3}$$

The optimal value T_P^* is determined by solving $\partial ETC[T_I,T_P]/\partial T_P=0$ as

$$T_P^*=\sqrt{\frac{2C_Pw}{dh_p(1-E[\beta]\cdot E[\alpha])}}.\tag{4}$$

Proposition 1. *The solution (T_I^* and T_P^*) is a global minimum point for $ETC[T_I,T_P]$.*

Proof. The Hessian matrix for the expected total cost function is

$$H(ETC[T_I,T_P])=\begin{bmatrix}\frac{2(C_I+C_R)D\cdot E[\alpha]}{iT_I^3} & 0\\ 0 & \frac{2C_Pw}{T_P^3}\end{bmatrix}.$$

Since all the parameters are assumed to be positive and the expected value of the return rate is positive, the first and second principal minors of the Hessian matrix are always positive. The Hessian matrix is therefore positive definite and the stationary point (T_I^* and T_P^*) is a global minimum. □

The optimal solution provides a balance between fixed and holding costs in the various inventory stations, At the solution (T_I^* and T_P^*) expected holding costs and fixed costs incurred in the IPC are equal. Suppose there is a T_P where these are equal such that

$$\int_0^1\left(\int_0^1\left(\frac{T_P(1-\alpha\beta)d}{2}\cdot h_p\right)f_\alpha(\alpha)f_\beta(\beta)\,d\alpha\right)d\beta=\frac{w}{T_P}\cdot C_P.$$

The left side simplifies as follows

$$T_P\frac{1}{2}dh_p(1-E[\alpha]E[\beta])=\frac{w}{T_P}\cdot C_P.$$

Solving this equation for T_P gives the expression on the right-hand side of (4). A similar explanation can be utilized to show that at the solution (T_I^* and T_P^*), the sum of expected holding costs incurred in the IUC, IRC, and ISC stations is equivalent to the sum of fixed costs incurred in the IUC, IRC, and ISC.

4.2. Safety stock

This section discusses safety stock levels that can be established in the IUC and IRC to buffer against uncertainty in the return rate and repairable container percentage. Safety stock has been discussed in the context of a single-supplier, single-retailer supply chain by Glock and Kim (in press) and Hariga et al. (in press). Here we consider a method for establishing safety stock in a system where RTI return via multiple distributors on a continuous basis.

4.2.1. IUC safety stock

The expected maximum inventory in the IUC is $E[T_I(i - \alpha d)]$, which is equal to the number of containers that accrue in this inventory bucket during the time the inspection function is idle. Because return rate is uncertain, there is a possibility that the inventory level will not rise to $E[T_I(i - \alpha d)]$, which means that there will not be enough containers to support production. A solution is to establish safety stock at the IUC.

To determine an appropriate safety stock level, we need to examine the probability distribution for the number of containers in the IUC after the idle period ends for inspection. A simulation experiment was executed to construct this distribution. As an example, suppose that the cycle time, CY, of a container follows a lognormal distribution with parameters, $\mu = 3.867$ and $\sigma^2 = 0.77^2$, i.e. $CY \sim LN(3.867, 0.77^2)$. Next, assume the return rate of containers in a given period has a beta distribution, i.e. $\alpha \sim Beta(26.17, 2.01)$ and that demand per period is $d = 100$. The cycle time and return rate distributions are estimated from empirical data for the case study that appears later in Section 6.

Algorithm 1 is used to simulate the number of container returns that occur in period $T = 300$ for the example. The period $T = 300$ is an arbitrary production period at some point in future operations. This is done for $N = 100$ simulation trials to construct a distribution and perform a statistical test. For each simulation trial, the idea is to first simulate the return rate for a one period production lot. For each container to be filled in that period, simulate a uniform random variate and compare it to the return rate to see if the container is returned. If it will be returned, simulate the cycle time to see whether or not it is returned on day T. If so, count this as a forecast return for period T. This process is repeated for each period through day $T - 1$ and the forecast returns are totaled to get the complete return forecast for period T.

Algorithm 1. An algorithm to simulate container returns on a given day T.

