USING DATA-DRIVEN PROGNOSTIC ALGORITHMS FOR COMPLETING INDEPENDENT FAILURE ANALYSIS

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Failure Analysis

ABSTRACT

Current failure analysis practices use diagnostic technology developed over the past 100 years of designing and manufacturing electrical and mechanical equipment to identify root cause of equipment failure requiring expertise with the equipment under analysis. If the equipment that failed had telemetry embedded, prognostic algorithms can be used to identify the deterministic behavior in completely normal appearing data from fully functional equipment used for identifying which equipment will fail within 1 year of use, can also identify when the presence of deterministic behavior was initiated for any equipment failure.

Key Words: Failure Analysis, Independent Failure Analysis, Fault Analysis, Prognostics, Failure Analysis, Diagnostics, Telemetry Analysis, Failure Isolation, Identification And Recovery

INTRODUCTION

When telemetry is not available from the equipment that failed, failure analysis engineers resort to speculation to create a list of prioritized, potential causes. Using speculation allows vehicle and equipment builders to reduce diagnostic information necessary to complete an accurate root cause failure analysis. Generic prognostic algorithms provide the next technology in diagnostic analysis for identification of the cause of space equipment failures of all types. Data-driven prognostic algorithms are generic, making independent failure analysis possible for any satellite, spacecraft and any launch vehicle failure. Along with identifying the equipment that failed, these generic algorithms identify the equipment, while still at the factory, that was going to fail during launch and within one year of in-orbit allowing the equipment to be repaired or replaced while it is still on the ground. Data-driven telemetry prognostic algorithms illustrate the deterministic behavior previously undetected by the most experienced vehicle manufacturing & test personnel using diagnostic tools, identifying failure liability accurately and dependently.

Failure analysis used with satellites and launch vehicles includes the collecting, processing and analysis of data to determine the source or cause of a failure. This information is often used to prevent the same failure from recurring in subsequent equipment and in determining liability. Failure analysis is an important discipline in many manufacturing industries, such as the electronics and aerospace industry, where it is a vital tool in the development of new products and for the improvement of existing products reliability and life.

Failure analysis is a forensic inquiry into the process or product upon the failure. Such inquiry is conducted using a scientific analytical method including information from electrical and mechanical measurements or through speculative approach when data is not available but an action has to be taken. An example of a speculative approach is analysis of an equipment failure on a satellite or launch vehicle and no data are available and where the evidence has been mostly destroyed but all parties are expecting corrective action. In such cases, one or more of the most viable theories are being implemented until an additional data is available.

PROGNOSTICS

Diagnostics is used to identify equipment that has failed. Prognostic technology is used to identify equipment that has failed and is going to fail. Prognostic technology is important because current diagnostic technology is inadequate to identify infant mortality failures. Prognostic technology is the next logical step in advancing traditional electronic and electro-mechanical equipment diagnostic technology. 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.

The first telemetry prognostic algorithms were developed and used to predict failures in atomic clocks on-board GPS satellites. The satellite engineering team was unable to understand the origin and reliability of the information used to predict equipment failures. By researching a large number of equipment failures over many years from space equipment used across many complex systems, a new understanding of the equipment failure process was obtained.

The behavior of these characteristics of this newfound process was what was used in the prognostic algorithms, which clearly illustrate equipment that is going to fail in the future. It is the knowledge that a failure process occurs which is unlike any process suspected in the past and the experienced gained by identifying a failure in process that is utilized to eliminate and manage failures advantageously that forms the foundation of prognostic technology and makes it superior to diagnostic technology.

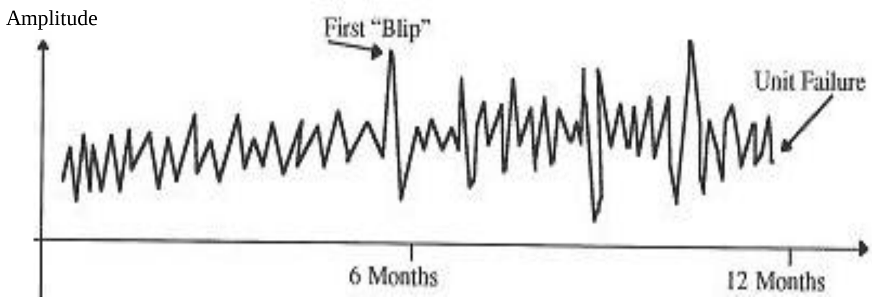

FIGURE 1 CLASSIC TELEMETRY FAILURE BEHAVIOR

Figure 1 is an example of the long-term telemetry behavior for complex electronic and electro-mechanical equipment used in prognostic algorithms. The use of prognostic algorithms on satellite and launch vehicles is extremely difficult. It was accomplished with the funding by the U.S. Air Force over 6 years, who was extremely motivated to have the GPS satellite equipment defined so that future equipment would not experience the same failure. The Air Force was willing to pay for all facilities, technical resources and management resources requested by

