Future Satellite Lifetime Prediction from the Historical Trend in Satellite Half-Lives

Venkata Jaipal Reddy BATTHULA
Department of Information Science
University of Arkansas at Little Rock, Little Rock, AR 72204 USA

Richard S. SEGALL
Department of Information Systems & Business Analytics
Arkansas State University, State University, AR 72467 USA

Daniel BERLEANT
Department of Information Science
University of Arkansas at Little Rock, Little Rock, AR 72204 USA

Hyacinthe ABOUDJA
Department of Computer Science & Mathematics
Oklahoma City University, Oklahoma City, OK 73106 USA

Peng-Hung TSAI
Department of Information Science
University of Arkansas at Little Rock, Little Rock, AR 72204 USA

ABSTRACT

Satellite lifetime is one of the important characteristics of satellite design and construction. When a satellite is about to fail, lifetime estimation is also a matter of practicality, as reentry and disposal can become operational matters. Satellite lifetime estimation is not necessarily a one-time action, but can be repeated, and it depends on many factors such as orbital parameters, operational requirements, and various others.

Many products today are designed with safety, quality, and service life in mind. Based on the historical trend in satellite lifetimes, the approach used here is to predict the lifetimes of satellites using half-life values of their launch year cohorts. Half-life calculations can be made using either launch year or failure year cohorts, making a comparison of these of interest in forecasting the future lifetimes of satellites.

This study focuses on analyzing satellite half-lives and using that information to project lifetimes of satellites that are still operational from the satellite launch year. We examine conformance of satellite lifetime data to fitted curves that remove noise from the data and thereby predict lifetimes of satellites from their launch year cohorts.

Key words: Half-life, Prediction, Regression, Space exploration, Technological progress.

1. INTRODUCTION

Various approaches for modeling and predicting the lifetimes of satellites have been the subject of research and development. The present study focuses on calculation of half-life time using historical satellite launch and failure data in order to focus on estimating and statistically predicting satellite lifetimes.

Half-life is the length of time it takes for a quantity to decay to half of its initial value. It is a measure of the time it takes for half of a set of entities to decay. Half-life is commonly used in nuclear physics to refer to the rate at which unstable atoms decay into stable atoms, thus characterizing the longevity of the unstable atoms.

For the satellite domain, in Earth orbit, all satellites are subject to a variety of perturbing forces that affect the trajectory of their orbits. Atmospheric drag has a significant effect on

ISBN: 978-1-950492-65-7
ISSN: 2771-0947

https://doi.org/10.54808/WMSCI2022.02.6

satellites in low Earth orbit with perigee altitudes below 2000 km. This force gradually makes the orbit more circular and decreases the altitude. As the satellite descends to around 180 km, the orbit begins to decay rapidly as it proceeds to catastrophic re-entry in only a few. Re-entry temperatures typically burn up a satellite, essentially vaporizing most of it. However, sometimes pieces may reach the ground for a large satellite or for various characteristics of specific components [1].

With the continued technological advancement of satellite components, design and manufacture, satellites have become more functional. Their longevities have also seen change over time. Fifteen-year design lifetimes are now typical for satellites placed in geosynchronous orbits. Many factors play a role in the end of life of a satellite. A major one is fuel exhaustion. The spacecraft runs out of fuel and can no longer perform essential functions. As satellite technology shifts increasingly to electric propulsion, fuel exhaustion is becoming less of a constraint, permitting longer operational lifetimes for satellites. This is one way for designers to increase satellite lifetimes. Refueling and tugs to maintain satellites are another approach which are becoming feasible and will likely see increasing use in the years ahead.

Nevertheless, interest has recently grown in relatively short lifespans of 7-8 years. Recent years have seen swift improvements in satellite design and manufacturing. As a consequence, state-of-the-art designs that meet market requirements including cost-effective performance leading to profitable operation has become a more complicated technical and financial endeavor. In an environment of rapid technological innovation, shorter lifetimes allow for faster quicker replacement, thus facilitating introduction of new technologies, leading to improved ability to meet new market demands and even open new market segments [2].

Still, longer lifetimes provide efficiency advantages causing many private and public sector satellite owners to extend satellite lifetimes by launching them into orbit with enough of a fuel charge to last a targeted 15 years. This also requires attention to component quality to withstand the radiation environment of space for that length of time. In the current market customers may demand CubeSats lasting six months, geostationary communications satellites lasting decades, or spacecraft of various intermediate lifetimes.

