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APPROXIMATE CONFIDENCE INTERVALS FOR AN EXPONENTIAL PARAMETER F--ETC(U)

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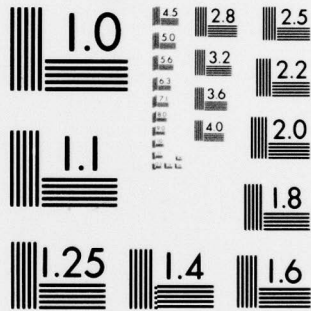
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University of Missouri-Columbia

**Approximate Confidence Intervals for
an Exponential Parameter from
a Sequential Life Test**

by

Kenneth B. Fairbanks

Technical Report No. 88
Department of Statistics

August 1979

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Approximate Confidence Intervals for an Exponential
Parameter from a Sequential Life Test

by

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University of Missouri - Columbia

Technical Report No. 88

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Richard W. Madsen, Project Director

This report is based on part of the author's Ph.D. dissertation.

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Approximate Confidence Intervals for an Exponential
Parameter from a Sequential Life Test

Abstract

↓
A sequential life test for the exponential location parameter was given by Epstein and Sobel (1955). This sequential test may be modified by truncating the test at r_0 failures and/or at total test time t' . There may be a need or a desire to also estimate the parameter after the test decision, using the test data. Bryant and Schmee (1979) have given confidence intervals for the mean lifetime, θ , from a truncated sequential test scheme, using methods which depend heavily on numerical techniques using a computer. A more flexible approach is considered using a martingale inequality which was also given by Wald (1947) in another context. Interval estimates are found which are functions of a positive constant d which must be chosen less than an upper bound which is itself a function of the number of failures observed. It is suggested that d be chosen as a function of the sample path (i.e., after the test is complete). The validity of the confidence coefficient comes into question if this posterior selection of d is employed. Simulation studies indicate that the resulting intervals are usually conservative.

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Approximate Confidence Intervals for an Exponential
Parameter from a Sequential Life Test

I. Introduction

The theory of sequential tests was developed by Abraham Wald (1947). Epstein and Sobel (1955) applied this theory directly to get a sequential life test in the exponential case. This requires the assumption that, if τ is the lifetime under consideration, the probability density function of τ is given by

$$f(\tau) = \begin{cases} \frac{1}{\theta} e^{-\tau/\theta} & \text{if } \tau \geq 0 \\ 0 & \text{elsewhere,} \end{cases}$$

where $\theta > 0$ is the average lifetime of an item. In the sequential exponential life test, the continuation region is bounded by two parallel lines in the failure-total time plane as depicted in figure 1.1. Initially n items are placed on test with or without replacement. At each failure time a decision is made to accept or reject the null hypothesis, or to continue the test. The test continues as long as the sample

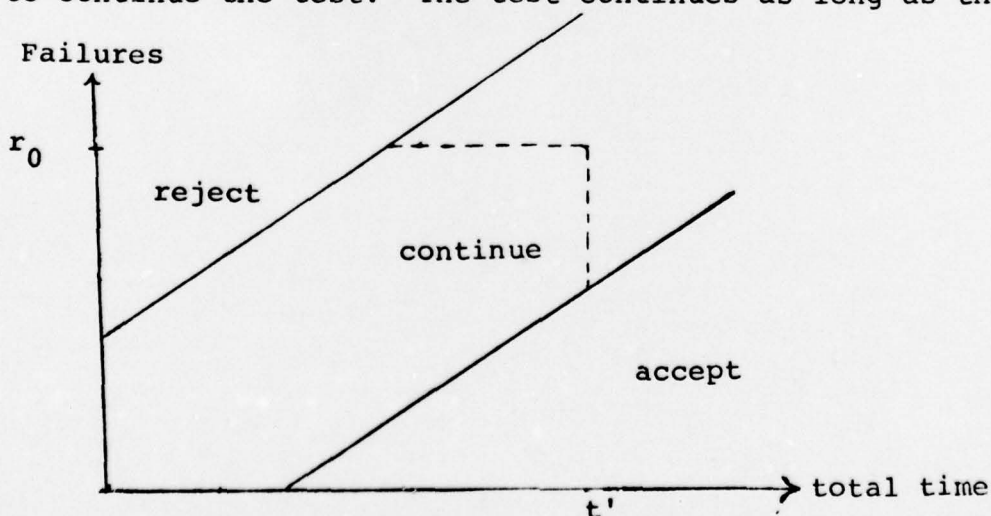


Figure 1.1. Sequential life test boundaries with time and failure truncation.

path remains inside the continuation boundaries. A modification of this test is to truncate the continuation region at r_0 failures and/or at total time t' . This truncation is also illustrated in figure 1.1. These truncated sequential tests are used by the Navy as reliability acceptance tests in MIL-STD-781C (1977). The tables given in MIL-STD-781C are for testing $H_0: \theta = \theta_0$ against $H_1: \theta = \theta_1$ where $\theta_1 < \theta_0$. Since values of θ considerably different from θ_0 or θ_1 could lead to the acceptance or rejection of H_0 , it may be of interest to also estimate θ following the test decision using the test data. This report gives a method for finding approximate confidence intervals for θ from the sequential test or the truncated sequential test.

