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# Optimal Burn-In Testing

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## Abstract

A mathematical model permits determining the duration of payoff-optimized burn-in testing program. It is assumed that system failure may be due to either poor components or good components. The payoff is difference between the s-expected profit in the field activities and the total testing cost. The mathematical tool is the optimal stopping problem of Markov chain. A numerical example illustrates these concepts.

## 1. Introduction and Assumptions

Today we have very complex systems in our society and the factories. Before the system is used, a burn-in testing is usually considered as effective means of eliminating early failures due to defective elements in a laboratory environment. Suppose the system consists of  $J$  components. It is assumed that system failure may be due to either poor components, or good components. Before testing begin, the system has  $i(i=0, \dots, J)$  poor components. (Kigawa, S. [1])

The following assumptions are made:

- (1) The failure rate of the good components is  $\phi_0$ , and the failure rate of the poor components is  $\phi$  ( $\phi_0 < \phi$ ).
- (2) When the component fails, the failed component is replaced by the new one. The probability that the new component is good one is  $(1-p)$ , therefore the probability that the new one is poor one is  $p$ .
- (3) The testing cost per time is  $c$  (yen)/time.
- (4) After we stop the burn-in program, until the system failure in the field activities we acquire the profit  $r$  (yen)/time. After the system fails, it is supposed that the system can't be used any more.

The s-expected profit associated with the field activities are tradeoff with the costs of implementing a burn-in testing program.

A mathematical model permits determining the duration of optimized burn-in. A numerical example illustrates these concepts.

## 2. Formulation of the problem (Dynkin et al. [2])

Let the system exist at each instant of time in one of the states formed by a finite or

denumerable set  $E$  (state space). Here we consider the state as the number of poor components, therefore we set  $E = \{0, \dots, J\}$ .

The process just described is a birth and death process  $Y = \{Y(t); t \in R_+\}$  with state space  $E$  and transition function

$$P_{i,j}(t) = P\{Y(t+s) = j | Y(s) = i\},$$

for any  $t, s \geq 0$  and  $i, j \in E$ .

This process satisfies the following conditions,

- (1)  $P_{i, i+1}(h) = \lambda_i h + o(h) \quad (h \downarrow 0), \quad 0 \leq i \leq J-1,$
- (2)  $P_{i, i-1}(h) = \mu_i h + o(h) \quad (h \downarrow 0), \quad 0 \leq i \leq J,$
- (3)  $P_{i, i}(h) = 1 - (\lambda_i + \mu_i)h + o(h) \quad (h \downarrow 0), \quad 0 \leq i \leq J,$
- (4)  $P_{i, j}(0) = \delta_{ij},$
- (5)  $\mu_i = i\phi(1-p), \quad \lambda_i = (J-i)\phi_0 p.$

where  $o(h)$  possibly depends on  $i$ . The matrix

$$A = \begin{pmatrix} -\lambda_0 & \lambda_0 & 0 & 0 & \dots & 0 & 0 \\ \mu_1 & -(\lambda_1 + \mu_1) & \lambda_1 & 0 & \dots & 0 & 0 \\ 0 & \mu_2 & -(\lambda_2 + \mu_2) & \lambda_2 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \mu_J & -\mu_J \end{pmatrix}$$

is the generator of this process.

The underlying Markov chain  $X = \{X(n) : n \in N\}$  where  $N = \{0, 1, \dots\}$ , has the transition probabilities

$$Q(i, i-1) = q_i = \frac{\mu_i}{\mu_i + \lambda_i},$$

$$Q(i, i+1) = p_i = \frac{\lambda_i}{\mu_i + \lambda_i},$$

$$Q(i, j) = 0 \quad (|i-j| \neq 1), \quad i, j \in E.$$

The time  $\xi_i$  from arrival at the point  $i$  to exit from this point is distributed according to the exponential law

$$P\{\xi_i \geq t\} = \exp\{-(\lambda_i + \mu_i)t\} \quad (t \geq 0).$$

From now we consider the underlying Markov chain  $X$  and *r. v.*  $\xi_i$ . Let us suppose that we observe the path  $X(0), X(1), \dots, X(n)$ , and can at any instant  $n$  stop the migration system. If at the time of stopping the system is situated at the point  $i$ , we acquire a profit  $f(i)$ . In our case,  $f(i)$  is the *s*-expected profit until the first system failure, therefore

$$\begin{aligned} f(i) &= r \int_0^\infty \exp\{-[(J-i)\phi_0 + i\phi]t\} dt \\ &= \frac{r}{(J-i)\phi_0 + i\phi}. \end{aligned}$$