2. HALF-LIFE

The half-life concept is an important model of decay. While an unstable atom's lifespan has a strong random component and is individually unpredictable, decay is always a possibility. Although one can't forecast when one unstable atom will break down, it is possible to estimate an expected lifetime if there are a lot of them. Atoms with equal decay probability decay exponentially, which is equivalent to saying they have a half-life that remains constant over time. The stochasticity of the behavior of individual atoms in this scenario means that many will disappear early on, but some will persist for a very long time.

Using the half-life model, this study focuses on the calculation of satellite half-life using the history of satellite launches and failures. We use their launch year as an independent variable. One potential complication is that satellites may still be currently operating, making it hard or impossible to know their lifetimes. Previous related research is presented in [3-12].

3. CASE STUDY

A sum of squares calculation was used to determine the fit of data to model as well as how well data dispersion is accounted for in a regression analysis. The sum of squares gets its name from calculating the sum of squared differences between measured and predicted values. In a regression model, the regression sum of squares describes how well the data is modeled. Squaring the residuals is motivated by the observation that N scalar data points and a curve that is being regressed to the data can each be represented by a single point in N-dimensional space. The quality of fit can then be taken as the Pythagorean distance between those two points – the square root of the sum of the squares of the differences between the two points along each of the dimensions.

Figure 1 shows the relation between the half-life of satellites with respect to their launch year. Data is from [3]. The graph pattern shows that when satellite technology started, half-life was relatively short. Half-life increased but then in recent years appears to have decreased.

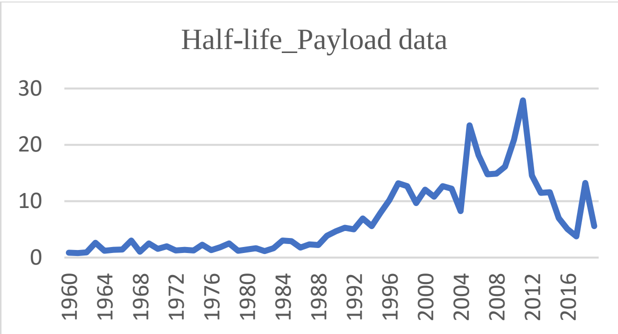

Figure 1. Satellite half-life calculation. The *x*-axis represents launch year, and the *y*-axis represents half-life in years.

Failure Year	Failure Count	Alive Count	Number Alive	Residual	Residual^2
1961	38	5	4.39	-0.020	0.000425
1962	3	2	2.12	0.097	0.009578
1963	1	1	0..03	-0.116	0.01349
1972	1	0	0	0.003	1.37E-07
Launch year=		1961			
# launched=		43			
Scaling factor=		4.97			
SSR=		0.023			
Half-life=		0.80			

Table 1. Satellite data half-life calculation.

Table 1 shows an example of half-life calculations on the 1961 launch cohort. The scaling factor is a standard parameter of exponential curves and half-life is the other. The half-life values were calculated using failure year numbers. Solver was used for the analysis. Solver is an Excel add-in that allows performing regressions. There were 5 data analysis conditions. Half-life was calculated using failures in:

Condition 1: All years
Condition 2: 10 years starting from launch year
Condition 3: All years except the launch year
Condition 4: 2 to 9 years after launch year
Condition 5: 5 years starting from launch year

Figures 2 and 3 provide summary reports and 3-parameter Weibull 95% probability plots for Condition 1. To calculate half-life, we used the following formula: number alive=[scaling factor*power (2, elapsed time/-(half-life))]. Elapsed time is the difference between death year and launch year.

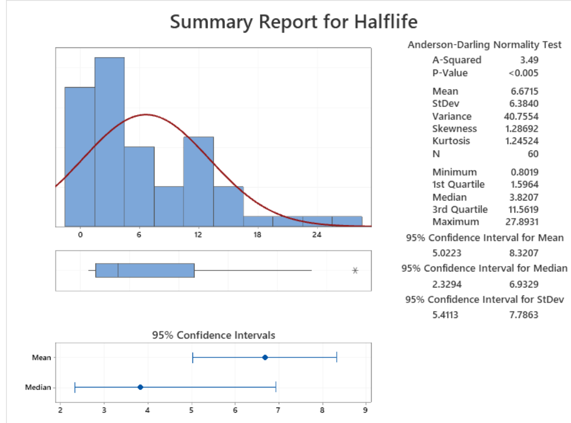

Figure 2. Summary report for half-life in Condition 1.

