A Reliability Growth Simulation Test Bed

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SUMMARY & CONCLUSIONS

This paper presents a reliability growth simulation test bed that is useful in examining the reliability growth of complex systems. It has many potential applications, including cost vs. reliability growth analyses and reliability growth program planning. The most significant application of the simulation though, is that it provides a method for examining the robustness of existing reliability growth models under varying assumptions and test conditions.

The simulation allows for a user to more accurately model the test event, in that corrective action strategies and corrective action delay times and can be employed. Because these events tend to violate the assumptions of some models, two existing and widely used reliability growth models are examined under a variety of test conditions and assumptions. The simulated system reliabilities from the test bed are compared to the projections obtained from both the Crow Extended Model and the AMSAA Maturity Projection Model (AMPM).

The results indicate that both models perform acceptably under test conditions that adhere to the assumptions of the models themselves. The performance of the Crow-Extended Model tends to degrade rapidly as the assumptions are violated, more specifically when the classification of modes is altered in any way. The AMPM appears to be robust to varying test conditions due to its limited assumptions. Other issues do exist though involving the selection of the proper form of the estimator which could have a significant impact on the accuracy of its projections.

1 INTRODUCTION

Reliability growth is defined as the improvement in a reliability parameter over time through changes in the design or manufacturing process. It is an important concept that is used when assessing the reliability of complex systems with strict reliability requirements. Depicting how the reliability changes throughout the developmental testing of the system is important, as it provides an indication of whether or not the system will be able to meet its requirements. These reliability depictions are usually made with established reliability growth models such as those specified in Military Handbook 189 [1] or the AMSAA Reliability Growth Guide [2]. The growth relationship depicted is between reliability and a continuous measure of test duration such as time or mileage. It is important to note though, that each of the models assumes a specific pattern of growth that may or may not be reasonable for the specific system and test environment under consideration.

1.1 Purpose

The purpose of this paper is to present a simulation test bed that can be used to examine the reliability growth of a complex system. The simulation can be used to better reflect the actual testing and growth environment, eliminating the need for certain simplifying assumptions that exist in many popular models. It can also help in examining the performance of existing reliability growth models under various test environments, and this is the application that is presented here.

1.2 Overview

In Section 2 the overall structure of the simulation is presented. Input requirements, modeling assumptions, and available output metrics are discussed.

Section 3 then presents a brief overview of two existing reliability growth models which are examined using the simulation. The Crow-Extended model [3] is discussed along with the AMSAA Maturity Projection Model [4]. Section 4 contains comparison results from the simulation test bed. The simulated Mean Time Between Failures (MTBF) from the test bed is compared to those of the two reliability growth models.

Section 5 provides a general discussion of the robustness of the two existing growth models. Results from the comparison tests are used to provide some knowledge of the appropriateness of an individual model. Section 6 discusses some potential areas for future work involving reliability growth modeling.

2 SIMULATION TEST BED

The simulation test bed was developed in Mathematica, with the overall intent of more realistically modeling the actual conditions under which growth occurs. The general structure of the simulation is to set up the test calendar and then determine the initial mode failure rates from input data. After determining the mode first occurrence times and fix effectiveness factors, each individual failure mode is then classified based on the chosen corrective action strategy. The main part of the simulation then involves generating the failure times for each mode, taking into account any corrective actions that may occur during the test event.

2.1 Test Calendar

The test is a calendar based event that includes test periods along with any Corrective Action Periods (CAPs) that may be used within the test. This allows the simulation to
more realistically reflect the growth of the reliability throughout the test. It is developed by first specifying the number of time units (i.e., months, weeks, etc.) that make up the test and then placing CAPs at specified intervals. The simulation assumes no testing occurs during a CAP. The total test time is then calculated based on the input number of test hours per unit time and the test-CAP structure.

2.2 Failure Modes

The number of failure modes is input into the simulation for both Type-A modes and Type-B modes. Type-A modes are those modes for which when surfaced, no corrective action will be implemented. Type-B modes are those modes for which a corrective action will be made. The number of each type of mode should reflect the overall characteristics of the system being examined.

