PRACTICAL APPLICATION OF STRUCTURAL RISK ASSESSMENT WITH SMART|DT

Viola Ferrari[1], Dr. Min Liao[3], Michea Ferrari[1] and Prof. Dr. Michel Guillaume[2]

[1] RUAG AG, Emmen, Switzerland
[2] Zurich University of Applied Sciences, Centre for Aviation, Winterthur, Switzerland
[3] National Research Council Canada (NRC), Aerospace, Ottawa, Canada

Abstract: Structural risk assessments are highly relevant to assure the structural integrity over the whole life-cycle of an aircraft. The Aircraft Structural Integrity Program (ASIP) from the US Air Force introduces design guidance based on deterministic crack growth prediction for safety critical components. Today, with the increase of computational power, probabilistic methods instead of deterministic analysis can be deployed. Probabilistic Risk Assessment (PRA) offers the benefit of taking uncertainty into account and leads to less conservative estimates while meeting safety requirements.
Research organizations such as the National Research Council Canada (NRC) or the Defence Science and Technology Organization in Australia (DSTO) are already assessing safety critical elements with PRA. RUAG AG is interested in the application of this method for current and future military aviation systems. Based on the research performed by these organizations, the application of PRA is assessed.
The probabilistic calculations are performed with the software tool SMART|DT. Structural engineering and fatigue data is needed for such an assessment, which includes equivalent crack growth data, pre-crack size distributions (EPS), loading distributions and probability of detection (POD). The possibilities of the tool are demonstrated with a case study from the Swiss F/A-18 fleet at knife edge of inner wing trailling edge flap hinge. The results are compared with analyses from ProDTA from NRC and with PROF from the United States Air Force (USAF).

Keywords: structure, risk assessment, probabilistic, ASIP, fighter jet, SMART|DT

INTRODUCTION

The ability to perform Structural Risk Assessments (SRA) is fundamental for fighter jet aircrafts and in order to explore new possibilities, this work elaborates on statistics and probabilistic tools that allow to mathematically model data for SRA. The selected tool for these assessments is SMART|DT [1] and the presented case study relay on actual maintenance and operational data provided by RUAG AG.

The data acquisition for military jet structure is regulated under the Aircraft Structural Integrity Program (ASIP). The program requires the performance of structural risk analysis in order to evaluate the safety of the aircraft structure [2]. The analysis must show that the aircraft can fly safely during its operational life. The safety of an aircraft is defined by the following probabilities:

"A probability of catastrophic failure at or below 1e-7 per flight for the aircraft structure is considered adequate to ensure safety for long-term military operations. A probability of catastrophic failure exceeding 1e-5 per flight for the aircraft structure is considered unacceptable." [2].

The ASIP also states that all significant variables affecting the risk shall be included in the risk analysis. With the combination of all the variables and the safety thresholds, a Probabilistic Risk Assessment (PRA) supports to fulfil the structural risk analysis requirements of the ASIP.

METHODS

SMall Aircraft Risk Technology (SMART|DT) is a tool developed by Juan D. Ocampo and Harry Millwater of the University of Texas. The goal of the program is to develop a probabilistic structural risk assessment tool based on damage tolerance for the general aviation industry. The tool was developed for the Federal Aviation Administration (FAA) for the performance of risk analyses. This tool is very versatile and can also be applied for aircraft not coming from the general aviation industry [3].