INPUT: Probability distribution for Cycle Time
    Probability distribution for Return Rate
    d = demand per period
    N = number of simulation trials
OUTPUT: $R_T^{(1)}, \ldots R_T^{(N)}$ = forecast container returns on each simulation trial
    $E[R_T]$ = Expected forecast container returns
INITIALIZATION
$R_{total} \leftarrow 0$
FOR $k = 1, \ldots, N$
$R_{trial} \leftarrow 0$
    FOR $j = 1, \ldots, T - 1$
    $\alpha_j \leftarrow$ Random variate in $[0, 1]$ from Return Rate distribution
    IF $F_j > 0$ **THEN**
        FOR $i = 1, \ldots, d$
        $u_i \leftarrow$ Random variate from $U(0, 1)$
        $x_i \leftarrow 0$
        IF $u_i \leqslant \alpha_j$ **THEN** $x_i = 1$;
        $c_i \leftarrow$ Random variate from Cycle Time distribution
        IF $j + \lfloor x_i \cdot c_i \rceil = T$ **THEN** $R_{trial} = R_{trial} + 1$;
        END FOR
    END IF
$R_T^{(k)} = R_{trial}$
$R_{total} = R_{total} + R_{trial}$
END FOR
    $E[R_T] = R_{total}/N$

The simulation results in 100 trial values with a sample mean of 91.73 and a sample variance of 91.43. An Anderson–Darling test (Darling, 1957; Scholz and Stephens, 1987) calculated under the null hypothesis that these simulated observations are from a normal distribution with mean 92.87 and variance 92.87 has a test statistic of 1.17 and a p-value of 0.28. The null hypothesis that $N(92.87, 92.87)$ is the correct return distribution is not rejected. The values for the mean and variance $E[\alpha] \cdot d = 0.9287 \cdot 100 = 92.87$ are used to define a normal approximation to a Poisson distribution with rate 92.87 and this is used as the production lot return distribution.

The inventory level in the IUC at the time the inspection run starts is based on the production lot return distribution and T_{idle} as defined in (1). Assuming production lot returns are independent, total inventory at the start of the inspection run, $\tilde{R}$, is equal to

$$\tilde{R} = R_1 + R_2 + \cdots R_j + \cdots + R_{T_{idle}}$$

where R_j is the random variable for containers returned in production lot j. The mean and variance of $\tilde{R}$ are

$$E[\tilde{R}] = T_{idle} \cdot E[\alpha]d \quad \text{and} \quad Var[\tilde{R}] = T_{idle} \cdot (E[\alpha]d)^2.$$

Since we are using a normal approximation to the Poisson distribution as the production lot return distribution, the distribution for $\tilde{R}$ is also approximately normal and safety stock to achieve a desired service level SL is established as

$$\text{Safety Stock} = E[\tilde{R}] - k_{SL} \cdot \sqrt{Var[\tilde{R}]}$$

where k_{SL} is a value from the standard normal distribution associated with a cumulative probability equal to SL. For example, if $SL = 95\%$, then $k_{SL} = 1.645$.

Algorithm 1 was utilized to simulate return values for many different functional forms and parameter values for the cycle time and return rate distributions. For example, lognormal, normal, and gamma distributions were inserted for cycle time, and uniform and beta distributions were examined for return rate. A normal approximation to the Poisson was nearly always an adequate representation of the resulting production lot return distribution and the number of trial cases that failed the Anderson–Darling tests were well below 5% of the trials. The IUC safety stock model presented here appears to be a reasonable for solution for a wide variety of situations.

4.2.2. IRC safety stock

During each cycle, meeting production requirements depends upon passing $iT_I E[\beta]$ containers from inspection to repair. The number of containers in an inspection run is $Q_I = iT_i$, and each inspection lot is comprised of returns from $T_{Q_I} = Q_I / E[\alpha]d$ period demands. Define $N_I = \lfloor T_{Q_I} \rfloor$ as the number of full days of returns processed in inspection per cycle and $\varepsilon_I = T_{Q_I} - N_I$. The random variable for total number of inspected containers delivered to the repair station per cycle is

$$\tilde{I} = \alpha_1 \beta_1 d + \cdots + \alpha_j \beta_j d + \cdots + \alpha_{N_I} \beta_{N_I} d + \varepsilon_I \cdot \alpha_{\varepsilon_I} \beta_{\varepsilon_I} d,$$

where each of the α and β are independent random variables for return rate and repairable percentage in a given period production lot.

The IRC safety stock level is determined by using an approximate distribution for $\tilde{I}$. Two possibilities for producing this distribution are:

1. Simulate the number of inspections per cycle and use the trial values to fit a probability distribution to the simulated data.
2. Utilize a normal approximation with the theoretical mean and variance of $\tilde{I}$.

