USING TELEMETRY TO MEASURE EQUIPMENT RELIABILITY AND UPGRADING THE SATELLITE AND LAUNCH VEHICLE FACTORY ATP

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FAILURE ANALYSIS

ABSTRACT

Satellite and launch vehicles continues to suffer from catastrophic infant mortality failures. NASA now requires satellite suppliers to provide on-orbit satellite delivery and a free satellite and launch vehicle in the event of a catastrophic infant mortality failure. The infant mortality failure rate remains high demonstrating that the factory acceptance test program alone is inadequate for producing 100% reliability space vehicle equipment. This inadequacy is caused from personnel only measuring equipment performance during ATP and performance is unrelated to reliability. Prognostic technology uses pro-active diagnostics, active reasoning and proprietary algorithms that illustrate deterministic data for prognosticians to identify piece-parts, components and assemblies that will fail within the first year of use allowing this equipment to be repaired or replaced while still on the ground. Prognostic technology prevents equipment failures and so is pro-active. Adding prognostic technology will identify all unreliable equipment prior to shipment to the launch pad producing 100% reliable equipment and will eliminate launch failures, launch pad delays, on-orbit infant mortalities, surprise in-orbit failures. Moving to the 100% reliable equipment extends on-orbit equipment usable life.

INTRODUCTION

Prognostics is a new area in reliability analysis which simply acknowledges that electrical and mechanical parts and assemblies do not fail instantaneously, but degrade in functional performance over a period of time and the behavior is identifiable using prognostic analysis and telemetry. This means that space equipment failures may occur randomly, but not instantaneously and so do not have the Markov property. The Markov property is a fundamental assumption in reliability analysis engineering so that stochastic processes can be used quantify parts, equipment, systems, processes and software reliability. Due to the wide spread use of reliability analysis engineering in the aerospace industry, engineers have come to believe that equipment failures are instantaneous and random and thus cannot be predicted or prevented.

Space vehicle factory testing includes exhaustive vibration, thermal, vacuum, shock and acoustic testing and records telemetry to measure equipment performance. Testing equipment before use is believed to somehow increase the overall reliability of electronic and electro-mechanical equipment. Engineers use diagnostic tools (e.g. data analysis, data trending, troubleshooting, failure analysis, root cause analysis etc.) to identify equipment that has failed so the equipment can be repaired or replaced. To increase equipment reliability for equipment used in space, the space vehicle dynamic environmental factory acceptance testing (ATP) was added and includes subjecting equipment used in launch vehicles, satellites and spacecraft to be the extreme the space environment the equipment will be exposed to on its journey to space and during it mission lifetime while in space. The existing high infant mortality rate demonstrates that space vehicle factory acceptance testing alone is inadequate for producing 100% reliable equipment.

Telemetry is embedded in equipment as part of the unit and is used to measure internal equipment performance, i.e. how well something in operating. Telemetry is also used as status information, helping to confirm equipment selection and configuration. Space vehicle builders will often minimize equipment telemetry because it adds mass, requires more electrical power, more equipment, much more wiring, increases complexity, slows testing and finally-increases cost. Minimizing telemetry has become commonplace. A failure analysis will often include engineers having to use speculation to generate a list of potential causes of a failure. Since the results of failure analysis are used to improve future equipment and vehicle reliability, when inadequate telemetry forces speculation, it undermines the credibility of the results.

Telemetry prognostics encourage having telemetry from all active and passive equipment as well as operating equipment continuously at the factory to spot accelerated aging.

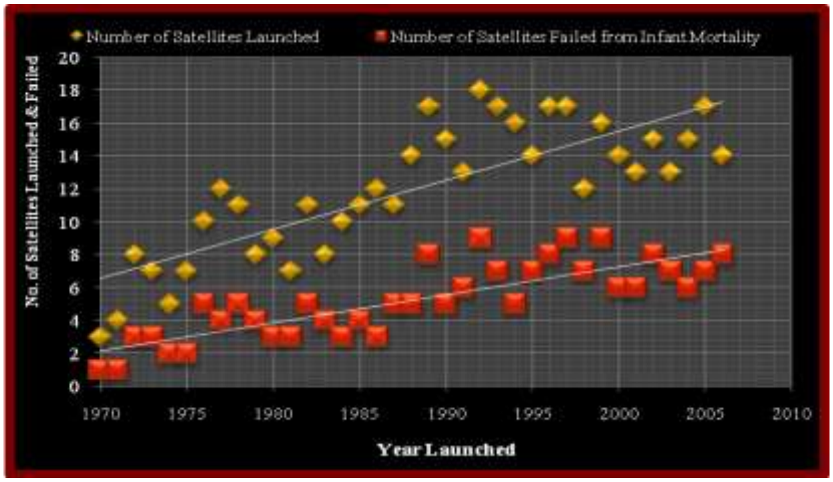

FIGURE 1 CATASTROPHIC SPACE VEHICLE INFANT MORTALITY FAILURE RATE FROM 1970 TO PRESENT

By considering infant mortality failures as a symptom of unreliable equipment rather than the problem, we identified the problem as relying on reliability analysis engineering for producing results that are probability of failures and ATP, which only measures equipment performance and status.

