Useful Metrics for Managing Failure Mode Corrective Action

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Key Words: reliability management strategy metrics, corrective action, Crow (AMSAA) model, learning curve

SUMMARY & CONCLUSIONS

A reliability growth program differs from a conventional reliability program in that there is a more objectively developed growth standard against which assessment techniques are compared. A comparison between the assessment and the planned value provides a good estimate of whether or not the program is progressing as scheduled and will attain the desired goal. If the program does not progress as planned, then new strategies should be considered. For example, a reexamination of problem areas may result in changing the management strategy so that more problem failure modes surfaced during the testing actually receive a corrective action instead of a repair. The management strategy may be driven by budget and schedule but it is defined by the actual actions of management in correcting reliability problems. The proper approach to what modes to fix and when, is often difficult for management to determined, even with ideal data. It becomes more difficult if certain failure patterns and trends are not measured and understood. In this paper we discuss management strategy concepts and provide a simple pie chart metric approach to aid management and engineering in interpreting the meaning of certain important trends and averages during reliability growth development testing.

1. *INTRODUCTION*

Although reliability tasks are typically conducted in a reliability program they often do not uncover many reliability issues, such as complex interactions, that can cause failures. (See Ref.1). Experience generally shows that if these problems are known early they can be corrected with reasonable costs and within the current state-of-the-art. If the reliability requirement is low then the effort to find and correct these additional failure modes may not be necessary. However, when an expensive new technology system is developed it is common for the reliability requirements and performance expectations to be high. If a reliability growth program is not properly managed, then extensive and expensive effort may be expended and still not reach an otherwise attainable goal. The problem is often associated with not understanding the impact of the existing management strategy and not understanding certain key metrics and trends. An additional practical complication is that the interpretation of some key trends and metrics may not be initially intuitive. The objective of this paper is to provide some important management metrics with interpretations and applications. A broader scope of the utility of these concepts is further illustrated in this paper by noting the Learning Curve property of the Crow (AMSAA) model.

1.1 *Notation*

λ	Scale parameter for Crow (AMSAA) model
β	Shape parameter for Crow (AMSAA) model
t	Test time
T	Total test time
$r(\cdot)$	Crow (AMSAA) model failure intensity
λ_P	Projected failure intensity
M_P	Projected MTBF
$h(\cdot)$	Rate of uncovering new failure modes

2. *BACKGROUND*

To lay the groundwork for the main results of this paper, we will first discuss two reliability growth models. The first model is the Crow (AMSAA) model applied to test-fix-test data and the second model is the Extended model applied to test-find-test data. For test-fix-test corrective actions are incorporated during the test. For test-find-test all corrective actions are delayed and incorporated at the end of the test. The main point of interest in the following discussion is that the Extended model also utilizes the Crow (AMSAA) model which addresses the occurrence of distinct failure modes.

2.1. *Crow (AMSAAA) Basic Model for Test- Fix- Test*

The Duane postulate, Ref.2, for reliability growth during test-fix- test development testing states that the instantaneous system MTBF at cumulative test time t is $M(t) = \left[\lambda\beta t^{\beta-1}\right]^{-1}$, where 0 < λ and 0< β are parameters.

Crow (Ref.3) modeled the Duane postulate stochastically as a non-homogeneous Poisson process (NHPP) with intensity

$$r(t) = \lambda\beta t^{\beta-1}, \qquad (1)$$

thus allowing for statistical procedures based on this process for reliability growth analyses. This model is applicable to test-fix-test data.

The parameter λ is referred to as the scale parameter and β is the shape parameter. For $\beta = 1$, there is no reliability growth. For $\beta < 1$, there is positive reliability growth. That is, the system reliability is improving due to corrective actions.

For $\beta > 1$, there is negative reliability growth.