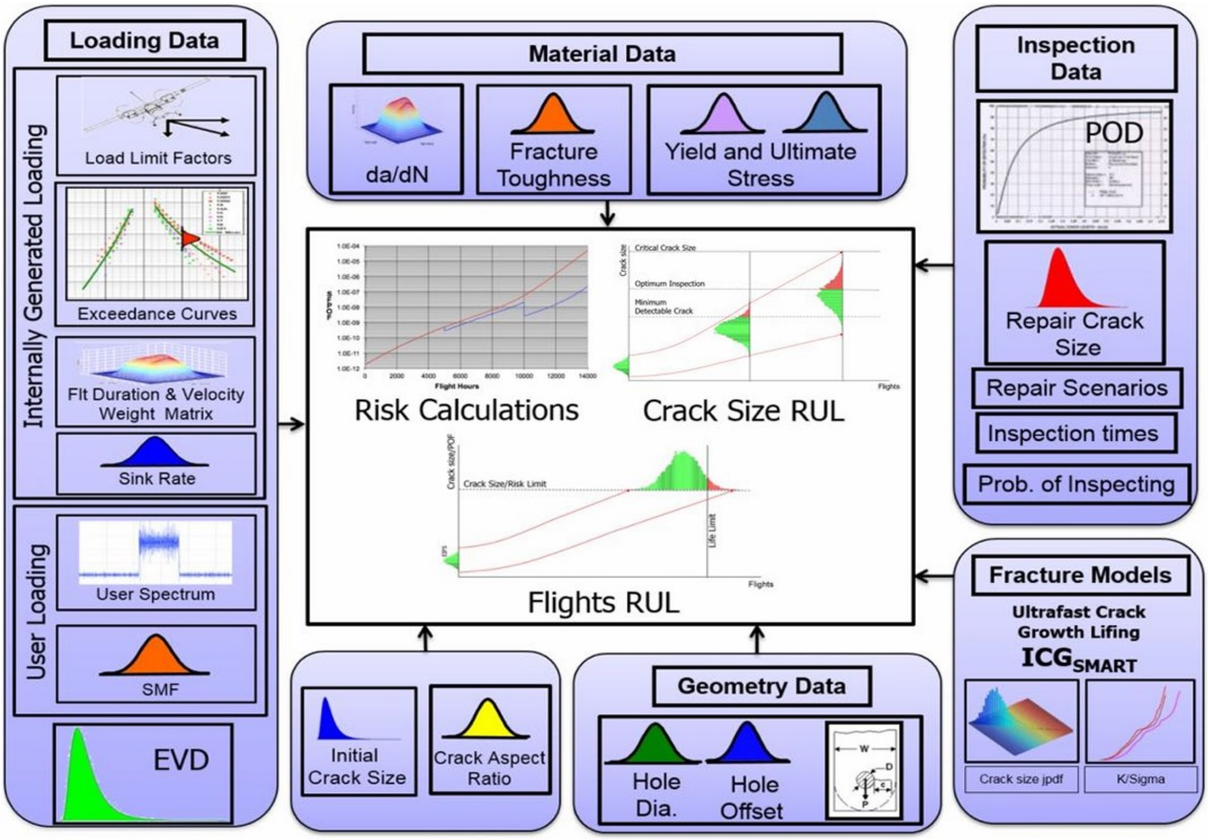

Figure 1: SMART|DT capabilities overview [3]

Figure 1 gives an overview of the data required for the analysis. Pre-selected inputs needed for the assessment of the Swiss jet fleet are depicted in Figure 2. Given the available data, several inputs were already included in the analysis and are not further discussed in this paper, e.g. is the hole diameter already implemented in the crack growth model. For the required data, source and quality are very important. Figure 2 shows the source of the required data and how it is prepared for the analysis in SMART|DT. The input data will be further explained to better understand the process of the SMART|DT tool.

Master Curve

The master curve methodology is used to predict deterministic crack growth from a deterministic fracture mechanic model. The deterministic fracture model is the output of a deterministic Damage

Tolerance Analysis (DTA). Based on an AFGROW analysis, the crack over time and the residual strength over time curves can be extracted. The residual strength can be calculated with the following equation:

$$\sigma_{RS} = \frac{K_{C_0}}{\beta \cdot \sqrt{\pi \cdot a}} \tag{1}$$

Where K_{C_0} is the fracture toughness of the master curve, β is the geometry factor and a the crack size. The master curve methodology then shifts and scales the master curve by using different initial crack sizes and fracture toughness values. This means that only one fracture mechanics model is needed. However, it only consists of two random variables, initial flow size and the fracture toughness. This means that it cannot be applied for random crack growth rates and random geometry values [1].