The Weibull distribution is an extremely close fit for the distribution of inspections per cycle if the first option is employed and α and β are modeled with beta distributions. The mean and variance required for the second option are:

$$E[\tilde{I}] = T_{Q_I} \cdot E[\alpha] \cdot E[\beta] \cdot d \quad \text{and} \quad Var[\tilde{I}] = \left(N_I d^2 + (\varepsilon_I \cdot d)^2\right) \cdot \left(E[\alpha]^2 Var[\beta] + Var[\alpha] E[\beta]^2 + Var[\alpha] Var[\beta]\right).$$

Under either option, the safety stock established for a given service level, SL, is

$$\text{Safety Stock} = E[\tilde{I}] - P_{(1-SL)}$$

where $P_{(1-SL)}$ is the percentile for one minus the service level percentage. These two options will be illustrated for the case study in Section 6.

5. Solution analysis

This section discusses some characteristics of the optimal inventory control policies and some implementation issues that should be considered by managers.

5.1. Cost parameters

In terms of the time between purchases, it is straightforward to see that purchasing less often is optimal when the fixed cost per order, C_P, is higher, whereas when the holding cost of purchased containers, h_p, increases the time between orders should be reduced. The fixed costs paid each cycle for inspection and repair, C_I and C_R, both have the effect of increasing the length of inspection runs as the parameter value increases. If fixed costs are higher, the manufacturer should allow more containers to build up in the IUC, then begin a longer inspection/repair run to clear the containers.

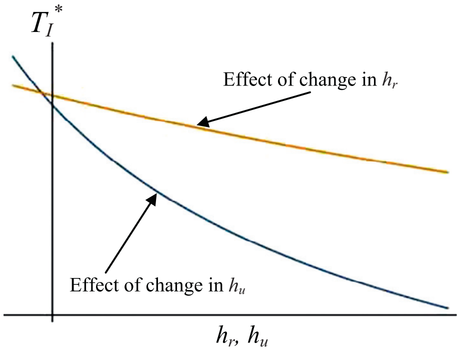

Fig. 3. The effect on optimal inspection run length of increases in h_r and h_u.

Unit holding costs for used and repaired containers both have the effect of decreasing the optimal length of an inspection run, although the holding cost, h_u, for used containers has a greater impact. Fig. 3 shows that when either h_r or h_u is held constant and the other decreases, T_I^* decreases at a faster rate for the same per unit change in h_u. This is partially due to the fact that since $\beta < 1$, more containers are inspected than are repaired.

5.2. Return rate and repairable percentage

Although return rate and repairable percentage are considered random variables in the model, only the expected values $E[\alpha], E[\beta]$, and $E[\beta^2]$ influence the optimal solutions in (3) and (4). The left panel of Fig. 4 shows that the optimal cycle lengths for both inspection and purchase increase as the return rate increases for a fixed set of cost and demand parameters. The effect is more dramatic for the purchase cycle length, T_P, particularly as α becomes close to 1.

The right panel of Fig. 4 illustrates that as the percentage of containers that can be repaired increases, the purchase cycle length also increases. The effect of $E[\alpha]$ and $E[\beta]$ on T_I^* and T_P^* is very similar. The inspection cycle length is not terribly sensitive to changes in the percentage of repairable containers.

The variability in containers returned and containers repaired per cycle is considered when establishing safety stock levels in the IUC and IRC.

5.3. Managerial considerations

The decisions regarding the length of an inspection run and the time between orders of new containers, with solutions in Eqs. (3) and (4), can be decoupled. This is in contrast to many of the inventory models presented in Table 1, where the number of repair lots and orders (purchase or production) are alternated. Those models are developed under a different set of operating assumptions.

The model here is implemented under the premise that the inspection and repair functions operate at maximum capacity for a specified length of time, then these processes are idle until they are required to produce additional serviceable containers to support production. In situations where labor and equipment can be redeployed to other useful functions or inspection and repair for other products during these idle periods, this is likely to be advantageous.

The optimal solution is determined under the scenario that inspection and repair begin simultaneously because this gives the lowest holding costs. If the resources are not available to run these two processes simultaneously, the solution can still be

