# NASA Physics of Failure (PoF) for Reliability

**Nancy J Lindsey [a], Jeffrey Dawson[a], Douglas Sheldon[b], Lionel-Nobel Sindjui [a], and Anthony DiVenti[c]**

[a] Goddard Space Flight Center, Greenbelt, MD, USA
[b] Jet Propulsion Laboratory, La Cañada Flintridge, California, USA
[c] NASA Headquarters, Washington, D.C., USA

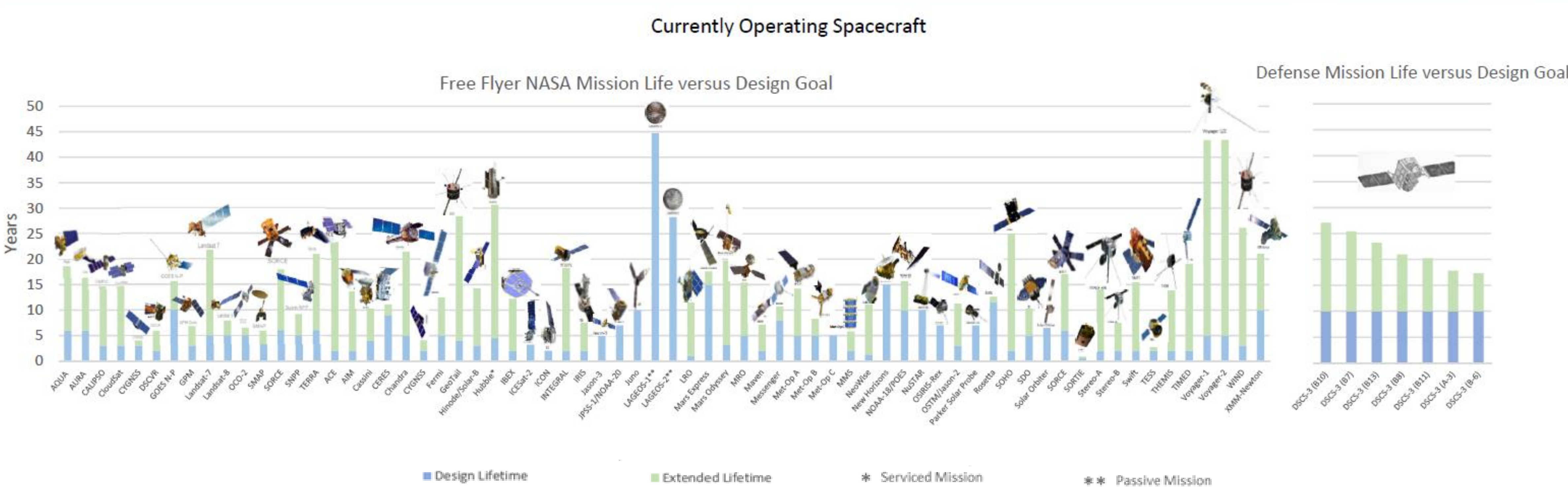
Keywords: Physics of Failure (PoF), Reliability, Risk Assessment, Failure Rates, NASA, Goddard Space Flight Center, Office of Safety and Mission Assurance (OSMA), Probability of Success, Physics

**Abstract:** An item's reliability or longevity is dependent not only on its design but also on how it is used, manufactured, tested, and the stresses it has or will experience. Stresses include operational and environmental exposures to thermal, voltage, current, age/exposure, mechanical, and radiation mechanisms. Therefore, in reliability analysis, it is important to consider the contributions of all these factors when predicting the failure rates of components. Historically, there has been a reliance on handbook data (e.g., MIL-HDBK-217), but experience has shown that these values and distributions are not representative of actual performance [1,2]. Therefore, to make more credible reliability and risk assessments for its missions, NASA must transition to estimating likelihoods of failure based on an item's reliability or longevity factors (or the physical susceptibilities and strengths impacting the design's performance) has or will experience, whenever possible. To facilitate this transition, a *Handbook on Methodology for Physics of Failure Based Reliability Assessments* has been developed by NASA to assist in applying physics experiences or experimental physics for empirical analysis and conceptualized physics exposures or theoretical physics for deterministic analysis, to develop and aggregate realistic likelihoods of failure leading to more credible forecasts of item performance and longevity. In addition, since it is NASA's intention that this document continues to evolve based on community lessons learned and the introduction of new assessment methodologies, NASA is encouraging and appreciates the contributions of current and future authors to maintain and enhance this handbook and its supporting case studies.