The costs associated with burn in testing is  $c$  (yen)/time. Clearly, the total payoff at  $X$

$(n)$  is  $f(X(n)) - c\tau_n$ , where  $\tau_n$  is the time for the  $n$ -th failure. The problem is stated as follows :

The underlying Markov chain  $X$  with transition probability  $Q(i, j)$  and the total payoff  $f(X(n)) - c\tau_n$  are given on  $E$ .

It is required to :

1) calculate the variable  $v(k) = \sup_n M_k(f(X(n)) - c\tau_n)$ , where  $n$  represent all the possible Markov times and  $M_k$  indicates the expectation for the initial position of the system at the point  $k$ .

2) find the Markov time  $n_o$  for which  $M_k(f(X(n_o)) - c\tau_{n_o}) = v(k)$ ,  $Q$  denote an operator to the formula for a function  $\varphi$

$$Q\varphi(k) = \sum_{\ell} Q(k, \ell)\varphi(\ell) \text{ (the one-step shift operator).}$$

By analogy with the theory of games, the variable  $v(k)$  is called the value of game, and the Markov time  $n_o$  is called the optimal stopping time.

Next we will show,

$$v(k) \geq Qv(k) - cM_k\tau_1. \tag{1}$$

We pick an arbitrary number  $\varepsilon > 0$  and denote by  $m$  the stopping time for which

$$M_{\ell}\{f(X(m)) - c\tau_m\} \geq v(\ell) - \varepsilon, (\ell \in E).$$

Obcause  $m$  is a function of  $\ell$ ,  $X(1), X(2), \dots$  : say  $m = t(\ell, X(1), X(2), \dots)$ . Now  $n = 1 + t(X(1), X(2), \dots)$ ; that is,  $n$  is the stopping time corresponding to the strategy which waits at  $X(0)$ , and if  $X(1) = \ell$ , then uses the strategy corresponding to  $m$  thereafter.

Then for any  $k \in E$ ,

$$\begin{aligned} v(k) &\geq M_k\{f(X(n)) - c\tau_n\} = M_k f(X(n)) - cM_k\tau_n \\ &= \sum_{\ell} Q(k, \ell) M_{\ell} f(X(m)) - cM_k\tau_1 - cM_{\ell}\tau_m \\ &= \sum_{\ell} Q(k, \ell) M_{\ell}\{f(X(m)) - c\tau_m\} - cM_k\tau_1 \\ &\geq \sum_{\ell} Q(k, \ell)\{v(\ell) - \varepsilon\} - cM_k\tau_1 \\ &= Qv(k) - \varepsilon - cM_k\tau_1 \end{aligned}$$

$$\therefore v(k) \geq Qv(k) - cM_k\tau_1.$$

Since  $n=0$  is a possible stopping time,  $v(k) = \sup_n M_k(f(X(n)) - c\tau_n) \geq M_k f(X(0)) = f(k)$  for all  $k$ .

To show that  $v$  is the minimal such function, let  $g$  be an another function satisfying (1) and suppose  $g \geq f$ .

For any stopping time  $n$ , since  $M_k f(X(n)) \leq M_k g(X(n))$ ,

$$M_k\{f(X(n)) - c\tau_n\} \leq M_k\{g(X(n)) - c\tau_n\} \leq g(k),$$

hence  $v(k) = \sup_n M_k\{f(X(n)) - c\tau_n\} \leq g(k)$ .

