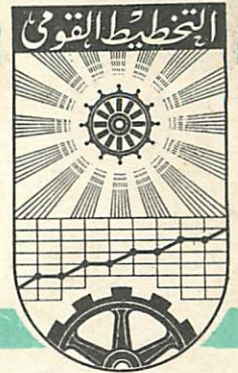


ARAB REPUBLIC OF EGYPT

THE INSTITUTE OF NATIONAL PLANNING



Memo. No. (1239)

Optimal And Approximate Ordering In
Solving Inventory Problems

By

Dr. Abdel-Kader Hamza

March 1979

Introduction

Since the development of the original lot-size inventory model in 1915, many researches were done analysing mathematical models for describing ordering policies for one or more products. Invariably, it was assumed implicitly that once units enter into inventory, they (live) for ever or else they expire after only a single planning period.

In most industrial environments, planning over the short run is essentially unaffected by problems of obsolescence, and the infinite-lifetime assumptions is not unreasonable.

However, there is a significant class of problems for which the perishable nature of the inventory cannot be ignored in the development of optimal ordering policies.

In the private sector the food industry is the most salient example of one concerned almost exclusively with inventory problems of a perishable nature. Inventory management is required at virtually every level of the food chain. Determining optimal planting policies, stocking policies at intermediate warehouse locations, and inventory policies in the retail marketplace are some examples. Although many canned or frozen products may be considered as having an essentially infinite lifetime, fresh produce, meat, etc are highly perishable in nature.

There are a number of significant inventory management problems arising in many fields such as the field of health administration that deal with perishable inventories. A very interesting case is blood banking.

The type of model we will deal with is as follows:

At the start of each period an order is placed for any number of fresh units, which are delivered immediately. During the period a random demand D (with known probability distribution F and density f) is either satisfied by available stock or backlogged.

In practice it is more realistic to allow the ordering cost to be composed of both fixed and proportional components; that is, it is of the form $K + CY$ for $Y > 0$, and 0 for $Y = 0$.

The purpose of our dealing with such a model is to consider the effect of the fixed charge, K , on the nature of the optimal ordering policy function.

Also we deal with the problem of determining both optimal and approximate ordering policies for a fixed-life perishable commodity when there is a fixed charge or set-up cost for placing an order. Our motivation is to construct an (s, S) type approximation.

1- Analysis of the problem,

For the sake of clarity, we state our assumption explicitly

- 1 - All orders are placed at the start of the period and received instantly (that is, Zero lead time)
- 2 - Demand in successive periods are independent identically distributed random variables with common distribution F and density f . in addition, $f(x) > 0$ for $x > 0$
- 3 - All stock arrives new.
- 4 - Inventory is depleted according to a (First in, First out) policy
- 5 - The following are the relevant costs:
 - a - ordering of C per unit ordered
 - b - set up of K per order
 - c - out dating of Q per unit that perishes.
 - d - shortage charged against the number of units that go short.
- 6 - if after m periods ($m \geq 2$) a unit has not been depleted by demand, it must be discarded at a cost given in $\delta(c)$
- 7 - All excess demand is back logged

We define X_i = amount of stock in inventory that is scheduled to out date in exactly i period (or equivalently that was acquired $m-i$ period ago). The state variable will be the vector quantity.

$$X = (x_{m-1}, x_{m-2}, \dots, x_1)$$

we will let y be the quantity of new product. The notation

$$x^{(k)} = (x_{m-k}, \dots, x_1) \quad \text{for } 1 \leq k \leq m$$

will be also used, where y will be understood to be y in this context. Normally, the solution to a one-period model would not take into account the effects of out dating since units do not expire for m periods. However, it is possible to include in an explicit way the effect of out dating by noting that the number of units of the current order y that will out date after m period is a random variable that depends upon both the vector x and the realizations of the demand over the next m periods. This is due to the fact that since we are using a (first input - first out put) depletion policy, all of y will necessarily have been used to satisfy demand before any further order. It is demonstrated in (3) and (4) that the expected number of units of the current order y scheduled to out date after m periods of demands is given by

$$G_n(x(n)) = \int_0^y G_{n-1}(x_{n-1}, x_{(n-2)}, \dots, x_{(n-m)}) f(x_{(n-m)}) dx_{(n-m)}$$

for $2 \leq n \leq m$
 and $G_1(x) = F(x)$

This is generally an extremely tedious computation which would have to be approached using numerical methods.