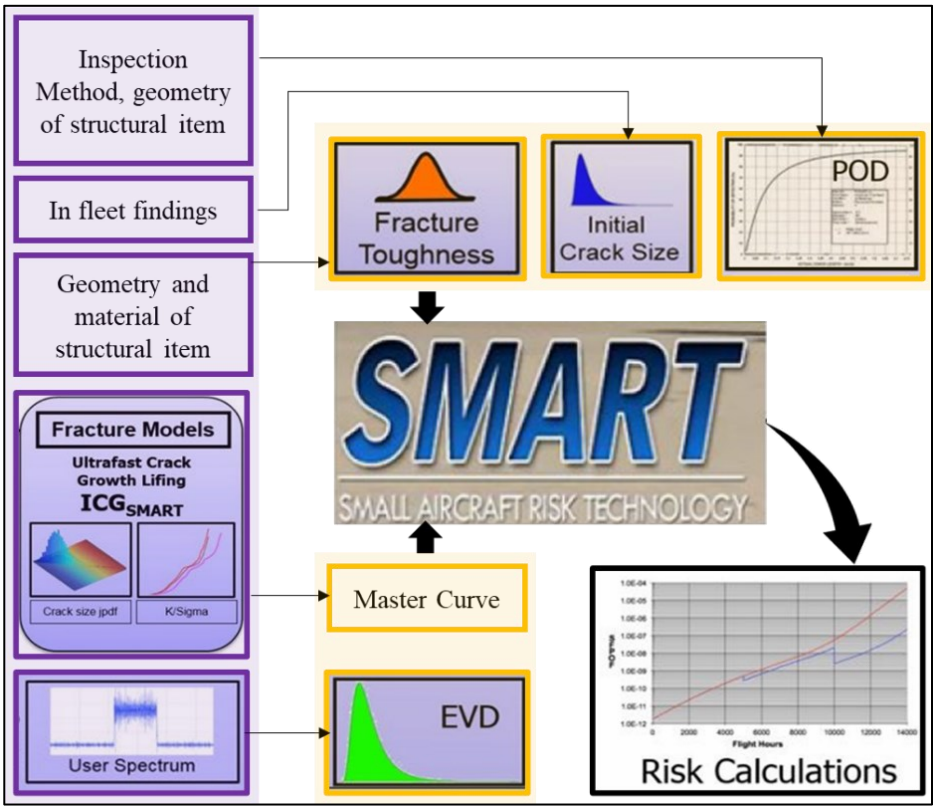

Figure 2: Data required for the PRA. In violet the source data, in orange the input data and in black the output of the assessment.

Given an initial crack size and a fracture toughness distribution, with equation (1) the residual strength can be calculated with a random initial crack size and a random fracture toughness. [1] With this method, from one fracture mechanics model several different models can be approximated in order to simulate the crack growth randomness in PRAs.

For the master curve methodology it is important that the master curve covers the complete range of crack sizes used for the PRA if reliable results shall be achieved. This means that the crack sizes of the Equivalent Pre-crack Size (EPS) distribution must be covered by the master curve. It is however still difficult to approximate fracture mechanic models in very small crack size ranges (< 0.01"). When data is not available and the master curve does not cover the EPS distribution, SMART|DT log-linearly extrapolates the crack growth curve to the initial crack size.

The data for the calculation of the master curve is taken from AFGROW crack growth analysis outputs carried out by the Structural Engineering at RUAG AG.

Material Data

The material properties are an important source of randomness for PRAs. The variables influencing the analysis are the fracture toughness, the yield and ultimate strength [1]. These distributions are often taken from literature and applied in probabilistic models [4]. The three variables are affected by different factors such as grain direction, treatment, form and thickness of the item. All this contributes in the variability of the material data [5]. The fracture toughness distribution has an impact on the calculation of the residual strength. The other two variables, yield and ultimate strength, affect the PRA only when the fracture model is tested on net section yielding [1] [5].

Data for material properties such as fracture toughness and yield strength can be given as a normal distribution or in form of A and B statistical values. When A and B basis are given, a normal distribution can be approximated.

Geometry (EPS)

The initial crack size distribution has proven to have the highest impact on PRA results. [6] A lot of effort has been put into initial crack size distribution derivations with different methodologies [6][7][8][9]. Two most applied methodologies are the Equivalent Initial Flow Size and the Equivalent Pre-crack Size. Only the latter one is applied for this presented case study.

The EPS is load and spectra independent since it is derived by back projection to time zero from fatigue crack growth FCG data. The fatigue life variation of a metallic structure appears to be more a characteristic of material surface conditions. A clear difference in the slopes of fitted distributions between the surface treatments is observed [7]. This means that depending on the surface treatments, the EPS distribution varies. However, in order to be able to define EPS distributions an adequate dataset must be available with as much data points as possible.

With regard to SMART|DT tool, this input shifts the master curve's residual strength on the time axis. The methodology of exponential crack growth to calculate the EPS is taken for the analysis of initial crack size data of the Swiss fleet. However, given the small data set of the fleet, a lack of accuracy in the fitting of the distribution occurs. For the case studies, the distribution of machined coupons, derived in the study of Molent [7], are used.

