An Overview of the 217Plus™

David Nicholls, Reliability Information Analysis Center

In the Third Quarter 2006 edition of the RIAC Journal, we introduced the "Handbook of 217Plus™ Reliability Prediction Models" that the RIAC has published to provide insight into the methodology and models that make up the 217Plus™ approach to system reliability assessment [Reference 1]. We briefly introduced the primary factors that form the basis of the methodology:

1. Whether information exists on a predecessor system
2. The amount of empirical reliability data that is available for that system
3. Whether the reliability analyst chooses to assess the processes used in system development

Figure 1 provides an overview of the 217Plus™ approach to failure rate estimation that is based on the above three factors. Note that, for the purposes of our discussion, "system" applies to the highest level definition of the item defined within 217Plus™. A "system", therefore, can be a true system, a product, an equipment, an assembly, a subassembly, i.e., any level of complexity that the user wishes to define.

If a system to be analyzed using 217Plus™ is an evolution of a predecessor system (i.e., an earlier, but similar, configuration to the new design), then a prediction can be performed on both the predecessor system and the new system. The results of these two predicted system failure rates form the basis of a ratio that can be used to modify the observed failure rate of the predecessor system. The result of this predecessor analysis is λ_1 in Figure 1.

If enough empirical data (field, test or both) is available on the new system to be analyzed, it can be combined with the 217Plus™ predicted failure rate of the new system using a Bayesian approach to form the "best" failure rate estimate possible. As the quantity of empirical data increases, the failure rate using the Bayesian combination will be increasingly dominated by the empirical data. The result of this Bayesian combination is presented as λ_2 in Figure 1.

The minimum amount of analysis required for a 217Plus™ reliability prediction is the summation of component estimated failure rates, plus other data that may be available to the analyst. The current twelve component models used by 217Plus™ are included in the Handbook, and will be introduced in more detail in future editions of the RIAC Journal. The result of the component-based prediction is represented by $\lambda_{IA,\ new}$ in Figure 1. This predicted value can be further modified within 217Plus™ through the application of the optional Process Grade Analysis, or other modifications to default environmental stress or operational profiles. These modifications are reflected in the failure rate represented by $\lambda_{predicted,\ new}$ in Figure 1.

The rest of this article will discuss each element of the 217Plus™ methodology presented in Figure 1 in more detail.

Note that the 217Plus™ methodology calculates failure rates in terms of failures per million calendar hours, not operating hours. Therefore, user inputs for field data or user-defined failure rates need to be converted to a calendar hour basis prior to incorporating them into a 217Plus™ reliability prediction. The conversion factors are:

Calendar hours = Operating hours / Duty cycle

Operating hours = Calendar hours x Duty cycle

$\lambda_{IA,\ predecessor}$

$\lambda_{IA,predecessor}$ represents the initial failure rate assessment of the predecessor system. This is the sum of the predicted component failure rates,