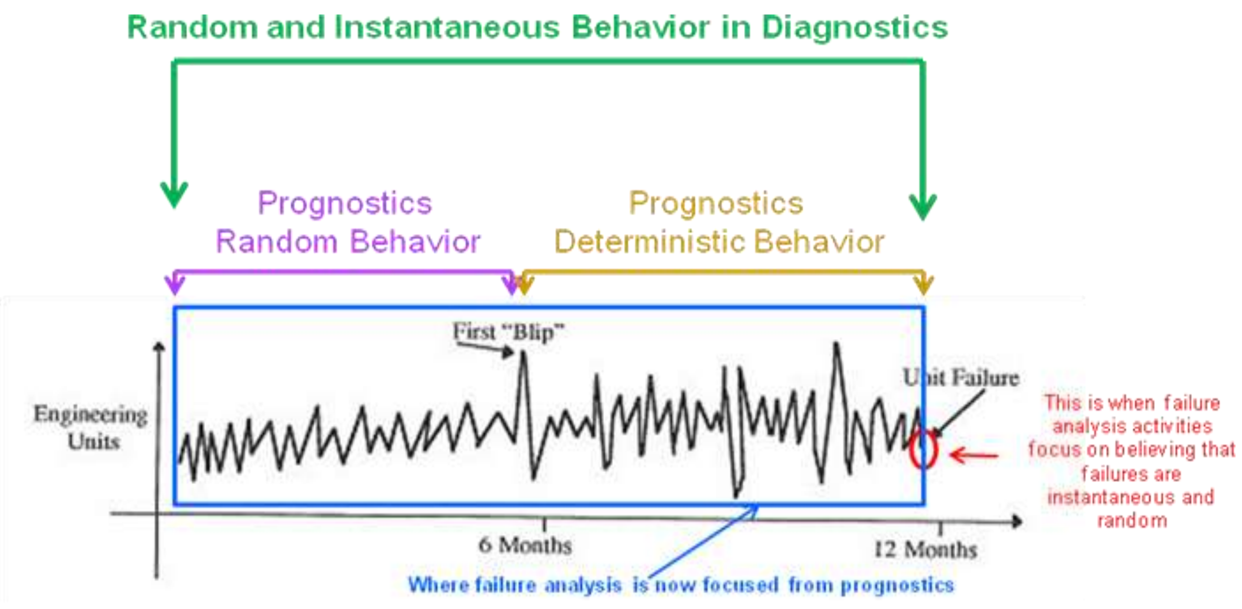

FIGURE 2 COMPARISON BETWEEN DIAGNOSTIC RANDOM AND INSTANTANEOUS BEHAVIOR AND PROGNOSTIC RANDOM AND DETERMINISTIC BEHAVIOR FOR AN EQUIPMENT FAILURE

Because equipment failures are assumed to be instantaneous and random (having the Markov property) so that reliability analysis can be used to quantify reliability, equipment failures are assumed by engineers to be random and instantaneous. To quantify reliability analysis, stochastic processes are used. Stochastic processes needs random and instantaneous behavior, thus our industry assumes equipment failures are random and instantaneous.

Currently failure analysis is accomplished by using data immediately around the time the failure occurs (se Figure 2). This is done because failures are believed to be instantaneous and random (Markov property) and thus there is no information of importance prior to the catastrophic failure. For vehicles and equipment in space, this is done to help provide important data that can be used to corroborate the results of a failure analysis with the part(s) suspected of failing.

After completing failure analysis activities over many years on different and similar equipment and having access to both the equipment that failed functional and performance data before, during and after the failure, we were able to identify that equipment failures were not instantaneous. We were able to identify the presence of accelerated aging in equipment telemetry prior to the failure indicating that the failure occurred at the conclusion of a single or a series of transients induced by piece-parts/components whose performance degradation was aging prematurely. This means that equipment failures do not have the Markov property, being both instantaneous and random but consists of both random and deterministic behavior.

In our prognostic analysis of equipment failures, we found that the first transient occurs randomly, but that the complete unit failure occurs with deterministic behavior, which is fully predictable and quantifiable.