Summarizing, we have deduced that the value of the game  $v$  is the minimum function satisfying ;

$$\begin{cases} v(k) \geq \sum_l Q(k, l)v(l) - cM_k\tau_1, \\ v(k) \geq f(k), \\ v(k) \geq 0. \end{cases} \quad (k \in E)$$

In our case these equations become

$$\begin{cases} v(k) \geq p_k v(k+1) + q_k v(k-1) - \frac{c}{(J-k)\phi_0 p + k\phi(1-p)}, \\ v(k) \geq \frac{r}{(J-k)\phi_0 + k\phi}, \\ v(k) \geq 0. \end{cases}$$

Therefore we have

$$v(k) = \max \left\{ \frac{r}{(J-k)\phi_0 + k\phi}, p_k v(k+1) + q_k v(k-1) - \frac{c}{(J-k)\phi_0 p + k\phi(1-p)} \right\}.$$

### 3. The Optimal Stopping time

We denote by  $\Gamma$  the set of all state  $k$  in which the profit function  $f(k)$  is equal to  $v(k)$ . We call this set the support set. Before giving a numerical example, we give the following main result characterizing the optimal stopping time.

#### THEOREM. 1

*Suppose the state space  $E$  is finite. Then the time  $n_0$  of the first visit to the support set  $\Gamma$  is an optimal stopping time.*

To prove this we shall need the following Lemma

#### LEMMA. 1.

*Let  $m$  be the time of first visit to a fixed set  $\Gamma$  of states. If  $g$  satisfies (1), then the function  $h$  defined by*

$$h(k) = M_k[g(X(m)) - c\tau_m], \quad k \in E,$$

*also satisfies (1).*

*(Proof).*

Let  $m$  be the time to first visit to  $\Gamma$ , and let  $n$  be the time of first visit to  $\Gamma$  at or after time 1; that is, let

$$\begin{aligned} m &= \inf\{\ell \geq 0; X(\ell) \in \Gamma\}, \\ n &= \inf\{\ell \geq 1; X(\ell) \in \Gamma\}, \end{aligned}$$

If  $X(0) \in \Gamma$ , then  $m=0 \leq 1 \leq n$ ; if  $X(0) \notin \Gamma$ , then  $m = \inf\{\ell \geq 1; X(\ell) \in \Gamma\} = n$ . Hence,  $m \leq n$ ; and it is clear that both  $m$  and  $n$  are stopping times.

Since  $g$  satisfies (1),

$$h(k) = M_k[g(X(m)) - c\tau_m] \geq M_k[g(X(n)) - c\tau_n] \geq M_k[g(X(n)) - c\tau_n], \quad k \in E \quad (2)$$

On the other hand, if  $m = t(X(0), X(1), \dots)$  for some function  $t$ , then  $n = 1 + t(X(1), X(2), \dots)$ ; hence

$$M_k[g(X(n)) - c\tau_n | X(1) = j] = M_j[g(X(m)) - c\tau_m] = h(j)$$

which implies that

$$M_k[g(X(n)) - c\tau_n] = \sum_j Q(k, j)h(j).$$

This together with (2) show that  $h(k) \geq Qh$  and since  $h \geq 0$  obviously,  $h$  satisfies (1), ■

(Proof of Theorem 1.)

Let us examine the average total payoff

$$h(k) = M_k\{f(X(n_o)) - c\tau_{n_o}\} \tag{3}$$

which corresponds to the stopping time  $n_o$ . It is required to prove that  $h = v$ . According to the actual definition of the value of the game  $h \leq v$ . To show the reverse inequality, we will first show that  $h$  satisfies (1) and  $h \geq f$ ; then since  $v$  is the minimal function satisfying (1) and  $v \geq f$ ,  $v \leq h$  as well.

Inasmuch as  $X(n_o) \in \Gamma$  while  $f$  and  $v$  coincide on  $\Gamma$ , the function  $f$  may be replaced in eq. (3) by  $v$ , and (3) becomes

$$h(k) = M_k[v(X(n_o)) - c\tau_{n_o}], k \in E. \tag{4}$$

The function  $v$  satisfies (1) and by Lemma 1, (2) implies that  $h$  also satisfies (1).