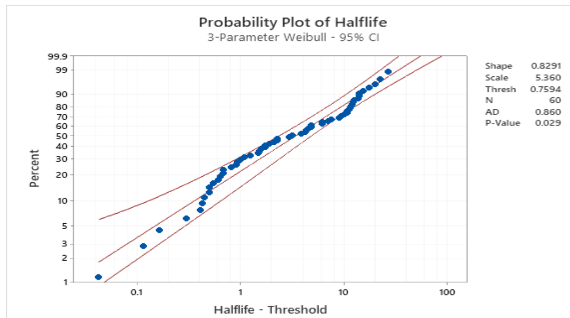

Figure 3. 3-Parameter Weibull 95% probability plot for Condition 1 dataset.

Figure 4 shows the half-life moving average curve. Time series data are typically smoothed out with moving averages to highlight longer-term trends by reducing noise.

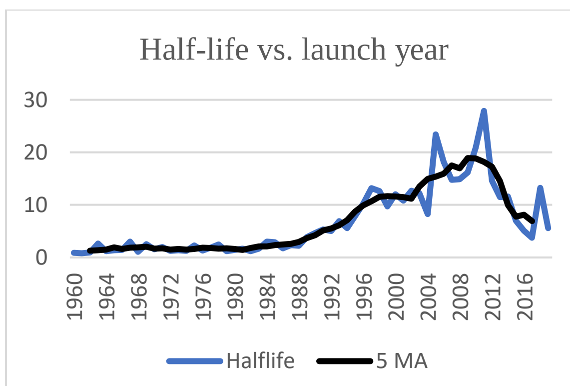

Figure 4. Half-life with moving average smoothing. The *x*-axis represents launch year and the *y*-axis represents half-life in years.

Figures 5 and 6 provide summary reports and 3-parameter Weibull 95% probability plots for Condition 2.

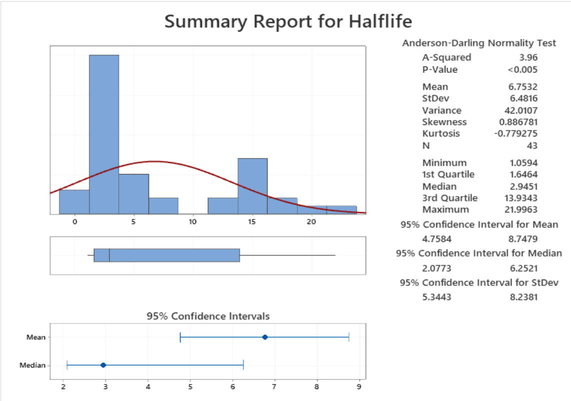

Figure 5. Summary report for half-life in Condition 2.

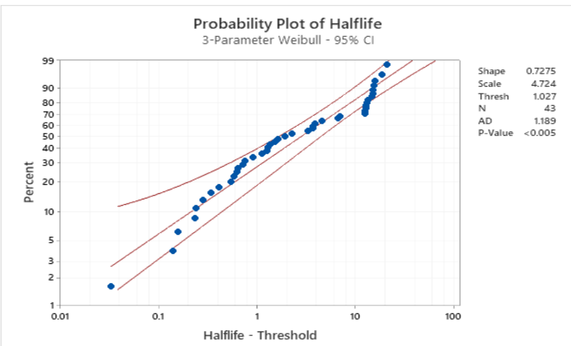

Figure 6. 3-Parameter Weibull 95% probability plot with Condition 2 dataset.

Figure 7 shows the half-life values without using the residual for failures occurring in the year of launch to avoid potential distortion due to the bathtub curve effect. The half-life trend increased gradually from the 1980s until 2012 and then fell.

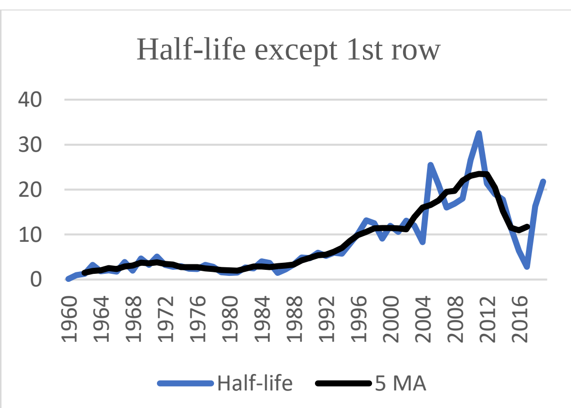

Figure 7. Half-life (without considering records for launch and failure in the same year). The *x*-axis represents launch year, and the *y*-axis represents half-life in years.