Loading

It is assumed that a failure of structural part occurs when the residual strength is smaller than the applied stress. The applied stress is approximated by an extreme value distribution (EVD) defining it as max stress per flight hour. The EVD is approximated by selecting the largest stress from each flight of the spectrum and fitting a distribution (either Gumble or Weibull) to the data. The loading distribution describes the probability of a load to occur during flight. If the load is bigger then the residual strength of the structural location (calculated with the master curve), a failure of the item occurs. The loading distribution can be approximated with the spectrum used for the AFGROW analysis. SMART|DT uses EVD concept to simplify the computations. For cases where spectrum data from the fleet is available, this is the best way to describe the variance of the loading.

For the calculation of the EVD, SMART|DT uses the generalized extreme value model where the CDF is:

$$F_{EVD} = (\mu, \sigma, \xi) = \exp\left\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{2}$$

With μ, σ and ξ as location, scale and shape parameters. The value of the shape parameter defines the type of distribution: Weibull ($\xi < 0$), Gumble ($\xi = 0$) and Frechet ($\xi > 0$). Since the max Weibull distribution is bounded above (no right tail), this distribution is not recommended for the representation of max stresses in a flight. The typical distribution used to describe max stresses is the Gumble distribution, which is unbounded in both directions and is therefore the most flexible and best suited for the representation of max stresses [1]. The spectrum for the case study of the knife edge from the Swiss F/A-18 fleet is taken as an example. Figure 3 shows the fitted distribution with the Gumbel fit and the

EVD fit, in this case as a min Weibull distribution. Both distributions have a slight variation at both ends and in the form of the curve. The impact of these variations did not lead to any significant impact on the POF given the performed sensitivity study.

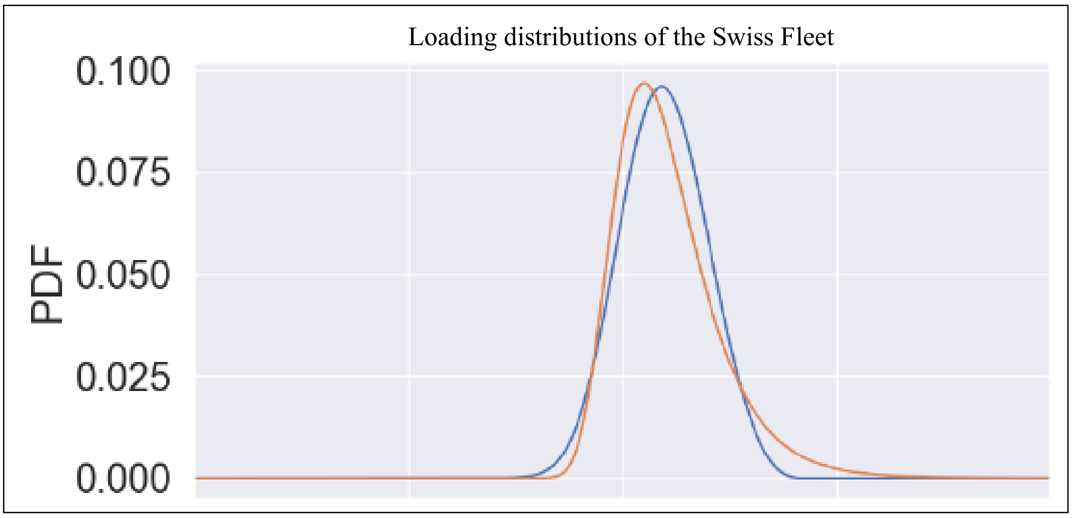

Figure 3: Loading distribution fitting with Python in orange with the Gumbel fit and in blue with the EVD fit (min Weibull)

Monte Carlo and Importance Sampling

Monte Carlo simulations is a well-known method to compute POF. It however requires a large sample size. For example, for a computation of a POF of 1e-7 around 1 billion samples are recommended. The generation of the samples is accomplished with a random number generator.

Importance Sampling is a more efficient way of calculating the POF. The main difference between this method and Monte Carlo simulations is that a sampling distribution is given to generate the samples used for the calculation of POF. If this sampling distribution is well optimized, the number of samples required to estimate the POF within a given confidence interval will be orders of magnitude less than for Monte Carlo simulations. Figure 4 shows an example of a region of importance for the POF. With the standard Monte Carlo sampling, most of the generated samples will not be relevant for the POF. By introducing q(x) only relevant samples can be generated and fewer sample sizes are needed to calculate the POF. The algorithm implemented in SMART|DT estimates the POF for PRA using six orders of magnitude fewer samples compared to the standard Monte Carlo sampling for probabilities of 1e-7.