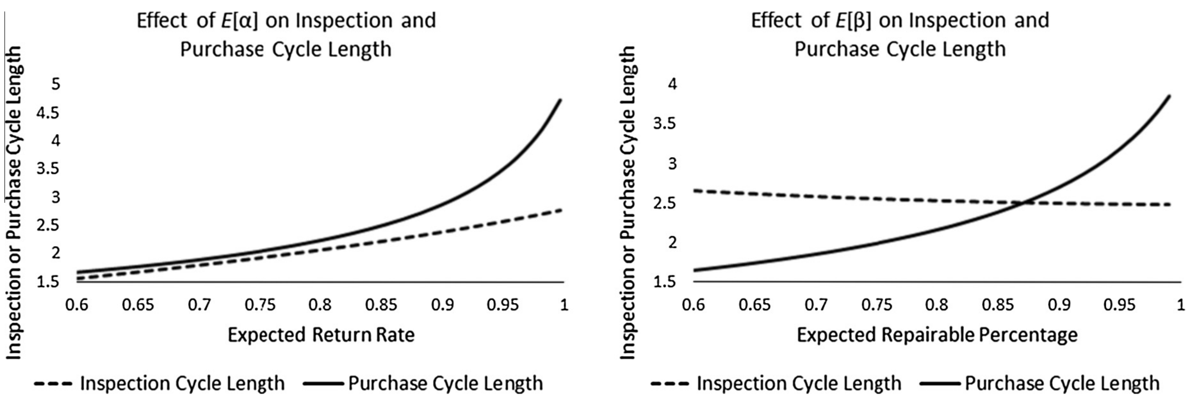

Fig. 4. The effect of expected return rate (left) and repairable percentage (right) on optimal inspection and purchase cycle lengths.

implemented at a higher holding cost. There are two scenarios that may arise when scheduling the inspection and repair functions.

Scenario 1: Inspection and repair overlap
This scenario occurs when the inspection rate, repair rate, and annual demand are such that inspection and repair must operate a combined number of days that is greater than the number of annual working days, or

$$E[\alpha]D/i + E[\alpha]E[\beta]D/r > w.$$

The effect of delaying repair start on the level of IRC inventory is shown in Fig. 5. The solid line replicates the pattern in Fig. 2. If repair is delayed until part of the inspection cycle is complete, repairable containers accumulate until repair begins as shown by the dashed line. Until inspection ends, repairable containers continue to accumulate ($\beta i > r$), but at a slower rate. Once inspection ends, the repair function clears out the remaining containers and transfers them to the ISC. The longer repair is delayed, the more inventory and holding cost accrue. Since the system is continuous in nature, the beginning inventory at the ISC can be adjusted to accommodate this change in the repair schedule and inventory in that bucket remains the same on average; holding costs in the IRC, however, will increase.

Scenario 2: Inspection and repair not required to overlap
The inspection rate, repair rate, and annual demand may also be such that the two functions are not required to overlap. This situation is relevant when

$$E[\alpha]D/i + E[\alpha]E[\beta]D/r \leqslant w.$$

Suppose the repair process is delayed until after the inspection process is completed. The containers processed in the inspection station will remain in the IRC and inventory will remain flat until repair begins. Once repair is initiated, the inventory level will decrease. This is shown in Fig. 6 for the case where the maximum delay is selected, i.e. repair is scheduled so it finishes immediately prior to the beginning of the next inspection cycle. The dashed line represents the inventory level that is experienced when the repair start is delayed. Clearly, this delay implies a much higher inventory level and holding cost in the IRC.

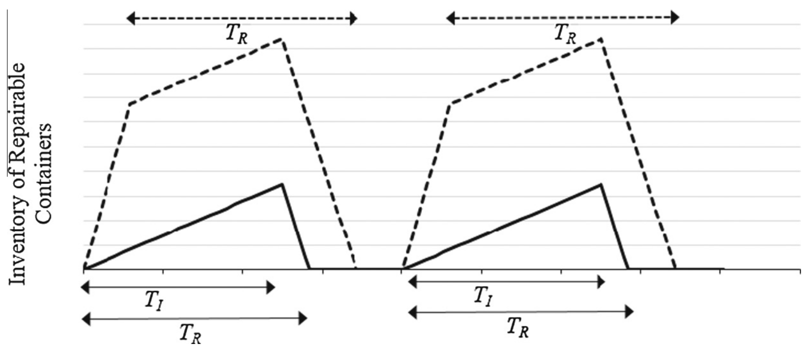

Fig. 5. IRC level under simultaneous start of inspection and repair (solid line) and delayed repair start (dashed line) when the two processes must overlap.

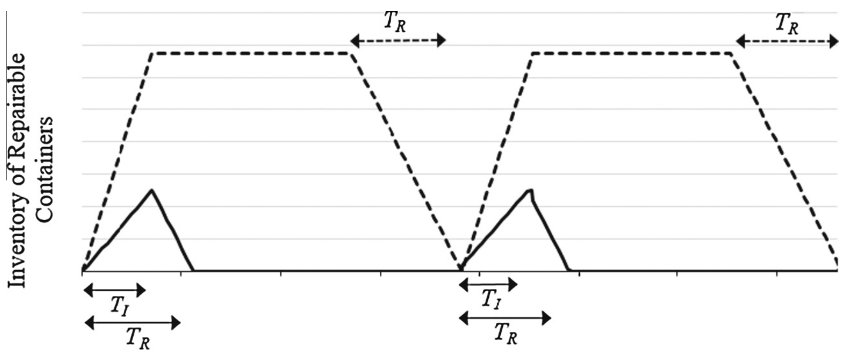

Fig. 6. IRC level under simultaneous start of inspection and repair (solid line) and delayed repair start (dashed line) when the two processes are not required to overlap.