Bryant and Schmee (1979) have found confidence intervals for θ following the truncated sequential tests in MIL-STD-781C. Their results require the application of a technique developed by Aroian (1963), and Epstein, Patterson and Qualls (1963). This technique, which Aroian calls the "direct method," reduces the continuation region to a grid of discrete points, including a set of points on the boundary of the continuation region. Using an iterative procedure and the properties of the exponential distribution, a probability for each point on the boundary can be found as a function of θ . Confidence intervals for θ can then be found using numerical techniques with the computer. A drawback of this

method is the amount of computation required and its dependence on the location of the continuation boundary. All computations may have to be repeated if the value of a test parameter is changed.

The objective of this report is to find a method which is easier to apply computationally and perhaps is more versatile. Our approach is to use density ratios defined at each failure time and apply an inequality which was given by Wald (1947). He suggested the inequality could be applied to sequential estimation problems. O'Brien (1973) uses this inequality to find sequential confidence intervals for the shape parameter of the gamma distribution. The inequality is also known to be a special case of a well known martingale inequality. Robbins (1970) and Lai (1976) also have results in sequential estimation from this inequality.

In this report, the inequality is applied in the manner used by O'Brien, wherein the density ratio involves a positive constant which must be chosen prior to the experiment in some optimal fashion. The derivation of the intervals in this report produces a constraint on this constant which is a function of the number of failures observed. Consequently, it is suggested that the intervals may be improved if the constant is chosen as a function of the sample path generated by the failure times. Whether this posterior method of selecting the constant invalidates the desired confidence coefficient remains an open question. Computer simulations indicate that the resulting intervals remain conservative, and that, while their width is

generally greater than the Bryant-Schmee intervals, the comparison is favorable in light of the utility of these intervals.

II. Testing without Replacement

If n items with exponential lifetimes are placed on test without replacement, then denote the ordered failure times as t_1, t_2, \dots, t_n . Define $X_i \equiv t_i - t_{i-1}$, where $t_0 = 0$. The $X_i, i = 1, 2, \dots, n$, are independent with density functions.

$$f(x_i; \theta) = \begin{cases} \frac{(n-i+1)}{\theta} e^{-\frac{(n-i+1)x_i}{\theta}}, & x_i > 0 \\ 0 & \text{elsewhere.} \end{cases}$$

Consequently we can write the joint density of X_1, X_2, \dots, X_k as

$$\prod_{i=1}^k f(x_i; \theta)$$

or as

$$f(x_1, x_2, \dots, x_k) = \begin{cases} \frac{n!}{(n-k)! \theta^k} e^{-\frac{1}{\theta} \sum_{i=1}^k (n-i+1)x_i}, & x_i > 0 \\ & i=1, 2, \dots, k \\ 0 & \text{elsewhere} \end{cases}$$

Equivalently,

$$f(x_1, x_2, \dots, x_k) = \frac{n!}{(n-k)! \theta^k} e^{-\frac{T_k}{\theta}},$$

where

$$T_k = \sum_{i=1}^k (n-i+1)x_i = \sum_{i=1}^k t_i + (n-k)t_k$$

= total time on test at t_k .

Also, define

$$Y_i = \begin{cases} \frac{f(x_1, x_2, \dots, x_i; d_1 \theta)}{f(x_1, x_2, \dots, x_i; \theta)} & \text{if } i = 1, 2, \dots, n \\ Y_n & \text{if } i > n. \end{cases}$$

At this point d_1 is an arbitrary positive constant. It can be shown quite easily that Y_1, Y_2, \dots is a martingale.

$$E[Y_{k+1} | Y_k, \dots, Y_1] = E \left[\frac{\prod_{i=1}^{k+1} f(X_i; d_1 \theta)}{\prod_{i=1}^{k+1} f(X_i; \theta)} \mid Y_k, \dots, Y_1 \right]$$

$$= \frac{\prod_{i=1}^k f(X_i; d_1 \theta)}{\prod_{i=1}^k f(X_i; \theta)} E \left[\frac{f(X_{k+1}; d_1 \theta)}{f(X_{k+1}; \theta)} \mid Y_k, \dots, Y_1 \right]$$

$$\begin{aligned} &= Y_k E \left[\frac{f(X_{k+1}; d_1 \theta)}{f(X_{k+1}; \theta)} \right] = Y_k \int_0^{\infty} \frac{f(x_{k+1}; d_1 \theta)}{f(x_{k+1}; \theta)} f(x_{k+1}; \theta) dx_{k+1} \\ &= Y_k . \end{aligned}$$

Thus, Y_1, Y_2, \dots is a martingale by definition. We can now use a well known martingale inequality (see Doob [1953]) which states that, for $\epsilon > 0$,

$$P[\max_{i \leq k} Y_i > \epsilon] \leq E \frac{(Y_k)}{\epsilon}, \text{ for all } k.$$

Since $E(Y_k) = 1$, the bound does not depend on k and the inequality becomes

$$P[\max_i Y_i > \epsilon] \leq \frac{1}{\epsilon},$$

or

$$P[Y_i \leq \epsilon, \text{ for all } i] \geq 1 - \frac{1}{\epsilon}. \quad (2.1)$$

We note that the inequality (2.1) was also given by Wald (1948), without relying on the martingale property, in the following lemma.