Under the Crow (AMSAA) basic model, the achieved or demonstrated failure intensity at time T, the end of the test, is given by r(T). We denote the achieved failure intensity by

$$\lambda_{CA} = r(T)\,. \tag{2}$$

Suppose a development testing program begins at time 0 and is conducted until time T and stopped. Let N be the total number of failures recorded and let $0 < X_1 < X_2 < \ldots X_N \leq T$ denote the N successive failure times on a cumulative time scale. We assume that the Crow (AMSAA) model assumptions apply to this set of data. Under the Crow (AMSAA) basic model the maximum likelihood estimates (MLEs) for λ and β are:

$$\hat{\lambda} = \frac{N}{T^{\hat{\beta}}} \quad , \quad \hat{\beta} = \frac{N}{\sum_{i=1}^{N} \ln(\frac{T}{X_i})} \tag{3}$$

Example 1. Test-Fix-Test

To illustrate the general application of this model consider a system tested for T=3256.3 hours with the 40 failure times given in Table 1. The first failure was recorded at .7 hours into the test; the second failure was recorded 2 hours later at 2.7, etc. Failure number 40, occurred at 3256.3 hours into the test, and the testing was stopped.

.7	2.7	13.2	17.6	54.5	99.2	112.2	120.9
151.0	163.0	174.5	191.6	282.8	355.2	486.3	490.5
513.3	558.4	678.1	699.0	785.9	887.0	1010.7	1029.1
1034.4	1136.1	1178.9	1259.7	1297.9	1419.7	1571.7	1629.8
1702.3	1928.9	2072.3	2525.2	2928.5	3016.4	3181.0	3256.3

Table 1. Test-Fix-Test Data

Applying equations (3) we get the estimates

$$\hat{\lambda} = 0.7615 \quad \hat{\beta} = 0.4898 \ . \tag{4}$$

The achieved or demonstrated failure intensity and MTBF are estimated by

$$\hat{\lambda}_{CA} = \hat{\lambda}\hat{\beta}T^{\hat{\beta}-1} \text{ or } \hat{\lambda}_{CA} = 0.0060\ , \tag{5}$$

$$\hat{M}_{CA} = \left[\hat{\lambda}_{CA}\right]^{-1} = 166.22. \tag{6}$$

It is important to note that the Crow (AMSAA) test-fix test model does not assume that all failures in the data set (e.g., Table 1) received a corrective action. Based on the management strategy some failures may receive a corrective action and some may not.

2.2 *Crow Extended Model for Test- Find -Test*

Suppose a system is tested for time T. During the testing, problem failure modes are identified, but all corrected actions are delayed and incorporated at the end of the test phase. This is test-find-test. These delayed corrective actions are usually incorporated as a group and the result is generally a distinct jump in the system reliability. The projection model, Ref. 4, estimates this jump in reliability due to the delayed fixes. This is called a "projection."

The projection model places all failure into two groups, A and BD. Type A failure modes are all modes such that if seen during test no corrective action will be taken. This accounts for all modes for which management determines that it is not cost-effective to increase the reliability by a design change. Type BD failure modes are all modes such that if seen during test a delayed corrective action will be taken. This Type A and Type BD designation plus the effectiveness of the fixes define the reliability growth management strategy. The basic projection model assumes that the Type A failure modes have constant failure intensity λ_A, the i-th Type BD failure modes follow the exponential distribution with failure rate λ_i, and the initial failure intensity for Type BD failure modes is λ_{BD} .

Example 2. Test-Find-Test

For the data in Table 2, the system is tested for T=400 hours. There is a total of N=42 failures and all corrective actions will be incorporated at the end of the 400 hour test. Each failure is designated as either a Type A failure mode (no corrective action) or Type BD failure mode (corrective action). There are $N_A = 10$ Type A failures and $N_B = 32$ Type BD failures during the test.