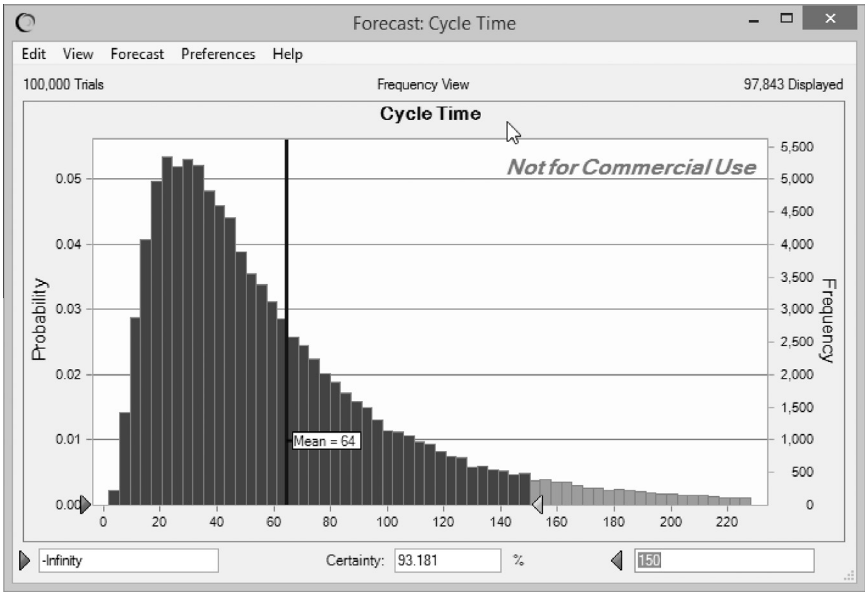

Fig. 7. Lognormal distribution for fill-to-fill cycle time.

The ability to delay the repair cycle beyond the start of the inspection cycle may provide managerial flexibility. A manager should have an understanding of the increased holding costs that will occur when selecting this option.

6. Case study

This section describes the case of a major brewery in the United Kingdom and the determination of an optimal inventory control policy for its fleet of returnable kegs. The brewery has a large distribution network with kegs returned continuously to the manufacturing facility by numerous distributors.

6.1. Cycle time and return rate distributions

Near the end of 2012, a random sample of 1000 containers returning to production facilities was selected and the backward fill-to-fill cycle time was calculated on all of these kegs. A portion of the kegs are fitted with an RFID tag that permits the company to scan each container at various points in the closed-loop supply chain. The unique tag IDs are recorded at each scan point and the tag ID and timestamp are stored in a database. Thus, a fill-to-fill cycle time is the time elapsed between the current fill and the previous fill.

The cycle time distribution fit to these cycle time observations is the lognormal PDF shown in Fig. 7. The chart shows that the mean cycle time is 64 days and that the probability of observing a cycle time less than 150 days is 93.181%. This fact is used to facilitate the determination of observations required to construct a distribution for return rates.

A method outlined by Cobb (2015) was utilized to create a return rate distribution from 38 daily observations of return rate collected over the production days between January 2, 2013 and February 23, 2013. The unique tag IDs for containers filled on each day are recorded, then these are matched with returns for the next 150 days to calculate the containers returned. Since some containers will have long cycles, this raw number of returned containers is divided by 0.93181 to obtain the adjusted returns, then this is divided by the original number filled to obtain the observation of return rate for that production lot. The process was repeated for each of the 38 production days and the results are shown in Fig. 8.

A beta distribution is fit to the empirical return rate observations via a maximum likelihood approach (Johnson and Kotz, 1970; Beckman and Tietjen, 1978), resulting in a $Beta(26.17, 2.01)$ PDF for return rate as shown in Fig. 9 and an expected return rate of $E[\alpha] = 0.9287$.