Formal analysis of the one period model will require a number of results concerning the G_n functions their derivatives we will use

the following notation:

If h is a function of an n dimensional vector U , then $h^{(i)}(u)$ represents the partial derivative of h with respect to its i th argument. note that if

$$u = (u_1, \dots, u_n) \text{ then}$$

$$h^{(i)} = \frac{\partial^i h(u)}{\partial x_{n-i+1}}$$

Also we let the functions $H_n(x(n))$ which can be computed by the recursion

$$H_n(x(n)) = \int_0^{x_n} H_{n-1}(x_{n-1} + x_{n-1} \frac{x - x_{n-1}}{x_n - x_{n-1}}) f(x_n - y) du$$

$$= H_{n-1}(x(n-1)) f(x_n)$$

for $2 \leq n \leq m$

and $H_1(x_1) = F(x_1)$

by differentiating both sides of the about equation with respect to x_n and integrating by parts, one obtain

$$H_n^{(1)}(x(n)) = \int_0^{x_n} H_{n-1}^{(1)}(x_{n-1} + x_{n-1} \frac{x - x_{n-1}}{x_n - x_{n-1}}) f(x_n - y) du$$

Since $H_1^{(1)}(x_1) = f(x_1) \geq 0$, it follows by induction that

$$H_1^{(1)}(x(n)) \geq 0 \text{ or equivalently that}$$

$H_n(x(n))$ is non - decreasing in the variables. The following results

indicates the relationship between the functions H_n and G_n and can be established by an induction argument.

Taking the following expression

$$(1) \int_0^y G_m^{(i)}(\mu, x) du = G_m(y, x) - \sum_{j=1}^{i-1} G_{m-j}(x(m-j)) H_j(y, \bar{x}(m-j))$$

for $2 \leq i \leq m$ where

$$\bar{x}(m-j) = (x_{m-1}, x_{m-2}, \dots, x_{m-j+1})$$

The left hand side of (1) represents the rate of change of the expected out dating with respect to x_{m-i+1} , which is on hand stock (i - 1) period old.

The first term on the right - hand side is the rate of change of the expected out dating with respect to y , which is new stock . hence one interpretation of expression(1) is that the expected out dating increases more rapidly in y than in each component of x . Note that expression 1 also implies that for $y > 0$

$$\int_0^y \left[G_m^{(i)}(\mu, x) - G_m^{(i-1)}(\mu, x) \right] du = G_{m-1}(x(m-i)) H_i(y, \bar{x}(m-i)) > 0$$

for $3 \leq i \leq m$

which mean that the expected out dating increases more rapidly with x_{m-i+1} than x_{m-i} in other words the expected number of units of the current order y to out date in m period is more sensitive to

change in the current inventory of newer stock than the older stock. This property must be reflected in the optimal ^{ordering} policy function as well

2 - A one - period Model with a set - up cost.

The purpose of looking at a single - period model is to determine the effect of out dating on the structure of the optimal policy when a fixed charge $K > 0$ is present. By substituting an expected out dating cost to be incurred m periods, rather than merely computing the expected cost incurred in the present period, the first - period the first - period model will take explicit account of the process dynamics. In approaching the $K = 0$ case in this fashion, H. Scarf (S) demonstrates that the optimal policy for the multi period model possesses all the properties of the optimal policy for the multi dynamic period model. It seems reasonable to conjecture that this holds when $K > 0$ as well computational experience bears out this conjecture. The structural results obtained are then used to motivate a suitable form for a simple approximation. Now let

$X = \sum_{i=1}^{m-1} x_i$, which has the usual interpretation as the total inventory on hand before ordering. Assuming that the cost of out dating of y is paid for when the order is placed, the expected present cost of ordering, set-up holding, shortage and outstanding is

$$cy + k(y) + \int_0^{x+y} h(x+y-t) f(t) dt + \int_{x+y}^{\infty} p(t-x-y) f(t) dt + \int_0^y \frac{G(u, x)}{m} du$$

when the cost of outstanding is paid for in the period of the outdating actually occurs, one must replace θ by $x^{m-1}\theta$ in the final term since the outdating charge then becomes a future cost. Chazan (6) discussed this point in details.

Now let

$$L(z) = \int_0^z h(z-t) f(t) dt + \int_z^y p(t-z) f(t) dt$$

and

$$B(x,y) = \begin{cases} cy + L(x+y) + \theta \int_0^y G_m(u,x) du & \text{for } y \geq 0 \\ L(x+y) & \text{for } y < 0 \end{cases}$$

$L(z)$ has the usual interpretation as the expected one-period cost of holding and shortage when Z is the inventory on hand after ordering.

When $y \geq 0$, $B(x,y)$ is merely the expected one period costs of ordering Y excluding the cost of set-up. It is convenient to extend $B(x,y)$ as a function of y to the entire whole line as indicated above even though disposal will not be allowed as a policy option.

By differentiating, it is easy to see that $B(x, y)$ is convex in y for all fixed vector x . We will denote by $y(x)$ the value of y that minimizes $B(x,y)$. A necessary and sufficient condition that $y(x) > 0$ is that $x < \bar{x}$, where \bar{x} solves $c + L(\bar{x}) = 0$.