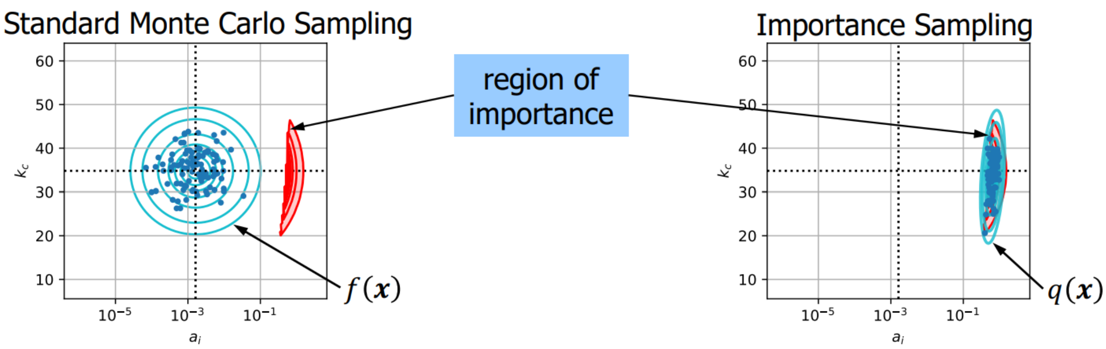

Figure 4: Monte Carlo sampling vs importance sampling. With an adequate sampling distribution q(x), only relevant samples can be generated for the PRA. The region of importance shows the samples which mostly affect the calculation of the POF [10].

SENSITIVITY STUDY

When PRAs are performed, it is relevant to understand the impact of the different inputs on the output (POF). Different data sources or different data distributions have the potential to lead to different results. It is important to establish this variation before each case study, in order to better understand, which input data needs to be tuned in order to achieve more accurate results.

The following input variations were tested for SMART|DT:

- Different sources for material data for the crack growth model calculation (AFGROW vs DST16[1] data)
- Different master curve models were compared, especially with different coverage in the small crack size region
- K_C variations for different crack orientations
- EPS variations
- Different spectrum depending on the flight missions of the fleet, including different loading distributions
- Different inspection technologies and schedules (first inspection and recurring inspections)

The most relevant observations from the performed sensitivity studies are the following:

- Given that the spectrum has an impact on the crack growth model and on the loading distribution, it is fundamental to apply an accurate spectrum for the PRA.
- The PRA results are very sensitive to the EPS distribution. However, if two EPS distributions cover a similar range of crack sizes, the differences of the POF between these two models is marginal.

RESULT OF CASE STUDY

For the case study the location on the Inner Wing Trailing Edge Flap (TEF) Knife Edge is selected. The Trailing Edge Flap is mounted on the Inner Wing over two hinges on the Inner Wing and the corresponding counterparts on the TEF. The case study is a hot spot because cracks have been found in the Swiss fleet during the inspections. These cracks are due to the severity of the Swiss usage spectrum. For this hot spot, the blue print (BP) model is evaluated for the PRA.

At the knife edge location, cracks were also found in the United States Navy (USN) and Royal Canadian Air Force (RCAF) fleets. Whereas, on the Swiss fleet, several cracks were found on in-service hinges.

For the results, the data is exchanged with the NRC and different tools are used for the evaluation of the knife edge results. ProDTA is the in-house tool from the NRC and PROF3.2 is the USAF tool. Both have the capability to calculate the POF with two equations, the Freudenthal and the Lincoln equations.The Freudenthal equation considers no-failure events, and is more complicated to calculate[13].

The results of SMART|DT can be seen in Figure 6. The SFPOF is calculated with the original Lincoln equation. ProDTA with the original Lincoln equation shows very similar results to SMART|DT. The results from PROF3.2 with a modified Lincoln equation [14] are less conservative when compared to the results of SMART|DT and ProDTA. In comparison to the calculations with Freudenthal equations from PROF3.2 and ProDTA, the SFPOF results from the Lincoln equation are conservative. Both ProDTA and PROF3.2 gave very similar POF results using the Freudenthal equation.

[1] DST16 data has higher accuracies in the small crack size range and allows better application of DTA in combination with the EPS concept.