(TELEMETRY) PROGNOSTIC TECHNOLOGY

Prognostic technology simply recognizes that equipment failures do not occur instantaneously but can occur over a very long period. Prognostics teaches that the source of the information from electronic circuits used to predict a catastrophic failure is created by the piece-part(s) or assembly that have an accelerated functional performance degradation and the information that prognostic algorithms illustrates is generated by circuits transient response caused by the increased change in piece-part functional performance. Often as piece-parts degrade in functional performance, the circuit they are in will experience several transients, which are illustrated by prognostic algorithms. Often, the piece-part that fails in a unit/circuit is the piece-part that is most susceptible to the circuit transients. The circuit behavior once the piece-part change in functional performance is large enough to cause a circuit transient, the prognostic algorithm will illustrate the circuit response and is the source of prognostic information.

Prognostics includes the use of model-based and data-driven algorithms for illustrating the accelerated aging occurring in normal appearing data from fully functional equipment that fails quickly when used. The Markov property requires both instantaneous and random behavior and is the foundation of reliability analysis since reliability analysis assumes random and instantaneous behavior to quantify reliability using stochastic processes. Individuals trained in prognostics, anticipates states/conditions before they occur.

This new property is a combination of random and deterministic behavior because we can use algorithms to illustrate the information prognosticians use to predict equipment failures and once this information is identified, the same conclusion results. The widespread use of prognostic algorithms corrects the inadequacy that allows so many complex space systems to fail within the first year of use after production and launch.

Prognostics include the identification of the data used to predict equipment that is going to fail. Prognostic technology is necessary because current diagnostic technology is inadequate to identify all equipment that will fail from an infant mortality failure. Prognostic technology is the next logical step in advancing electronic and electro-mechanical equipment reliability. Prognostics and prognostic health management as part of equipment operations and maintenance is a critical technology for accurately predicting impending failures and providing a mechanism for replacing equipment and parts safely before failure for ground-based equipment and preparing for and executing recovery plans for space-based equipment.

Using telemetry prognostics in the space flight equipment and at vehicle factories, upgrades space equipment processes by identifying more unreliable piece-parts and assemblies during equipment and vehicle factory acceptance test, reducing the time to test equipment, identifying equipment that has failed, is failing and will fail, increasing reliability and eliminating infant mortalities. The shorter equipment and vehicle test time reduces cost.

MEASURING EQUIPMENT RELIABILITY AND ADOPTING A 100% RELIABILITY MEANS EXTENDING EQUIPMENT USABLE LIFE

The remaining-usable-life for equipment once a catastrophic failure has been predicted can be determined by understanding the piece-part failure characteristics determined under test in an operating circuit. This information is considered proprietary by the piece-part manufacturer since it is an indication of the quality of their products and not available in the popular domain.

Electrical and electro-mechanical piece-part and assembly failures occur over a very long period of operational life. This period can be as long as 1 year. We use a technique shared by companies that build spacecraft to agree on mission life of the spacecraft they sell. Spacecraft usable life, called the mission life is determined by quantifying the expected life of all piece-parts and mechanical systems on a vehicle. Mission life will not exceed the shortest life of any non-redundant circuits or mechanical systems. If there are no life-limiting piece-parts or mechanical systems, mission life is derived by quantifying the risk to the company of meeting a mission life based on past vehicle mission life actually reached.

Since there is not a financial penalty other than loss of in-orbit incentives for suppliers of space vehicles if the mission life isn't achieved, companies can claim very long mission life, some over 20 years. This is confirmed with the actual life of many in-orbit satellites, some of which have operated for over 40 years.

To accurately predict remaining-usable-life for equipment that has been predicted to fail, Failure Analysis maintains a database of flight equipment failures that were analyzed. This information is used to determine the probability of success (Ps) of a circuit with a failure precursor identified reaching its predicted remaining-usable-life. This same technique is used by spacecraft building companies to decide their satellite mission life. Satellite mission life that a company will agree to is based on a history of the mission life of their past satellites in-orbit lifetimes.