Figures 8 and 9 show a summary report and lognormal 95% probability plot for Condition 3.

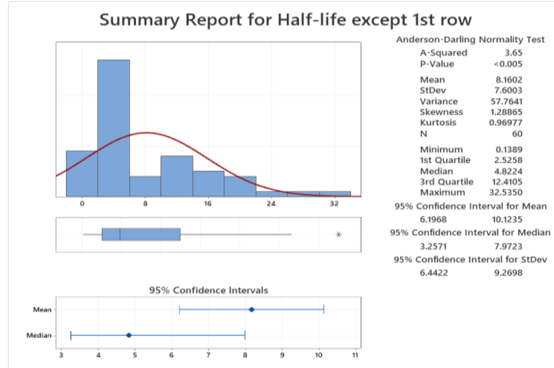

Figure 8. Summary report for half-life, Condition 3.

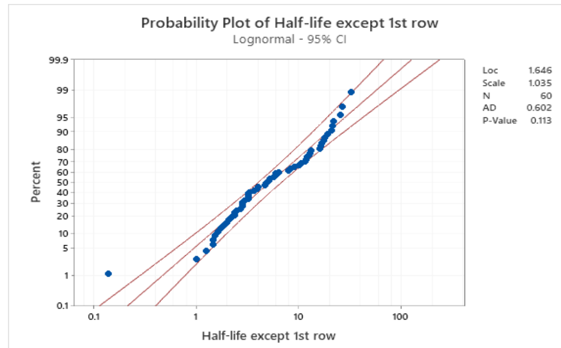

Figure 9. Lognormal 95% probability plot for Condition 3 dataset.

Figure 10 shows the trend based on failures in the first ten years starting with the launch year (Condition 2). The half-life trend was relatively flat until 1985 and then moved up roughly exponentially until 1997.

Figures 11 and 12 show a summary report and lognormal 95% probability plot for Condition 4.

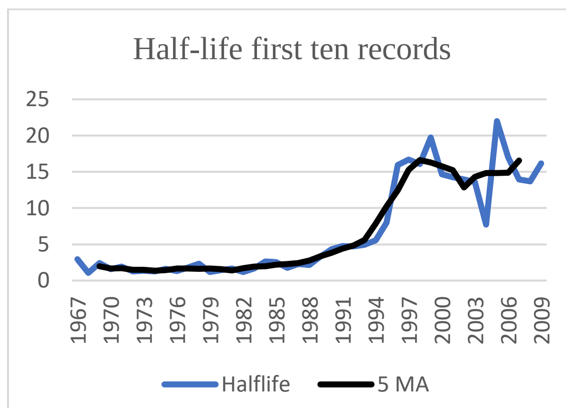

Figure 10. Satellite data half-life calculation (for the first 10 records from the year of launch). *X*-axis represents launch year, and *y*-axis represents half-life in years.

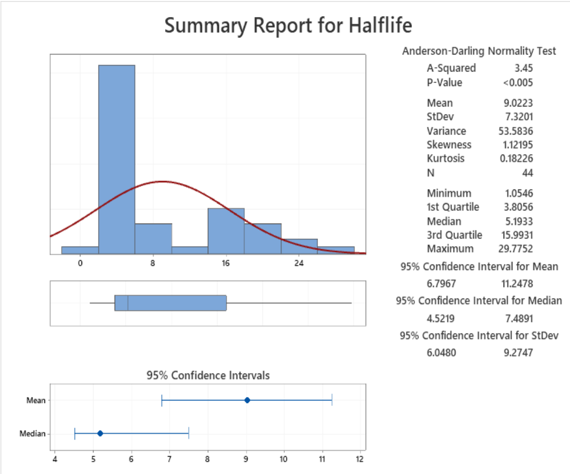

Figure 11. Summary report for half-life, Condition 4.