Wald Lemma: Let X_1, X_2, \dots, X_n be a sequence of random variables with joint density $f_{1n}(x_1, \dots, x_n)$, $n = 1, 2, 3, \dots$, under hypothesis H_1 and $f_{0n}(x_1, \dots, x_n)$ under hypothesis H_0 . Let α be a constant between 0 and 1. Then, under H_0 ,

$$P\left\{\left(\frac{f_{1n}}{f_{0n}}\right) < \frac{1}{\alpha}, \text{ for all } n\right\} \geq 1 - \alpha.$$

In the context of the sequential exponential life test

$$Y_i = \frac{\theta^k e^{-\frac{T_k}{d_1 \theta}}}{(d_1 \theta)^k e^{-\frac{T_k}{\theta}}} = d_1^{-k} e^{-\frac{T_k}{\theta} \left(\frac{1}{d_1} - 1\right)}.$$

Then, applying inequality (2.1), we get

$$P\left[d_1^{-k} e^{-\frac{T_k}{\theta} \left(\frac{1}{d_1} - 1\right)} \leq \frac{1}{\alpha}, \text{ for all } k\right] \geq 1 - \alpha.$$

Equivalently,

$$P\left[\frac{T_k (1-d_1)}{\theta d_1} > -k \ln d_1 + \ln \alpha, \text{ for all } k\right] \geq 1 - \alpha.$$

The right side of the inequality in brackets is positive if $d_1 < \alpha^{1/k}$. Finally we have, for $d_1 < \alpha^{1/k}$,

$$P\left[\theta < \frac{T_k (1-d_1)}{d_1 \ln \left(\frac{\alpha}{d_1^k}\right)}, \text{ for all } k\right] \geq 1 - \alpha. \quad (2.2)$$

We will refer to this upper bound on θ as U_k .
Inequality (2.2) can also be expressed as

$$P(\theta < \min_k U_k) \geq 1 - \alpha.$$

Likewise define

$$Z_i = \begin{cases} \frac{f(X_1, X_2, \dots, X_i; \theta/d_2)}{f(X_1, X_2, \dots, X_i; \theta)} & \text{if } i = 1, 2, \dots, n \\ Z_n & \text{if } i > n, \end{cases}$$

where d_2 is an arbitrary positive constant. From inequality
(2.1) we have

$$P[Z_k < \frac{1}{\alpha}, \text{ for all } k] \geq 1 - \alpha,$$

where

$$Z_k = \left(\frac{d_2 \theta}{\theta} \right)^k \frac{e^{-T_k d_2 / \theta}}{e^{-T_k / \theta}} = d_2^k e^{-\frac{T_k}{\theta} (d_2 - 1)}.$$

This yields

$$P[d_2^k e^{-\frac{T_k}{\theta} (d_2 - 1)} < \frac{1}{\alpha}, \text{ for all } k] \geq 1 - \alpha,$$

or

$$P\left[\frac{T_k(1-d_2)}{\theta} < -\ln(\alpha d_2^k), \text{ for all } k\right] \geq 1 - \alpha.$$

If $-\ln(\alpha d_2^k) > 0$, i.e., $d_2 < 1/\alpha^{1/k}$, then

$$P\left[\frac{T_k(1-d_2)}{-\ln(\alpha d_2^k)} < \theta, \text{ for all } k\right] \geq 1 - \alpha. \quad (2.3)$$

We shall refer to this lower bound on θ as L_k . If L_k is to be positive it must be true that $d_2 < 1$ and $d_2 < 1/\alpha^{1/k}$. Since $\alpha^{1/k} < 1$, we have the single constraint $d_2 < 1$. Here also, it is true that

$$P[\max_k L_k < \theta] \geq 1 - \alpha,$$

since (2.3) is valid for all k . Applying the Bonferroni inequality gives

$$P(\max_k L_k < \theta, \min_k U_k > \theta) \geq P(\max_k L_k < \theta) + P(\min_k U_k > \theta) - 1,$$

or

$$P[\max_k L_k < \theta < \min_k U_k] \geq 1 - \alpha + 1 - \alpha - 1 = 1 - 2\alpha.$$

This establishes the following theorem.

Theorem 2.1 If a sequential exponential life test is conducted without replacement and terminates with r failures, then a two-sided confidence interval for the

mean lifetime θ , having confidence coefficient at least $1 - 2\alpha$, is given by

$$\left[\max_{k \leq r} \frac{T_k(1-d_2)}{-\ln(\alpha d_2^k)} , \min_{k \leq r} \frac{T_k(1-d_1)}{d_1 \ln\left(\frac{\alpha}{d_1^k}\right)} \right]$$

where $0 < d_1 < \alpha^{1/k}$ and $0 < d_2 < 1$.