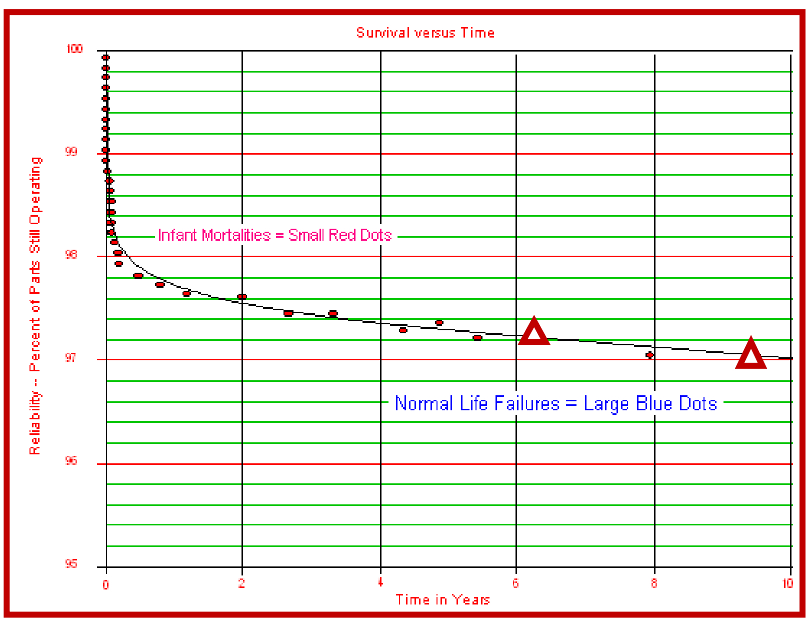

FIGURE 3 WEIBULL DISTRIBUTION FOR COMPLEX SYSTEM'S INFANT MORTALITY FAILURES (DOTS) AND NORMAL LIFETIME FAILURES (TRIANGLES) FOR 10 YEARS

We maintains a historical database of flight equipment failures researched over the past 32 years consisting of several hundred years of telemetry and uses a probability of success (Ps) to determine the day of failure and remaining-usable-life based on actual satellite equipment failures.

In reliability analysis, large quantities of parts and equipment are used. When individual performance of parts and equipment is not measured, the stochastic process in reliability analysis provides probabilities of events occurring based on commonly acceptable distribution curves. These distribution curves model many behaviors.

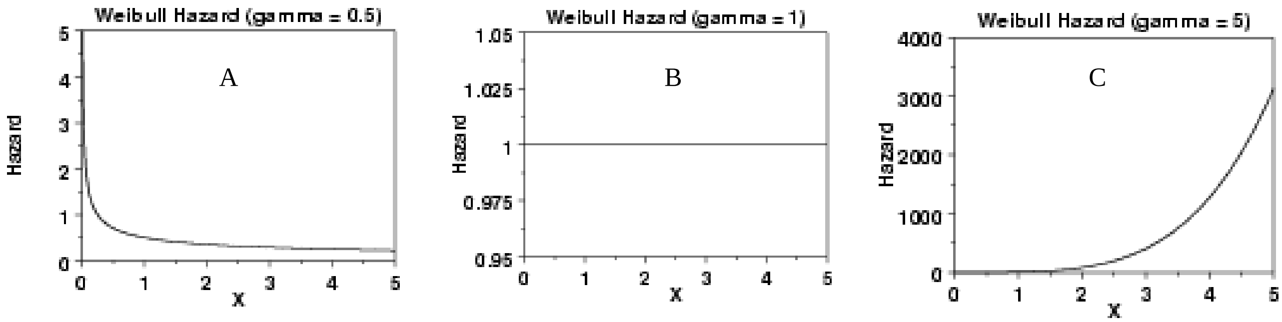

FIGURE 4: WEIBULL HAZARD DISTRIBUTION FUNCTIONS THAT MODEL THE 3 SEGMENTS OF THE RELIABILITY FAILURE-IN-TIME BATH TUB CURVE (BOL, N and EOL)

Several Weibull distributions are used to model the shape of the standard bathtub reliability curve in Figure 4. The infant mortality failure rates are modeled accurately for a 10-year period in Figure 3. The failures in time (FITS) reflect real world behavior/ due to the minor differences of parts, their failure rate behavior is never repeated. In probability theory and statistics, the Weibull distribution is a continuous probability distribution named after Waloddi Weibull, who described it in detail in 1951, although it was first identified by Fréchet (1927) and first applied by Rosin & Rammler (1933) to describe the size distribution of particles. The probability density function of a Weibull random variable **x** is:

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Where $k > 0$ is the *shape parameter* and $\lambda > 0$ is the scale parameter of the distribution. Its complementary cumulative distribution function is a stretched exponential function. The Weibull distribution is related to a number of other probability distributions; in particular, it interpolates between the exponential distribution ($k = 1$) and the Rayleigh distribution ($k = 2$).