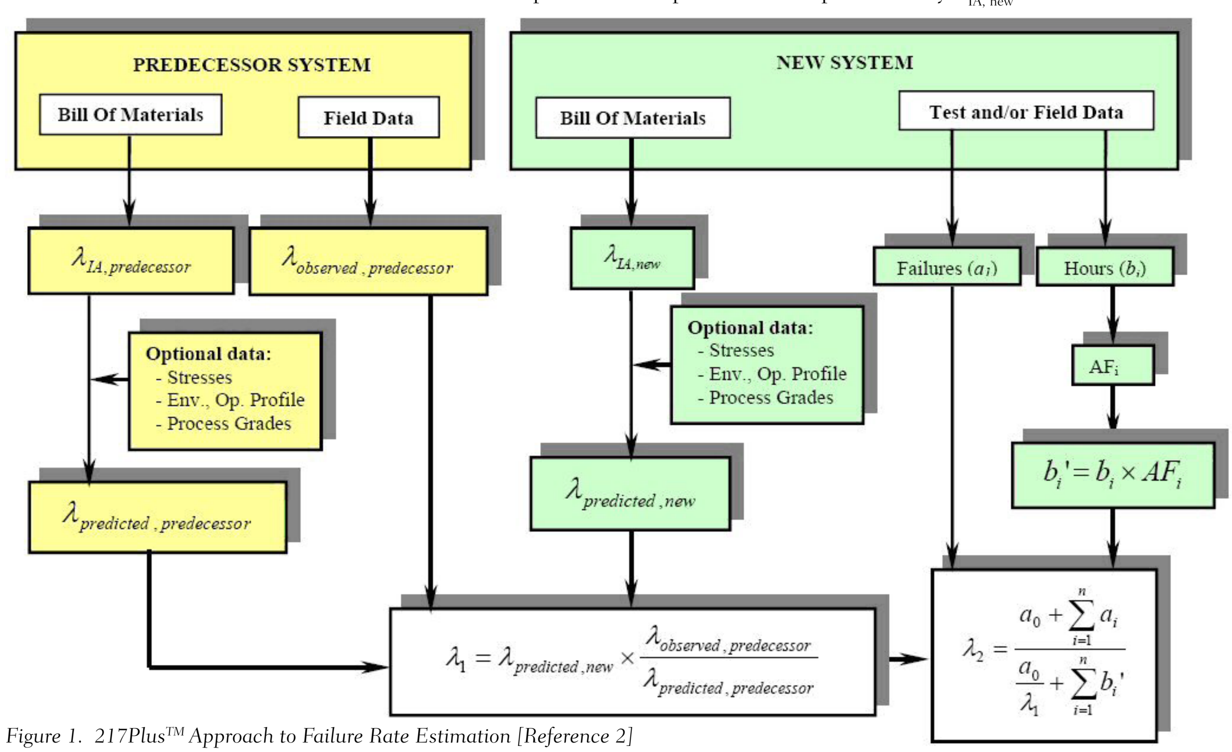

Figure 1. 217Plus™ Approach to Failure Rate Estimation [Reference 2]

System Reliability Assessment Methodology

and uses the twelve 217Plus™ component failure rate models, data from the RIAC Nonelectronic (NPRD) and Electronic (EPRD) Part Databases, or user-defined data on components from other sources.

$\lambda_{observed, predecessor}$

$\lambda_{observed, predecessor}$ is the observed failure rate of the predecessor system, and represents the point estimate of the failure rate, which is equal to the number of observed failures divided by the cumulative number of operating hours.

Optional Data

Optional data is used to enhance the predicted failure rate by factoring in more detailed information pertaining to environmental stresses, operating profile factors, and Process Grades. 217Plus™ contains default values for the environmental stresses and operational profile, but in the event that actual values of these parameters are known, either through analysis or measurement, they should be used instead of the defaults. The application of Process Grades within 217Plus™ is also optional, allowing the user the option of evaluating the specific processes used in the development and sustainment of a system. If the process grades are not used, default values are provided for each process (failure cause), so that the user can evaluate any or all of the processes. The use of the Process Grade option of 217Plus™ is included in the Handbook, and will be addressed in more detail in a future edition of the RIAC Journal.

$\lambda_{predicted, predecessor}$

$\lambda_{predicted, predecessor}$ is the predicted failure rate of the predecessor system after combining the initial assessment ($\lambda_{IA,predecessor}$) with the Optional Data, if used.

$\lambda_{IA,new}$

$\lambda_{IA,new}$ represents the initial assessment of the new system. This is calculated as the sum of the predicted component failure rates, and uses the 217Plus™ component failure rate models, data from the RIAC NPRD and EPRD databases, and other data that may be available to the analyst. A reliability prediction performed in accordance with this method is the minimum level of analysis that will result in a predicted reliability value. Applying the Optional Data can further refine this value.

$\lambda_{predicted, new}$

$\lambda_{predicted, new}$ is the predicted failure rate of the new system after combining the initial assessment with the Optional Data, if used. If the Optional Data is not used, then $\lambda_{predicted, new}$ is equal to $\lambda_{IA,new}$.

λ_1

λ_1 is the failure rate estimate of the new system after the predicted failure rate of the new system ($\lambda_{predicted, new}$) is combined with the predicted and observed information from the predecessor system ($\lambda_{predicted, predecessor}$ and $\lambda_{observed, predecessor}$, respectively). The equation that translates the failure rate of the predecessor system to the new system is:

$$\lambda_1 = \lambda_{predicted,new} \times \frac{\lambda_{observed,predecessor}}{\lambda_{predicted,predecessor}}$$

The values of $\lambda_{predicted,new}$ and $\lambda_{predicted,predecessor}$ are obtained using the component reliability prediction procedures, equations and data previously described. The ratio "$\lambda_{observed,predecessor}/\lambda_{predicted,predecessor}$" accounts for the differences in the predicted and observed failure rates of the predecessor system. This ratio inherently accounts for the differences in the systems that are accounted for in the component reliability prediction methodology.