In Table 2 there are M = 16 unique Type BD failure modes, which means there are 16 distinct corrective actions incorporated into the system at the end of test. The total number of failures for the j-th observed distinct Type BD mode is denoted by and the total number of Type BD failures seen during the test is See Table 3.

j	X_j	Mode	j	X_j	Mode
1	15	B1	22	260.1	B1
2	25.3	B2	23	263.5	B8
3	47.5	B3	24	273.1	A
4	54	B4	25	274.7	B6
5	56.4	B5	26	285	B13
6	63.6	A	27	304	B9
7	72.2	B5	28	315.4	B4
8	99.6	B6	29	317.1	A
9	100.3	B7	30	320.6	A
10	102.5	A	31	324.5	B12
11	112	B8	32	324.9	B10
12	120.9	B2	33	342	B5
13	125.5	B9	34	350.2	B3
14	133.4	B10	35	364.6	B10
15	164.7	B9	36	364.9	A
16	177.4	B10	37	366.3	B2
17	192.7	B11	38	373	B8
18	213	A	39	379.4	B14
19	244.8	A	40	389	B15
20	249	B12	41	394.9	A
21	250.8	A	42	395.2	B16

Table 2: - Test-Find-Test Data

An effectiveness factor (EF), d_j is the fraction decrease in λ_j after a corrective action has been made for the j-th Type B mode. The failure rate of the j-th Type B failure mode after a corrective action is (1-d_j) λ_j . In practice the projection model EFs are assigned based on engineering assessments, test results, and other factors. Studies indicate that an average EF d of .70 is typical for a reliability growth program. Individual EFs may vary. The assigned EFs for distinct Type B modes are given in Table 3.

B Mode j	Number N_j	First Occurrence	EF d_j
1	2	15.0	.67
2	3	25.3	.72
3	2	47.5	.77
4	2	54.0	.77
5	3	56.4	.87
6	2	99.6	.92
7	1	100.3	.50
8	3	112.0	.85
9	3	125.5	.89
10	4	133.4	.74
11	1	192.7	.70
12	2	249.0	.63
13	1	285.0	.64
14	1	379.4	.72
15	1	389.0	.69
16	1	395.2	.46

Table 3: Test-Find-Test Type B Failure Mode Data and Effectiveness Factors

For test-find-test, the system failure intensity is constant during the testing and then jumps to a lower value due to the incorporation of corrective actions. The intensity at the end of the test T, before delayed corrective actions are introduced into the system, is the achieved intensity. The reciprocal of the intensity is the achieved MTBF,

We estimate the achieved failure intensity λ_S by

$$\hat{\lambda}_S = \hat{\lambda}_A + \hat{\lambda}_B\ ,\quad \hat{\lambda}_A = NA/T\ ,\quad \hat{\lambda}_B = N_B/T\ . \tag{7}$$

Based on the data in Table 2,

$$\hat{\lambda}_S = 0.105 \quad \hat{\lambda}_A = 0.025\ ,\quad \hat{\lambda}_B = 0.08\ . \tag{8}$$

The estimated achieved MTBF M_S at time T = 400 before the jump is $\hat{M}_S = 9.5$. We estimate the jump next.

The estimated projected failure intensity, Ref. 4, is

$$\hat{\lambda}_P = \hat{\lambda}_A + \sum_{j=1}^{M}(1-d_j)\frac{N_j}{T} + \bar{d}\,\hat{h}(T) \tag{9}$$

where

$$\bar{d} = \frac{\sum_{j=1}^{M} d_j}{M}\ ,$$

is the average EF, M is the number of unique Type BD modes, and

$$\hat{h}(T) = \hat{\lambda}\,\hat{\beta}\,T^{\hat{\beta}-1} \tag{10}$$

is the Crow (AMSAA) model applied to the first occurrences of distinct Type BD failure modes.

The projection model $\hat{\lambda}$ and $\hat{\beta}$ for (10) use only the M first occurrence failure times of the seen and unique Type BD failure modes. These first occurrences are given in Table 3. Applying equations (3) to the first occurrence data in Table 3 we have:

$$\hat{\lambda} = 0.1820\ ,\qquad \hat{\beta} = 0.7472\ . \tag{11}$$

Based on the data in Tables 2 and 3, we have M = 16,

$$\bar{d} = .72\ ,\qquad \hat{h}(400) = 0.0299. \tag{12}$$

Also,

$$\bar{d}\,\hat{h}(T) = 0.0215\ ,\ \hat{\lambda}_A = 0.025$$

$$\sum_{j=1}^{M}(1-d_j)\frac{N_J}{T} = 0.0196\ . \tag{13}$$

From (9) the projected failure intensity and MTBF are:

$$\hat{\lambda}_p = 0.0661\ ,\ \hat{M}_p = 15.1. \tag{14}$$

The projection model estimates that the MTBF jumps to 15.1 hrs. from 9.5 hrs due to the 16 distinct corrective actions.