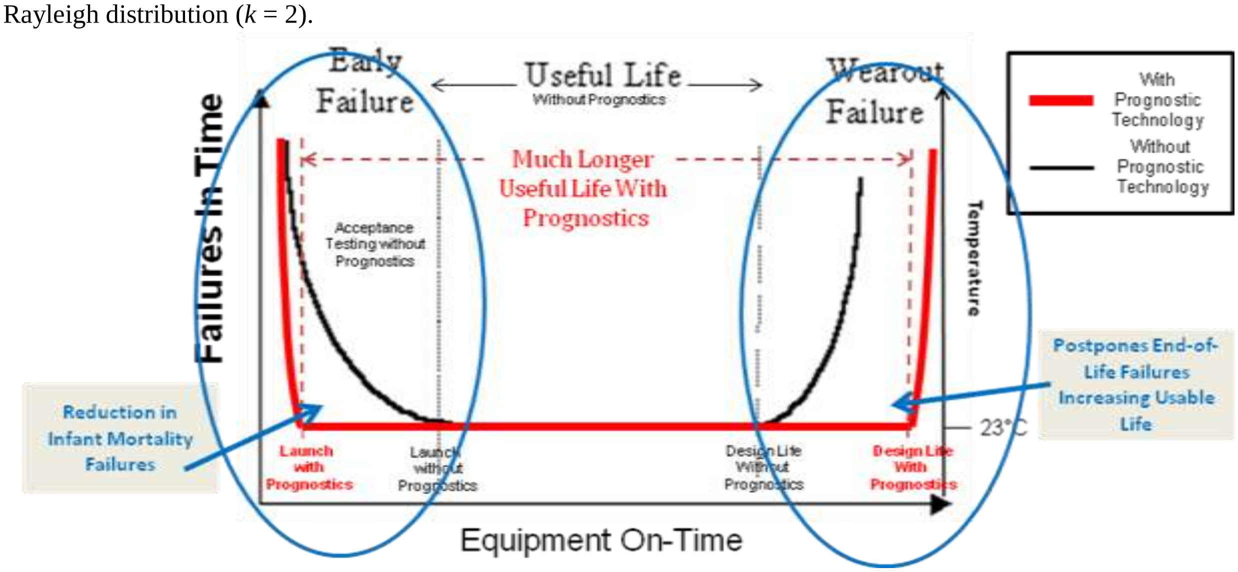

FIGURE 5 THE IMPROVEMENT TO COMPLEX SYSTEMS RELIABILITY AND USABLE LIFE BY ELIMINATING INFANT MORTALITY FAILURES CALCULATING TIME-TO-FAILURE

To predict an accurate remaining-usable-life after the early signs of failure are detected, we use the cumulative distribution curve developed from our proprietary database of high-reliability aerospace/vehicle equipment failures we have analyzed over 30-years. Distribution curves model normal occurring behavior and are tools used to before understand and quantify the failure rates at a complex system such as an aircraft the beginning-of-life, normal lifetime and end-of-lifetime failure rate. In the equipment failures we analyzed, we measured the duration of time between the failure precursor and the actual failure to generate the cumulative distribution. We have used this cumulative distribution to predict the duration of remaining usable life achieving 100% accuracy.

To understand why our cumulative distribution is an accurate method for measuring the equipment with the early signs of premature aging/failure present remaining usable life, understanding the use of normal (random) distributions will help. Figure 6 is a Weibull distribution illustrating the infant mortality failures (dots) for a complex system such as an aircraft continue to occur as parts and equipment are replaced due to failure and normal lifetime failures (triangles) are occurring simultaneously. Weibull distributions are accepted in many industries as modeling the failure rate behavior of complex system/aircraft failure rates at all stages life/use. Figure 3 also illustrate an 8-month to 1 year burn-in duration would decrease most infant mortality failures (dots).

The cumulative distribution curve in Figure 7 is also known as the Fermi-Dirac distribution in nuclear physics. The Fermi-Dirac describes the probability that one can expect particles to occupy the available energy levels in a given system. Each curve in Figure 6 is the normal distribution curve such as the exponential distribution in Figure 6.

