A Comprehensive Reliability Assessment Tool for Electronic Systems

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SUMMARY AND CONCLUSIONS

The Reliability Analysis Center (RAC) has developed a new methodology and associated engineering software tool, PRISM®, to assess the reliability of electronic systems. The methodology includes new component-level reliability prediction models (RACRates) as well as a process for assessing the reliability of systems due to non-component variables which are major contributors to electronic system reliability. This new methodology factors in all available test and/or field reliability data as it becomes available on a program to form the best estimate of field reliability.

1. INTRODUCTION

The premise of traditional methods of reliability predictions, such as MIL-HDBK-217, is that the failure rate of a system is primarily determined by the components comprising that system. RAC data shows (Figure 1) that more than 78% of failures stem from non-component causes, namely: design deficiencies, manufacturing defects, poor system management techniques such as inadequate requirements, wearout, software, induced, and no-defect-found failures. These have not been explicitly addressed in previous prediction methods.

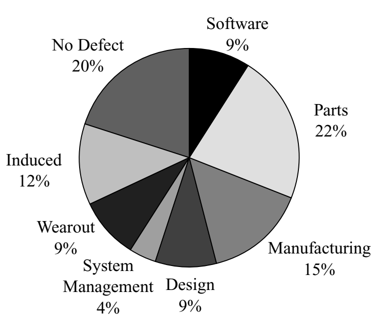
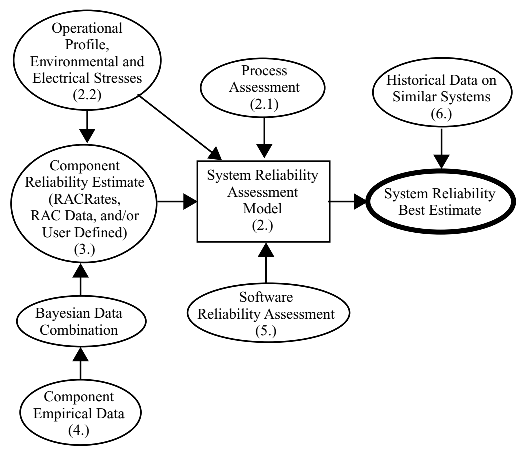


Figure 1. RAC Data: Failure Cause Distribution of Electronic Systems (nominal %)

In response to this, RAC has developed a new methodology and associated software tool called PRISM for estimating the failure rate of electronic systems. This methodology incorporates new component reliability prediction models (RACRates), a process for assessing the reliability of systems due to non-component variables, and a software reliability model in one comprehensive tool.

The PRISM methodology is illustrated in Figure 2. An initial base reliability estimate is developed based on RACRates component models, RAC failure experience data, and/or user-defined failure rates. This initial base failure rate is then modified with system-level process assessment factors for the following failure causes: Parts, Design, Manufacturing, System Management, Wearout, Induced, and No Defect Found. These process grades correspond to the degree to which actions have been taken to mitigate the occurrence of system failure due to these failure categories. A RACRates model for the estimation of software reliability is available since modern electronic systems typically contain significant amounts of software.



(Note: refer to numbers in parenthesis for corresponding paper section).

Figure 2. Conceptual Overview of PRISM

PRISM is structured to allow the user the ability to first estimate the reliability of a system in the initial design stages when little is known about the system. However, as additional information becomes available, the model allows the incremental addition of empirical test and field data to refine the initial prediction and form the best estimate of reliability.

2. PRISM SYSTEM RELIABILITY ASSESSMENT MODEL

The PRISM failure rate model for a system is as follows:

$$\lambda_P = \lambda_{IA}\left(\Pi_P\Pi_{IM}\Pi_E + \Pi_D\Pi_G + \Pi_M\Pi_{IM}\Pi_E\Pi_G + \Pi_S\Pi_G + \Pi_I + \Pi_N + \Pi_W\right) + \lambda_{SW} \quad (1)$$

where,

λ_P = predicted failure rate of the system

λ_{IA} = initial assessment of the failure rate
Π_P = parts process multiplier
Π_{IM} = infant mortality factor
Π_E = environmental factor
Π_D = design process multiplier
Π_G = reliability growth factor
Π_M = manufacturing process multiplier
Π_S = system management process multiplier
Π_I = induced process multiplier
Π_N = no-defect process multiplier
Π_W = wearout process multiplier
λ_{SW} = software failure rate prediction

The initial assessment of the failure rate, $\lambda_{IA,}$ is the seed failure rate value which is obtained by using a combination of the RACRates component reliability prediction models, the failure rate data contained in the RAC databases, or user-defined failure data. The Pi-factors within the parentheses account for specific processes used in the design and manufacture of the system, along with the reliability growth, infant mortality, and environmental characteristics of the system. The software failure rate prediction is based upon the Software Engineering Institute (SEI) Capability Maturity Model (CMM). The development of each of the main components of this model are discussed in the following sections.