## 1. INTRODUCTION

As new spaceflight missions are planned, it is important for designers and analysts to look at where NASA and the spacefaring industry are in terms of mission reliability/success. The missions shown in figure 1 were launched between 1993 and 2020, with the exception of Voyager (1977) and LAGOES-1 (1976). These missions have lasted on average 14.8 years which is an average exceedance (green bars) of their design lifetimes (blue bars) of 8.9 years. Though the technology inherent in these designs has varied and the design and assurance strategies applied have evolved over the years, this trend of exceeding expectations or predictions points out that the underlying values (e.g., handbook data such as MIL-HDBK-217) used historical information for predicting probability that is not representative of spacecraft experience. For example: Aqua was predicted to have a 13-14% chance of making its 6-year design-life and is now 20 years into its mission and still on the primary side of redundant systems [3]; SDO had a probability of success value of 0.96 for the minimum mission duration of 2 years and 0.44 for the full mission duration of 5 years and is now 12 years into a successful science mission.

Figure 1. A Summary of currently operating spacecraft (as of 1/2021) [2]



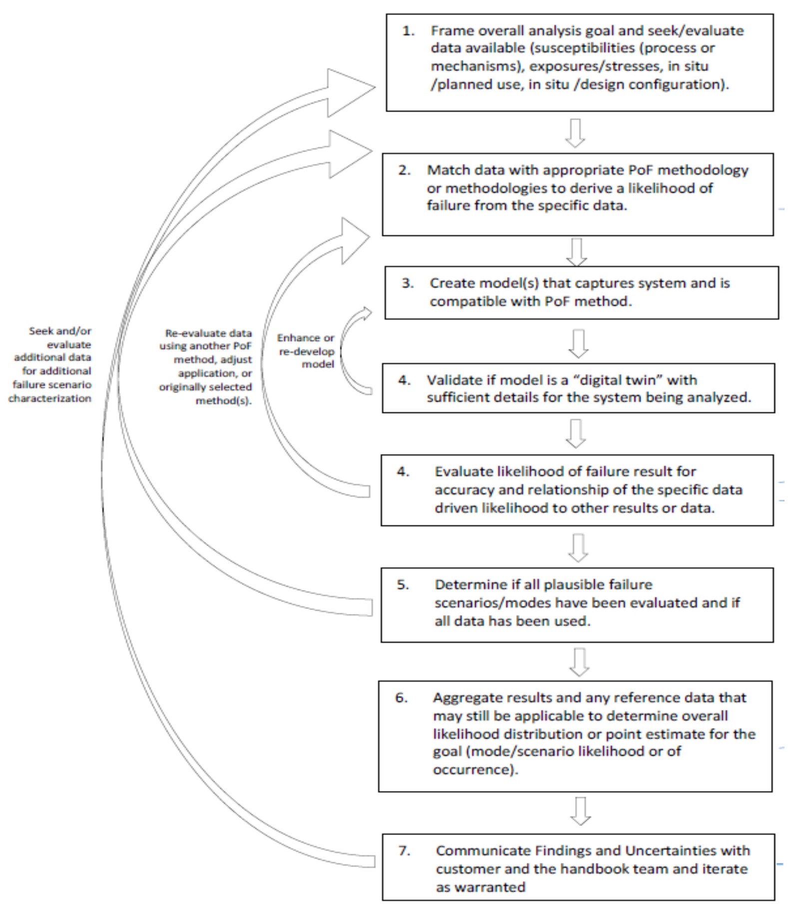
Therefore, to make more credible reliability and risk assessments for its missions, NASA is transitioning to estimating likelihoods of failure based on an item's reliability or longevity factors and physical susceptibilities. To estimate these likelihoods, NASA is planning on using Physics of Failure to assess component and system reliabilities to ensure continued success with optimized designs that meet difficult cost and schedule challenges. The NASA *Handbook on Methodology for Physics of Failure Based Reliability Assessments* was created, as described within this paper.

## 2. NASA PoF Handbook

The NASA *Handbook on Methodology for Physics of Failure (PoF) Based Reliability Assessments* is intended to educate analysts and engineers on PoF methods, determine data needs for deriving failure rates using physics, guide analyses, and to further PoF methods. It explains the applicable experimental derivations or theoretical physics and includes case study examples for each to facilitate understanding and application.