If $x < \bar{x}$ and it is optimal to place an order, then it is optimal to order $y(x)$ and incur an expected cost of

$$K + B(x, y(x))$$

If no order is placed, then an expected cost $B(x, 0)$ is incurred.

Define $S(x)$ to solve: $B(x, y(x)) + K, s(x) \leq y(x)$.

from figure (1) it is clear that $s(x) < y(x)$ and the following equivalence hold because of convexity of $B(x, y)$ in y

$$s(x) > 0 \leftrightarrow B(x, 0) > B(x, y(x)) + K$$

$$s(x) \leq 0 \leftrightarrow B(x, 0) \leq B(x, y(x)) + K$$

Hence it is optimal to place an order for $y(x)$ of new product if and only if $s(x) > 0$. The function $y(x)$ determines the optimal order quantity, while $s(x)$ determines the ordering region. The optimal ordering function $y(x)$ possesses the following property:

$$0 > y^{m-1}(x) \gg y^{m-2}(x) \gg \dots \gg y^1(x) \gg -1$$

This may be seen from the result of (S)

This may be interpreted as follows:

If one increases the stock on hand before ordering by one unit (of any age), then the optimal ordering quantity will decrease but by less than one full unit. In addition, the optimal ordering policy function is more sensitive to changes in newer inventory than older inventory: if one increase x_i , then $y(x)$ decreases more than if one increases x_j , by the same amount whenever $i > j$.

We will show that the function $s(x)$ possesses essentially the

same structure as $y(x)$. In order to do this we need the following: (ϵ)

$$1 - B^{(i,m)}(x,u) > \epsilon \text{ for } 1 \leq i \leq m \text{ and for all } x \text{ and } u > 0$$

$$2 - B^{(i)}(x,u) = B^{(m)}(x,u) - c \cdot \sum_{j=1}^i G(x^{(m-j)})$$

$$3 - \epsilon \gg s^{(m-1)}(x) \gg s^{(m-2)}(x) \gg \dots \gg s^{(1)}(x) \gg 1$$

Depending on the smoothness of $B(x,y)$, the function $s(x)$ and $y(x)$ may be essentially parallel surfaces.

For $m = 2$ case, the situation is as in fig 2.

The functions $y(x)$ and $s(x)$ are pictured as the projections onto the (x,y) plane.

it is interesting to compare these results with $K = 0$ case. For $K=0$ the decision of whether to place an order dependent on x through the sum x . In that case, if the total inventory on hand entering any period was less than \bar{x} then it was optimal to place an order. However when $k > 0$, the ordering region becomes much more complex. The region boundary is given by the locus of points $(x \in \mathbb{R}^{m-1} : s(x) = 0)$, which will be a continuously differentiable hyper-surface in Euclidean $(m-1)$ space.

when $m=2$ the state vector x and x are identical. The set $(x \in \mathbb{R}^1 : s(x)=0)$ consists of exactly one point which means that for the $m=2$ case only there is a constant $s^* < \bar{x}$, such that it is optimal to place an order if and only if $x < s^*$.

Only for $m = 2$ does the optimal ordering region have the same form as in the non-perishable case- it seems likely that similar hold for the multiperiod dynamic problem.

In the following part we will show how to construct two simple approximations and compare their performance to the optimal policy.

3- An (s, S) approximation

The first problem encountered when constructing an approximation is the specification of the form of the approximate policy. Since it is well known that an (s,S) policy is optimal for the corres

pondering non-perishable problem this would seem like a reasonable form for an approximate policy for perishable problem. There is additional evidence for its suitability. From (7) and (9), a critical number or S policy (that is one that requires ordering to a fixed level each period) provides an excellent approximation to the optimal order quantity for $K=0$. That would tend to imply that the function $y(x)$ can be closely approximated by $S-x$. Since $s(x)$ and $y(x)$ possess essentially the same structure, $s(x)$ can also be closely approximated by the term $s-x$. The ordering region, namely $(x > s(x) > 0)$, becomes the region $x < s$.

Hence one obtains the (s,S) approximation:

if $x < s$ order to S ; otherwise, do not order. Having determined a suitable form for approximated at best we would like to obtain the optimal (s,S) policy. However, this appears to be an extremely difficult problem. For simpler case of $K=0$ Cohn(10) could obtain an explicit expression for the stationary distribution of the stock level only for the $m=2$ case. This computation would be substantially more difficult for $K > 0$.

In fact, determining the optimal (s, S) policy might be more difficult than determining the optimal policy itself.

Another possibility would be to determine an approximate (s,S) policy. Since we would be approximating in two directions (finding a suboptimal policy from a class of suboptimal policies), it would be important

to compare the performance of the approximation with that of the optimal policy .