2.1 Process Assessments

An objective of the PRISM system model is to explicitly account for the factors contributing to the variability in traditional reliability prediction approaches. (Reference 1 presents the basis of the system assessment methodology which was developed for the Air Force by the RAC and Performance Technology.) This is accomplished by grading the process for each of the eight system level failure cause categories identified in Figure 1. The resulting grade for each cause corresponds to the level to which an organization has taken the action necessary to mitigate the occurrence of failures of that cause. This grading is accomplished by assessing the processes in a self-audit fashion. Process grading is used to quantify the following factors: Π_P (parts process multiplier), Π_D (design process multiplier), Π_M (manufacturing process multiplier), Π_S (system management process multiplier), Π_I (induced process multiplier), Π_N (no-defect process multiplier), and Π_W (wearout process multiplier). The sum of these Π factors is equal to unity for the average grade. For example, the nominal percentage of failures due to parts is 32%. Therefore, Π_P is equal to 0.32 if an average process grade (50th percentile) is obtained. Likewise, it will increase if "less than average" processes are in place and decrease if better than average processes are in place.

The premise of the model developed in this study is that the failure rate attributable to the predominant system-level failure causes can be quantified. RAC conducted a Delphi survey to provide the baseline data that quantifies the failure rate of each cause. Each data source surveyed identified the percentage of failures attributable to each of the eight predominant failure causes. (It should be noted here that the reported percentages of failure due to some failure causes may be underestimated. For example, system management and software may be under reported because failures are usually not attributed to those categories, even when they are the root cause of failure. This also means that the percentages from the other causes may be overestimated. Although the authors recognize that this is likely, the values in the model reflect the reported values.)

A Weibull analysis was performed on the survey data to quantify the distributions of percentages for each failure cause. The resulting distributions are summarized in Table 1.

Table 1. Weibull Parameters for Failure Cause Percentages

Failure Cause	**Characteristic Percentage**	**Shape Parameter**
Parts	33.9	1.62
Manufacturing	23.2	0.96
Design	13.9	1.29
System Management	7.1	0.64
Wearout	14.7	1.68
Induced	19.8	1.58
No Defect	31.9	1.92
Software	15.0	0.70

Failure rate multiplier values were then derived by calculating the multiplier required to achieve the cumulative percentage (listed in the first column of the table) of the Weibull reliability value. This was calculated using the following equation, which is the Weibull reliability function solved for the multiplier. In this case the multiplier is synonymous with the time that is usually used as the life. The generic formula for the multiplier is given as:

$$\Pi_i = -\alpha \bullet (\ln G_i)^{1/\beta} \qquad (2)$$

In this calculation, the characteristic percentages listed in Table 2-1 are scaled by a factor of 0.833 to ensure that the sum of the multipliers is equal to one when each grade is equal to 0.50. In this case, a grade of 0.50 represents an "average" process, and since the model is normalized to an average process, the total multiplier of the initial assessment failure rate is equal to one under these conditions.

2.1.1 Reliability Growth

The PRISM model also includes a factor for assessing the reliability growth characteristics of a system. The premise of this factor is that the processes that contribute to system reliability growth in the field may or may not exist. The degree to which growth exists is estimated by a grading factor that assesses the processes contributing to growth. The PRISM growth factor calculation is based upon the Duane Model and is given by the formula:

$$\Pi_G = \frac{1.12(t+2)^{-\alpha}}{2^{-\alpha}} \qquad (3)$$

Figure 3 illustrates the growth Pi-factor multiplier for various values of growth rates as a function of time in years (t).