The architecture of this handbook allows PoF learners, analysts, and data generators to find guidance and insights quickly. In the handbook, PoF methods were presented with supporting case study references across three sections: Empirical (experimental physics), Deterministic (theoretical physics), and Aggregation (deterministic and empirical estimation combination methods). This means that users can concentrate on any of the experimental or theoretical physics application methods for reliability individually, research data needs to define tests or experiments that support PoF-based likelihoods development, or review sections and select the best PoF method or methods for deriving or updating failure rates based on the data available, until all failure mechanisms or modes that are possible for the scenario of interest are characterized through physics (see figure 2).

Figure 2. PoF Handbook Analysis Guide Use Cases



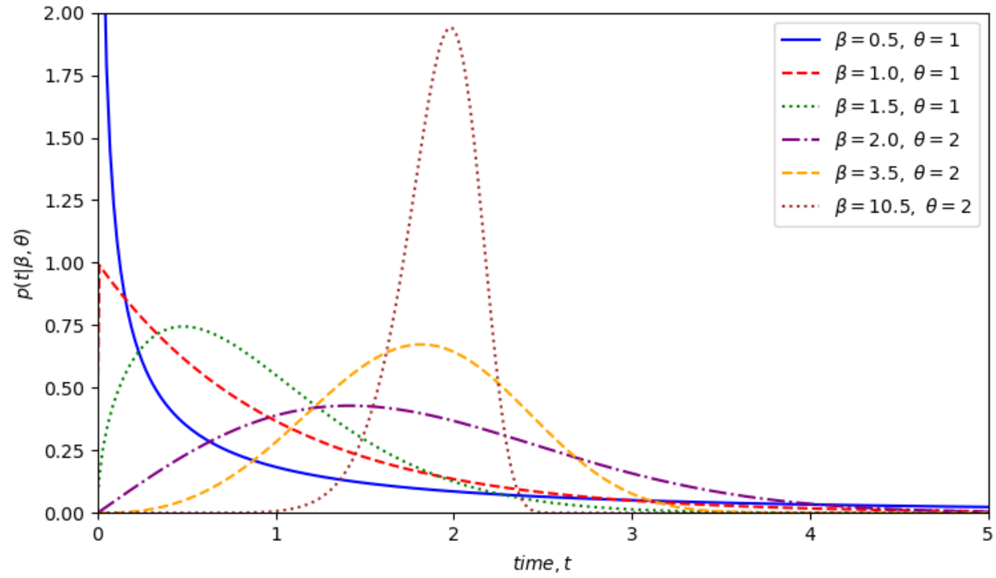

### 2.1. Handbook Empirical Section

Failure rate empirical estimation methods used in science and engineering are often based on past data or experienced/experimental physics. Using component failure data from field studies, warranty claims, and lab tests, reliability engineers have developed techniques to predict the reliability of systems. Therefore, the Empirical Section of the subject NASA handbook includes the following methods:

- Statistical Modeling Analysis (Exponential, Weibull, Lognormal, Normal)
- Peck's Temperature-Humidity Relationship Prediction
- Electromigration Structural/Electrical Time to Failure (TTF) Analysis
- Bayesian Statistical Inference for Updating Failure Rates

Statistical modeling analysis was included in the empirical section of this handbook, since it uses mathematics to describe the observed physical behavior of components and systems (i.e., experienced/ experimental physics from testing or field use). Successful statistical modeling matches (or approximately matches) observed failures to probability density function distributions. One distribution used to perform this modeling is the Weibull distribution, as shown in Figure 3. In the Weibull probability density function, β is the shape parameter, and θ is the characteristic lifetime, the time when 63.2% of items in a lot will have failed. When a best fit is made to the observed data, the distribution will define the failure rate's characteristics as increasing or decreasing as follows: If $\beta = 1$, the distribution reduces to the exponential distribution (constant failure rate); if $\beta < 1$, then the failure rate decreases with time (infant mortality risk); if $\beta > 1$, then the failure rate increases with time (e.g., wear out failure risks in the forms Rayleigh, Lognormal, or Extreme Value forms).