This methodology can be used when the new system is an evolutionary extension of predecessor designs. If similar processes are used to design and manufacture a new system, and the same reliability prediction processes and data are used, then there is every reason to believe that the predicted/observed ratio of the new system will be similar to that observed on the predecessor system.

This methodology implicitly assumes that there is enough operating time and failures on which to base a value of $\lambda_{observed,predecessor}$. For this purpose, the observance of failures is critical to derive a point estimate of the failure rate (i.e., failures divided by hours). A single-sided confidence level estimate of the failure rate should not be used.

a_i

a_i represents the number of failures for the i^{th} set of data on the new system.

b_i

b_i is the cumulative number of operating hours for the ith set of data on the new system.

AF_i

AF_i is the acceleration factor between the conditions of test or field data on a new system and the conditions under which the predicted failure rate is desired. If the data is from field applications in the same environment for which the prediction is desired, the AF value will be one. If the data is from accelerated test data or from field data in a different environment, then the AF value needs to be determined. If the applied stresses are higher than the anticipated field use environment of the new system, AF will be a value greater than one. The acceleration factor can be determined by performing a reliability prediction at both the test and use conditions, but AF can only be determined in this manner if the reliability prediction model is capable of discerning the effects of the accelerating stress(es) of the test. As an example, consider a life test in which a system was exposed to a temperature higher than what it would be exposed to in field-deployed conditions. In this case, the AF can be calculated as follows:

$$AF = \frac{\lambda_{T1}}{\lambda_{T2}}$$

where,

λ_{T1} = the predicted failure rate at the test conditions obtained by performing a prediction of the system at the test conditions

λ_{T2} = the predicted failure rate at the use conditions obtained by performing a prediction of the system at the use conditions

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b_i'

b_i' is the effective cumulative number of hours of the test or field data used. If the tests were performed at accelerated conditions, the equivalent number of hours needs to be converted to the conditions of interest, as follows:

$$b_i' = b_i \times AF_i$$

a_o

a_o is the effective number of failures associated with the predicted failure rate. If unknown, use 0.5. In the event that predicted and observed data is available on enough predecessor systems, this value can be tailored. This tailoring method will be discussed shortly.

λ_2

λ_2 is the best estimate of the new system failure rate after using all available data and information. As much empirical data as possible should be used in the assessment. This is done by mathematically combining λ_1 with empirical data. Bayesian techniques are used for this purpose. This technique accounts for the quantity of data by weighting large amounts of data more heavily than small amounts. λ_1 forms the "prior" distribution, comprised of a_0 and a_o/λ_1. If empirical data (i.e., test or field data) is available for the system under analysis, it is combined with λ_1 based on the following equation:

$$\lambda_2 = \frac{a_0 + \sum_{i=1}^{n} a_i}{\frac{a_0}{\lambda_1} + \sum_{i=1}^{n} b_i'}$$

λ_2 is the best estimate of the failure rate, and a_o is the "equivalent" number of failures of the "prior" distribution corresponding to the reliability prediction. For these calculations, 0.5 should be used unless a tailored value can be derived. An example of this tailoring is provided in the next section. a_o/λ_1 is the equivalent number of hours associated with λ_1, and a_1 through a_n are the number of failures experienced in each source of empirical data. There may be "n" different sources of data available (for example, each of the "n" sources corresponds to individual tests or field data from the population of systems). b_1' through b_n' is the equivalent number of cumulative operating hours experienced for each individual data source. These values must be converted to equivalent hours by accounting for any accelerating effects between the use conditions.

Tailoring the Bayesian Constant, a_0, in λ_2

This section discusses tailoring of the a_o value used in the Bayesian equations. The value of a_o is proportional to the degree of weighting given to the predicted value (λ_1). The constant a_0 is chosen such that the uncertainty in the failure rate estimate, as calculated with the Chi-square distribution, equates to the observed uncertainty. The default value of 0.5 to be used in the equation is based on the observed/predicted ratio from a wide variety of systems, applications, industries, etc. As such, there are many "noise factors' contributing to the variability in this ratio. However, if the user of the 217Plus™ methodology has enough data on which to derive a tailored value of a_0, it should be derived and used. While the default value of 0.5 represents the large degree of uncertainty inherent when a diverse data set is used, a typical 217Plus™ user will generally be analyzing systems with a much more narrow focus, in terms of system type, environment, operating profile, etc. As such, with enough data, the value of a_0 can be increased.