3. *CROW (AMSAA) MODEL LEARNING CURVE APPLICATIONS*

In both of the models discussed above the Crow (AMSAA) model as a non-homogeneous Poisson process (NHPP) (Ref. 3) with intensity function $r(t) = \lambda\beta t^{\beta-1}$ is utilized. In the first application, test-fix-test, the Crow (AMSAA) model is used with all the system failure data to describe the decrease in the failure intensity due to corrective actions. In this application all failures, including first occurrences of each unique problem receiving corrective actions, all repeat failures, and all failures for modes not receiving corrective action, are used in the analysis. In the second application, test-find-test, the Crow (AMSAA) model is embedded in the overall failure intensity function to describe the decrease in the rate of occurrence of unique Type BD failure modes. In this application only the first occurrence of distinct Type BD failure modes are used in the analysis. Both use the failure intensity function $r(t) = \lambda\beta t^{\beta-1}$ and have foundations in the Learning Curve property of the Crow (AMSAA) model

Under the Crow (AMSAA) model, the expected number of failures by time T is given by $E\left[(N(T)\right] = \lambda T^{\beta}$ and is the basis for the Crow (AMSAA) Model Learning Curve applications.

What is a Learning Curve? The concept of the learning curve was introduced to the aircraft industry in 1936 when T. P. Wright published an article in the February 1936 Journal of the Aeronautical Science (Ref. 6). Wright described a basic theory for obtaining cost estimates based on repetitive production of airplane assemblies. Since then, learning curves have been applied from simple tasks to complex jobs like manufacturing a Space Shuttle. Under the Learning Curve concept, costs or labor will decrease by a constant percentage each time the production quantity is doubled. What this means from a Learning Curve approach is that the costs of the i-th production unit is $C(i) = \lambda i^{\beta}$. The parameter λ is the cost of the first unit. As we double the number of units, the cost will decrease by a fixed amount. That is, for unit 2 the cost is $C(2) = \lambda 2^{\beta}$ and the learning rate is $\frac{C(2)}{C(1)} = \frac{\lambda 2^{\beta}}{\lambda} = 2^{\beta}$.

This learning rate is the same each time we double the production units from 1 to 2, 2 to 4, 4 to 8, etc. If $\beta = .5$ then the learning rate is 1.4. That is, each time we double the production units the cost is increased only by a factor of 1.4 instead of 2. The rate of improvement is 60 %.

The learning curve can be easily extended to failures, safety, manufacturing, and many other varied applications. Duane (1962) introduced the learning curve concept for the reliability growth test-fix-test case and in 1972 Crow developed the statistical framework for estimation of the associated parameters. For the Crow (AMSAA) model reliability growth test-fix-test applications the Learning Curve is $E\left[(N(T)\right] = \lambda T^{\beta}$, where N(T) is the total number of failures by time T.

4. *LEARNING CURVE APPLICATION TO UNIQUE FAILURE MODES*

Studies and extensive experience indicate that the learning cure model generally represents the occurrence of unique Type BD problem failure modes. In our application, let H(t) be the total number of unique Type BD failure modes occurring over the test time (0,t). Under the Learning Curve approach $H(t) = \lambda t^{\beta}$, and each time we double the test time, the additional number of unique problems seen will have the same constant learning rate $\frac{H(2)}{H(1)} = \frac{\lambda 2^{\beta}}{\lambda} = 2^{\beta}$.

Under most reasonable practical conditions, we will expect β to be less than one. If $\beta = .7$. The learning rate is 1.6, which is a decrease of 40 % in unique problems seen.