Due to the nature of the interval, it may happen that

$$\max_{k \leq r} L_k > \min_{k \leq r} U_k.$$

This leaves us with a confidence interval whose lower limit exceeds its upper limit. Computer simulation studies have shown that this inversion of the endpoints occurs infrequently, often as a consequence of an unusually early failure. To avoid this predicament, the following iterative scheme is proposed whenever

$$\max_{k \leq r} L_k > \min_{k \leq r} U_k.$$

- (1) The upper limit of the confidence interval, say U , is assigned the value of the next larger member in the set $\{U_k : k = 1, 2, \dots, n\}$.

- (2) If U is greater than the lower limit, say L , the endpoints are ordered correctly and the procedure stops.
- (3) If U is smaller than the lower limit, assign to L the value of the next smaller number of the set $\{L_k : k = 1, 2, \dots, n\}$.
- (4) If $L \geq u$ return to step (1).

Since inequalities (2.2) and (2.3) are valid for all k , the interval that results from applying this procedure will still have a confidence coefficient at least $1-2\alpha$.

Accept decisions in the sequential test occur between failure times. Consequently, if an accept decision occurs and j failures have been observed, the total time on test when the decision is made to accept H_0 , denoted by $T_{a,j}$ say, will exceed T_j , the total time on test at the j^{th} failure. Furthermore

$$\frac{T_{a,j}(1-d_2)}{-\ln(\alpha d_2^k)} > \frac{T_j(1-d_2)}{-\ln(\alpha d_2^k)}$$

and it may also be true that

$$\frac{T_{a,j}(1-d_2)}{-\ln(\alpha d_2^k)} > \max_{k \leq j} \frac{T_k(1-d_2)}{-\ln(\alpha d_2^k)} .$$

This suggests that we might shorten the confidence interval for θ by increasing the lower limit utilizing this

total test time at the time of an accept decision. Note that the upper limit cannot be improved in the same manner since there we seek the minimum of a set, and $T_{a,j} > T_j$ implies the minimum will occur at a failure time. The lower limit of the interval in Theorem 2.1 was chosen as the maximum of the set $\{L_k, k = 1, 2, \dots, r\}$. The following lemma admits the use of

$$\frac{T_{a,j}(1-d_2)}{-\ln(\alpha d_2^k)}$$

as the lower limit when an accept decision occurs.

Lemma 2.2 If the sequential life test terminates in an accept decision with j failures and total test time $T_{a,j}$, then

$$P \left[\theta > \frac{T_{a,j}(1-d_2)}{-\ln(\alpha d_2^j)} \right] \geq 1 - \alpha .$$

Proof: We note that this is an exponential life test, without replacement, which is observed for a total test time t' . This test can be shown to be equivalent to a Poisson process with parameter $\lambda = 1/\theta$ which is observed for actual time t' . We will apply that result here with $t' = T_{a,j}$. A well known result for a Poisson process (see Barlow and

Proschan (1975), Theorem 3.7) may be adapted as follows:

Given j failures in a Poisson process in $[0, T_{a,j}]$, the distribution of the failure times (here interpreted as actual times) T_1, T_2, \dots, T_j is the distribution of the order statistics from the uniform distribution over the interval $[0, T_{a,j}]$.

As a consequence, if y_i represents the observed value of T_i , then

$$f(y_1, y_2, \dots, y_j | j) = \frac{j!}{T_{a,j}^j},$$

and

$$P(j \text{ Failures}) = \frac{e^{-\frac{T_{a,j}}{\theta}} (\frac{T_{a,j}}{\theta})^j}{j!}.$$

Thus

$$f(y_1, y_2, \dots, y_j, j) = \frac{e^{-\frac{T_{a,j}}{\theta}}}{\theta^j}.$$

Now if we apply Wald's lemma in the manner leading to Theorem 2.1 letting

$$f_{1j} = \frac{d_2^j e^{-d_2 T_{a,j}/\theta}}{\theta^j} \quad \text{and} \quad f_{0j} = e^{-T_{a,j}/\theta}.$$

the conclusion of the lemma follows by the same algebraic manipulations.

There remains the problem of selecting the values of d_1 and d_2 which are in some sense optimal, or near optimal, while satisfying the given constraints. We shall say the values of d_1 and d_2 are optimal if they minimize the length of the confidence interval in Theorem 2.1. The constraint $d_1 < \alpha^{1/k}$, $k = 1, 2, \dots, r$, poses a dilemma. If d_1 is a fixed constant as the theory behind Theorem 2.1 requires, then it must be true that $d_1 < \alpha$. It is not likely that a value of d_1 in this range will be "optimal" in any sense of the word. On the other hand if a value of d_1 is chosen greater than α , and the test terminates with one failure, then there is no upper bound (other than $+\infty$) for the confidence interval.

The martingale inequality on which Theorem 2.1 is based has wide applicability. It is reasonable to suspect that in a specific application the bound may be quite conservative. Specifically the probability in Theorem 2.1 may considerably exceed $1-2\alpha$. This suggests that some liberties might be taken in selecting d_1 and d_2 without violating the probability inequalities in (2.2) and (2.3). Therefore, we propose to choose d_1 and d_2 as

functions of the sample path generated by the sequential test. The following scheme implements this proposal.