Next we show that  $h \geq f$ . For  $k \in \Gamma$ ,  $P_k\{n_o = 0\} = 1$  and therefore

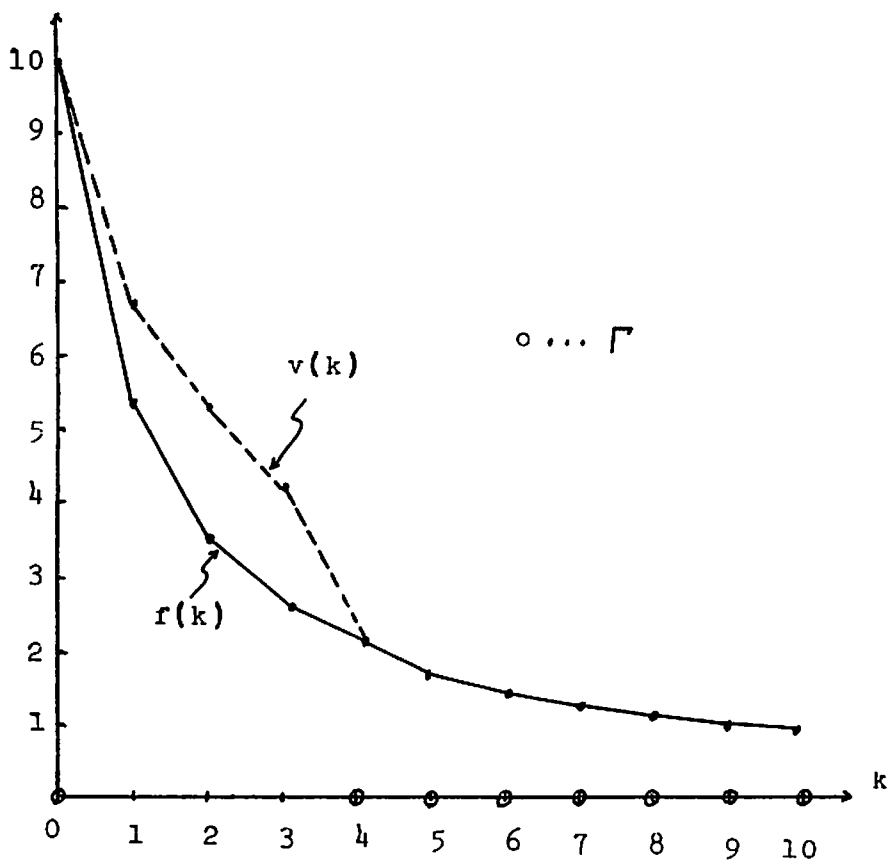


Fig. 1

$$h(k) = M_k[f(X(n_o)) - c\tau_{n_o}] = f(k).$$

Suppose for a moment that for some  $k \in \Gamma$ ,  $h(k) < f(k)$ . Since  $E$  is finite, there is a state  $j \in \Gamma$  at which the difference  $f(k) - h(k)$  is maximized; let  $c = f(j) - h(j)$  be this maximum value. By the way  $c$  is picked,  $h_1(k) = h(k) + c \geq f(k)$  and  $h_1(k)$  coincides with  $f(k)$  at the point  $j$ , and, as the sum of  $h(k)$  (satisfying (1)) and the positive constant  $c$ , is also satisfies (1). Consequently,  $h_1(k) \geq v(k)$  and  $f(j) = h_1(j) \geq v(j)$ . This means that the point  $j$  chosen outside the support set  $\Gamma$  belongs to  $\Gamma$ . The ensuing contradiction reveals the inequality  $h(k) < f(k)$  is inadmissible. The optimality of the strategy  $n_o$  is thus proved. ■

Next we will find the support set  $\Gamma$ .

$$v(k) = \max\left\{f(k), p_k v(k+1) + q_k v(k-1) - \frac{c}{a_k}\right\},$$

where  $a_k = (J-k)\phi_o p + k\phi(1-p)$ .