Boeing GPS space and ground system manager and program management from many companies and organizations. This is why prognostic technology hasn't been developed in the past. Prognostic algorithms are the result of a combination of information and experience from many sources generally not obtained in traditional space systems design and test process.

The successful use of prognostic algorithms requires extensive training and experience, without which, the results could be unsatisfactory and costly. Prognostic technology requires properly trained and experienced prognosticians to identify behavior in data that appears the same as normal appearing behavior. No two failures signatures are alike and so the experience gained in identifying one failure cannot be used to identify another. The ability to identify failure behavior is obtained through training by others who have successfully identified failure behavior

Components of a prognostic system are the algorithms for equipment failure detection, isolation, prediction. Some approaches for equipment failure prediction require knowledge of the system model. Attempting to use model-based prediction methods when working with complex electrical and electro-mechanical systems is often not feasible because the approximations necessary to develop computationally tractable models of complex systems based on fundamentals of physics are difficult to make without introducing significant modeling inaccuracies in the time and length scale of interest.

Prognostics offers to change the entire design, manufacturing and test process to improve reliability to eliminate infant mortality failures reducing if not eliminating launch failures, launch pad delays, on-orbit infant mortalities, surprise in-orbit failures and extend in-orbit equipment usable life by identifying unreliable equipment long before its shipped to the launch pad. For the first time, all the information to identify unreliable equipment can be financially justified. Prognostics technology adds many financial rewards for using telemetry, easily justifying the need for increasing the number and resolution of telemetry measurements.

Using telemetry prognostics in the space flight equipment and at vehicle factories, upgrades space equipment processes by identifying unreliable piece-parts and assemblies during equipment 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. Telemetry prognostics algorithm determines of remaining-usable-life based on information available in existing equipment telemetry.

An ideal general-purpose prognostic system is a data-driven approach that does not require *a priori* knowledge of system. The prognostic system would learn the characteristics of the monitored system so that anomalies could be predicted more quickly as it is learned, and remaining life estimates could be given with smaller associated uncertainty.

Telemetry prognostic technology includes the use of telemetry as an engineering data source in data-driven prognostic technology. Prognosticians, using prognostic algorithms identify telemetry behavior that are transient, unrepeatable, and have gone undetected by the most experienced design and test personnel for the past 60 years.

Prognostics technology is an evolutionary step forward in traditional diagnostics technology for both hardware and software. Telemetry prognostics technology can be used by prognosticians to identify equipment that has failed, is failing, and will fail for up to one year in advance. Prognostic technology uses engineering data to identify circuit/equipment behavior that are precursors to catastrophic failure. Failure Analysis' data-driven telemetry prognostics technology also provides the determination of remaining-usable-life and even a day of failure for unreliable equipment.

PROGNOSTICS	DIAGNOSTICS
Identifies equipment failures that have occurred, is occurring and will occur and when it will occur	Identifies failures that have occurred and after/when they occur
Identifies equipment failure in process and when	Only identifies equipment failures after they have already occurred
Identifies equipment failures that will occur in the future	Only identifies equipment failures after they have already occurred
Requires major changes in analysis attitude and behavior	Training is done from example
Overcomes shortcomings in diagnostic techniques	Diagnostics were developed from ground test equipment
Prognostician actively monitors data to provide knowledge of whether a failure has occurred, is occurring or when a failure is likely to occur	After the fact response, if error messages are used, diagnostician waits for error message if any action is taken
All events are considered failure precursors until ruled out by research – analyst doesn't stand by and watch failures occur	Data is recorded and analysis is completed post event
A fault propagation model is assumed to encompass parametric data related to acceptable operating ranges, behavior and identification of degradation of functions over time.	Suspect behavior is considered system noise, any action is taken after completion of events
Requires highly skilled and trained personnel, must have in-depth knowledge of what is being actively monitored	Allows lower skilled personnel, doesn't require in-depth understanding of what's being monitored, diagnostician just sits and waits to complete event
Requires training across several disciplines	Taught in elementary electronics and is common throughout many industries
Stops life threatening situations from occurring	Inadequate for mission critical events