Treat U_k , $k = 1, 2, \dots, n$, as a function of d_1 and for each failure time, t_k , find the value of d_1 which minimizes U_k . This optimal value is found to be the root of the equation

$$g(d) = 1 - \left(\frac{1}{k}\right) \ln \alpha - d + \ln d.$$

Note that the solution is not dependent on T_k and so, for a given α , a set of optimal values of d_1 , say $\{d_{11}, d_{12}, d_{13}, \dots, d_{1n}\}$ can be computed by numerical methods. A table of these values, for several values of α , is given in Appendix 1. At each failure time, t_k , compute U_k using d_{1k} . Then if the minimum value of U_k occurs at t_m say, we set $d_1 \equiv d_{1m}$. The following lemma shows that for each k , the relationship $d_{1k} < \alpha^{1/k}$ will hold.

Lemma 2.3 . If d_{1k} is the root of the equation $g(d) = 1 - (1/k) \ln \alpha - d + \ln d$, then $d_{1k} < \alpha^{1/k}$.

Proof: First, $g'(d) = 1/d - 1 > 0$, which implies that $g(d)$ is increasing on the interval $(0, 1)$. Also $g(0) = -\infty$ and $g(1) = -(1/k) \ln \alpha > 0$. It follows that $g(d)$ crosses the axis once from below in $(0, 1)$. But $g(\alpha^{1/k}) = 1 - \alpha^{1/k} > 0$. Thus $d_{1k} < \alpha^{1/k}$.

In the same way, consider L_k as a function of d_2 and find the set $\{d_{21}, d_{22}, \dots, d_{2n}\}$ of values which maximizes

L_k for $k = 1, 2, \dots, n$. These values are the roots of the equations $h(d) = 1 - (1/k) \ln \alpha - \ln d - d^{-1}$ and are also tabled for some specific values of α in Appendix 1. If the maximum value of L_k occurs at t_{ℓ} , set $d_2 \equiv d_{2\ell}$. Using the same steps as in lemma 2.3, it is seen that $d_{2k} < 1$ for each k .

To clarify this procedure, consider the following example: Test plan I of MIL-STD-781C is used to test $H_0 : \theta = \theta_0$ against $H_1 : \theta = \theta_1$, where $\theta_0/\theta_1 = 1.5$, $\alpha = \beta = .1$. The test ends with an accept decision based on six observed failures. At each failure time, the total time on test was computed as were the upper and lower 95% confidence limits using (2.2) and (2.3) and the optimal values of d_1 and d_2 given in Appendix 1. These computations are summarized in Table 2.1. A lower confidence limit was also computed at the acceptance boundary as described by lemma 2.2, using $T_{a,6} = 13.91$. Failure times were simulated using $\theta = \theta_0 = 1.5$. According to our procedures based on Theorem 2.1, an approximate 90% confidence interval for θ is $[.984, 4.101]$ with $d_1 = .2628$ and $d_2 = .4244$. The Bryant-Schmee 90% confidence interval for this example is $[1.108, 4.681]$.

The second method is really a simplification of this first method. During computer simulations it was noticed that, for a fixed d_1 or d_2 , $\max_{k < r} L_k$ and $\min_{k < r} U_k$

TABLE 2.1
Computation Results for Confidence Interval Example

Failure k	Total Test Time T_k	d_{1k}	U_k	d_{2k}	L_k
1	1.362	.0187	72.649	.1741	.2371
2	2.623	.0900	14.572	.2601	.3411
3	4.618	.1589	9.690	.3181	.4896
4	4.815	.2159	5.576	.3615	.4351
5	5.389	.2628	4.101	.3959	.4267
6	12.555	.3020	6.928	.4244	.8880
$T_{a,6}$	13.91	--	--	.4244	.9838

usually occurred at or near t_r , the last observed failure time. Hence, if we set $d_1 \equiv d_{1r}$ and $d_2 = d_{2r}$ we should get results nearly the same as with the first method. It was also felt that this second method would be easier to justify analytically. Unfortunately, an analytic justification of either of these methods remains an unsolved problem. It is not known if these posterior methods of selecting d_1 and d_2 invalidate the probability inequalities (2.2) and (2.3).

To obtain some empirical conclusions, we conducted computer simulations of two truncated sequential test plans from MIL-STD-781C. At the time of test decision 60%, 80%, and 90% confidence intervals for the mean failure time θ were formed using both methods discussed here for selecting d_1 and d_2 . These confidence coefficients were chosen so that our results could be compared with those obtained by Bryant and Schmee (1979). Each simulation used 500 trials. Estimates of the confidence coefficient, and the average value of the endpoints were computed for our methods and for the Bryant and Schmee intervals. Partial results are given in Tables 2.2 through 2.5. It was noted that, when the test ended with an accept decision and one failure, the upper endpoint on the confidence interval was often very large, which tended to inflate the average endpoints. Because of this, the average endpoints were also computed excluding those trials which terminated in an accept