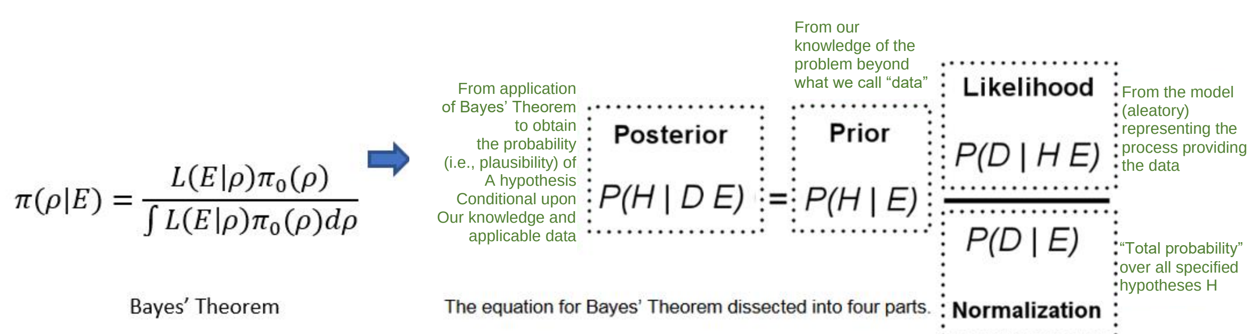
Figure 3. Weibull Probability Density Functions [7]




If humidity or electromigration sensitivity has been observed to be an issue for an item, such as an electronic part, then Peck's temperature-humidity model or Electromigration TTF analysis can be used to predict its life. However, if there is insufficient data to develop a life estimate or a new best-fit distribution or the characteristic distribution is known for an item, then Bayesian statistical inference can be used to refine the failure distribution characteristics to more closely match observed performance.

Since Bayesian statistical inference can be used to apply the observed physical behavior of components and systems (i.e., experienced/experimental physics), it was included in the empirical section of the NASA PoF handbook. Bayesian inference uses Bayes' Theorem (See figure 4) to perform continual statistical inference to update the probability of a hypothesis or failure rate estimate, as more evidence or information about the system's responses to operational physical stresses becomes available. In terms of reliability, this method uses all of an item's previously known failure characteristics (prior distribution) and the effects of physics on a system and develops refined failure rate estimates (posterior distribution) and can be repeated as often as new relevant experience data (i.e., field data) becomes available.

Figure 4. Bayes' Theorem [7]




### 2.2. Handbook Deterministic Section

Deterministic modeling analyzes the dominant failure mechanisms behind a failure based on physics theories and how they limit the functional capability of the component [5]. Failure mechanisms described by deterministic models include degradation (due to accumulated damage from stress), erosion, diffusion, and corrosion phenomena leading to sudden or eventual failure [6]. Therefore, the following methods were included in the Deterministic Section of the NASA PoF handbook to cover the designated physics disciplines:

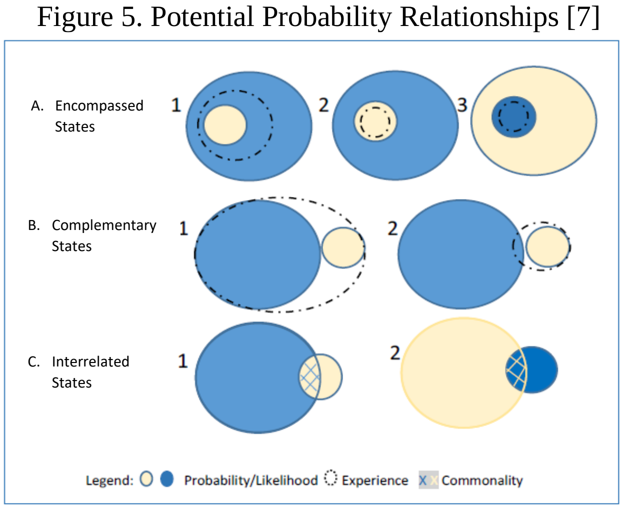
- Thermodynamics– Arrhenius, Inverse Power, and Coffin-Mason Analysis
- Thermofluctuation – Zhurkov Analysis
- Mechanics - Palmgren Modeling
- Multiphysics (voltage, humidity, or mechanical stress) – Eyring Modeling,
- Thermal Physics– Temperature and Heat Transfer Analysis
- Fluids Modeling – Fluid Flow/Forces Analyses
- Electromagnetics – Performance Interference/Disruptions, Failure, and Aging Analyses
- Mechanics/Dynamics – Fatigue and Fracture Analysis
- Acoustics - Harmonics and Vibration Modeling
- Chemical Physics (atomic, molecular, and thermodynamics**)** – Chemical/Material Life/Decomposition Analysis
- Radiation - Susceptibility Analysis (single event and cumulative)