5. *TWO APPLICATIONS OF CROW (AMSAA) MODEL*

Based on the above discussion, the Crow (AMSAA) model may be used under practical conditions to represent all failures during reliability growth development testing and also be used to represent the occurrence of unique Type BD failure modes during the same test. For the test-find-test case there are no corrective actions during the test, which would imply that the system level Crow (AMSAA) beta should be close to one. This assumption can be evaluated by applying the model to all the data. For example, if we apply the Crow (AMSAA) model to all the data in Example 2, we have the estimated parameters

$\hat{\lambda} = 0.0252$ $\hat{\beta} = 1.2384$ $\hat{\lambda}_{CA} = 0.1300$ and

$\hat{M}_{CA} = \left[\hat{\lambda}_{CA}\right]^{-1} = 7.66.$

The system level beta estimate is greater than one, and for this data set, this is due to statistical variability. The actual beta is one. Also, in Example 2 there are Type A modes, first occurrence of Type BD modes and repeats of Type B modes. If we apply the Crow (AMSAA) model to each of these individual sets of data, we would have separate estimates of the parameters and the corresponding failure intensity functions at time T. For example, for the first occurrence of unique Type BD modes $\hat{h}(400) = 0.0299$. With rare exceptions, these individual estimates of the intensity functions at time T will not add up to be the intensity function at the system level at time T and, because of statistical variability, the estimated value for h(t) could be larger than the system level estimate, $\hat{\lambda}_{CA}$.

6. *MANAGEMENT STRATEGY METRICS*

A reasonable management strategy metric approach is to estimate the percent of the total system failure intensity being allocated by management to Type A and Type BD modes. The system reliability can not be any greater than the Type A reliability, so it must not be too large. In addition, the percent allocated to Type BD modes is indicative of the effort expended toward corrective actions. For the Type BD modes, we also have the first occurrences and the repeat failures. Because the estimated failure intensities will not generally add, we can not simply take the ratios of the respective individual Crow (AMSAA) model estimated failure intensities to the estimated total.

7. *MANAGEMENT STRATEGY METRICS METHODOLOGY*

Now, from equations (1) and (3) it follows that at the system level $\hat{r}(T) = \frac{N\hat{\beta}}{T}$. If we estimate the intensity functions for each of the subgroups, Type A, first occurrence of Type BD modes and repeats of Type BD modes, we have estimates

$$\hat{r}_A(T) = \frac{N_A \hat{\beta}_A}{T}, \hat{r}_{FO}(T) = \frac{N_{fo} \hat{\beta}_{fo}}{T} \quad \hat{r}_R(T) = \frac{N_R \hat{\beta}_R}{T} .$$

As noted earlier, these estimates will rarely add exactly to the system $\hat{r}(T)$ estimate. It is straightforward to show, however, that:

$$\hat{r}(T) = \left(\frac{\hat{\beta}}{\hat{\beta}_A}\right)^2 \hat{r}_A(T) + \left(\frac{\hat{\beta}}{\hat{\beta}_{FO}}\right)^2 \hat{r}_{FO}(T) + \left(\frac{\hat{\beta}}{\hat{\beta}_R}\right)^2 \hat{r}_R(T) . \qquad (15)$$

In the special case when the beta estimates for the subgroups equal the beta estimate for the total system, then the estimated failure intensities add to the total.

If we apply the Crow (AMSAA) model to the Type A failures and the Type BD failures then, it is also true that

$$\hat{r}(T) = \left(\hat{\beta}/\hat{\beta}_A\right)^2 \hat{r}_A(T) + \left(\hat{\beta}/\hat{\beta}_{BD}\right)^2 \hat{r}_{BD}(T)$$

and

$$\hat{r}_{BD}(T)=\left(\hat{\beta}_{BD}\Big/\hat{\beta}_{FO}\right)^2\hat{r}_{FO}(T)+\left(\hat{\beta}_{BD}\Big/\hat{\beta}_{R}\right)^2\hat{r}_{R}(T).$$

The practical interpretation of equation (15) is $\left(\hat{\beta}\Big/\hat{\beta}_A\right)^2\hat{r}_A(T)$ is that part of $\hat{r}(T)$ which is attributable to Type A mode failures over (0,T); $\left(\hat{\beta}\Big/\hat{\beta}_{FO}\right)^2\hat{r}_{FO}(T)$ is that part of $\hat{r}(T)$ which is attributable to First Occurrence BD failure modes over (0,T; and . $\left(\hat{\beta}\Big/\hat{\beta}_R\right)^2\hat{r}_R(T)$ is that part of $\hat{r}(T)$ which is attributable to Repeat BD failure modes over (0,T).