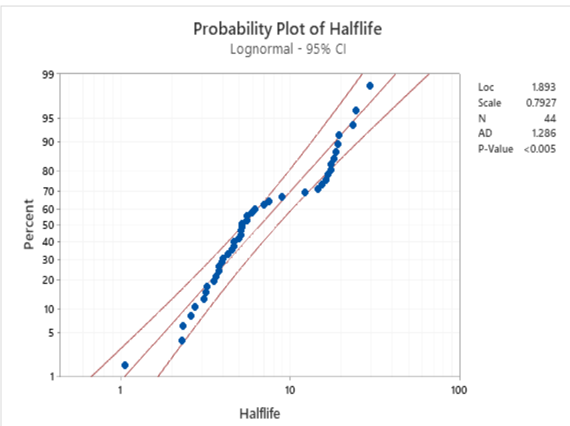

Figure 12. Lognormal 95% probability plot with Condition 4 dataset.

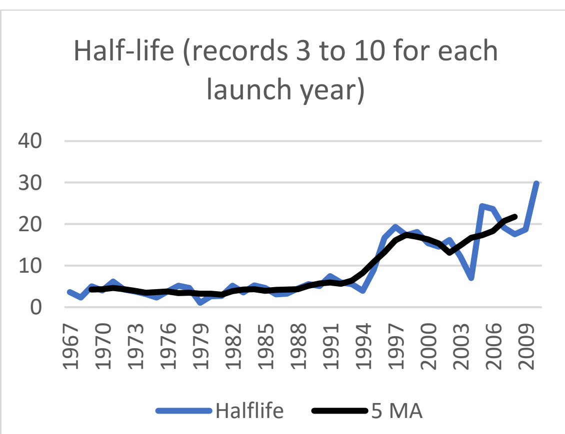

Figure 13. Payload data half-life calculation (from 2 to 9 years from the year of launch, Condition 4). The *x*-axis represents launch year, and the *y*-axis represents half-life in years.

Figure 14 indicates the launch count, death count and alive count of satellites by date of launch cohort. Launch count increased in recent years but death count did not. Figures 15 and 16 show the summary report and 3-parameter log-logistic 95% probability plot for Condition 5.

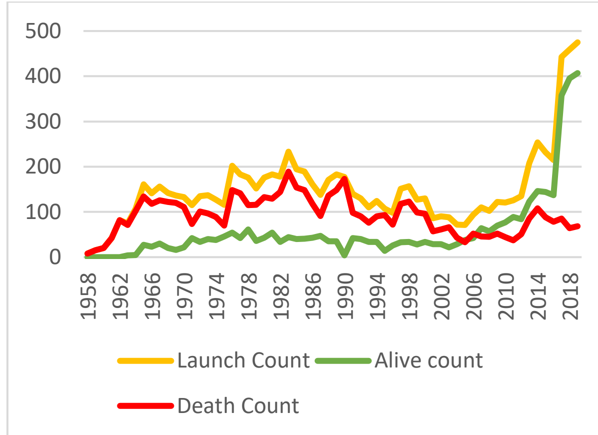

Figure 14. Payload data showing launch, death, and alive counts.

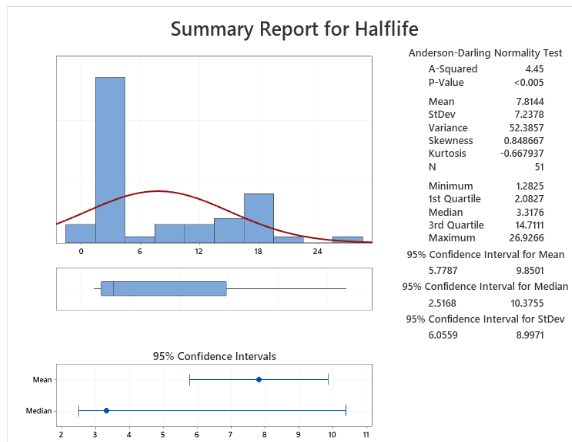

Figure 15. Summary report for half-life data, Condition 5.