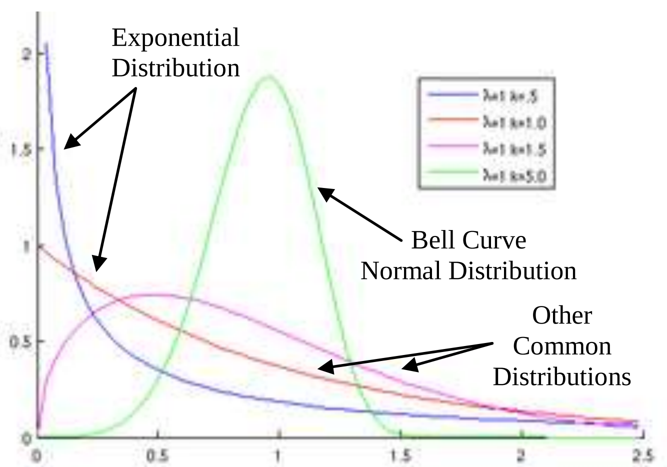

FIGURE 6 EXAMPLES OF DISTRIBUTION FUNCTION PROBABILITY DISTRIBUTION FUNCTIONS WITH VARIOUS SHAPE CONSTANTS

The integral of a normal distribution function is it cumulative distribution. The integral of all the probability functions in Figure 7 are the cumulative distribution functions for the normal distribution functions in Figure 6. Figure 7 cumulative distributions illustrate the likelihood that a piece-part failure in a population of piece-parts duration will occur. Knowing that piece-parts should have a Gaussian distribution, piece-part manufacturers test a sample of piece-parts from a population and determine if their failure rate matches a Gaussian distribution to find if manufacturing flaws or design flaws are in the population of piece-parts.

The Weibull hazard distributions in Figure 4A, Figure 4B and Figure 4C are often used due to their flexibility—they mimic the behavior of other well-defined natural occurring distributions like those in Figure 4. Figure 4A is the Weibull hazard distribution model for infant mortality failure rates for complex systems. Figure 4B is the Weibull hazard distribution model for the failures in time during normal usable lifetime of a complex system such as the "normal" or Bell distribution in Figure 6 and the exponential distributions. Figure 4C is the Weibull hazard distribution model for the end-of-life failures for complex systems.

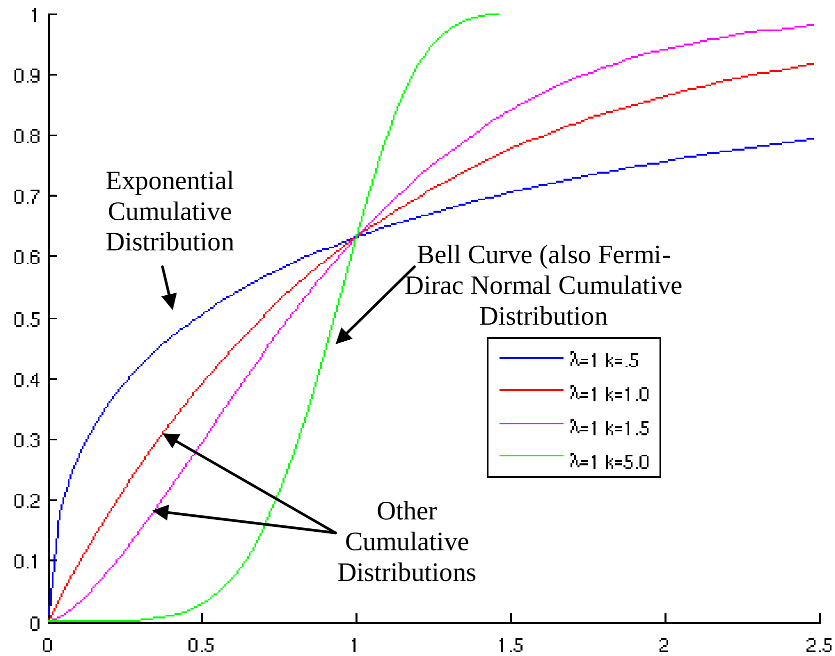

FIGURE 7 EXAMPLES OF CUMULATIVE DISTRIBUTION FUNCTIONS (INTEGRAL OF THE NORMAL DISTRIBUTIONS) FOR PROBABILITY DISTRIBUTION FUNCTIONS IN FIGURE 6

In the relationship below used to define the normal distributions, if equipment/piece-part failure rate decreases over time, then k is < 1. If the failure rate is constant over time, then k is = 1. If the failure rate increases over time, then k is >1. An understanding of the failure rate may provide insight as to what is causing the failures:

- A decreasing failure rate (gamma = 0.5 in Figure 4A) would suggest "infant mortality" failures. That is, defective items fail early and the failure rate decreases over time as they fall out of the population.
- A constant failure rate (gamma = 1 in Figure 4B) suggests that items are failing from random events.
- An increasing failure rate (gamma = 5 in Figure 4C) suggests "wear out" - this means that parts are more likely to fail as time goes on.

Where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. The Weibull distribution is related to a number of other probability distributions; in particular, it interpolates between the exponential distribution ($k = 1$) and the Rayleigh distribution ($k = 2$). The cumulative distribution function for the Weibull distribution in Figure 4 for $x \geq 0$, and $F(x; k; \lambda) = 0$ for $x < 0$ is:

$$F(x;k,\lambda) = 1 - e^{-(x/\lambda)^k}$$

The failure rate h (or hazard rate) is given by:

$$h(x;k,\lambda) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}.$$

Our proprietary cumulative distribution (a.k.a Fermi-Dirac distribution) curve in Figure 6 is generated from 30 years of measuring the remaining-usable-life of high-reliability aerospace/vehicle equipment failures we put into our database of failures. The results are not random because they are based on actual equipment failures and so are a probability (Ps) of occurring based on many past failures and real durations of remaining usable life. We have been 100% accurate in predicting the remaining usable life for all our equipment failures we have used prognostic analysis on (please see Table 15).