While many physical effects can impact the performance of a system, the ones noted above were included in the NASA PoF handbook since they are known to impact space-flight systems during their mission-lives (e.g., launch, operations, extensions, disposal/decommissioning). Specifically, thermal, mechanical, voltage, humidity, electromagnetics, and acoustical stresses can reduce a system's life by inducing thermal, mechanical, or electrical fatigue/failure, whereas electromagnetics and radiation can damage a system directly and cause it to fail. For electromagnetics, this takes the form of high electrical and magnetic energy exposure, from in-situ or adjacent systems, that destroys, disables, or interferes with the operations of electronics as is seen from the naturally occurring ionizing and non-ionizing radiation of space. Therefore, radiation failure mechanisms can be assumed for electromagnetic exposures. These radiation (or electromagnetics) failure mechanisms result in noise induced via trapped charges, sensor hot spots via dark current manifestation, output power decreases via increased non-radiative recombination centers, high current states sustained from Single Event Latch-ups (SELs), component losses from Single Event Burn-out (SEB) or Single Event Gate Rupture (SEGR), and data or system (hardware/software) interruptions and corruptions induced from Single or Multiple Bit Upsets (SBU/MBUs). In contrast, chemical physics limits the life of a system through systemic molecular reactions (e.g., battery chemical depletion and decomposition, electrolyte development, additional new-material generation), but can also induce thermal stresses on the system or adjacent systems.

### 2.3. Aggregation Section

The NASA PoF handbook is completed with a section on combining the findings of individual PoF likelihood assessments for an item into an inclusive failure likelihood. An inclusive or aggregated failure likelihood or aggregated likelihood of failure is built based on the relationship between each of the individual findings. The relationship between any two or more findings can be described in one of three ways. Findings are considered encompassed when any likelihood covers the same failure scenarios or is part of another likelihood or the working aggregated likelihood (see figure 5.A). If likelihoods are encompassed, then the analyst will need to determine which likelihood (the encompassed or the encompassing) is more indicative of performance and use that one. The findings are considered complementary when two or more likelihoods (individual or aggregated) do not cover the same failure scenarios (see figure 5.B). If the likelihoods are complementary, then they must be combined, as recommended in the handbook, via fault trees or Bayesian networks with the appropriate weightings, given experience or engineering judgment, to formulate a complete likelihood estimation. If any of the likelihoods to be combined have intersecting failure scenarios (see figure 5.C) they are considered interrelated. If likelihoods are interrelated, then the inclusive likelihood will require evaluation and elimination of or compensation for common scenarios to avoid over counting the likelihood of any scenario(s). This can be done, as recommended in the handbook, using a fault tree, conditional probability, or Bayesian networks with appropriate handling of intersecting probabilities.

Figure 5. Potential Probability Relationships [7]



## 3. PATH FORWARD

While the physics underpinnings of the PoF practices are well defined, the methodologies and supporting infrastructures to determine the likelihood of failure are constantly being refined and advanced. Therefore, the NASA PoF handbook also includes a section on technology infusion to facilitate NASA plans to continually advance the handbook's content with continual community sourcing.

### 3.1 Technology Infusion

Analysis and modeling are currently, and will continually be, advanced by technology. For PoF, this could take the form of Physics-Based Modeling with Machine Learning (ML). Therefore, the NASA PoF handbook includes a synopsis of current research in applying ML to PoF analysis challenges for information and to inspire additional research. ML and related Artificial Intelligence (AI) approaches are drivers for innovation across the entire spectrum of PoF tools and methodologies, but additional research into specific focus areas (e.g., physics-guided initialization and residual modeling) is needed.