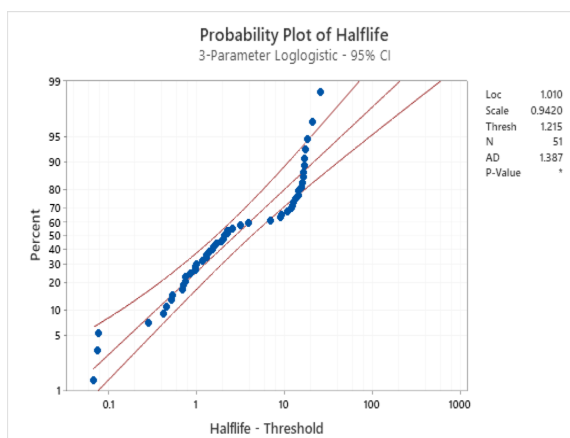

Figure 16. 3-Parameter log-logistic 95% probability plot for Condition 5 dataset.

4. CONCLUSION

This article discusses half-life calculation of satellites. The half-life of satellites rose during part of the history of space age, but then leveled off and even declined. One of the reasons behind this is likely the rapid changes in satellite technology and fast-growing satellite business incentivizing turnover in satellites as newer ones are produced with greater functionality.

It was found that the following distributions yielded the best fits after testing five different models against the data, based on average deviation (AD) numerical values.
Condition 1: 3-parameter Weibull distribution (AD = 0 .860)
Condition 2: 3-parameter Weibull distribution (AD = 1.189)
Condition 3: Lognormal distribution (AD = 0.602)
Condition 4: Lognormal distribution (AD = 1.286)
Condition 5**:** 3-parameter Log-logistics distribution (AD = 1.215)

Condition 3 yielded the best fit with the smallest Average Deviation.

As a result of shorter satellite lifetimes, new technologies can be introduced and implemented faster, new markets can be targeted, and new products are better positioned to compete with for market share. Future research is suggested that focuses on taking both of average lifetime and satellite weight into consideration to define a composite measure.

5. REFERENCES

[1] Satellite Orbital Lifetimes, available at https://www.spaceacademy.net.au/watch/debris/orblife.htm.

[2] Satellite EOL: Not One Size Fits All, July 25, 2018, http://www.nsr.com/Satellite-Eol-Not-one-Size-Fits-All.

[3] Jonathan McDowells' Space Pages, available at http://planet4589.org/space.

[4] In-depth details on the 2,787 satellites currently orbiting Earth, including their country of origin, purpose, and other operational details, Union of Concerned Scientists (UCS) Satellite Database, updated August 1, 2020, available at www.ucsusa.org/resources/satellite-database.

[5] VJR Batthula, RS Segall, V Kodali, M Howell, D Berleant and H Aboudja (2020), Time series modeling of lifespans of Earth satellites, *Proceedings of 24th World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI 2020)* , Orlando, FL, July 15-18, Vol. 2, pp. 1-6.

[6] VJR Batthula, RS Segall, V Kodali, M Howell, D Berleant and H Aboudja (2020), Time series modeling of lifespans of Earth satellites, *Journal of Systemics, Cybernetics and Informatics*, Vol.18, No. 5, pp. 62-67.

[7] M Howell, V Kodali, RS Segall, H Aboudja and D Berleant (2019), Moore's law and space exploration: new insights and next steps, *Journal of the Arkansas Academy of Science*, Vol. 73, Art. 6.

[8] VJR Batthula, RS Segall, M Howell, H Aboudja, D Berleant and P-H Tsai (2021), Forecasting of a technology using quantitative satellite lifetime data. *Journal of Systemics, Cybernetics and Informatics*, Vol. 19, No. 5, pp. 78-83.

[9] P-H Tsai, D Berleant, RS Segall, H Aboudja, VJR Batthula and M Howell (2021), Spacecraft for deep space exploration: combining time and budget to model the trend in lifespan. *Proceedings of the Future Technologies Conference (FTC 2021)*, October 22-23, Springer.

[10] J Wang and C Zhou (2021), Statistical modeling and analysis of satellite failure based on 2-Weibull segmented model, *IEEE Access*, Vol. 9, pp. 128747-128754, doi: 10.1109/ACCESS.2021.3113155.

[11] W Huang, R Andrada and D Borja (2021), A framework of big data driven remaining useful lifetime prediction of on-orbit satellite, 2021 *Annual Reliability and Maintainability Symposium (RAMS)*, pp. 1-7, doi: 10.1109/RAMS48097.2021.9605711.

[12] D Berleant, M-P Cheong, C Chu, G Yuan, A Kamal, G Sheble, S Ferson, JF Peters (2003), Dependable handling of uncertainty, *Reliable Computing*, Vol. 9, No. 6, pp. 407-418.