

A Parametric Reliability Prediction Tool for Space Applications

Nkiru U. Ogamba, The Aerospace Corporation

Key Words: Parametric Reliability Prediction, Operational Reliability, Rule-based reliability prediction, Reliability database.

SUMMARY & CONCLUSIONS

This paper demonstrates several analytical techniques used to predict units (from a group) that are more likely to fail in operation. The paper specifically examines the least reliable units used by a number of US space programs. In this paper, the methodology used to develop the Parametric Reliability Prediction Tool (PRPT) is presented. The parameter used is the failure rate/MTBF for the unit. The application of the tool to the DMSP X program has been presented as well. The PRPT will support “preventative” failure analysis by identifying items that could lead to failures and their probability of occurrence. PRPT will also capture lessons learned to mitigate failure reoccurrence. PRPT will facilitate design reliability trade studies. The PRPT will be expanded to include a process for prediction of early failure modes and mean life time of new products, based on comparisons and similarity derived from the analysis.

PRPT provides a disciplined and adequate technique to obtain a more accurate reliability prediction for space systems and subsystems possibly up to Line Replaceable Unit level. Utilizing PRPT in the concept, design and development phases will be an opportunity to improve reliability predictions for space vehicles.

1 INTRODUCTION

Some critical reliability problems that could be identified from design, manufacturing, test and operational data often go unrecognized until they lead to a critical system failure. System engineering processes have a wealth of reliability engineering data but current reliability assessment methods and tools are not well suited to seamless integration with these processes. This may be due to the lack of correlation of parametric trends in preflight data with subsequent operational flight history data for various spacecraft. One way to enable better use of reliability engineering data is to build a system of failure-mitigating rules and analytical techniques using empirical and analytical data. However, meaningful risk analysis using rules and techniques requires a foundation of meaningful data. This paper demonstrates a methodology used for parametric reliability prediction analysis through the development of a reliability engineering database, consisting of analytical and empirical data from space and launch vehicle baseline designs that can be used to create high-fidelity reliability data. These data can then support system or equipment level reliability trade studies. The reliability analysis used in this paper can overcome data inaccuracies by

incorporating actual failure dates and times. These data for the most part are often quite accurate because they require no interpretation by the user and in many systems are captured automatically.

To mitigate the impact of the quality and integrity of the data in the reliability-engineering database, the following actions must be taken.

- Parametric reliability prediction factors and fields must be determined for each failure in the database (see Appendix 1).
- Root cause categories must be defined and determined.
- Standard industry-accepted subsystems must be defined and determined.
- Each failure must be classified by category and severity.
- The completeness and accuracy of the system failure data must be verified.

2 PARAMETRIC PREDICTION TOOL ISSUES

A Parametric Reliability Prediction Tool (PRPT) has been developed to enable the assessment of system reliability using system failure information. During the development of the PRPT, several issues were identified and addressed.

- Several examples of actual program reliability and maintainability processes were studied to determine which information and required fields were most useful and should be incorporated into the reliability-engineering database.
- Using these data, predictions were made and tested to estimate the reliability over time for certain system performance parameters.
- Rules were developed from the database investigation to be used for reducing future system failures.
- Failure modes were identified that can support other activities in the system engineering process.

3 PRPT PROCESS DEFINITIONS AND TERMS

3.1 Failure Classification

The PRPT methodology is a parametric analysis technique that focuses on on-orbit failure modes and classifications that affect mission success. The failure impact severity classifications used in the computation of failure rates for line replaceable units, referred to as noteworthy failures, are:

Catastrophic: This category refers to an uncorrectable hardware or software event, which causes a catastrophic loss of hardware function.

Significant: This category refers to a hardware or software event that results in loss of hardware usefulness, based on unreliable, inconsistent, or degraded performance such that switching to redundant hardware is required.

Major: This category applies to a hardware or software event that results in the implementation of redundant hardware based on unreliable, inconsistent, or degraded performance of current hardware in use.

Noteworthy: This applies to any failures that resulted to Catastrophic, Significant and/or Major failures.

3.2 Root Cause Categories

Once the failures are classified, the root cause of each failure can be categorized. A typical set of root cause categories are defined in Table 1, along with typical examples of each.