6.2. Inventory control policies

Parameters consistent with annual values for the specific product in this example are:

$$d = 8000, \quad w = 240 \text{ days}, \quad E[\beta] = 0.95, \quad i = 12,000, \quad r = 10,000, \quad s = 40.$$

The demand represents the typical daily value for the product and container size under consideration. Since RTI are returned continuously by multiple distributors in varying quantities, operationally it makes sense to collect the containers for a period of time, then perform the inspection and repair functions in batches. The finite inspection and repair rates are

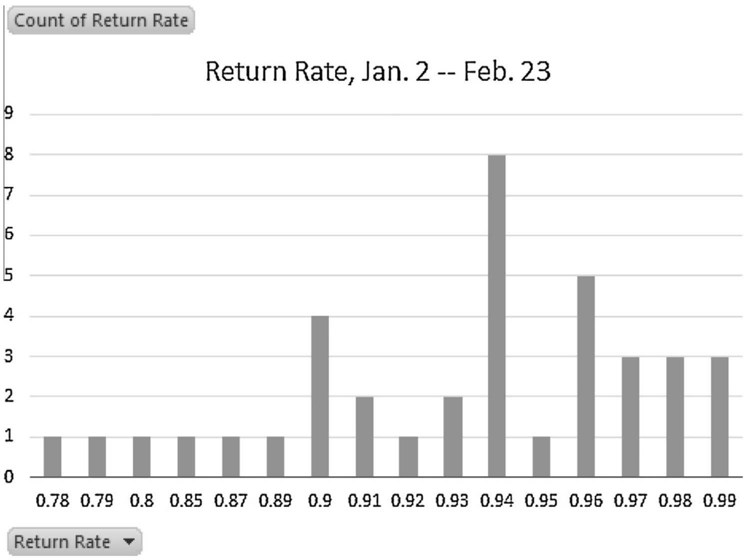

Fig. 8. Histogram of return rate observations for 38 production days between January 2 and February 23.

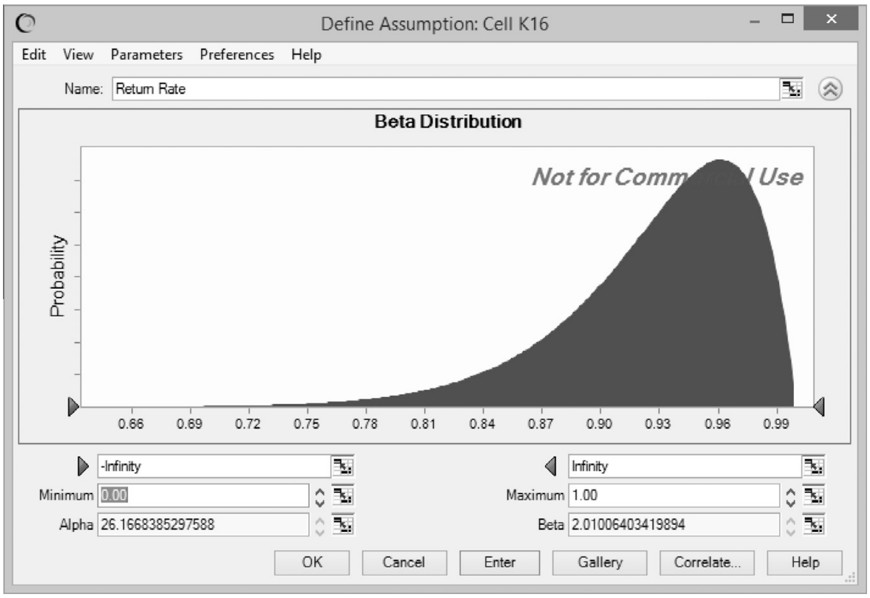

Fig. 9. Beta distribution for return rate developed from empirical data.

reasonable given the labor force and capacity in the facility. The repairable percentage is modeled with a $Beta(95, 5)$ distribution in this example based on input from managers regarding minimum, maximum, and most likely values. Fixed, variable, and holding cost assumptions are displayed in Table 4.

Using expressions (3) and (4) to solve for the optimal inventory control parameters gives $T_I^* = 2.5$ days and $T_P^* = 3.2$ days. Substituting T_I^* and T_P^* into (1) reveals that the idle time for the inspection operation is 1.52 days per cycle. Since $E[\alpha] \cdot d = 7430$, the maximum IUC inventory level is modeled with a $N(11{,}325, 11{,}325)$ distribution as shown in Fig. 10. For a 95% service level, the safety factor is $k_{SL} = 1.645$ and the safety stock is $1.645 \cdot \sqrt{11{,}325} = 175$. The safety stock provides a reserve of used containers that are available to enter the inspection process in the event that the IUC inventory does not build up to 11,325 containers at the beginning of the cycle. As long as at least 11,150 containers are available, enough will be on hand – on average – to meet production requirements. A service level of 99% would require a safety stock of 248 used containers.

Table 4
Cost assumptions for the example problem.