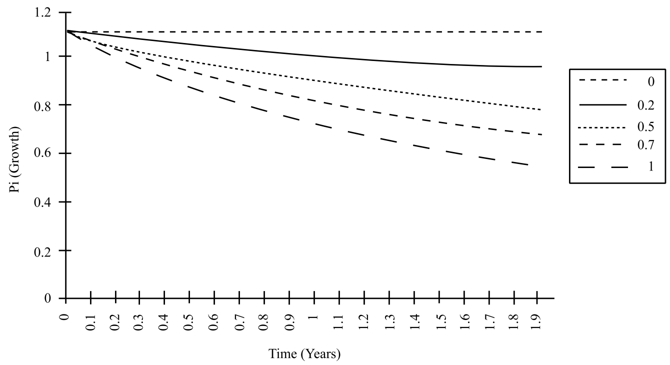


Figure 3. Π_G vs. Time and Growth Rates

The value of α is estimated by determining the degree to which the potential for growth exists. This estimation is accomplished in a manner similar to the process grading methodology by assessing and grading the processes that can contribute to reliability growth.

2.1.2 Infant Mortality

Infant mortality is accounted for in the model with a time-variant factor that is a function of the level to which ESS has been applied. The infant mortality factor, $\Pi_{IM,}$ was derived from Weibull analysis of RAC component time-to-failure data and is calculated as:

$$\Pi_{IM} = 1 - \frac{t^{-.62}}{1.77} SS_{ESS} \tag{4}$$

where,

t = time in years

SS_{ESS} = the screening strength of the screen(s) applied, if any

The above expression represents the instantaneous failure rate. If the average failure rate for a given time period is desired, this expression must be integrated and divided by the time period.

2.2 Environmental Factor

A factor is also included in the model to account for the environmental effects of vibration and temperature cycling at the system level.

If the specific environmental stresses to which the system will be exposed in field use are known, then the environmental correction factor is calculated using the formula:

$$\Pi_E = \frac{P_{TC} \bullet SS(TC_{use}) + P_{RV} \bullet SS(RV_{use})}{P_{TC} \bullet SS(TC_{env}) + P_{RV} \bullet SS(RV_{env})} \tag{5}$$

where,

P_{TC} = percentage of failures resulting from temperature cycling stresses

P_{RV} = percentage of failures resulting from random vibration stresses

SS = screening strength applicable to the application environmental values

If the actual values of these variables are unknown, the default values that should be used are P_{TC} = 0.80 and P_{RV} = 0.20. The SS value is the screening strength and has been derived from MIL-HDBK-344. It is an estimate of the probability of both precipitating a defect to failure and detecting it once precipitated by the test. Whenever possible, the actual values of delta T (ΔT) and vibration (G_{rms}) should be used for the intended application environment. The PRISM software tool includes default values for these values as a function of the generic environment in the event that the model user does not know the specific environmental stresses to which the system will be exposed.

3. COMPONENT RELIABILITY ESTIMATE

The PRISM system reliability model requires an initial assessment failure rate to be used as a seed value (λ_{IA}). This is derived from a combination of RACRates models, RAC empirical field failure rate data, or user-defined failure rates. This section summarizes the derivation of the new RACRates models.

Traditional methods of reliability prediction model development have included the statistical analysis of empirical failure rate data. The statistical methods typically result in model form that is multiplicative (i.e., the predicted failure rate is the product of a base failure rate and several factors that account for the stresses and component variables that influence reliability).

A primary disadvantage of the multiplicative model form is that the predicted failure rate value can become unrealistically large or small under extreme value conditions (i.e., when all factors are at their lowest or highest values). This is an inherent limitation of this type of model, primarily due to the fact that individual failure mechanisms, or classes of failure mechanisms, are not explicitly accounted for.

The RAC believes that a better approach is a combination of an additive and multiplicative model that predicts a separate failure rate for each generic class of failure mechanisms. Each of these failure rate terms is then accelerated by the appropriate stress or component characteristic. This model form is as follows:

$$\lambda_p = \lambda_o\pi_o + \lambda_e\pi_e + \lambda_c\pi_c + \lambda_i + \lambda_{sj}\pi_{sj} \tag{6}$$

where,

λ_p = predicted failure rate

λ_o = failure rate from operational stresses

π_o = product of failure rate multipliers for operational stresses

λ_e = failure rate from environmental stresses

π_e = product of failure rate multipliers for environmental stresses

λ_c = failure rate from power or temperature cycling stresses

π_c = product of failure rate multipliers for cycling stresses

λ_I = failure rate from induced stresses, including electrical overstress/ESD

λ_{sj} = failure rate from solder joints

π_{sj} = product of failure rate multipliers for solder joint stresses

By modeling the failure rate in this manner, factors that account for the application and component-specific variables that affect reliability (Pi-factors) can be applied to the appropriate additive failure rate term.