Let $Z=x + Y$ represent the total quantity of inventory on hand after ordering (z may be thought of as an order up- to point). we will require

- 1 - The expected one - period costs of ordering, holding, shortage, and outdating to be approximated by a separable function of the variables x and z
- (Recall $x = \sum_{i=1}^{m-1} x_i$)

- 2 - The transfer function, $t(x,y,D) = t_{m-1}(x,y,D), \dots$
- $t_j(x,y;D)$,

the vector of starting inventories one period hence , when x is the current vector of inventories, y is the order quantity, and D is the demand in the period.

Formally, for $1 \leq j \leq m-2$

$$t_j(x, y, D) = \begin{cases} -x_{j+1} & \text{if } 0 \leq D \leq \sum_{i=1}^j x_i \\ -y + \sum_{i=1}^{j+1} x_i - D & \text{if } \sum_{i=1}^j x_i < D \leq \sum_{i=1}^{j+1} x_i \\ -0 & \text{otherwise} \end{cases}$$

$$\text{and } t_{m-1}(x, y, D) = \begin{cases} y & \text{if } D < x \\ y+x -D & \text{if } D > x \end{cases}$$

This form assumes full backlogging of demand.

The rationale for the approximate transfer functions that we will construct is based on the fact that both the starting inventories in each period and the number of units outstanding each period are random variables whose distributions converge when following a stationary(s,S) policy. (Cohen(2) has developed rigorous arguments to prove this for the case $s = S / 2$.)

We expect that similar results should hold for $K > 0$.

For convenience, we will henceforth use the notation x_n , $n \geq 1$ to represent the total inventory on hand at the start of period n , when following a stationary policy x_n will form a sequence of random variables that converge in distribution. Since our interest is in constructing a stationary approximation, we treat x_n and x_{n+1} as approximately identically distributed.

Let $V(z) = \hat{V}(x)$ represents the approximate expected one period costs of ordering, holding, shortage and outstanding, and $t(z, D)$ represent the approximate transfer function (that is, $B(x, y) \approx V(x) - \hat{V}(x)$) and $\sum_{i=1}^{m-1} t_i(x, y, D) \approx t(z, D)$

optimal policies for the approximate model will satisfy the functional equations :

$$G_n(x) = \min_{z \geq x} \left\{ k(z-x) + v(z) - \hat{V}(x) + \alpha \int_0^{\infty} c_{n+1}(z, u) \right.$$

$$\left. \text{for } 1 \leq n \leq N \quad \text{and} \quad c_{N+1}(\cdot) = 0 \right.$$

Note that periods are numbered forward and N is the length of the planning horizon. The actual for $v(z)$, $\hat{v}(x)$ and $t(z,u)$ will depend upon the particular approximate forms used for expected out-dating. In general, it is difficult to prove that an (s,S) policy is optimal for a model of this form.

Scarf's (10) original approach would require proving inductively that $V(z) - \hat{v}(x) + \alpha \int_0^{\infty} C_{n+1}(z,u) f(u) du$ is k -convex in the variable z .

For one of our models we can show that $c_N(x)$ is not convex for all values of $k = 0$.

However, by using a clever device developed by Veinott (16), we can convert this model to an equivalent one having only holding, shortage, and set up costs. To do so we will need the additional assumption that there is a return of $\hat{v}(x_{N+1})$ at the end of the horizon. The physical significance of this assumption will be discussed relative to the two forms of $\hat{v}(x)$ considered.

The total (approximate) expected discounted cost for N periods may be written as

$$E \left\{ \sum_{n=1}^N \alpha^{n-1} (KS(z_n - x_n) + V(z_n) - \hat{v}(x_n) - \alpha^n \hat{v}(x_{N+1})) \right\}$$

$$= E \left\{ \sum_{n=1}^N \alpha^{n-1} (KS(z_n - x_n) + V(z_n) - \alpha \hat{v}(x_n) (t(z_n, D_n))) \right\} - \hat{v}(x_1)$$

which results from using the relationship

$$x_{n+1} = t(z_n, D_n)$$

and shifting the term $\hat{v}(x_n)$ back one period the starting inventory, x_1 , is a fixed constant.

Define

$$w(z) = v(z) - \alpha E(\hat{v}(t(z, D)))$$

Then the total expected discounted cost for the N periods may be written

$$E \left\{ \sum_{n=1}^N \alpha^n [k \delta(z_n - x_n) + W(z_n) - \hat{V}(x_1)] \right\}$$

The final term is ignored as it is a constant that does not affect the computation of the optimal policy.