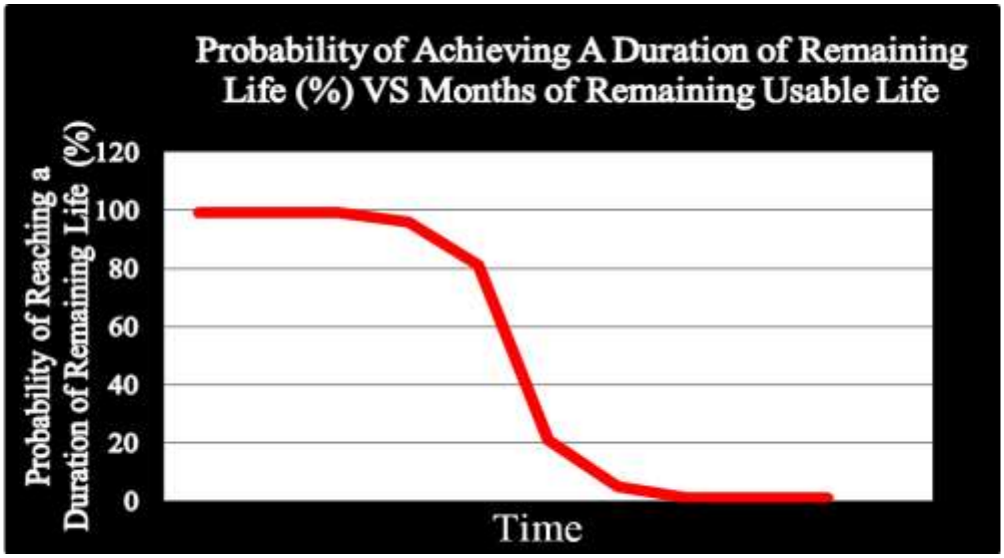

FIGURE 8 OUR CUMULATIVE DISTRIBUTION CURVE

The early signs of aging/failure/cannot duplicates/failure precursors/prognostic markers/prognostic indicators are caused from the degradation in the functional performance of parts/piece-parts used in electrical and mechanical equipment and products and their effect of their degraded performance on the other parts in the circuits. If a part's, functional performance degrades much faster than other parts in the circuit/assembly, it will eventually affect the circuit/assembly behavior it is in by causing transient behavior in equipment telemetry. When a part's performance has degraded so that the circuit/assembly it is in can no longer function as designed, transients will occur and these transients will expose the other parts to unpredictable operating condition stresses not designed to operate. The effect of the transient(s) on any other part is unpredictable. The transients may increase the degradation in part performance or may not. If the relationship between failure precursors and piece-part degradation provided in 20 were known in 1986 and 2004, neither the Space Shuttle Challenger nor the Columbia tragedies killing 14 astronauts would have occurred.

Since all electrical/mechanical parts in a circuit/assembly degrade at different rate, there will be one part that will degrade the quickest. This part initiates the early signs of aging/failure but is usually not the part that fails. These parts with the accelerated aging behavior are the source of cannot-duplicates/early signs of aging/failure etc. One part will degrade in functional performance until its performance causes transients to occur. The transients effect on other parts are unpredictable but the part that eventually fails as a consequence of the exposure to the transients will generally not be the part that started the transients. If the part that fails is replaced, other parts that were not replaced that have been exposed to the transients previously may fail and need to be replaced. Eventually parts can continue to fail so often that the circuit/unit will be scrapped because its reliability will be so low that personnel are uncomfortable using it.

RESULTS OF USING TELEMETRY PROGNOSTIC ALGORITHMS OF THE NASA EXTREME ULTRA-VIOLET EXPLORER ASTROPHYSICS SATELLITE EQUIPMENT TELEMETRY

Between 1994 and 1995, the NASA/U.C. Berkeley Space Sciences Laboratory EUVE low earth orbiting astrophysics satellite was utilized to demonstrate the ability predict spacecraft equipment failures using prognostic algorithms. The results of this effort were sent to the NASA GSFC Space Sciences Directorate and published at several technical conferences between 1995 and 1997. The EUVE satellite payload was controlled from the Center for EUV Astrophysics at the University of California, Berkeley. The EUVE satellite bus was built by Fairchild Aerospace (now Orbital) as 1 in a group of 10 common-core, multi-mission bus' for GSFC science missions. The self-contained and multi-payload, modular bus consisted of an attitude determination and control which included highly accurate reaction wheels and gyroscopes, electrical power, STDN/TDRSS telemetry, tracking, command and data storage, thermal control and structure subsystems.