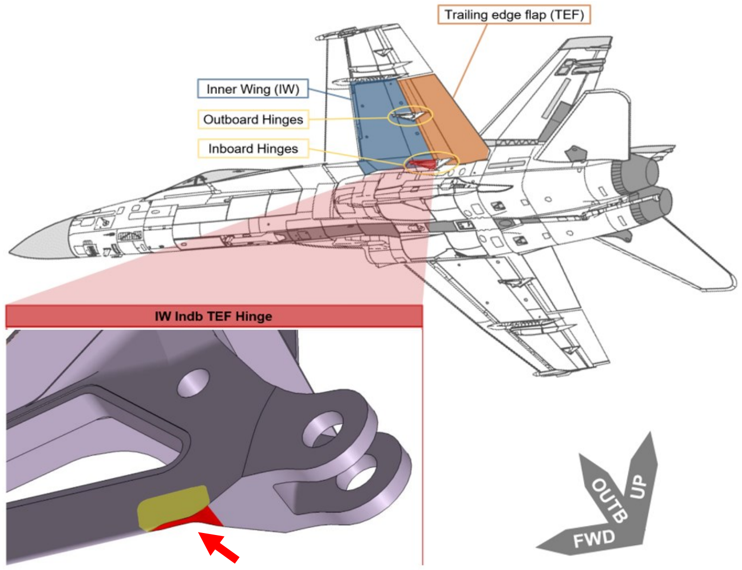

Figure 5: Overview of the IW inbd TEF on the F/A-18 and the Knife Edge location [11]

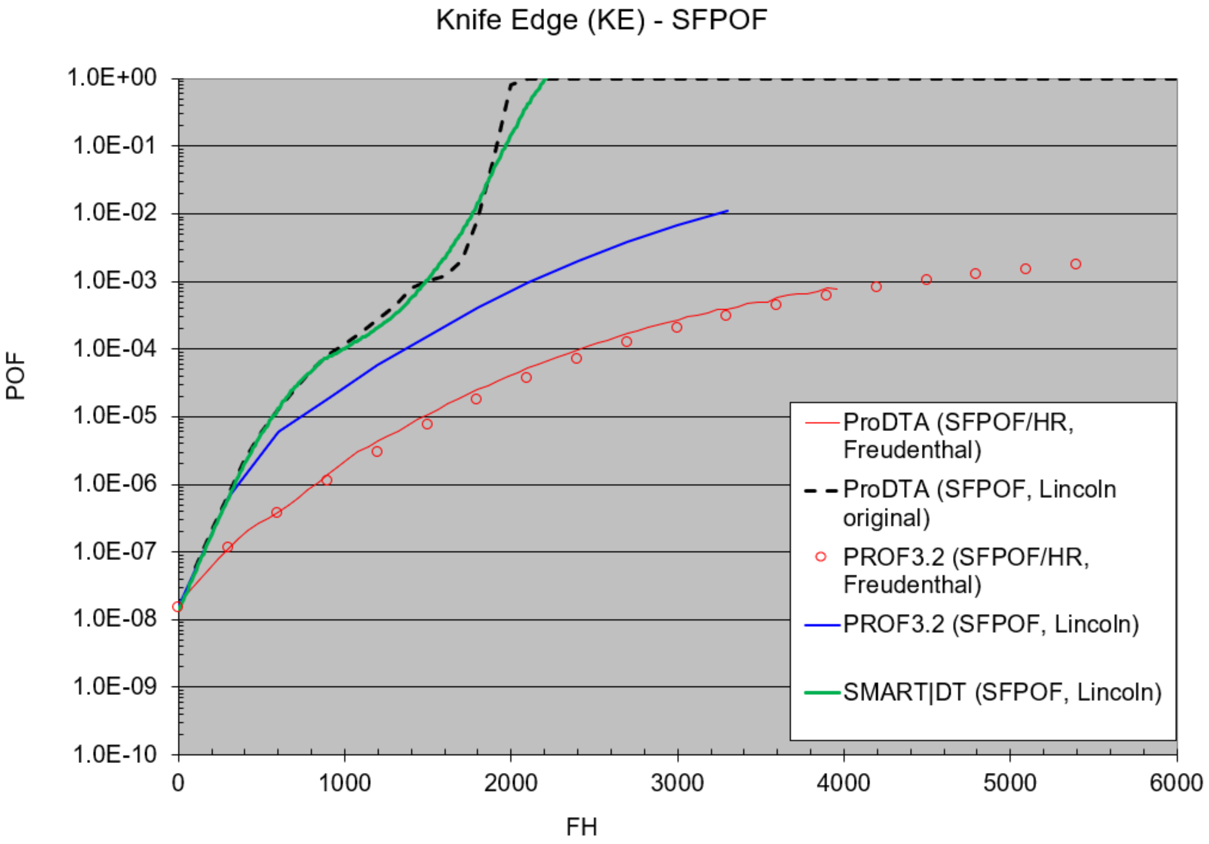

Figure 6: SFPOF results with different tools: ProDTA, PROF3.2 and SMART|DT (SFPOF: single flight probability of failure).