The failure rates for the individual modes are taken as a realization from a chosen parent population. The available parent populations are a Gamma Distribution, Weibull Distribution, Lognormal Distribution, LogLogistic Distribution, or a geometric sequence. The only distribution parameter inputs to the simulation are for the Gamma Distribution. The parameters for each of the remaining distributions are then calculated based on an equivalent mean and coefficient of variation to the Gamma. For the Geometric sequence, a similar procedure is used involving the percent of failure modes surfaced. This is done to ensure valid comparisons from one parent population to another.

2.3 Corrective Actions

The simulation test bed is unique in comparison to others in that it allows for flexibility in implementing corrective actions. The corrective actions may be implemented during the test phase of the system, or delayed until the end of the overall test period, which follows the assumptions of many current reliability growth models. Those that are implemented during the test are further classified as Type-BC modes, while those that are delayed are Type-BD modes. The uniqueness of the test bed deals with those corrective actions that are implemented during the test phase. The corrective actions can be implemented within the pre-defined CAPs or during the test periods themselves, more accurately reflecting the actual test environment.

Once the placement of a corrective action has been determined, the Fix Effectiveness Factor (FEF) for the corrective action is assigned. They are chosen from a Beta Distribution, with the mean and coefficient of variation of the distribution chosen as input. A FEF is the fraction reduction in a failure mode rate of occurrence after a corrective action has been implemented. They are applied to the realized failure rates after fixes have been implemented to the specific failure mode as in Equation (1).

\[ \lambda_{\text{Final}} = (1 - \text{FEF}) \times \lambda_{\text{Initial}} \]  

(1)

3 RELIABILITY GROWTH MODELS

Before discussing the performance of the existing reliability growth models, we provide a brief overview of their capabilities and assumptions.

3.1 Crow Extended Model

The model proposed by Crow in [3] is used widely in both government and industry alike, and it consists of two main parts. The first is the reliability growth tracking model found in [1] and [2]. The underlying assumption of the tracking model is that individual failures in a test event occur according to a nonhomogeneous Poisson process with a failure intensity represented by

\[ \rho(t) = \omega \beta t^{\beta-1}. \]  

(2)

The parameter \( \omega \) is used in place of the customary \( \lambda \) in order to avoid any conflicting terminology that may occur later. The model assumes that all corrective actions are implemented instantaneously in what is known as a test-fix-test environment. The corresponding mean time between failures (MTBF) is given by

\[ M(t) = \frac{1}{\rho(t)}. \]  

(3)

\( \beta > 1 \) implies that the reliability of the system is actually decreasing, while \( \beta = 1 \) implies a constant reliability. Reliability growth corresponds to the case when \( \beta < 1 \).

The maximum likelihood estimates (MLE) for \( \lambda \) and \( \beta \) (unbiased) are given in (4) and (5) respectively, where the time to failure data is \( X_1, X_2, X_3, \ldots X_N \) and \( T \) is the length of the test.

\[ \overline{X} = \frac{N}{T} \]  

(4)

\[ \overline{\beta} = \frac{N - 1}{\sum_{i=1}^{N} \frac{T}{X_i}} \]  

(5)

The tracking model estimate of the failure intensity is then just

\[ \hat{\rho}_T(t) = \overline{\omega} \overline{\beta} t^{\overline{\beta}-1}. \]  

(6)

The second part of the Crow-Extended Model consists of the reliability growth projection model found in [4] and [5]. It assumes a nonhomogeneous Poisson process with intensity of the same form as that in (2), but in this case the process governs the occurrence of the failure modes instead of the individual failures. The underlying assumption of the projection model is that the corrective actions are delayed until the end of the test. The reliability projection then assumes that the delayed corrective actions have been implemented. The expected failure intensity with respect to Type-B mode first occurrence times is shown in [5] to be

\[ \rho_P(t) = \lambda_A + \sum_{i=1}^{K} (1-d_i) \lambda_i + \sum_{i=1}^{K} d_i \lambda_i e^{-\lambda_i t}. \]  

(7)

where \( K \) is the total number of Type-B failure modes, \( \lambda_A \) is the failure rate for Type-A modes, and \( d_i \) and \( \lambda_i \) are the respective FEF and rate of occurrence for the \( i \)th Type-B mode.