Cause Category	Cause & Examples of Failure
design	Cable Harness - faulty cable or connector design
environment	Atomic Oxygen (AO) – AO in the atmosphere
operational	Command Error - incorrect command(s) sent
other	Other - repeated or already known anomaly
part	Broken weld inside the part
software	Database – incorrect values causing malfunction
test	Operator Error - untrained operator caused the failure
unknown	Unknown - control signal jitter source unknown
workmanship	Workmanship - inaccurate alignment

Table 1 – Root Cause Categories

3.3 Satellite Subsystems

To permit uniform application of the reliability-engineering database, it must also capture a standardized set of spacecraft and launch vehicle subsystems. Table 2 shows a list of industry-wide subsystem assignments that have generally been incorporated into launch vehicle systems.

Nomenclature	Subsystem
DMS	Data Management Subsystem
EPDS	Electrical Power and Distribution Subsystem
FTS	Flight Termination Subsystem
GN&C	Guidance, Navigation and Control Subsystem
Hydraulics	Hydraulic Subsystem
Payload	Payload Subsystem
Pneumatic	Pneumatic Subsystem
Propulsion	Propulsion Subsystem
S&MS	Structure and Mechanisms Subsystem
TT&C	Telemetry, Tacking and Command Subsystem
Thermal	Thermal Subsystem

Table 2: Subsystems

4 PARAMETRIC PREDICTION TOOLS PROCESS

The methodology previously described has been developed and exercised by utilizing data and research information gathered from the engineering reliability anomaly database for beta program DMSP X.

The process involved the following tasks:

- Data gathering of ground and on-orbit anomaly data from the date of satellite launch to end-of-life for space vehicles S6 through S14.
- Development and population of a configuration and timeline template for the reliability database.
- Verification and classification of subsystem failure causes and failure modes.
- Identification of failure drivers by subsystems and by line replaceable units (LRUs).
- Identification of failure drivers across the population in DMSP X S6-S14 vehicles.
- Classification of the LRU failure causes.
- Calculation of actual failure rates of units based on compiled operating hours and number of line replaceable units in the system.
- Determination of the complexity of failure drivers based on their failure rates.
- Analyses of failure data on identified parameters, using Bayesian and Weibull techniques.

4.1 Evaluating Parameters and Identification of Noteworthy Drivers

Noteworthy subsystem failures impacting mission were selected, and on-orbit and pre-launch failures were separately analyzed. Figure 1 shows that sixty-five percent of all failures occurred on the payload subsystem. The top drivers were selected for further analysis, including the failure causes. Figure 2 shows payload module noteworthy failures, which shows that sixty-four percent of the failures occurred within the operational line scanner (OLS). Figure 3 shows payload noteworthy failure causes, which shows that workmanship is the highest cause of failure with ten failures attributed to it.

5 RESULTS

Further top-down analysis of the failure drivers within the OLS showed that seventy-one percent of those failures were caused by the primary tape recorder as shown in Figure 5, and the driving failure cause within the primary data recorder is workmanship as shown in Figure 4.

5.1 Bayesian Reliability Analysis of Primary Data Recorder

The mean time between failures (MTBF) for any component is calculated by dividing the total number of operating hours by the number of noteworthy failures. Table 3 illustrates the failure rate calculation for the primary data recorder for DMSP X satellites S6-S14 for all thirty-six recorders (4 per satellite) and the predicted failure rate developed by the manufacturer for the primary data recorder. Here is an example of Table 3 Primary Recorder (pr) failure rate calculation using satellite s7:

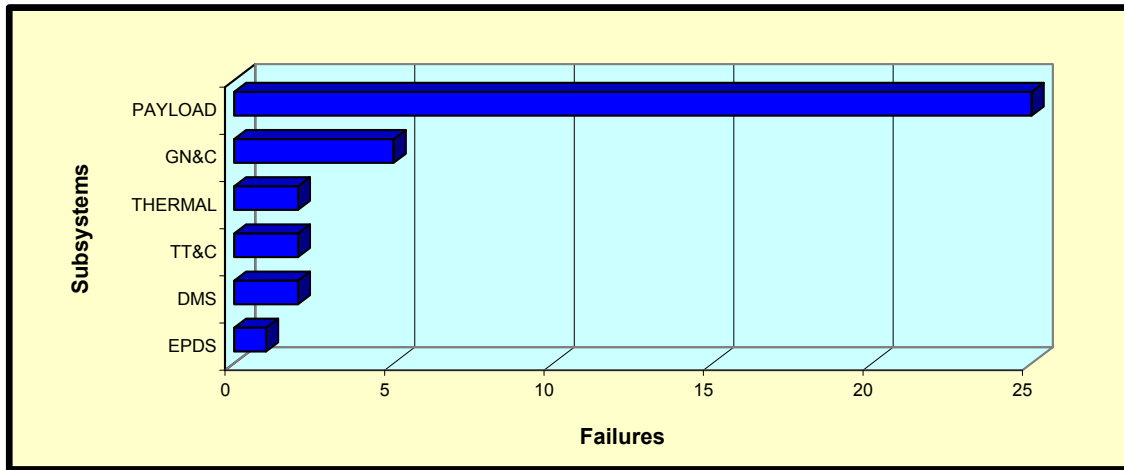


Figure 1 – DMSP 'X' Noteworthy Subsystem Failures.