TABLE 2.2

Simulation Results for 90% Confidence Interval from
 MIL-STD-781C, Test Plan I; $\theta_0/\theta = 1.5$
 $\alpha = \beta = .1$

θ	Estimated Coefficient	Ave. Endpoints, at Least 1 Failure		Ave. Endpoints, at Least 2 Failures	
.5	.884	.307 ,	.917	.307 ,	.917
	.898	.259 ,	1.059	.259 ,	1.059
	.946	.256 ,	1.102	.256 ,	1.102
1	.912	.714 ,	2.399	.708 ,	1.637
	.917	.655 ,	3.208	.650 ,	1.760
	.964	.647 ,	3.228	.642 ,	1.804
1.5	.916	1.020 ,	7.038	1.003 ,	3.743
	.912	.942 ,	8.487	.930 ,	4.192
	.962	.941 ,	8.553	.930 ,	4.367
2.0	.912	1.137 ,	15.331	1.096 ,	5.800
	.870	1.018 ,	20.113	.989 ,	6.734
	.906	1.017 ,	20.265	.988 ,	7.081

Note: In each of Tables 2.2 through 2.5 ,

- (1) The first entry in each cell corresponds to Bryant-Schmee results.
- (2) The second entry corresponds to the first method: using the optimal d_1 and d_2 at each failure.
- (3) The third entry corresponds to the second method: using the optimal d_1 and d_2 from the final failure time.

TABLE 2.3

Simulation Results for 90% Confidence Interval from
MIL-STD-781C, Test Plan III; $\theta_0/\theta_1 = 2$,
 $\alpha = \beta = .1$

θ	Estimated Coefficient	Ave. Endpoints, at Least 1 Failure		Ave. Endpoints at Least 2 Failures	
.5	.886	.259 ,	1.398	.259 ,	1.398
	.944	.195 ,	1.733	.195 ,	1.733
	.974	.193 ,	1.803	.193 ,	1.803
1	.912	.868 ,	3.746	.558 ,	2.396
	.931	.472 ,	4.344	.463 ,	2.715
	.962	.469 ,	4.401	.460 ,	2.797
1.5	.938	.792 ,	8.729	.768 ,	3.891
	.944	.707 ,	11.239	.688 ,	4.272
	.970	.706 ,	11.430	.687 ,	4.521
2.0	.956	.940 ,	18.898	.895 ,	5.838
	.962	.855 ,	25.942	.825 ,	7.232
	.986	.855 ,	26.140	.825 ,	7.616

TABLE 2.4
Simulation Results for 80% Confidence Interval from
MIL-STD-781C, Test Plan I

θ	Estimated Coefficient	Ave. Endpoints, at Least 1 Failure		Ave. Endpoints, at Least 2 Failures	
.5	.784	.342 ,	.798	.342 ,	.798
	.816	.286 ,	.907	.286 ,	.907
	.898	.281 ,	.964	.281 ,	.964
1	.810	.760 ,	1.871	.752 ,	1.504
	.845	.696 ,	2.434	.691 ,	1.611
	.920	.680 ,	2.492	.674 ,	1.696
1.5	.808	1.125 ,	4.485	1.103 ,	3.022
	.790	1.018 ,	5.323	1.003 ,	3.456
	.892	1.011 ,	5.385	.996 ,	3.609
2.0	.867	1.290 ,	8.433	1.247 ,	4.661
	.802	1.120 ,	10.425	1.091 ,	5.298
	.867	1.118 ,	10.661	1.089 ,	5.657

TABLE 2.5
Simulation Results from 80% Confidence Interval from
MIL-STD-781C, Test Plan III

θ	Estimated Coefficient	Ave. Endpoints, at Least 1 Failure		Ave. Endpoints at Least 2 Failures	
.5	.788	.294 ,	1.085	.294 ,	1.085
	.872	.215 ,	1.346	.215 ,	1.346
	.922	.212 ,	1.437	.212 ,	1.437
1.0	.830	.601 ,	1.857	.601 ,	1.857
	.887	.489 ,	2.098	.489 ,	2.098
	.920	.484 ,	2.198	.484 ,	2.198
1.5	.856	.916 ,	5.356	.882 ,	2.978
	.849	.798 ,	7.064	.772 ,	3.527
	.900	.794 ,	7.188	.769 ,	3.731
2.0	.892	1.081 ,	9.882	1.020 ,	4.311
	.912	.946 ,	12.656	.903 ,	5.043
	.956	.945 ,	12.693	.903 ,	5.332

decision with one failure. As expected, the Bryant-Schmee intervals, on the average, were somewhat shorter than the intervals from both of our methods. However, we also noted that for some sample paths, our methods gave shorter intervals than the corresponding Bryant-Schmee intervals. The simulation results also indicate that the intervals generated from our posterior methods of selecting d_1 and d_2 remain conservative. We also note that our methods may be just as easily applied to an untruncated sequential test, while this is not so with the Bryant-Schmee approach. Their method requires non-trivial computation of probabilities at every discrete acceptance point up to that point where the sample path ended. In the untruncated sequential test the sample path may continue for a long time, resulting in a rather formidable computation problem to get the Bryant-Schmee intervals. We believe that, considering the relative ease of computation and application, these approximate confidence intervals provide a competitive alternative to those of Bryant and Schmee.