The Crow-Extended Model projection is then made by combining the tracking and projection models. The tracking model is used first with all cumulative time to failure data. The Type-B modes are then subdivided into Type-BC and Type-BD modes, and the projection model is applied only to the Type-BD mode times of first occurrence. No Type-A
modes are assumed in the projection component because they are accounted for in the tracking portion of the model. The extended model failure intensity is given in [2] as

\[ \hat{\rho}_{EM}(t) = \hat{\rho}_T(t) - \hat{\lambda}_{BD} + \sum_{i=1}^{K}(1-d_i)\hat{\lambda}_i + \sum_{i=1}^{K}d_i\hat{\lambda}_i e^{-\hat{\lambda}_i t}, \]  

(8)

where \( K \) is now the number of Type-BD modes, \( \hat{\lambda}_{BD} \) is the failure rate of the Type-BD modes, and \( d_i \) and \( \hat{\lambda}_i \) are the respective FEF and rate of occurrence for the \( i \)th Type-BD mode. Intuitively, the failure intensity due to the Type-BD modes is subtracted from the tracking assessment and then replaced with the projection assessment. This accounts for the delayed fixes that are to occur. The estimation procedure for the model uses the MLEs from the tracking model to obtain \( \hat{\rho}_T(t) \), and the corresponding estimates of \( \hat{\lambda}_{BD} \) and \( \hat{\lambda}_i \) are given by

\[ \hat{\lambda}_{BD} = \frac{N_{BD}}{T}, \]  

(9)

\[ \hat{\lambda}_i = \frac{N_{BD,i}}{T}, \]  

(10)

where \( N_{BD} \) is the total number of Type-BD mode failures and \( N_{BD,i} \) is the number failures for the \( i \)th Type-BD mode. If the FEF for each mode is assumed equal, the last term in (8) can also be approximated as

\[ \bar{d}(T / BD) = \bar{d}_{BD} \bar{\beta}_{BD} T^{\bar{\beta}_{BD} - 1}, \]  

(11)

where the \( \bar{d} \) and \( \bar{\beta} \) parameters are MLEs based on the Type-BD mode times of first occurrence and \( \bar{d} \) is the average FEF. More details on the model, along with management metrics associated with its use, can be found in [3].

3.2 AMPM

The AMPM is a reliability projection model. Unlike the Crow-Extended Model, it does not contain a separate tracking and projection component. It also makes no assumptions about when corrective actions are employed. They are assumed to have been performed at some time prior to the time of the projection. The foundation of the AMPM is that underlying rates of occurrence for individual failure modes result from a parent population that is a Gamma distribution. The failure intensity is given in [4] as

\[ \hat{\rho}_{AMPM}(t) = \lambda_A + (1-d)K\beta(\alpha+1) + dK\beta(\alpha+1)\left(1+\beta t\right)^{\alpha+2}, \]  

(12)

where \( d \) is the average FEF for the failure modes that are corrected, \( K \) is the total number of Type-B failure modes in the system, and \( \alpha \) and \( \beta \) are the parameters from the Gamma distribution parent population. The \( \beta \) parameter in the AMPM is different from that discussed earlier in the Crow-Extended Model, but the form of the projection in (12) is similar to that in (8) when the approximation in (11) is used.

MLEs of \( \alpha \) and \( \beta \) are found in terms of a fixed \( K \) and the failure data \( X_1, X_2, X_3, \ldots, X_N \). Because the value of \( K \) is not known in practice, the limiting behavior of the estimates with respect to \( K \) is also available, leading to two potential forms of the estimator. The estimated failure intensity for the finite and infinite \( K \) cases is given in (14) and (15), respectively. \( \bar{d} \) is the average FEF of the \( m \) observed Type-B failure modes, and \( \hat{\lambda}_{BD,\infty} \) is given in (13). Further details on the model can be found in [4].

\[ \hat{\lambda}_{BD,\infty} = \lim_{K \to \infty} K\hat{\beta}(\hat{\alpha}+1) = \frac{m\hat{\beta}_{\infty}}{\ln(1+\hat{\beta}_{\infty}T)}. \]  