The optimal solution of the approximate model will now satisfy the functional equations

$$C_n(x) = \min_{z \geq x} \left\{ K \delta(z-x) + W(z) + \alpha \int_0^{\infty} c_{n+1}(t(z, u)) f(u) du \right\}$$

We will consider two different forms for the approximate one - period cost and transfer function.

In (9) it is demonstrated that

$$G_m(A, x) \leq F^{m*}(A+x)$$

where F^{m*} is m fold convolution of the one - period demand distribution, F_1 . It follows that the expected outdating may be approximated

by $H(z) - H(x)$ where

$$H(t) = \begin{cases} \int_0^t f^{m*}(u) du & \text{for } t \geq 0 \\ 0 & \text{for } t < 0 \end{cases}$$

from this bound it follows that

$$V(z) = cz + L(z) + \alpha H(z) \text{ and}$$

$$\hat{V}(x) = cx - \alpha H(x)$$

The approximate transfer functions are obtained by using the identity:

$$x_{n+1} = z_{n+1} - D_n$$

number of units perishing in period, n. In this case we have

$$x_{n+1} \approx z_n - D_n + H(z_n) \approx z_n - H(z_n) + H(x_{n+1})$$

Since x_{n+1} and x_n are respectively approximated distributed for long n, This suggests that the approximate transfer function satisfy the functional equation

$$t(z_n - D_n) = z_n - D_n - H(z_n) + H(t(z_n, D_n))$$

This appears to be a difficult equation to solve, but since $H(z_n)$ is likely to be small compared to z_n ,

$$H(t(z_n - D_n)) \approx H(z_n - D_n)$$

and we obtain the approximation

$$(z_n - D_n) = z_n - D_n - H(z_n) + H(z_n - D_n)$$

It now follows that, ignoring constant

$$W(z) = ((1 - \alpha)z + L(z) + (\alpha + \alpha c)H(z) - \alpha(c+c) \int_0^x H(z-u) f(u) du,$$

where the approximation

$$H(z - D - H(z) + H(t(z, D))) \approx H(z - D)$$

was again used in the final term. Note that by an integration by parts

$$\int_0^z H(z-u) f(u) du = \int_0^z F^{(m+1)*}(u) du.$$

The solvage value as assumption for this model (that there is a return of $\hat{V}(x_{n+1})$ at the end of the horizon) corresponds to a return of $cx_{n+1} + QH(x_{n+1})$ at the end of the horizon if $x_{n+1} > c$ and an additional cost of $-cx_{n+1}$ if $x_{n+1} < 0$ since we have implicitly assumed that the out dating cost is paid for when the order arrives, the term $QH(x_{n+1})$ may be considered to be a return on the out dating charge on stock that never actually out dates under the assumption that one order to z each period. Chazan and Gol (1) show that the expected out dating per period is bounded below by

$$z/m - a(z)$$

and above by $z/m - b(z)$, where

$$a(z) = \int_0^{z/m} m x f^{m*}(mx) dx + (z/m)(1 - F^{m*}(z))$$

and

$$b(z) = \int_0^{z/m} x f(x) dx + (z/m)(1 - F(z/m))$$

it is easy to see that $a(z)$ is the expected average demand over m period truncated at z/m and $b(z)$ is the expected demand in one period truncated at z/m . Note that by an integration by parts one obtains.

$$a(z) = \int_0^{z/m} (1 - F^{m*}(t)) dt$$

$$b(z) = \int_0^{z/m} (1 - F(t)) dt$$

A reasonable estimate of the expected out dating per period based on these bounds is

$$A(z) = z/m - 0.5(a(z) + b(z))$$

Using this approximation for the expected outdating per period, one obtain :

$$V(z) = (z + L(z) + \theta u(z)) ,$$

$$\hat{V}(x) = -c x \quad \text{and}$$

$$t(z, D) = z - D - M(z)$$

It follows then in this case that ignoring constant,

$$W'(z) = c(1 - \alpha)z + L(z) + (\theta + \alpha c) u(z)$$

In this case the salvage value assumption corresponds to the usual one, namely, that stock remaining at the end of the horizon is salvaged at a return of c per unit and excess demand is made up at a cost of c per unit.

It is also easy to see that $W(z)$ will be convex in z so that it again follows that an (n, s) policy will be optimal for this approximate model. We will denote by $(\underline{s}_1, \underline{S}_1)$ the stationary solution to the system of equations $c_n(x)$,

Computational Results

Having determined two approximate (s,S) policies, we must compare their performance with that of the optimal policy. Each (s,S) approximation is computed by solving the appropriate functional equations for $C_n(x)$ and iterating until the values obtained for (s,S) converged (value iteration). Policy convergence generally occurred within less than four periods. For convenience, we assumed that demands each period were discrete random variables and the reorder and order to points were integers.