Inventory bucket	Fixed per lot (C)	Variable per container (c)	Holding cost (h)
Used	200	2	2
Repairable	400	4	3
Serviceable	–	–	5
Purchased	100	100	5

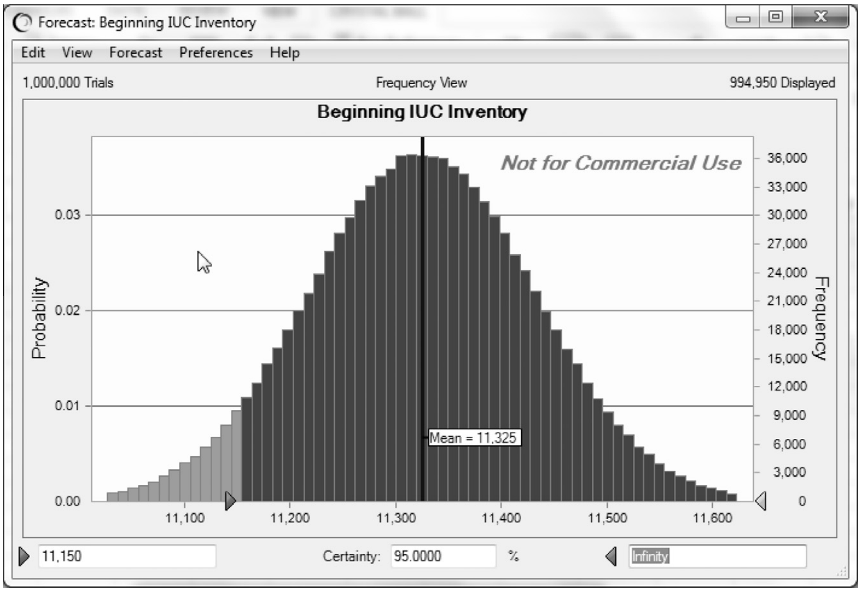

Fig. 10. Probability distribution for IUC maximum inventory and the service level provided by a safety stock of 175 containers.

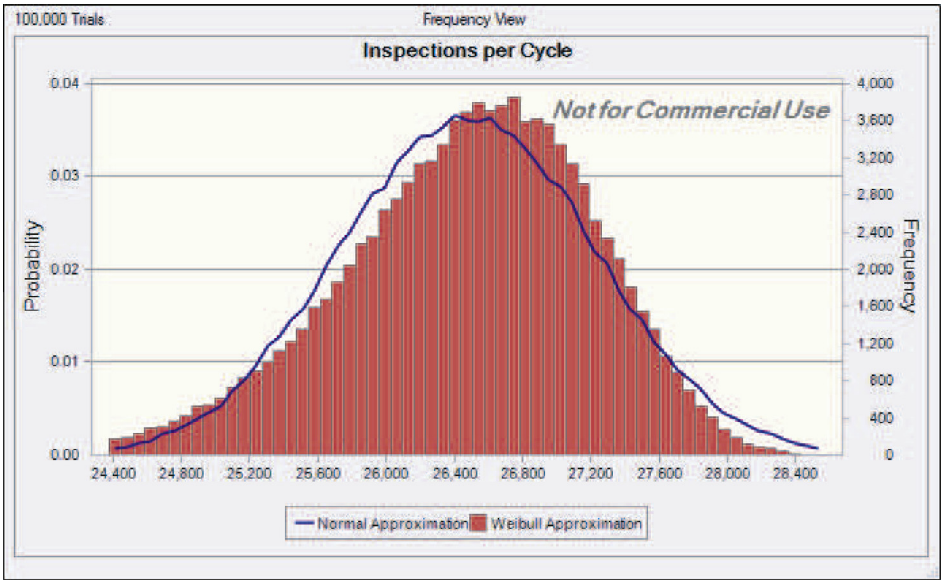

Fig. 11. Approximate distributions for inspections per cycle in the case study. A Weibull distribution is displayed as a simulated histogram and a normal approximation is shown with a solid line.

Table 5
Process scheduling and volume information at the optimal solution.

Process	Length of run (days)	Annual lots	Expected lot size	Expected annual volume (000s)
Inspection	2.5	60	29,819	1783
Repair	2.8	60	28,328	1694
Purchase	3.2	75	3007	226
Demand				1920

Table 6
Annual inventory costs at the optimal solution (000s).

Inventory bucket	Fixed costs	Variable costs	Holding costs	Total costs
Used	12	1783	11	1806
Repairable	24	6776	4	6804
Serviceable	0	0	21	21
Purchased	8	22,611	8	22,627
Total	44	31,170	44	31,258

Table 7
Increase in fixed and holding costs versus optimal solution for other possible inspection and purchase schedules.