(13)

\[ \hat{\rho}_{AMPM,\infty}(t) = \hat{\lambda}_A + (1-\bar{d})K\hat{\beta}(\hat{\alpha}+1) + \frac{dK\beta(\alpha+1)}{(1+\beta t)^{\alpha+2}} \]  

(14)

\[ \hat{\rho}_{AMPM,\infty}(t) = \hat{\lambda}_A + (1-\bar{d})\hat{\lambda}_{BD,\infty} + \frac{\bar{d}\hat{\lambda}_{BD,\infty}}{(1+\beta_{\infty} t)}. \]  

(15)

4 RESULTS

Twelve baseline test cases are presented in Table 1. The number of Type-A and Type-B modes were 5 and 75 for each case. The mean FEF was 0.7 with a coefficient of variation of 0.1, and 50 replications were used for each case. The probability of a mode being classified a Type-BC or Type-BD was set at 0.80 and 0.20 respectively. The cases were then subjected to varying corrective action strategies, to include a corrective action delay time and a different Type-BD mode classification strategy.

<table>
<thead>
<tr>
<th>Case</th>
<th>Test Time</th>
<th>A Mode Initial Failure Intensity</th>
<th>B Mode Initial Failure Intensity</th>
<th>Parent Pop</th>
<th>Beta (A Modes)</th>
<th>Beta (B Modes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500</td>
<td>0.005</td>
<td>0.195</td>
<td>Gamma</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>2</td>
<td>500</td>
<td>0.005</td>
<td>0.195</td>
<td>Gamma</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>3</td>
<td>500</td>
<td>0.005</td>
<td>0.195</td>
<td>Gamma</td>
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<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>10000</td>
<td>0.005</td>
<td>0.095</td>
<td>Gamma</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>5</td>
<td>10000</td>
<td>0.005</td>
<td>0.095</td>
<td>Gamma</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>6</td>
<td>10000</td>
<td>0.005</td>
<td>0.095</td>
<td>Gamma</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>7</td>
<td>500</td>
<td>0.005</td>
<td>0.195</td>
<td>Weibull</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>8</td>
<td>500</td>
<td>0.005</td>
<td>0.195</td>
<td>Weibull</td>
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<td>0.002</td>
</tr>
<tr>
<td>9</td>
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<td>Weibull</td>
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<td>0.05</td>
</tr>
<tr>
<td>10</td>
<td>10000</td>
<td>0.005</td>
<td>0.095</td>
<td>Weibull</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>11</td>
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<td>0.005</td>
<td>0.095</td>
<td>Weibull</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>12</td>
<td>10000</td>
<td>0.005</td>
<td>0.095</td>
<td>Weibull</td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 1 – Comparison Cases

4.1 Baseline Cases

Comparison results for the baseline cases are shown in Figure 1. The results show that the Crow-Extended Model performs well, but it may provide an optimistic assessment of the MTBF in certain cases. Examination of the model reveals some insight about this behavior. The tracking estimate given in (6) simplifies to

\[ \hat{\rho}_T(t) = \frac{N_A(1-\bar{\alpha})}{T} + \frac{N_{BC}(1-\bar{\alpha})}{T} + \frac{N_{BD}(1-\bar{\alpha})}{T}, \]  

(16)

where \( \bar{\alpha} = 1-\hat{\beta} \) is the estimated unbiased growth rate for the model and the \( N \) terms are the number of failures for each mode type. The Crow-Extended Model subtracts the estimated failure intensity for the Type-BD modes from the tracking assessment and replaces it with the projection assessment for the Type-BD modes. The expression in (16) is
just the sum of the estimated failure intensities for each of the individual mode types, and so subtracting the estimated Type-BD mode failure intensity should result in a failure intensity estimate for only Type-A and BC modes. But the \((1 - \bar{\alpha})\) term in (16) leaves a bias of \(-\frac{\alpha N_{BD}}{T}\), implying that the estimated failure intensity for the Type-A and Type-BC modes will be underestimated in growth situations. The bias is present because the original assumption of a nonhomogeneous Poisson process for the individual failures is violated when