TABLE 1 CHARACTERISTICS OF PROGNOSTIC AND DIAGNOSTIC TECHNOLOGIES

Table 1 shows comparison of characteristics between prognostics and diagnostics. A prognosis denotes the prognostician's prediction of whether a failure will progress, and when the equipment/circuit will fail.

Data-driven prognostic algorithms use available data from a system to determine normal behavior and failure behavior. Our data-driven prognostic algorithms are independent of the vehicle or source of data. Generate prognostics. As the name implies, data-driven techniques utilize monitored operational data related to system health. Data-driven approaches are appropriate when the understanding of first principles of system operation is not comprehensive or when the system is sufficiently complex that developing an accurate model is prohibitively expensive.

FIRST DOCUMENTED USE OF PROGNOSTIC TECHNOLOGY ON SPACECRAFT

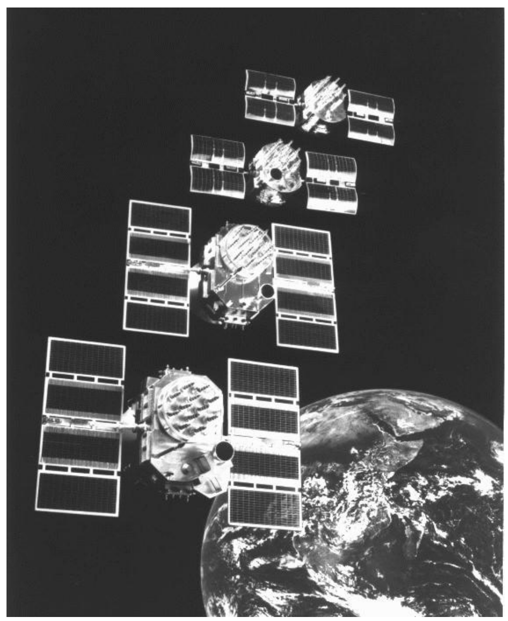

FIGURE 2 GPS SATELLITES

Model-based prognostic algorithms use a-priori knowledge to identify changes in behavior, which can be identified as failure behavior. This a-priori knowledge can be obtained from several sources including equipment experts and/or operational experience. When all acceptable operational behavior can be defined, model-based prognostics is suitable for use with pattern recognition systems. Model-based prognostics incorporate physical and operational understanding (physical modeling) of the system into the estimation of remaining useful life (RUL). Modeling physics can be accomplished at different levels. At the micro level (also called material level), physical models are embodied by series of dynamic equations that define relationships, at a given time or load cycle, between damage (or degradation) of a system/component and environmental and operational conditions under which the system/component are operated. The micro-level models are often referred as damage propagation model. Micro-level models need to account in the uncertainty management the assumptions and simplifications, which may pose significant limitations of that approach.

Figure 2 is an example of the resulting 40 Boeing/GPS Block II and IIA satellites designed using results from telemetry prognostic analysis on Boeing/GPS Block I satellites. In 1978, the U.S. Air Force contracted with Boeing for an engineering team to assist in the integration of the Air Force Global Positioning System (GPS) program into the existing Air Force satellite control network, which operated most CIA/NRO/military space control assets. Boeing satellite engineers determined each GPS satellite subsystem performance and the GPS on-orbit support requirements levied on other Air Force program contractors. The Air Force was highly motivated to fund the GPS program because of its multi-service use and better navigation solutions than existing satellite-based navigation systems. GPS was competing against APL's TRANSIT and the NRL's TIMATION systems.

DATA-DRIVEN ALGORITHMS

Unlike model-based prognostic algorithms that need long-term normal behavior modeled, data-driven algorithms only use the information available to determine normal behavior. Failure Analysis' telemetry prognostic algorithms are unique and their performance will be different from prognostic algorithms from another source.

Table 2 are a list of the prognostic algorithms developed and used on the Air Force GPS program to predict equipment failure behavior in normal appearing telemetry and a brief description of their purpose.