The determination of an optimal policy we carried on in the following manner. If the cost of outdating is paid at the time the outdating actually occurs, then the one-period expected cost of ordering, holding, shortage, and outdating, $B(x,y)$, becomes $B(x,y) = cy + ks(y) + (x+Y) + \alpha \int_0^x (x-t)f(t)dt$. An optimal policy satisfies the functional equations.

$$A_n(x) = \min_{y \geq 0} \left\{ B(x,y) + \alpha \int_0^{\infty} A_{n+1}(t(x,y,u))f(u) du \right\} .$$

Charging the outdating cost in this manner is entirely consistent with charging it as we did in section 3. If the term $\alpha \int_0^x (x-t)f(t)dt$ is replaced with $\alpha \theta \int_0^y G_m(u,x) du$ above, then the stationary policy obtained by solving for $A_n(x)$ will be identical. This point is discussed in detail in a recent note (4). In order to be consistent θ must be replaced by $\alpha \theta$ in both expressions for $W(z)$

derived in the previous section. We chose this approach for convenience only. Note that when solving a discrete version of the problem integral signs must be wins and the minimization is over the set $y = 0, 1, \dots$

Computational experience indicates that the structure of the policy obtained for the one - period model in section 3 is identical to the structure of the optimal stationary policy . Because the state variable has dimension m^{-1} , the computations quickly become unrealizable as m increases for this reason we consider only the case $m = 2$ (A test of a few cases with $m = 3$ yielded results that were consistent with those reported here.) For $m = 2$ the optimal stationary policy is specified by a function $y^*(x)$ that is non increasing in x . As an example, suppose the demand distribution is geometric with mean 10 and $C = 5, P=10, H=1, \theta = 5, K=50, \lambda = 0.25$. for this particular case the stationary policy obtained was the following: For $x \leq 0, y^*(x) = -x$ and for $x \geq 0$

$x =$	0	1	2	3	4	5	6	7	8	9	10	11
			12	13								
$y^*(x) =$	24	23	22	21	21	20	19	19	18	18	17	17
	17	0										

This is certainly not an (s,S) policy. It would be necessary that $x+y^*(x)$ remain fixed in order to be bona. fide (s,S) policy . In

this case it was necessary to solve the recursive equations for $A_n(x)$ iteratively for seven periods before policy convergence was obtained. The approximate policies (s_1, S_1) and (s_2, S_2) obtained by solving for $C_n(x)$ were, respectively, $(3, 31)$ and $(12, 25)$. Each calculation required only two periods until policy convergence. Even for $m=2$, the difference in computing time is dramatic (about 5 minutes for the exact policy versus 10 seconds for the approximate policy on a POP 10). The computation times required for determining the approximate policies are essentially independent of the size of m , while that for the optimal policy increases insignificantly. Computations for $m=3$ require as much as 60 or more minutes of CPU time.

Having determined the optimal policy, $Y^*(x)$, and the approximations (s_1, S_1) and (s_2, S_2) the expected discounted cost associated with each must be computed in order to determine the effectiveness of each approximation. The average cost per period using the optimal policy and each approximation is obtained from an algorithm developed by MacQueen(5) to an accuracy of 0.01 cost units per period. Rather than report the actual costs obtained we give the percentage differences between each of the approximations and the optimal policy for the various cases tested. These results are given in Table I.

The particular probability distributions for the one period demand used in the study are (1) uniform on $(0, 20)$, (2) geometric with parameters $\theta = 1/11$, and (3) poisson with $\lambda = 10$. The

distribution parameters are chosen so that mean demand was 10 in each case. These particular distributions were considered in order to compare the effects of skewness and unequal variance (the variances are respectively, 33, 110 and 10).

An experimental design was chosen that considered the cost parameters (c, r, θ) at two levels each ($c=5$ and $c=15$, $r=20$, $\theta=5$ and $\theta=20$) and the test-up cost k at three levels ($k=10$, $k=50$, and $k=100$). The holding cost was $h=1$ and the discount factor $\alpha = 0.95$. This particular design was a compromise between the desirability of varying as many parameters as possible and the limitations of computing time.

Overall, the approximation (s_2, S_2) based on Chazan and Gal's bounds yielded somewhat lower expected costs, with on average percentage difference under 1% for each of the three demand distributions and a maximum error of 3.7% in all cases tested. The (s_1, S_1) approximation performed slightly better under uniform demand and significantly worse under geometric and poisson demands.

The largest errors invariably occurred for the case $K = 100$ although it is clear that there is a great deal of interaction between the cost parameters and demand distributions. (For example, for (c, r, θ) held fixed at $(15, 20, 20)$ the errors decreased under uniform and geometric demand and increased under poisson demand as K increased.)