$$\frac{\alpha N_{BD}}{T} \geq 1.\,$$

Table 2 – Comparison of Results

<table>
<thead>
<tr>
<th>Case</th>
<th>BC Failures</th>
<th>BD Failures</th>
<th>Ratio BC/BD</th>
<th>MTBF Delta (True - Estimated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>34</td>
<td>20</td>
<td>2.70</td>
<td>1.343</td>
</tr>
<tr>
<td>2</td>
<td>48</td>
<td>23</td>
<td>2.09</td>
<td>0.909</td>
</tr>
<tr>
<td>3</td>
<td>33</td>
<td>21</td>
<td>1.57</td>
<td>-4.496</td>
</tr>
<tr>
<td>4</td>
<td>266</td>
<td>203</td>
<td>1.31</td>
<td>-3.587</td>
</tr>
<tr>
<td>5</td>
<td>268</td>
<td>211</td>
<td>1.27</td>
<td>-2.599</td>
</tr>
<tr>
<td>6</td>
<td>196</td>
<td>238</td>
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<td>-6.142</td>
</tr>
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<td>1.421</td>
</tr>
<tr>
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<td>49</td>
<td>21</td>
<td>2.33</td>
<td>0.922</td>
</tr>
<tr>
<td>9</td>
<td>33</td>
<td>17</td>
<td>1.94</td>
<td>-0.483</td>
</tr>
<tr>
<td>10</td>
<td>270</td>
<td>188</td>
<td>1.44</td>
<td>-3.136</td>
</tr>
<tr>
<td>11</td>
<td>275</td>
<td>176</td>
<td>1.56</td>
<td>-3.301</td>
</tr>
<tr>
<td>12</td>
<td>236</td>
<td>213</td>
<td>1.11</td>
<td>-2.860</td>
</tr>
</tbody>
</table>

Figure 1 – Baseline Comparisons

MTBF projection will be insensitive to the value of \(K\). But this appears to be conservative for the cases examined here. The projection appears to be insensitive to the estimator form when the ratio of \(K/m\) is greater than two. This may indicate that a much lower multiple of \(m\) is sufficient to cause insensitivity in the estimator, but more work is necessary before such a claim could be asserted.

It is interesting to note that the behavior of the individual forms of the estimator follow the results outlined in [4]. The limiting form of the \(\hat{\alpha}\) parameter as \(K \to \infty\) is shown to be -1. Examining the test cases shows that the projection is insensitive to the form of the estimator in cases where the parent population has a value of \(\alpha\) near -1. Cases 3 and 9 have values of -0.95, while cases 6 and 12 have values of -0.97.

4.2 Corrective Action Delay Times

This section contains results for cases when a corrective action delay time is used. The twelve cases were simulated in the same manner as the baseline, with the exception of having a delay time applied to each of the corrective actions that occurred. Corrective actions that should occur during the test for Type-BC modes may not occur until the end of the test, resulting in their being classified as Type-BD modes. This violates the assumption of a nonhomogeneous Poisson process for the Type-BD mode first occurrence times, as the classification will be dependent on the first occurrence time. It also violates the tracking model assumptions that the corrective actions are implemented instantaneously.

A potential danger of delay times is the incorrect classification of modes as Type-BC. Figure 2 shows comparison results for cases when the delayed Type-BC modes are not properly classified as Type-BD modes. A six month delay time was used, resulting in a large number of modes of this type. Examination of the model shows that an error in the number of Type-BC failures carries more weight than an error in the number of Type-BD failures. This is due

Figure 2 – Incorrect Mode Classification Comparisons
When the delayed Type-BC modes are correctly classified as Type-BD modes, the Crow-Extended Model still provides conservative estimates of the failure intensity. Figure 3 shows the results for a six month corrective action delay time with the correct mode classification. Because the delay time violates multiple model assumptions it is useful to examine the goodness of fit of the comparison cases. Table 3 shows the average Cramer-von Mises statistic [2] for both the tracking assessment and the Type-BD mode first occurrence times. The test uses a null hypothesis that a nonhomogeneous Poisson process with failure intensity in (2) is appropriate, rejecting for large values of the statistic. Results for the tracking model show that the null hypothesis is rejected at a significance of 0.20 for all cases except 1, 7, and 8. But the Type-BD mode results for these cases show that the null hypothesis is rejected at a significance of 0.20. This indicates that the data do not fully fit the model, and it should not be used. Hypothesis testing may not always indicate a problem with the data though, so caution should be used when the data are known to have corrective action delay times.