When  $v(k) = f(k)$ , since we have

$$v(k) \geq p_k v(k+1) + q_k v(k-1) - \frac{c}{a_k},$$

we get

$$f(k) \geq p_k f(k+1) + q_k f(k-1) - \frac{c}{a_k}, \text{ therefore,}$$

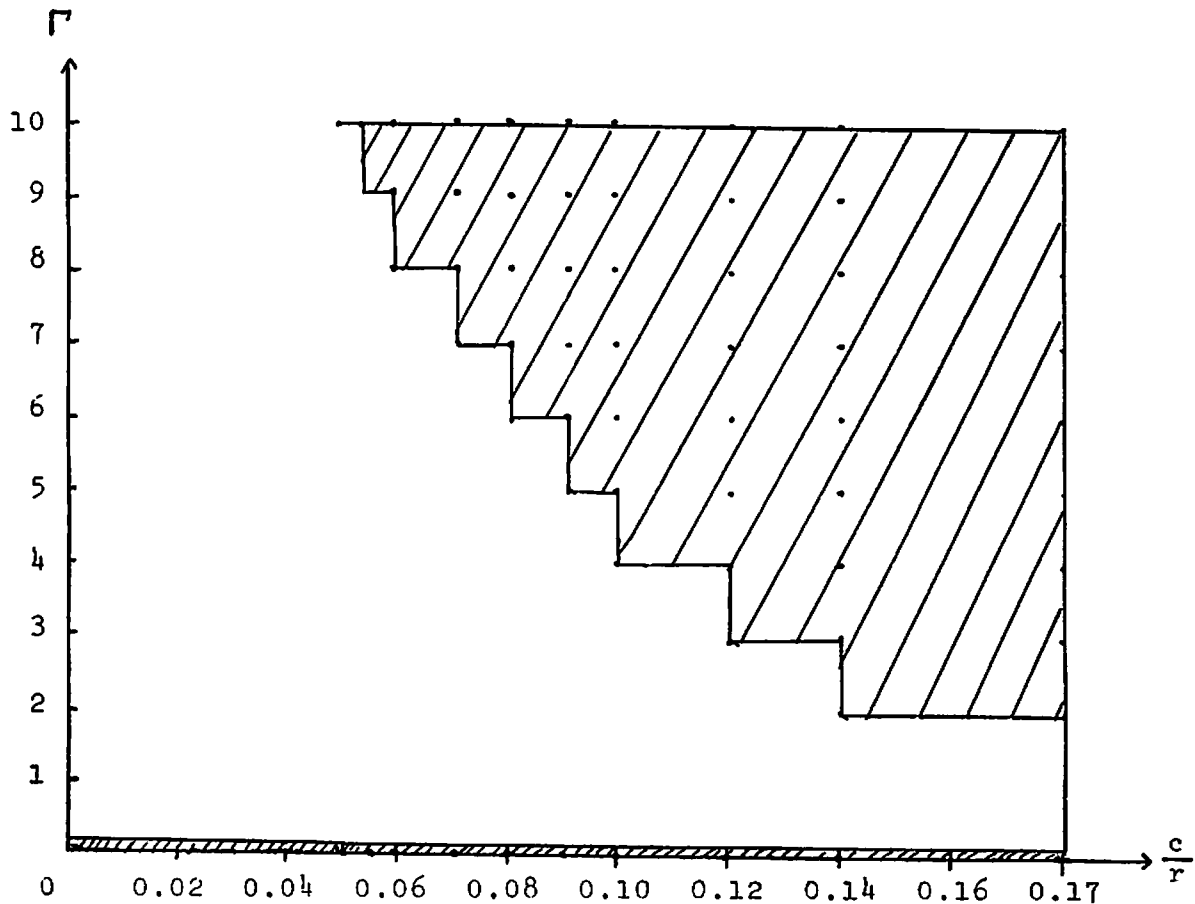


Fig. 2

$$\frac{k\phi(1-p) + (J-k)\phi_0 p}{(J-k)\phi_0 + k\phi} \geq \frac{(J-k)\phi_0 p}{(J-k-1)\phi_0 + (k+1)\phi} + \frac{k\phi(1-p)}{(J-k+1)\phi_0 + (k-1)\phi} - \frac{c}{r}.$$

[Numerical Example]

$N=10$ ,  $\phi_0=0.1$ ,  $\phi=1$ ,  $p=0.5$ ,  $c/r=0.1$ .

$\Gamma = \{0, 4, 5, \dots, 10\}$ .

It  $k \in \Gamma$ , we have  $v(k) = f(k) = \frac{r}{(J-k)\phi_0 + k\phi}$

It  $k \in \Gamma$ , we have  $v(k) = p_k v(k+1) + q_k v(k-1) - \frac{c}{a_k}$  and from this equation,  $v(1)=6.67$ ,

$v(2)=5.14$ ,  $v(3)=4.03$ .

Fig. 1 indicates a graph of the function  $f(k)$  and  $v(k)$  in the above case.

Fig. 2 represents  $\Gamma$  varying  $c/r$  from 0.00 to 0.17.

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