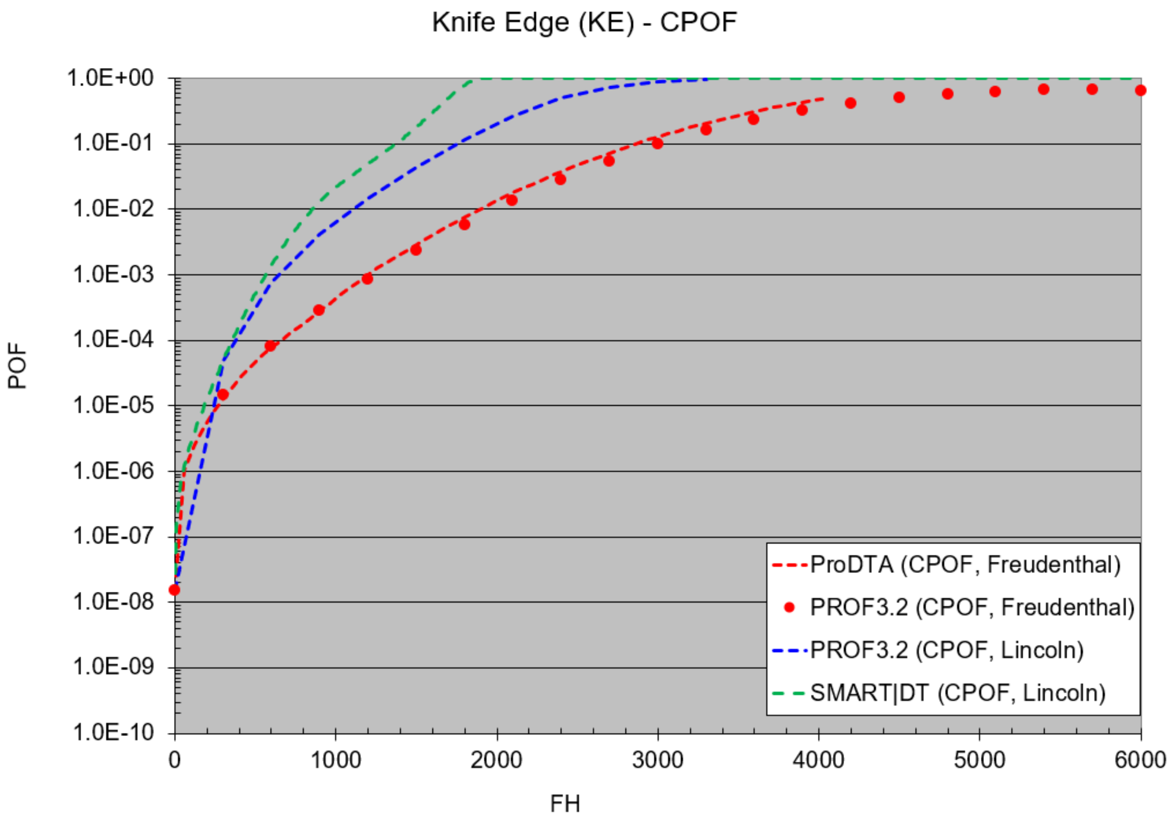

Figure 7: CPOF results with different tools: ProDTA, PROF3.2 and SMART|DT (CPOF: cumulative probability of failure).