The AMPM makes no assumptions about when corrective actions occur, and as such the performance of the model should not be degraded when a corrective action delay time is used. The choice of the form of the estimator will still remain an issue as expected.

### 4.3 Weighted Type-BD Mode Classification

This section contains results for test cases where the Type-BD mode classification strategy was not random throughout the test. The probability of a mode being classified as Type-BD was an increasing function of the time of first occurrence of the failure mode, resulting in Type-BD modes occurring more frequently toward the end of the test. This violates the implicit assumption of the Crow-Extended Model that modes are classified independently of their time of first occurrence. Nonetheless it is a case that may occur frequently in realistic testing situations. As mentioned previously, corrective action delay times may have the unintended impact of “weighting” the Type-BD modes at the end of the test. Results are shown in Figure 4.

![Figure 4 – Weighted Type-BD Mode Classification](image)

The performance of the Crow-Extended Model varies greatly in these cases. As mentioned previously, when the number of Type-BD mode failures is large enough the bias in the estimate will be large. As the number of Type-BD failures increases the estimated failure intensity decreases, leading to an optimistic projection of the MTBF. Further examination of these cases shows that the proportion of Type-BD failure modes also has an effect on the resulting projection. Table 4 shows the average number of failures and modes surfaced for each mode type, along with the percent error in the projection. When the proportion of Type-BD modes is large the projection tends to be grossly optimistic. This is due to the corresponding large number of Type-BD failures and the bias associated with them. The effect may be mitigated somewhat if the number of repeat failures for Type-BD modes is small, as seen in cases 1 and 2.

![Table 4 – Mode Classification Results](image)
5 DISCUSSION

The results presented here indicate the usefulness of simulation in examining reliability assessment methods for complex systems. The ease of use that it provides for examining the two existing reliability growth models allows us to quickly gain insight into some of the potential issues surrounding the use of the models. The results indicate that both models appear to perform well in many test environments, but caution should be exercised before using either of them. Use without consideration of their limitations can potentially lead to grossly inaccurate projections of the MTBF.

If the assumptions of the Crow-Extended Model are violated, the projected MTBF will tend to be inaccurate. Delay times tend to result in conservative projections of the MTBF, while weighting the Type-BD modes towards the end of the test may result in overly optimistic projections in certain cases. The fit of the data to the model should be examined in these cases, and hypothesis tests may indicate that the model is not valid for use. In general caution should be exercised anytime the model is used under non-ideal conditions.

The AMPM appears to perform well in most cases, assuming that the user has some prior knowledge of the total number of Type-B failure modes inherent in the system. If the infinite form of the estimator is used when inappropriate, the resulting MTBF projection could be grossly conservative. This highlights a potential issue involved with using the AMPM, and also provides an area for future work.

6 FUTURE WORK

While the concept of the Crow-Extended Model is reasonable, the results here demonstrate that it may be useful to consider an alternate form the Crow-Extended model which uses better estimates of the component failure intensities. Replacing the individual components of the model with more accurate parts may provide a much improved projection of the system MTBF. It may also prove reasonable to consider a model form that does not rely on classification of failure modes in forming its projection.

In the context of the AMPM, the results show that it would be useful to examine a method for determining when to choose the infinite-k or finite-K estimator. While Ellner and Wald [4] point out some of the potential dangers of attempting to estimate K statistically due to the possibility of obtaining an overly optimistic assessment of the overall system reliability, the results shown here indicate that it is desirable to obtain at least some knowledge of whether K is finite or infinite. Beyond this it may also be reasonable to estimate K in a manner that provides an accurate assessment of the system reliability. The development of such a reasonable method would greatly enhance the usefulness of the AMPM and lead to more accurate reliability projections.

REFERENCES


BIOGRAPHY

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