The same interpretation applies if we partition $\hat{r}(T)$ into only the two subgroups, Type A and Type BD modes. Type BD modes are partition into first occurrences and repeats.

The respective ratios of the attributed amount divided by the estimated total system failure intensity provide a practical metric of the management strategy over the interval (0, T). For the partition in (15) these ratios are:

$$p_A=\left(\frac{\hat{\beta}}{\hat{\beta}_A}\right)^2\frac{\hat{r}_A(T)}{\hat{r}(T)},\quad p_{FO}=\left(\frac{\hat{\beta}}{\hat{\beta}_{FO}}\right)^2\frac{\hat{r}_{FO}(T)}{\hat{r}(T)},\quad \text{and}$$

$$p_R=\left(\frac{\hat{\beta}}{\hat{\beta}_R}\right)^2\frac{\hat{r}_R(T)}{\hat{r}(T)}.$$

These fractions are characteristic of averages over (0, T.) and are proportional to $\hat{r}_A(T)$, $\hat{r}_{FO}(T)$, $\hat{r}_R(T)$, the instantaneous values at time T. This means that most practical management strategy interpretations for the $\hat{r}_A(T)$, $\hat{r}_{FO}(T)$, $\hat{r}_R(T)$, also apply to the fractions .

8. *CALCULATION OF MANAGEMENT STRATEGY RATIOS*

For a simple method to calculate the strategy ratios, let N be the total number of failures recorded and let $0<X_1<X_2<\ldots X_N\le T$ denote the N successive failure times on a cumulative time scale. Let Y_{Ai}, Y_{FOi}, Y_{Ri}, denote those Xi's designated as Type A modes, BD first occurrence modes, and BD repeat modes, respectively. Then it follows that

$$p_A=\frac{\sum_{A_i}\ln(T/Y_{Ai})}{\sum_{i=1}^{N}\ln(T/X_i)}\quad p_{FO}=\frac{\sum_{FO_i}\ln(T/Y_{FOi})}{\sum_{i=1}^{N}\ln(T/X_i)}\quad p_R=\frac{\sum_{R_i}\ln(T/Y_{Ri})}{\sum_{i=1}^{N}\ln(T/X_i)}.$$

9. *INTERPRETATION OF FIRST OCCURRENCE RATE*

Suppose a system has constant failure rate, all modes have a constant failure rate, and assume the simple case when all failure modes are Type BD. The very first failure seen in the test will represent the first occurrence of a unique BD failure mode. The rate in which we saw this first unique BD mode is exactly equal to the failure rate of the system. Now visualize a system without that failure mode. The failure rate for the new system is the original failure rate less the failure rate for the failure mode seen. Now the rate in which we will see the second unique BD failure mode is equal to the failure rate for the second system. As we repeat this process it becomes clear that the rate, in which we are seeing new, unique BD failure modes, is exactly equal to the total failure rate for the BD failure modes not yet seen. In other words, $\hat{r}_{FO}(T)$ (or h(T)) has two interpretations. One interpretation is it is the rate in which we are seeing new Type BD modes. The other is it is the total amount of failure rate represented by all BD failure modes not yet seen in the test. That is, it is the unseen BD failure rate. Clearly, we want this rate to start "high" and be reduced toward zero as we uncover new problems. In addition, it is noted that we can not reduce by a corrective actions the failure rates for modes not yet seen. That is, $\hat{r}_{FO}(T)$ represents the unseen failure intensity and will not be reduced with the current corrective.

Therefore, p_{FO} is that fraction of $\hat{r}(T)$ which is attributable to unseen Type BD failure modes over (0,T).