III. A Confidence Interval with No Observed Failures

The sequential life test may end in acceptance with no failures observed. In this situation the confidence interval should be one sided since there is no information on which to base an upper limit. If no failures are observed by total time T_0 , then we have observed a Poisson

process with parameter $\lambda = n/\theta$ for a total time T_0 , or actual time T_0/n . This is equivalent to type I, or time, censoring and Epstein (1960) showed that a one-sided $100(1-\alpha)$ percent confidence interval for θ is

$$\left[\frac{2T_0}{\chi_{\alpha,2}^2}, \infty \right]. \quad (3.1)$$

When no failures are observed, the two-sided confidence interval of Theorem 2.1 reduces to

$$\left[\frac{T_0(1-d_2)}{-\ln \alpha}, \frac{T_0(1-d_1)}{d_1 \ln \alpha} \right] \quad (3.2)$$

If $k = 0$, the constraint on d_1 becomes $0 < d_1 < 0$, leaving the upper endpoint undefined. Since no failure times are known, we define the upper endpoint to be infinity. The lower endpoint decreases as d_2 decreases and approaches $T_0/(-\ln \alpha)$ as d_2 goes to zero in the limit. The resulting interval is

$$\left[\frac{T_0}{-\ln \alpha}, \infty \right]. \quad (3.3)$$

But from the relationship between the chi-square and Poisson distributions we have

$$P(\chi_2^2 > \chi_{\alpha,2}^2) = e^{-\chi_{\alpha,2}^2/2} = \alpha.$$

Hence,

$$- \ln \alpha = \chi_{\alpha, 2}^2 / 2 ,$$

and (3.1) is equivalent to (3.3), and either provides a one-sided $100(1-\alpha)$ percent confidence interval for θ when no failures have been observed in the life test.

IV. Testing with Replacement

In this section we will show that the derivations in Section II are also valid if the sequential test is conducted with replacement. Testing with replacement is equivalent to observing a Poisson process with parameter $\lambda = n/\theta$, where again, n is the number of items placed on test. As in Section II, define $X_i \equiv t_i - t_{i-1}$. The X_i , $i = 1, 2, \dots, n$, are independent and are exponentially distributed with mean lifetime θ/n . Hence,

$$f(x_1, \dots, x_k; \theta) = \frac{n^k}{\theta^k} e^{-\frac{n}{\theta} \sum_{i=1}^k x_i} = \frac{n^k}{\theta^k} e^{-\frac{nt_k}{\theta}} = \frac{n^k}{\theta^k} e^{-\frac{T_k}{\theta}} ,$$

where $T_k = nt_k =$ total time on test at t_k . We see that the joint densities of X_1, X_2, \dots, X_k when testing with or without replacement differ only by a constant involving n and k . Thus, the density ratios in Section II will be the same as here in the replacement case. It follows that

Theorem 2.1 also holds when testing with replacement.

Now, to establish the analogous result to Lemma 2.2 , we note that a total test time of $T_{a,j}$ is equal to actual time $t_{a,j} = T_{a,j}/n$ if failed items are replaced. If t_i is the i^{th} ordered failure time and y_i represents the observed value of t_i , then

$$f(y_1, y_2, \dots, y_j | j) = \frac{j!}{t_{a,j}^j} ,$$

and

$$P(j \text{ Failures}) = \frac{e^{-\frac{nt_{a,j}}{\theta}} \left(\frac{nt_{a,j}}{\theta} \right)^j}{j!} .$$

Thus

$$f(y_1, y_2, \dots, y_j, j) = \frac{n^j}{\theta^j} e^{-\frac{nt_{a,j}}{\theta}} = \frac{n^j}{\theta^j} e^{-\frac{T_{a,j}}{\theta}} .$$

Except for the constant n^j , this is the same result obtained in the proof of Lemma 2.2 . The conclusion of Lemma 2.2 , for testing with replacement, follows in the same manner as in that proof.

It follows that all results and conclusions of Section II, where testing is without replacement, also

apply to the sequential test scheme where failed items are replaced.

APPENDIX 1

Tabled here are the optimal d_2 values for determining the lower limit of the $100(1-\alpha)$ percent two-sided confidence interval.