Currently, technology for PoF analysis is limited to statistical analysis and multiphysics simulation tools. Statistical analysis tools (e.g., R, SPSS, Weibull++, BlockSim, ITEM ToolKit, Excel, Matlab, R-DAT, etc.) are rooted in data analysis and fitting observed physics to mathematical expressions. Statistical analysis tools are often the starting point for introduction of ML and AI applications. Data analysis and empirical fitting have been commoditized with extensive AI-based visualization and data aggregation scripts that operate as simple drop-down menus. Multiphysics simulations packages (e.g., COMSOL, MATLAB, Windchill, Ansys Sherlock, Cadence, and Altair) are also rapidly advancing with complex and sophisticated use of ML and AI techniques. Historically, supervised learning approaches with their limitations of time-consuming data processes and non-physics-based extrapolation and error generation have been replaced with a variety of neural network solvers. These solvers can provide parametrized simulations that are often embedded. For example, neural network forward solvers can be supervised based on governing physical laws only and do not require any extrapolated training data for example [8]. The constantly evolving capabilities of High-Performance Computing (HPC) is a constant source of innovation and evolution of PoF techniques and adaptations. AI and ML have been infused into computationally challenging PoF concepts to allow them to become almost ubiquitous across all engineering domains. However, current multiphysics tools still generally use a limited set of coupled physics equations and Monte Carlo simulations that give damage accumulation estimates, time-to-failure forecasts, or fatigue life predictions and statistical tools that still rely on curve fitting.

### 3.2 Community Evolution Sourcing

NASA's intention is that the NASA PoF handbook continues to evolve based on community lessons learned and the introduction of new assessment methodologies. Therefore, to allow for reliability engineers, physicists, designers, and operations/research teams to provide additions, updates, modifications, and case studies that may extend or enhance the concepts discussed in the handbook, NASA has shared this handbook via symposia, webinars, and data sharing platforms (e.g., NODIS, SharePoint, NASA-Wiki, NASA Knowledge Portals (i.e., the NASA-only RMA Knowledge portal - https://rmakp.msfc.nasa.gov/)).

## 4. CONCLUSION

With the advent of the *Handbook on Methodology for Physics of Failure Based Reliability Assessments*, PoF methods can be better understood and applied today. However, given that many PoF methods have not achieved full development or closed-form solution of the underlying physics contributions to the likelihood of failure, application will need to be done on a case-by-case basis at this time. In addition, caution and diligence are still needed to ensure a fully inclusive failure likelihood is attained, and a full risk profile is given to stakeholders.

### References

[1] Secretary of the Army, "*MIL-HDBK-217 Secretary of the Army Memo*", 1996.
[2] C. Smith, N. Lindsey, S. Battel, D. Kusnierkiewicz, and M. Pecht, "*Reliability of Systems for Long Duration Missions*", SCiTech - EXPL-09/NASA Webinar, 2021.
[3] M. Alimardani et al, 371-EOS/AQUA-ANYS-0001EOS Aqua Extended Mission Reliability Study, 2009-2018.
[4] Mathew Samuel, 371-SDO-ANYS-0001Solar Dynamics Observatory (SDO) Project Reliability Block Diagrams and Predictions, 2005.
[5] Varde, P. (2010). Physics-of-failure based approach for predicting life and reliability of electronics components. BARC Newsletter. 313: 313.
[6] Schenkelberg, F. (2020). "Introduction to Physics of Failure Models." Retrieved 17 July 2020, from https://accendoreliability.com/introduction-physics-of-failure-models/.

[7] NASA OSMA, "*Handbook on Methodology for Physics of Failure Based Reliability Assessments" (draft)*, October 2021.
[8] Hennigh, Oliver, et al. "NVIDIA SimNet™: An AI-accelerated multi-physics simulation framework." *International Conference on Computational Science*. Springer, Cham, 2021.

**Acknowledgements**

This document would not have been developed without the support of NASA OSAM and the expertise and insights of the NASA PoF handbook contributors. Therefore, the authors would like to acknowledge and extend their appreciation to those who have already contributed to the handbook's development from across NASA, JPL, and Aerospace.

Jonathan Barth (NASA-GSFC)
Michael J. Campola (NASA-GSFC)
Milton C. Davis (NASA-GSFC)
Brendon J. Foran (Aerospace)
Mathew Forsbacka (NASA-OSMA)
David G. Gilmore (Aerospace)
Eric W. Grob (NASA-GSFC)
Ray Ladbury (NASA-GSFC)
Henning W. Leidecker (NASA-GSFC)
Daniel S. Mcguinness (NASA-GSFC)
David J. Petrick (NASA-GSFC)
Steven Rickman (NASA-JSC)
Kaitlyn Ryder (NASA-GSFC)
Bhanu Sood (NASA-GSFC)
John Welch (Aerospace)
Edward J. Wyrwas (NASA-GSFC)