	Weekly purchase (%)	Bi-weekly purchase (%)	Monthly purchase (%)
Weekly inspection	23	34	59
Bi-weekly inspection	96	107	132
Monthly Inspection	257	268	294

The mean and variance of the distribution of inspections per cycle calculated as shown in Section 4.2.2 are 26,467 and 748^2, respectively. The inspection process was also simulated to determine the necessary values for a three-parameter Weibull distribution, and this distribution was fit using the estimation tool in Oracle® Crystal Ball. The *p*-value for the Anderson–Darling test statistic is 0.45, indicated the Weibull distribution with location, scale, and shape parameters of 21,877, 4894, and 7.25 is a good fit. The normal and Weibull distributions for inspections per cycle are shown in Fig. 11. The normal distribution is shown as a solid line overlaid on a simulated histogram of the Weibull distribution. The 5th percentile of the Weibull distribution is 25,123, so obtaining a 95% service level requires holding safety stock of $26{,}467 - 25{,}123 = 1344$ containers at the IRC. The normal approximation indicates that safety stock of 1221 containers provides a 95% service level. The Weibull distribution has a heavier left tail than the normal approximation, so if the normal distribution is utilized to determine safety stock, increasing the service level slightly may be advisable.

Table 5 contains the process scheduling and annual volume information at the optimal solution. An inspection run starts about once every two-and-a-half days, while containers are purchased in lots about 3 days apart. The kegs required to produce 1,920,000 units are comprised of 1,694,000 inspected and repaired kegs and 226,000 new containers.

Table 6 shows the total costs in each inventory bucket and overall at the optimal solution. We can observe that total fixed costs equal total holding costs at the optimal solution. Table 7 gives the percentage increase in the combination of fixed and holding costs that would occur if other inspection and purchase schedules were implemented at periodic intervals (weekly, bi-weekly, and monthly are considered). Inspection and repair are idle for 1.52 and 1.18 days, respectively, of the four day inspection and repair cycle. If this idle repair time is scheduled at the beginning of the cycle (instead of scheduling inspection and repair simultaneously), an additional holding cost of $28,690 per year occurs. Of course, shorter delays imply smaller increases in the optimal holding costs.

7. Conclusions and limitations

This paper has presented an inventory control model for returnable transport items in a closed-loop supply chain. The inventory levels for used, inspected, repaired (serviceable), and purchased containers are explicitly modeled and the holding costs are accounted for in the models based on the average inventory levels. Fixed and variable costs are also detailed to provide a cost model that captures all inventory-related costs. The model assumes that inspection and repair occur at a constant, finite rate over time.

The optimal solutions for the inspection/repair and purchase functions are decoupled in the sense that the length of the inspection run selected does not affect the costs for purchased containers, and vice versa. Thus, these operations do not have to be coordinated, so long as the number of serviceable (repaired) and new containers available each production day is equal to demand. The total expected holding costs are equal to the total expected fixed costs at the optimal solution.

The return rate for containers filled in each production lot and the percentage of repairable containers are modeled as random variables; however, the optimal solutions are determined only by the expected values for these random variables. The variability is considered when establishing the safety stock levels. Safety stock can be established in the inventory of used containers to offset potential shortfalls that may occur in the containers returned during the period inspection is idle. Additional safety stock at the inventory of repairable containers ensures that random fluctuations in the percentage of containers that are deemed repairable during an inspection run do not halt operations.

There are some limitations to the model proposed in this paper. The optimal solution for inventory control parameters assumes that inspection and repair runs begin simultaneously. This assumption may be necessary if the finite inspection and repair rates are not too much larger than the demand rate. If inspection and repair can be accomplished at expedited rates, it may be advantageous to delay repair. A discussion of the increased holding costs that occur when repair is delayed was included in the paper, but under the assumption that the cycle lengths implemented were those found in the original model. Further study of scheduling of these functions under other arrangements may reveal that alternate types of inventory processing schedules are also cost-effective.

Additionally, if inspection and repair are accomplished at rates exceeding the demand rate, it might be possible to alternate inspection/repair and purchase lots to satisfy the RTI requirements dictated by demand. Many of the existing models in the literature (detailed in Table 1) design systems that alternate these functions, although none of the previous work included a system where inspection and repair were modeled separately for a single-supplier, multiple-distributor system where containers return to the manufacturing facility continuously. There is a possibility that a system of alternating repair and purchase batches might reduce costs when holding costs are assumed to be higher for new containers.

As with numerous models suggested in the literature for managing RTI and remanufactured inventory, the demand and repair rates considered in this paper are deterministic. Future research in this area can continue to focus on situations where inputs to the problem are random. This is particularly the case in practice for demand, which often has random and seasonal components.

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