3.1 Acceleration (Pi) Factor Development

Acceleration factors (or Pi-factors) are used in the RACRates models to estimate the effect of various stress and component variables on failure rate. Since the traditional technique of multiple linear regression was not used in the derivation of the failure rate models, the Pi-factors were derived by utilizing either industry accepted values, values determined separately from data available to RAC, or values from previous modeling efforts. For example, the models typically include both operating and nonoperating temperature factors based on the Arrhenius relationship. This requires an activation energy for both operating and nonoperating conditions. To estimate these values for the model, previous modeling studies (along with existing prediction methodologies) were used. Similarly, some factors were based on test data. For example, the exponent used in the ΔT Pi-factor for the integrated circuits RACRates model is based on fallout-rate data from temperature cycling tests that were performed at various levels of ΔT.

3.2 Time Basis of the RACRates Models

Traditional reliability prediction failure rate models have been based on the operating time of the part, and the values were typically stated in failures per million (or billion) operating hours. The RACRates models (and the empirical data contained in the RAC databases used in the PRISM tool) predict the failure rate in units of failures per million calendar hours. This is necessary because it represents the common basis for all failure rate contribution terms used in the PRISM methodology (i.e., operating, nonoperating, cycling, and induced). If an equivalent operating failure rate is desired (in units of failures per million operating hours), the failure rate (in f/10^6 calendar hours) can be divided by the operational profile duty cycle to yield a failure rate in terms of f/10^6 operating hours.

3.3 Failure Mode to Failure Cause Mapping

There are two primary types of data upon which the RACRates models are based, i.e., failure rate and failure mode. The model development process required that the failure rate data be apportioned into the five defined failure cause categories. Since the failure mode data contained in the RAC databases is typically not classified according to these categories, it was necessary to transform the failure mode distribution data into the failure cause distribution. This was accomplished by assessing the stresses that accelerate the specific class of failure categories, and estimating the percentage of failures that could be attributed to those stresses. The primary stresses that potentially accelerate operational failure modes are operating temperature, vibration, current and voltage. The stresses that accelerate environmental failure causes are nonoperating ambient temperature, corrosive stresses (contaminants/heat/humidity), aging stresses (time), and humidity. As an example, Table 2 summarizes this process for a general resistor. Each of the six failure modes is listed across the top of the table, i.e., EOS, contamination, etc., along with its associated relative percentage of occurrence. This data was collected by the RAC and is based primarily on failure analysis results of parts that have failed in the field.

Table 2. Example of Failure Mode to Failure Cause Category Transformation

Failure Category	**Accelerating Stresses/Causes**	**Failure Mode**						**Percentage**	**Total Percentage**
		EOS	**Contamination**	**Cracked**	**Chipout**	**Leakage**	**Unverified**		
		41.20%	**23.50%**	**17.60%**	**7.10%**	**5.90%**	**4.70%**		
Operational Stresses	Op. Temp.						s	0.00	
	Vibration				p		s	0.04	0.05
	Current						s	0.00	
	Voltage						s	0.00	
Environmental	Ambient Temperature		p				s	0.08	0.31
	Corrosion		p			p	s	0.09	
	Aging		s			p	s	0.05	
	Humidity		p			p	s	0.09	
Power Cycling	Power Cycling			p	p	s	s	0.22	0.22
Induced/EOS	Induced/EOS	p					s	0.42	0.42

Notes: "p" = primary "s" = secondary

3.4 Derivation of Base Failure Rates

Once the Pi-factors were defined for each component type that was modeled, and once the failure rate was apportioned amongst the failure causes, the base failure rate could be determined. This was accomplished by (1) gathering all of the failure rate data within the RAC database, (2) estimating the model input variables (temperatures, stresses, etc.) for each source of data, (3) calculating the associated Pi-factor for each failure rate, and (4) deriving a base failure rate for each of the failure cause categories. For example, the failure rate associated with operational stresses equated to the product of the base failure rate and the operational Pi-factors:

$$P_{FC} \bullet \lambda_{obs} = \lambda_b \pi_o \tag{7}$$

where,

P_{FC}	=	percentage of failure rate attributable to operational failure causes
λ_{obs}	=	observed failure rate
λ_b	=	base failure rate to be derived
π_o	=	product of model Pi-factors

Solving for λ_b and adding a factor to account for data points which have had no observed failures yields:

$$\lambda_b = \frac{P_{FC} \bullet \lambda_{obs}}{\pi_o} \bullet P_F \tag{8}$$

where,

P_F	=	percentage of total observed calendar hours associated with components that have had observed failures.