Unit Failures Analyzed	FP Expected?"	FP Detected?	Date of FP	Date of Failure	Time from FP and EOL	RUL
Transmitter A	No	No	None	None	None	> 6 mos
Transmitter B	Yes	Yes	12/93	4/94	4.5 mos.	< 6 mos
Rate Gyro A	No	No	None	N/A	N/A	> 6 mos
Rate Gyro B	Yes	Yes	1/93	Unknown	Unknown	< 6 mos
Rate Gyro C	No	Yes	6/92	note 1	note 1	> 6 mos
T/R A	Yes	Yes	3/94	12/94	9 mos.	< 6 mos
T/R B	Yes	Yes	4/94	9/94	5 mos.	< 6 mos

TABLE 1 SUMMARY OF RESULTS FROM COMPLETING A PROGNOSTIC ANALYSIS ON THE NASA/U.C. BERKELEY EUVE SATELLITE EQUIPMENT TELEMETRY

In 1994, reliability analysis engineers at Lockheed Missiles and Space Company Advanced Technology Center began an internally funded program to validate the use of prognostic algorithms to illustrate the information used to predict equipment failures. Their results were documented in an interim and final report published by Lockheed martin in 1995 and 1996.

EUVE Telescope Payload Monitors	Date Telemetry Processed	Suspect "Failure Precursor" Expected?	Suspect "Failure Precursor" Found?	Remaining Service Life Estimate	Accuracy of FPP
DET6HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET7HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET1HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET2HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET3HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET4HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET5HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET6HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET7HSUP	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET1HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET2HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET3HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET4HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET5HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET6HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET7HCUR	1/1/95 - 3/1/96	No	No	> 6 Months	100%

TABLE 2A RESULTS FROM PROGNOSTIC ANALYSIS COMPLETED ON THE NASA EUVE SATELLITE TELESCOPE EUV DETECTOR TELEMETRY

The NASA EUVE satellite three-scanner telescopes and the deep survey/spectrometer telescope are mounted in the payload module, which is installed as a unit on the Explorer Platform spacecraft. Each of the EUVE scanner telescopes weighed 260 pounds. In addition, a deep survey telescope/spectrometer weighed 710 pounds.

The NASA EUVE satellite was launched into a low earth orbit in 1992, one of many orbiting telescopes funded by NASA Space Science Directorate. The EUVE mission was extended twice, but cost and scientific merit issues led NASA to terminate the mission in 2000. EUVE satellite operations ended on January 31, 2001 when the spacecraft was placed in a safe hold, both telemetry transmitters were commanded off on January 2, 2001 and EUVE re-entered the Earth's atmosphere over central Egypt at approximately in 2002. Telemetry from all satellite bus and payload equipment was analyzed. Five equipment failures were accurately predicted and all other equipment were accurately predicted to operate for another 6 months without failure. Satellite

EUVE Telescope Payload Monitors	Date Telemetry Processed	Suspect "Failure Precursor" Expected?	Suspect "Failure Precursor" Found?	Remaining Service Life Estimate	Accuracy of FPP
DET1HVLT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET2HVIT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET3HVLT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET4HVIT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET5HVIT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET6HVIT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET7HVIT	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET1HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET2HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET3HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET4HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%
DET5HVPF	1/1/95 - 3/1/96	No	No	> 6 Months	100%

TABLE 2B RESULTS FROM PROGNOSTIC ANALYSIS COMPLETED ON THE NASA EUVE TELESCOPE EUV DETECTOR TELEMETRY

Conclusion

Prognostic technology includes proactive diagnostics, active reasoning and data-driven algorithms that illustrate the information in equipment telemetry that prognosticians use to identify equipment that will fail within 1 year of use and thus preventing equipment failures. Telemetry is embedded in electrical and mechanical equipment and provides unique visibility into equipment performance. A prognostic analysis converts performance information into a reliability measurement by identifying accelerated aging and calculating the Time-to-Fail. If prognostic technology is used in the design and test process, it upgrades the space vehicle factory testing process, eliminating equipment that will suffer from an infant mortality failure allowing the production of equipment with 100% reliability. Our prognostic algorithms have been flight proven on Air Force, NASA and commercial satellite, missiles and launch vehicles to identify the equipment that was going to fail prematurely.

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