Percentage Differences Between Optimal Approximate
Costs

Cost case (c,r,k,e)	Uniform		Geometric		Poisson		Fixed Parameters are $h=1, \alpha=0.95$
	(s_1, S_1)	(s_2, S_2)	(s_1, S_1)	(s_2, S_2)	(s_1, S_1)	(s_2, S_2)	
(5,20,10,5)	0.29	0.12	0.96	0.96	0.03	0.31	Fixed Parameters are $h=1, \alpha=0.95$
(5,20,50,5)	0.11	0.27	0.76	0.05	2.35	0.00	
(5,20,100,5)	0.04	0.04	4.03	2.96	1.85	0.93	
(5,40,10,5)	0.52	0.12	2.15	0.75	0.05	0.05	
(5,40,50,5)	0.24	0.24	4.35	0.22	1.15	1.15	
(5,40,100,5)	0.32	1.01	9.01	2.12	4.69	3.70	
(15,20,10,5)	0.36	0.19	0.24	0.24	0.10	0.10	
(15,20,50,5)	0.33	0.31	0.22	0.22	0.28	0.11	
(15,20,100,5)	0.00	0.89	0.28	0.03	2.11	0.22	
(15,40,10,5)	0.28	0.28	0.91	0.91	0.15	0.00	
(15,40,50,5)	0.11	0.57	0.72	0.10	0.30	0.00	
(15,40,100,5)	0.15	0.09	2.20	0.80	2.52	0.00	
(5,20,10,20)	1.13	0.77	0.65	0.80	0.56	0.56	
(5,20,50,20)	0.24	0.24	0.35	1.12	0.37	0.39	
(5,20,100,20)	0.15	0.15	1.18	0.44	2.78	0.87	
(5,40,10,20)	0.16	0.47	1.47	1.15	0.51	0.01	
(5,40,50,20)	0.26	0.26	1.39	0.67	0.61	0.00	
(5,40,100,20)	0.12	0.47	1.51	0.23	2.86	0.14	
(15,20,10,20)	0.48	0.35	0.24	0.41	0.02	0.02	
(15,20,50,20)	0.10	0.26	0.04	0.04	0.25	0.25	
(15,20,100,20)	0.12	0.00	0.51	0.00	0.53	0.53	
(15,40,10,20)	0.56	0.79	0.99	0.99	0.03	1.23	
(15,40,50,20)	0.26	0.19	0.30	0.05	0.10	1.10	
(15,40,100,20)	0.40	0.07	0.47	2.02	0.49	0.49	
Mean	0.31	0.34	1.46	0.72	1.03	0.51	

The performance of each of the approximations depends upon two factors- how closely the form of an (s,S) policy approximates the optimal (s,S) policy. We assumed the optimal value of s were the largest values of x such that $y^*(x) > 0$ which determines uniquely s . The optimal values of S are estimated by inspection the function of the $y^*(x)$. For example in the case listed above, $x + y^*(x)$ varied from 24 to 29 as x varied from 0 to 12. Averaging these values and rounding up we estimate the optimal s value to be 27. We expect that this method should yield fairly reliable estimates for the optimal (s,S) values when $m=2$. Estimates obtained for the optimal (s,S) values when $m = 2$.

Estimates obtained for the optimal (s,S) values as well as the values obtained for (s_1, S_1) and (s_2, S_2) are given for each case in Table II. For uniform demand both approximation yielded values that were consistently within one unit of each other and were generally within one unit of the optimal values (s_1, S_1) . For geometric demand the value of S_1 overshoot the optimal S in most of the cases thus accounting for the errors observed in Table I, the value of S_2 also overshoot S in many cases, but the differences were significantly smaller. For poisson demand, S_1 was consistently lower than S , while S_2 varied equally above and below. The degree of error was highest when K was large relative to the other cost parameters. Errors in s appeared to have a more significant effect than errors in S . For example, in cost (15, 40, 10, 5) under geometric demand, both s_1 and s_2 undershot the optimal s

by five units, but resulted in less than 1% error in the expected cost. A similar overshoot of s occurred in cost case (5,20,100,5) also under geometric demand and resulted in errors of 4.03 % and 2.96% , respectively.

An important point to note is that whenever the approximate and optimal (s,S) values were close, the expected costs were also close. This indicates that the form of an (s,S) policy is an excellent approximation to the more complex optimal policy $Y^*(x)$. In general both approximation yielded expected costs that were within 1% of the optimal with (s_2, S_2) generally giving better results. The largest errors can be anticipated for long - toiled demand distributions and large set-up cost. For which cases, where greater accuracy is needed, testing other values in the neighborhood of the approximate s value can be accomplished by imulating the inventory process. However the degree of precision obtained with the approximate policies derived here should be suitable for most applications.