This factor was necessary to prorate the base failure rate that was calculated from data records with failures. Once this value of λ_b was calculated for each data record, the geometric mean was used as the best estimate of the base failure rate.

4. EMPIRICAL COMPONENT DATA

The reliability estimate for a component can be further modified by empirical data taken throughout system development and testing. This modification is accomplished within PRISM using Bayesian techniques that apply the appropriate weights for the various data sources.

5. SOFTWARE RELIABILITY ASSESSMENT

The RACRates model for software failure rates has a unique set of model parameter requirements, and the form of the failure rate model is structured differently than that of hardware components.

The basic form of the RACRates Software Model is based upon the SEI Capability Maturity Model (CMM):

$$\lambda_{t_i} = \left(\frac{F_{t_{(t_{i-1})}} - F_{(t_i)}}{730} \right) (DC)(FER) 10^6 \tag{9}$$

where,

λ_{t_i}	=	Predicted failure rate at t_i (in failures per million calendar hours)
$F_{(t_{i-1})}$	=	Number of faults remaining at time, t_{i-1}
F_i	=	Number of faults remaining at time, t_i
t_i	=	Time After Deployment
DC	=	Duty cycle (% of calendar time the software is in operation (this is derived from the operating profile))
FER	=	Fault Expansion Ratio (number of observed critical failures to number of faults actually removed). *This value is the product of % Fault Activation, Fault Latency and Average Severity.*
730	=	Average number of hours per month

If this is not a widely deployed system and the user has no feel whatever regarding the numeric value of these input parameters some default values are supplied. These default values are:

a) Fault Latency = 2.0 (dimensionless number)
b) Time to Stabilization = 48 (months) for initial software release. However, this value should be changed to 24 (months) for subsequent software releases.
c) Fault Activation = 100 (%)
d) Average Severity = 50 (%)

For a widely deployed system the user would need to establish more accurate input values for *Fault Latency* and *Fault Activation* and use those as the input values rather than the supplied default values. For all systems, *Lines of Code* and (*Initial) Fault Density* will always require user input.

6. HISTORICAL DATA ON SIMILAR (PREDECESSOR) SYSTEMS

If empirical data exists on a predecessor system; that is, a similar system operating under similar conditions; a "top-down" analysis can be performed which leverages from the knowledge and experience gained from that predecessor system. The equation that translates the failure rate from the old system to the new system is as follows:

$$\lambda_{predicted, new} = \lambda_{predecessor, observed} \bullet \frac{\lambda_{predicted, new}}{\lambda_{predicted, predecessor}} \tag{10}$$

The (predicted, new)/(predicted, predecessor) failure rate ratio accounts for the differences in application environment, complexity, stresses, date, etc. The predicted failure rates for the predecessor and the new system are determined by applying the complete PRISM detailed methodology to each system. The observed predecessor failure rate is entered directly into PRISM, and is used as a baseline against which the new system predicted failure rate is calculated.

CONCLUSIONS

The Reliability Analysis Center has developed a new methodology and associated engineering software tool, PRISM, to assess the reliability of electronic systems. Features of this methodology are that it:

- Models reliability based upon observed failure mode distributions
- Incorporates RAC's new component reliability models, RACRates
- Incorporates software reliability
- Models component reliability growth based upon observed industry trends
- Is tailorable based upon user failure experience data

FUTURE WORK

The Reliability Analysis Center, as a chartered Department of Defense Information Analysis Center (IAC) in the area of Reliability and Maintainability, perfoms on-going collection of data and information pertaining to the reliability and maintainability of electronic components, equipment and systems.

RAC's new system reliability assessment methodology and associated software tool, PRISM is a "living methodology", periodically updated based upon data and information collected by the RAC. Future updates will include the development of RACRates models for additional component types, continued refinement of the system level modifiers, on-going model verification, and modifications to reflect significant advances in the state-of-the-art in electronic systems and equipment.

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