Prognostic Algorithm	Purpose
Baseline Analysis	Determines change in normal behavior is occurring
Change Analysis	Determines change in normal behavior
Comparison Analysis	Determines change in normal behavior
Data Integration	Compiles data for cluster analysis
Data Base Creation	Creates minimal amount of telemetry for analysis
Day-of-Failure (DOF)	Identifies day of equipment failure
Digital Processing	Improves resolution of failure signature
Discrimination Analysis	Identifies normal telemetry from failure behavior
Mathematical Modeling	Predicts normal telemetry behavior
Multi-Variant Limit Analysis	Identifies telemetry to be analyzed for failure behavior
Rate-Change Analysis	Identifies telemetry to be analyzed for failure signature
Remaining-usable-life (RUL)	Determines when equipment will fail
Statistical Sampling	Reduces telemetry databases before analyzing
State Change Analysis	Identifies telemetry to be analyzed for failure signature
Super Impositioning	Enhances normal telemetry behavior for analysis
Super Precision	Improves resolution of final telemetry diagnostic products
Telemetry Authentication	Eliminates unreliable telemetry eliminating false positives
Virtual Telemetry	Creates future normal telemetry behavior

TABLE 2FAILURE ANALYSIS' TELEMETRY PROGNOSTIC ALGORITHMS VEHICLES

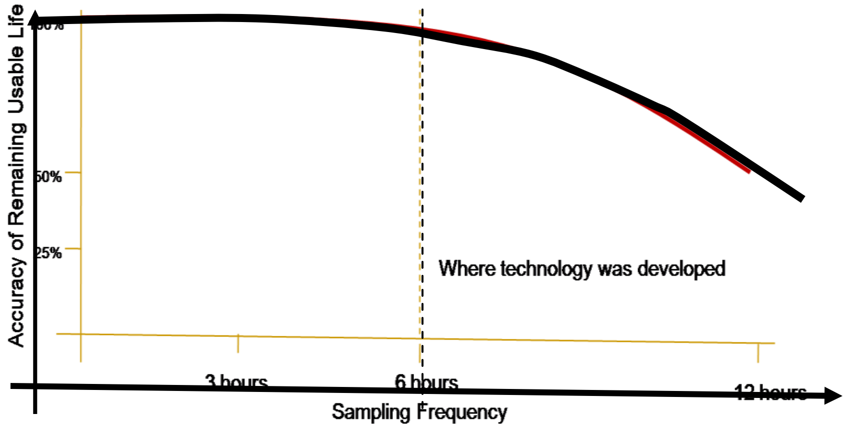

FIGURE 3 PROGNOSTIC ALGORITHM'S ACCURACY FOR REMAINING-USABLE-LIFE ESTIMATE BASED ON FIXED-TIME SAMPLING FREQUENCY

The remaining-usable-life for complex equipment can be calculated 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. Based on the analysis of many in-flight piece-part failures, historically, piece-part failure occurs over a very long period of operational life once a failure precursor is identified.