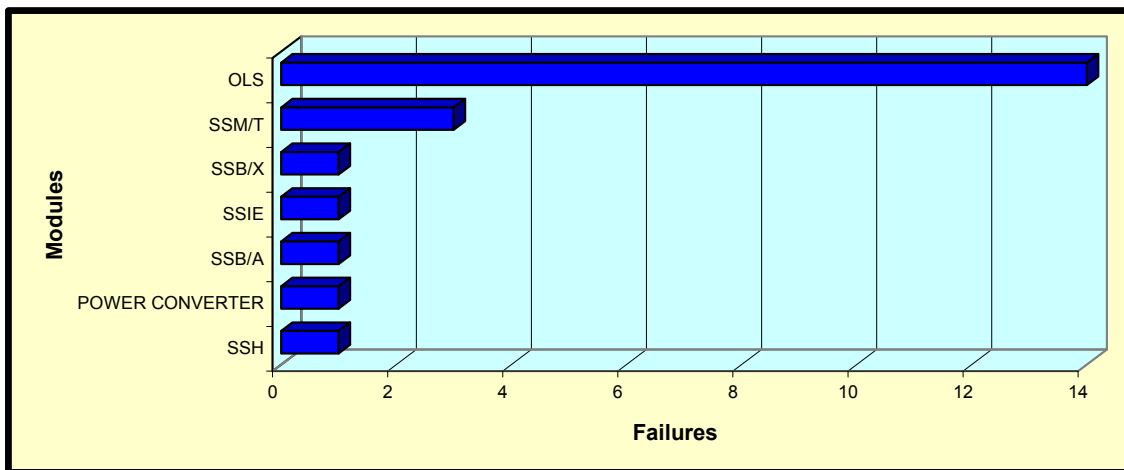


Figure 2: Payload Module Noteworthy Failures

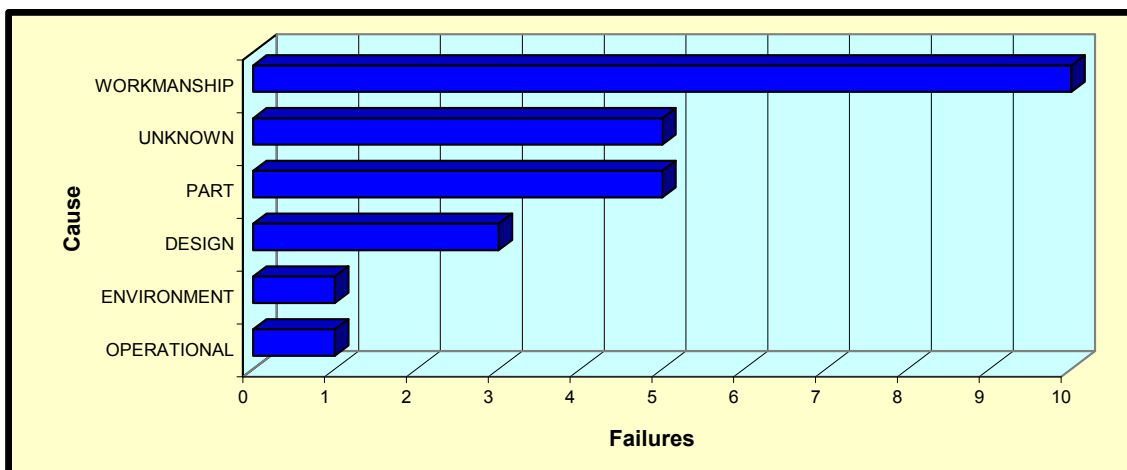


Figure 3: Payload Noteworthy Failure Causes

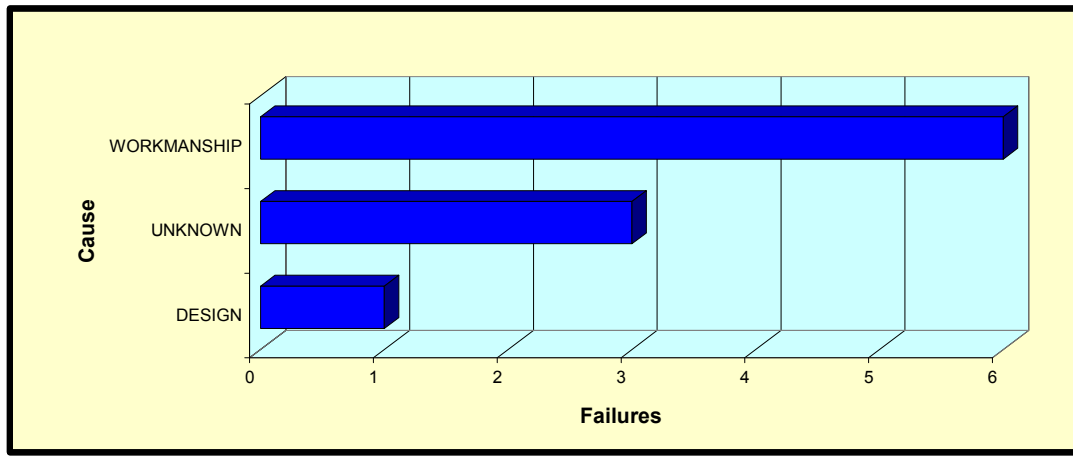


Figure 4: Primary Recorder Noteworthy Failure Causes

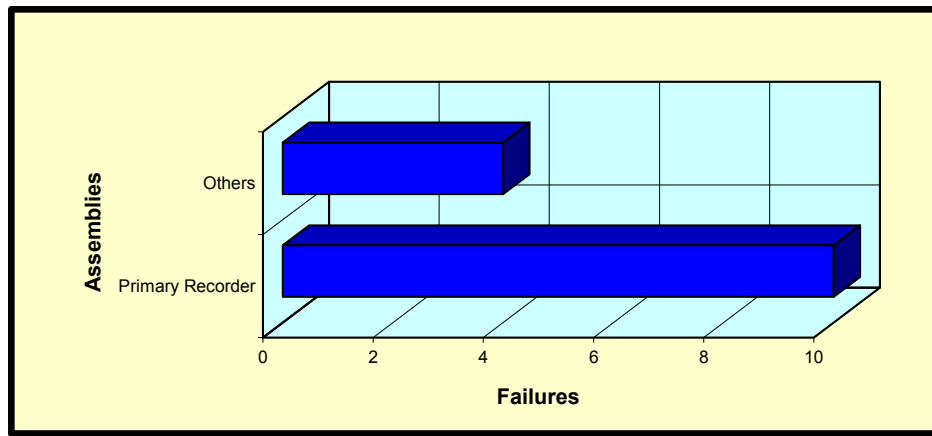


Figure 5: OLS Noteworthy Assembly Failures

- the mission time (hrs) for each pr with zero failure is the time from launch date to end-of-life (eol) = 42312 hrs,
- mission time for primary recorders pr1, pr2 and pr4 = $42312 \times 3 = 126936$ hrs,
- mission time for pr3 (@ failure) = 18024 hrs,
- total hours = $b + c = 144960$ hrs.
- pr1-pr4 units are hours

Figure 6 shows the primary recorder failure rate, using Bayesian analysis, with

- a) prior (Estimated Failure Rate Distribution Prior to the Availability of Actual On-Orbit Data) = 6.318 failures per million hours,
- b) likelihood (Probability of Actual On-Orbit Outcome Data) = 4.3 failures per million hours and
- c) posterior (Probability that has been revised in light of actual On-Orbit data) = 5.7 failures per million hours

Note that the actual failure rate of the primary recorder was less than the predicted failure rate (estimated failure rate) of 6.318 failures per million hours. For failure missions, the most recommended reliable failure rate for the primary recorder to be used will be the posterior failure rate of 5.7 failure per million hours.

5.2 Weibull Reliability Analysis of Primary Data Recorder

Figure 7, Reliability versus Time plot, shows the Weibull analysis for the primary data recorder. The historical reliability data are ranked according to the cumulative probability of failure and plotted on Weibull probability paper. In Figure 7, the ordinate (y) shows the probability of failure and the abscissa (x) represents the life value. This analysis resulted in a Weibull parameter beta of 1.99, which indicates a wearout failure mode. This is contrary to the manufacturer's prediction, which implies that the failures can be attributed to design deficiency. Further investigation revealed that the primary recorders seem to be from two distinct batches. This analysis was critical in bringing attention to the failure of the primary recorders so that mitigating tasks can be put into place to prevent recurrence of the failure. The Weibull results provide additional information that further defines and illustrates the severity of the problem. Identifying and eliminating these types of problems through regular analysis as described in this paper can lead to marked improvements in efficiency and cost performance.