Failures k	Confidence Coefficient				
	99%	98%	95%	90%	80%
1	0.1186	0.1309	0.1522	0.1741	0.2045
2	0.1879	0.2045	0.2323	0.2602	0.2973
3	0.2380	0.2568	0.2876	0.3180	0.3575
4	0.2771	0.2973	0.3298	0.3615	0.4023
5	0.3092	0.3301	0.3637	0.3962	0.4371
6	0.3364	0.3575	0.3918	0.4243	0.4656
7	0.3597	0.3812	0.4160	0.4485	0.4894
8	0.3804	0.4023	0.4366	0.4691	0.5096
9	0.3988	0.4208	0.4551	0.4876	0.5271
10	0.4151	0.4371	0.4718	0.5034	0.5430
11	0.4300	0.4516	0.4867	0.5184	0.5570
12	0.4437	0.4656	0.4999	0.5315	0.5702
13	0.4560	0.4779	0.5122	0.5430	0.5816
14	0.4674	0.4894	0.5236	0.5544	0.5922
15	0.4779	0.4999	0.5342	0.4641	0.6027
16	0.4885	0.5096	0.5430	0.5746	0.6115
17	0.4973	0.5192	0.5518	0.5825	0.6203
18	0.5061	0.5271	0.5605	0.5904	0.6273
19	0.5148	0.5359	0.5685	0.5992	0.6344
20	0.5219	0.5430	0.5764	0.6062	0.6414
21	0.5298	0.5509	0.5834	0.6115	0.6484
22	0.5368	0.5570	0.5904	0.6186	0.6537
23	0.5430	0.5641	0.5957	0.6238	0.6590
24	0.5500	0.5702	0.6027	0.6309	0.6660
25	0.5553	0.5764	0.6080	0.6361	0.6695
26	0.5614	0.5816	0.6133	0.6414	0.6748
27	0.5676	0.5869	0.6186	0.6449	0.6801
28	0.5729	0.5922	0.6238	0.6520	0.6836
29	0.5781	0.5975	0.6273	0.6555	0.6871
30	0.5816	0.6027	0.6326	0.6590	0.6924
31	0.5869	0.6062	0.6379	0.6643	0.6977
32	0.5922	0.6115	0.6414	0.6678	0.7012
33	0.5957	0.6150	0.6449	0.6730	0.7047
34	0.5992	0.6203	0.6484	0.6766	0.7082
35	0.6045	0.6238	0.6520	0.6801	0.7117

Failures k	Confidence Coefficient				
	99%	98%	95%	90%	80%
36	0.6080	0.6273	0.6555	0.6836	0.7152
37	0.6115	0.6309	0.6590	0.6871	0.7152
38	0.6150	0.6344	0.6625	0.6889	0.7187
39	0.6186	0.6379	0.6660	0.6906	0.7223
40	0.6221	0.6414	0.6695	0.6941	0.7258
41	0.6256	0.6449	0.6730	0.6977	0.7293

Tabled here are the optimal d_1 values for determining the upper limit of the $100(1-\alpha)$ percent two-sided confidence interval.

Failures k	Confidence Coefficient				
	99%	98%	95%	90%	80%
1	0.0018	0.0037	0.0093	0.0187	0.0382
2	0.0267	0.0382	0.0619	0.0900	0.1329
3	0.0673	0.0864	0.1215	0.1590	0.2108
4	0.1090	0.1329	0.1742	0.2156	0.2712
5	0.1478	0.1742	0.2190	0.2625	0.3190
6	0.1825	0.2108	0.2576	0.3020	0.3590
7	0.2137	0.2429	0.2907	0.3356	0.3912
8	0.2415	0.2712	0.3190	0.3639	0.4195
9	0.2664	0.2966	0.3444	0.3893	0.4439
10	0.2888	0.3190	0.3678	0.4107	0.4654
11	0.3098	0.3405	0.3873	0.4312	0.4849
12	0.3288	0.3590	0.4059	0.4498	0.5005
13	0.3464	0.3756	0.4225	0.4654	0.5161
14	0.3620	0.3912	0.4381	0.4800	0.5298
15	0.3766	0.4068	0.4517	0.4927	0.5434
16	0.3903	0.4195	0.4654	0.5064	0.5551
17	0.4029	0.4322	0.4771	0.5181	0.5668
18	0.4146	0.4439	0.4888	0.5278	0.5746
19	0.4264	0.4556	0.4985	0.5376	0.5844
20	0.4371	0.4654	0.5083	0.5473	0.5942
21	0.4458	0.4751	0.5181	0.5571	0.6020
22	0.4667	0.4849	0.5278	0.5649	0.6098
23	0.4654	0.4927	0.5356	0.5727	0.6176
24	0.4732	0.5005	0.5434	0.5785	0.6234
25	0.4810	0.5083	0.5512	0.5864	0.6293
26	0.4888	0.5161	0.5571	0.5942	0.6371
27	0.4966	0.5239	0.5629	0.6000	0.6410
28	0.5044	0.5298	0.5707	0.6059	0.6488
29	0.5109	0.5376	0.5766	0.6117	0.6527
30	0.5161	0.5434	0.5824	0.6176	0.6566
31	0.5239	0.5493	0.5883	0.6215	0.6605
32	0.5298	0.5551	0.5942	0.6273	0.6683
33	0.5356	0.5610	0.5981	0.6332	0.6722
34	0.5395	0.5668	0.6039	0.6371	0.6761
35	0.5454	0.5707	0.6098	0.6410	0.6800
36	0.5512	0.5746	0.6137	0.6449	0.6839
37	0.5551	0.5805	0.6176	0.6488	0.6878
38	0.5610	0.5844	0.6215	0.6527	0.6917
39	0.5649	0.5903	0.6254	0.6566	0.6956
40	0.5707	0.5942	0.6293	0.6605	0.6995
41	0.5746	0.5981	0.6332	0.6644	0.7034

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