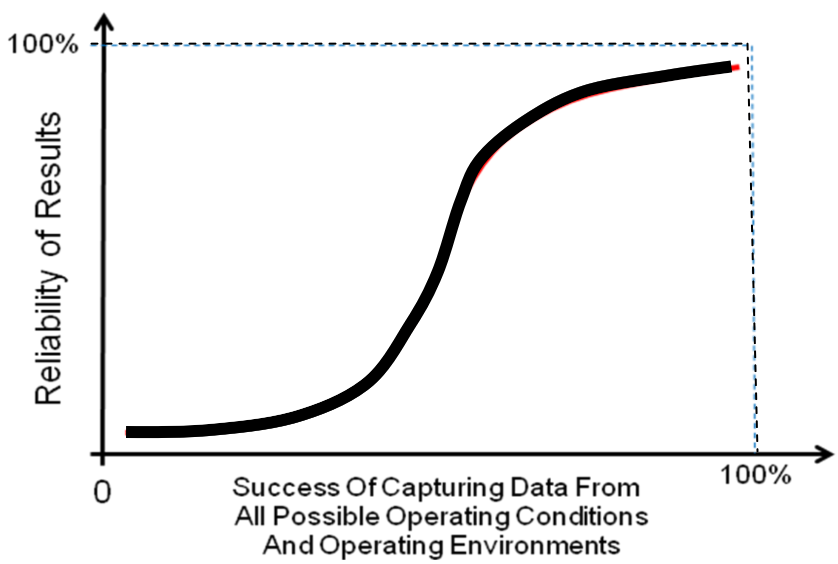

FIGURE 4 PROGNOSTIC ALGORITHM'S RELIABILITY VS OPERATING CONDITIONS AND ENVIRONMENTS AVAILABLE IN DATA

This period can be as long as 1 year. Using the technique shared by companies that build spacecraft to agree on mission life, spacecraft usable life, called the mission life is determined by quantifying the expected life of all piece-parts and mechanical systems on a vehicle. Figure 3 illustrates the performance of the algorithms based on telemetry fixed, sampling frequency. The highest reliability using telemetry prognostics is obtained by having telemetry from all environmental operating conditions, diurnal effects, seasonal effects and equipment operating conditions. When the total operating environment and conditions are not available, a decrease in accuracy may occur. Figure 4 illustrates the reliability performance of the data-driven algorithms based on the availability of data from different equipment operating environments.

In any industry, infant mortality failures are considered a normal part of doing business. This is an outcome of the infant mortality failures have occurred in the industries that first used electrical components in their systems. Prognostics will decrease the number of launch vehicle and satellite infant mortality failures significantly.

FALSE POSITIVES AND FALSE NEGATIVES

Any prognostic algorithm should have a zero false positive and false negative rate. The use of any prognostic algorithm will only remain useful if it is accurate and reliable. Telemetry prognostic algorithms have been used with over 100 satellite and launch vehicle electrical and electro-mechanical units. Current accuracy performance of our remaining-usable-life algorithm has been 100% accurate.

With adequate training and experience by prognosticians, the reliability of prognostic technology is strongly related to the capture of equipment behavior during all different operating conditions. Because there are many sources of data that can be interpreted as failure behavior, the more data available from each environmental and operational condition that can be used to identify failure behavior, the more reliable the results. Figure 5 illustrates the accuracy of the algorithm for predicting usable remaining life and the fixed sampling frequency of the data available for analysis.

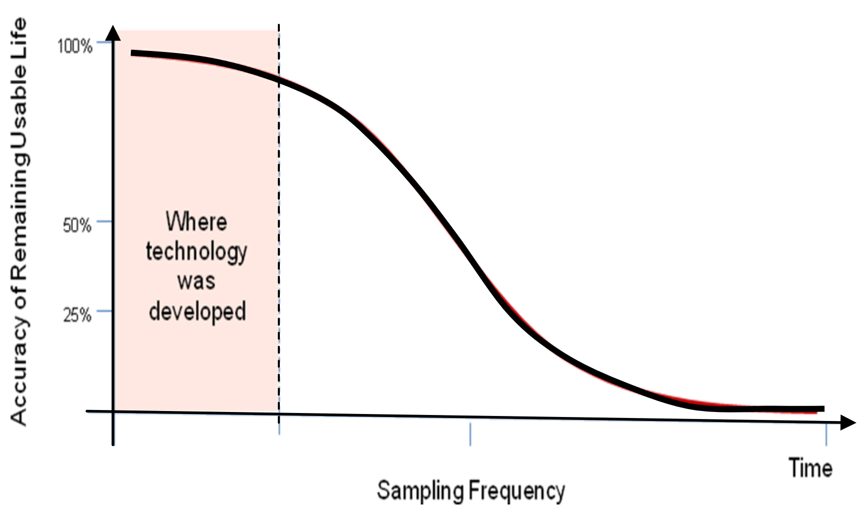

FIGURE 5 RELIABILITY OF TELEMETRY PROGNOSTIC TECHNOLOGY REMAINING-USABLE-LIFE ALGORITHM BASED ON FIXED DATA SAMPLING FREQUENCY DURATION

These false results cannot be completely eliminated, but they can be reduced. People can demand a second opinion.

CONCLUSION

Telemetry prognostic algorithms are generic and usable across systems that use telemetry to identify equipment status and performance. Prognostic technology provides the capability to identify equipment that has failed and is going to fail across any vehicle regardless of design. Prognostic technology is the next step in the evolution of diagnostic techniques that can identify equipment that failed during launch or in space, while it was still at the vehicle factory. This new capability offers to improve the reliability of space vehicles by forcing vehicle builders to adopt prognostic technology to eliminate liability.

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