6 CONCLUSION

PRPT provides a disciplined and adequate technique to

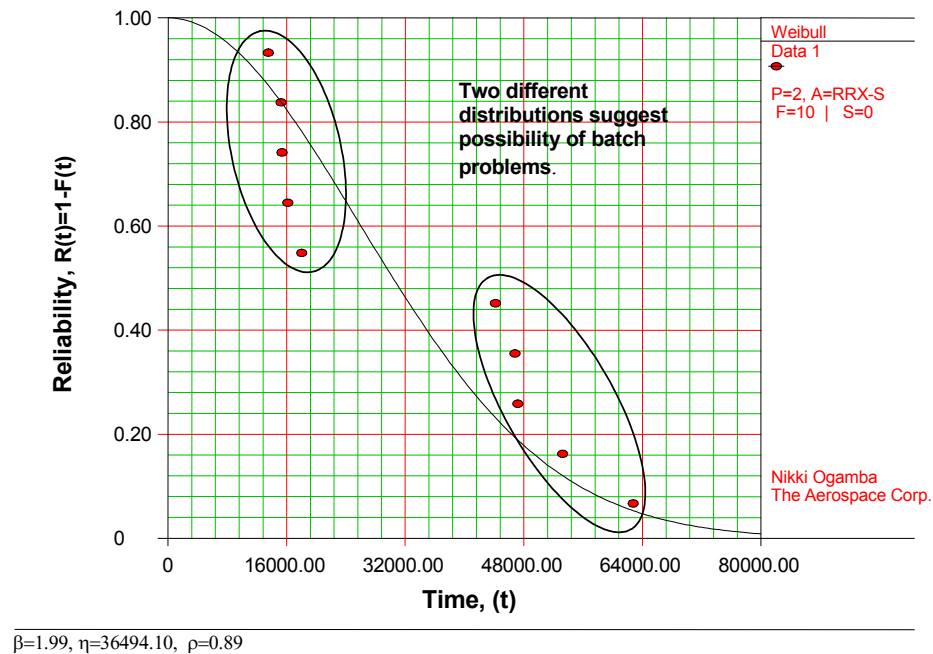


Figure 7: DMSP X Primary Data Recorder Reliability vs. Time Plot

7 APPENDIX I: SPACE/ LAUNCH VEHICLE PERFORMANCE PARAMETER

Key space vehicle performance parameters that have been determined to be relevant to a reliability database and can be used to correlate failure data with overall system reliability are:

- Anomaly Name
- Anomaly Probable Location
- Anomaly Type/Description
- Corrective Action Taken
- Date and Time of Anomaly
- Item Manufacturer
- Key Reliability Factors
- Operational Workarounds
- Probable Cause
- Program
- Symptom Category
- Type Orbit

REFERENCES

1. J. P. Rooney, "Aging in Electronic Systems", Proc. Ann. Reliability & Maintainability Symp., 1999, pp 293-299.
2. P. I. Hsieh, "A Framework of Integrated Reliability Demonstration in System Development", Proc. Ann. Reliability & Maintainability Symp., 1999, pp 258-264.
3. Gelman, A., Carlin, J., Stern, H., and Rubin, D. (1995)

Bayesian Data Analysis, Chapman & Hall, New York.

4. Abernathy, Robert, The New Weibull Handbook, Gulf Publishing Company, 1993.
5. A.H. Quintero, "Space Vehicle Anomaly Reporting System (SVARS) Electronic Data Interchange (EDI) Template, September 1996.
6. Matusheski, Robert, "Meridium Reliability Guidelines." Meridium Enterprise Reliability Management System, 1999.

BIOGRAPHIES

Nkiru U. Ogamba
 The Aerospace Corporation
 2350 E. El Segundo Blvd.
 M4/994
 El Segundo, CA 90245-4691

e-mail: Nkiru.U.Ogamba@aero.org

Nkiru Ogamba is an Engineering Specialist at The Aerospace Corporation in the Electronics Engineering Subdivision, Space Electronics Vulnerability Office. Prior to joining The Aerospace Corporation, she was employed by Litton Industries as a Senior Engineer in the Reliability/Maintainability Group. N. Ogamba has BS and MS degrees in Electrical Engineering, with over twenty-five years experience in Reliability, Quality, Test Engineering Applications and Design.