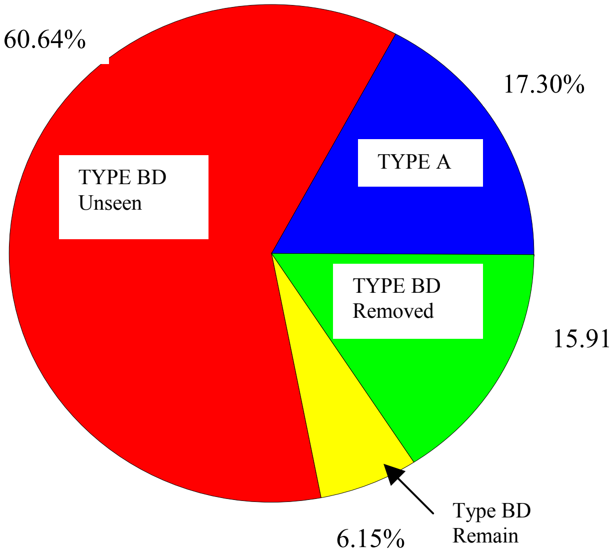
10. *INTERPRETATION OF REPEAT RATE*

The total BD mode failure intensity at time T consists of the failure intensity at time T for those BD modes not seen in (0,T) and the failure intensity for Type BD modes seen in (0,T). Therefore the repeat ratio p_R is the fraction of the total system failure intensity estimate that is attributable to the Type BD failure modes seen during (0, T). Corrective actions can only reduce the failure rates for Type BD modes actually seen during the test period (0, T). The fraction p_R is proportional to the estimated seen failure rate $\hat{r}_R(T)$. This is an estimate of the failure rate that will be reduced by corrective actions. The metric p_R is the fraction of $\hat{r}(T)$ which is attributable to seen Type BD failure modes over (0,T) and will be reduced by the corrective actions.

11. *EXAMPLE OF FAILURE MODE MANAGEMENT STRATEGY CALCULATION*

For the data in Example 2 $\hat{r}(T)$=0.1300. the calculated management strategy fractions are $P_A=.01730$, $P_{BD}=0.8270$, $P_{FO}=0.6064, P_R=0.2206$. The average effectiveness factor for the 16 unique BD failure modes is d = 0.72. Therefore, (.72)(P_R) = 0.1591 is the fraction of the total system failure intensity which is attributable over (0, T) to the Type BD modes seen and removed by a corrective action. Also, (0.28)(P_R) = 0.0615 is seen and will remain. The repeat beta should be greater than one. For this data the repeat beta = 2.19.

A pie chart of the management strategy is given below.



This pie chart should be used in conjunction with the test-find-test Projection model which estimates the projected MTBF of 15.1 hrs. The Pie Chart represents the management strategy over the test period (0, T) that yielded the projected MTBF. With this methodology the two main metrics are the Type A and Type BD percentages. These metrics are key to a successful program and can be changed if necessary. Of the system failure intensity 17.3 % was due to Type A mode failures over (0, T) and 82.7 % was due to Type BD problem mode failures over (0, T). The 17.3 % for Type A modes is often considered high. From studies, a value of 5 % or less for successful programs is not unusual. Another key metric is the unseen Type BD percentage. At time = 0 the unseen equaled the total BD percentage of 82.7 and moved to a lower value as unique problems were found. The 60.64 % is viewed as an average for the unseen Type BD percentage over (0, T) If the potential in the system is reached then the unseen percentage will be low. This average result together with Projection model metrics indicate that it is possible to further increase the 15.1 hr. MTBF with additional testing and corrective actions. It is very important that the beta for the first occurrences be checked and be less than one. In this example the first occurrences beta equals .797. For a beta less than one the 60.64 percent can be expected to decrease with addition testing. If we double the test time from 400 to 800 then, based on the learning curve property of the Crow (AMSAA) model, we can expected to see a total of 16*2^(.797)= 27.8 distinct Type BD modes or 11.8 more from the unseen group.

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