Table II

Values obtained for (s_1, s_2)

Cost case (c, r, k, e)	Uniform			Geometric			Poisson		
	(s_1, s_2)	(s_1, s_2)	Opt(s_1, s_2)	(s_1, s_2)	(s_1, s_2)	Opt(s_1, s_2)	(s_1, s_2)	(s_1, s_2)	Opt(s_1, s_2)
(5,20,10,5)	(13,17)	(14,17)	(15,17)	(12,19)	(12,19)	(15,17)	(11,14)	(11,15)	(12,14)
(5,20,50,5)	(9,18)	(9,19)	(9,18)	(8,21)	(7,19)	(8,19)	(8,15)	(8,19)	(8,19)*
(5,20,100,5)	(6,19)	(6,19)	(7,19)	(5,26)	(5,25)	(5,20)	(6,18)	(6,22)	(6,20)*
(5,40,10,5)	(16,18)	(16,19)	(17,19)	(19,26)	(17,23)	(22,24)	(13,15)	(13,15)	(13,15)
(5,40,50,5)	(13,19)	(13,19)	(13,20)	(14,31)	(13,25)	(13,27)	(10,15)	(10,15)	(10,18)
(5,40,100,5)	(10,20)	(10,19)	(10,22)	(12,36)	(10,30)	(10,27)	(8,18)	(9,25)	(9,22)*
(15,20,10,5)	(11,15)	(12,15)	(14,16)	(9,13)	(9,13)	(12,13)	(11,13)	(11,13)	(11,14)*
(15,20,50,5)	(7,75)	(8,15)	(8,16)	(5,15)	(5,15)	(5,14)*	(8,14)	(7,15)	(8,15)
(15,20,100,5)	(5,17)	(5,19)	(5,17)	(3,16)	(3,15)	(3,14)	(5,15)	(5,19)	(6,18)*
(15,40,10,5)	(15,17)	(15,17)	(17,18)	(14,19)	(14,19)	(19,19)	(12,14)	(13,18)	(13,15)
(15,40,50,5)	(11,18)	(12,19)	(12,18)	(11,21)	(10,19)	(10,20)	(10,14)	(10,15)	(10,15)*
(15,40,100,5)	(9,18)	(9,19)	(9,19)	(8,24)	(8,22)	(8,20)	(8,15)	(8,19)	(8,19)
(5,20,10,20)	(11,14)	(11,15)	(14,15)	(8,12)	(9,13)	(12,12)	(11,13)	(11,13)	(12,14)
(5,20,50,20)	(7,15)	(7,15)	(8,16)	(5,14)	(5,15)	(5,13)	(8,14)	(7,15)	(8,15)
(5,20,100,20)	(5,17)	(5,17)	(5,16)	(2,16)	(3,15)	(2,14)	(6,15)	(5,19)	(6,18)*
(5,40,10,20)	(11,17)	(15,17)	(17,18)	(14,18)	(13,17)	(19,19)	(12,14)	(13,15)	(13,15)
(5,40,50,20)	(11,17)	(11,17)	(12,18)	(10,20)	(9,19)	(10,18)	(10,14)	(10,15)	(10,15)*
(5,40,100,20)	(9,18)	(9,19)	(9,18)	(8,21)	(7,19)	(8,19)	(8,15)	(8,19)	(8,18)
(15,20,10,20)	(10,13)	(11,13)	(13,14)	(7,10)	(7,9)	(10,10)	(11,13)	(11,13)	(11,13)
(15,20,50,20)	(6,14)	(7,15)	(7,14)	(3,11)	(3,11)	(4,11)*	(7,13)	(7,13)	(8,14)
(15,20,100,20)	(4,14)	(4,15)	(4,15)*	(1,13)	(1,11)	(1,11)*	(5,15)	(5,15)	(6,17)*
(15,40,10,20)	(13,16)	(14,17)	(16,16)	(11,15)	(11,15)	(17,17)	(12,14)	(13,13)	(13,14)
(15,40,50,20)	(10,16)	(11,17)	(12,17)	(8,16)	(8,15)	(9,15)	(9,14)	(9,13)	(10,14)
(15,40,100,20)	(8,16)	(9,17)	(9,18)	(6,17)	(6,19)	(6,16)	(8,15)	(8,15)	(8,16)

Note: The optimal values of s_1 and s_2 , in general only estimates. The cases where they are exact are worked with an asterisk.

1. D. Chonzan and S. Gal. "A Markovian Model product Inventory" Management science 23, 512-521 (1977)
2. H. Scarf. "The optimality of (s, S) policy in dynamic inventory problems. In Mathematical Methods in Social science P 196 - 202 1960 .
3. Van Zyt . inventory control for perishable commodities ph. D. University of north Carolina. 1964 .
4. A. F. Veinott. On the optimality of (s, S) inventory policies, new conditions and new proof SAIM 14 1067-1083 (1966)