To estimate the value of a_o that should be used, a distribution of the following metric is calculated for all systems for which both predicted and observed data is available:

$$\frac{\lambda_{observed,predecessor}}{\lambda_{predicted,predecessor}}$$

The lognormal distribution will generally fit this metric well, but others (i.e., Weibull) can also be used. The cumulative value of this distribution is then plotted. Next, the failure rate multipliers, as determined from the Chi-square distribution, are calculated and plotted. This Chi-square distribution should be determined and plotted for various numbers of failures to ensure that the distribution of observed/predicted failure rate ratios falls between the Chi-square values. In most cases, one, two and three failures should be sufficient. Next, the plots are compared to determine which Chi-square distribution most closely matches the observed uncertainty values. The number of failures associated with that distribution then becomes the value of a_0. Figure 2 illustrates an example for which this analysis was performed.

As can be seen from Figure 2, the observed uncertainty does not precisely match the Chi-square calculated uncertainty for any of the one, two or three failures used in this analysis. This is likely due to the fact that the population of systems on which this analysis is based is not homogeneous, as assumed by the Chi-square calculation. However, the confidence levels of interest are generally in the range of 60 to 90 percent. In this range, the Chi-square calculated uncertainty with 2 failures most closely approximates the observed uncertainty. Therefore, in this example, an a_0 value of 2 was used.

The uncertainties represented by the distribution of observed/predicted failure rates are typical of what can be expected when historical data on predecessor systems are collected and analyzed to improve the reliability prediction process. For example, using this example, one can be 80% certain that the actual failure rate for a system or product will be less than 2.2 times the predicted value.

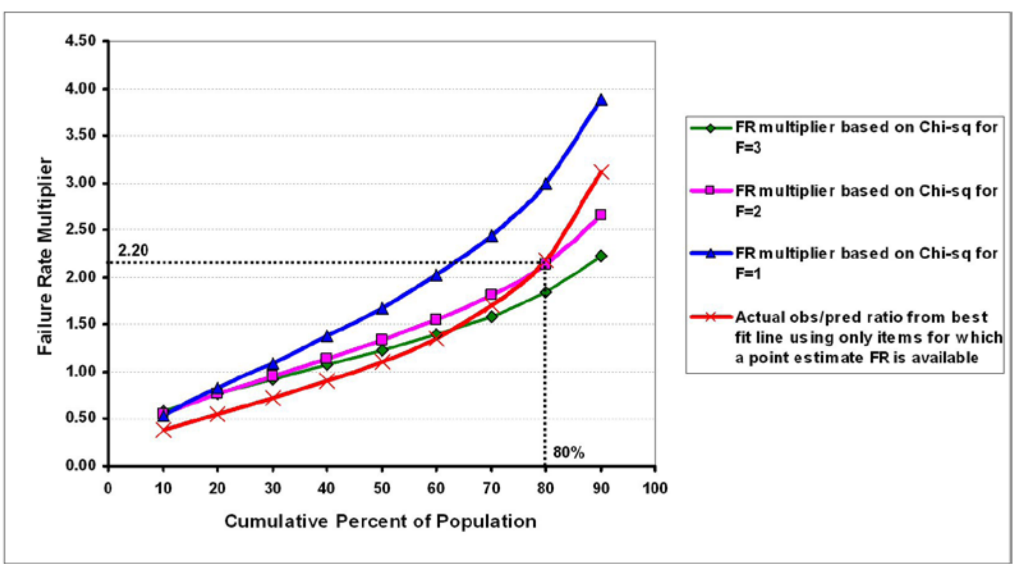

Figure 2. Comparison of Observed Uncertainty with the Uncertainty Calculated Using the Chi-Square Distribution

Next Issue

The next edition of the RIAC Journal (1st Quarter 2007) will present an introduction to the 217Plus™ component failure rate models.

References

1. "The RIAC 'Handbook of 217Plus™ Reliability Prediction Models'", Journal of the Reliability Information Analysis Center, Third Quarter 2006, available for PDF download from the RIAC at http://theRIAC.org

2. Denson, W.K., "Handbook of 217Plus™ Reliability Prediction Models", Reliability Information Analysis Center (RIAC), 26 May 2006, ISBN 1-933904-02-X