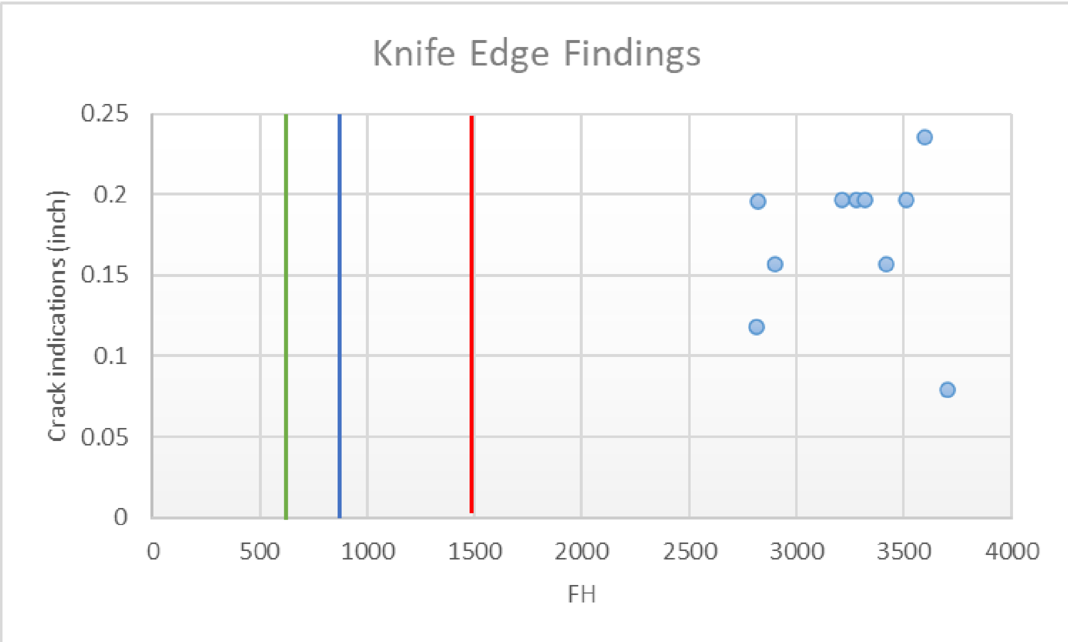

Figure 8: Knife Edge Fleet findings. The red vertical line is the threshold to $1e^{-5}$ from the Freudenthal calculations. The green and blue line are the same thresholds from Lincoln (SMART|DT and PROF3.2).

Figure 7 presents the cumulative probability of failure (CPOF) results from the three tools using both Lincoln and Freudenthal equations. The CPOF results are more comparable to the in-service findings, as shown in Figure 8, the Freudenthal equation is the more accurate for this case study. Given that inspections are performed when the SFPOF reaches $1e^{-5}$, the Freudenthal equation leads to a less conservative inspection interval. With the Lincoln calculation the inspections are started too early in the life of the structural item.

DISCUSSION

The implementation of a PRA using SMART|DT in the daily business of the Structural Engineering at RUAG is a challenging task. Nevertheless, a greater knowledge of SMART|DT is gained and a deeper understanding of the inputs and their dependencies between each other is achieved.

From the sensitivity study the most relevant inputs were established: spectrum, EPS and POD. These are at the same time also the inputs with the highest uncertainties. The spectrum developed at RUAG can be used with high confidence for the PRA. The EPS and the POD on the other hand are more difficult to define and to derive from known data. Extensive studies must be performed in order to gather enough data to generate statistically relevant datasets. For EPS definition extensive coupon testing is needed and for the POD inspections must be planned and carried out with different inspectors for different methods and on different items. In both cases it is very time consuming to acquire reliable data. Here it is recommended to use external data and to rely on engineering judgement and the methods described in this report to derive the required data for the PRA.

This case study is further analysed with the PRA tools from NRC ProDTA and USAF PROF3.2. In comparison to these calculations, SMART|DT leads to more conservative results when compared to Freudenthal calculations. When compared to the Lincoln calculation from ProDTA and PROF3.2, the results are similar. It should be noted that the Lincoln equation between SMART|DT and PROF3.2 deviate from each other: SMART|DT uses the original equation, whereas PROF3.2 uses an modified equation [14]. Finally, the comparison of the POF results against the in-service findings of the fleet is relevant. Based on Freudenthal calculations, the $1e^{-5}$ threshold is at 1500 FH. This is a realistic value for the start of inspections when compared to the in-service findings. In comparison to the NRC Canada in-house tool, ProDTA, which can use the Freudenthal equation to calculate the POF, SMART|DT is still in development to include the Freudenthal method. ProDTA is also capable to simulate the impact of corrosion [12]. Therefore, compared to ProDTA, SMART|DT is simpler. This however makes it perfect for the application of supporting daily business since the data acquisition is simpler and faster.

From the result, SMART|DT mostly shows to be a conservative tool. If a good data situation is reached, the probability that the POF for a specific case study will be higher than the calculated one, is very small. This outcome can help to define higher inspection intervals thus improving the reliability of the fleet. As for the moment, the tool could be applied in the decision-making process for fleet safety matters but is insufficient to be a leading decision-making tool. From this tool arise the opportunities to kick-off data acquisition strategies and to start planning and preparing a database for PRA. Moreover, a know-how of PRA can be built up for the Swiss F/A-18 fleet and for future systems. Given the results, the severity of SF (safety factor) can be assessed based on the POF given by SMART|DT. This however leads also to an important threat. The threat of making wrong decisions based on unreliable data. The PRA is only helpful if the input data is reliable with reasonable statistics.

CONCLUSION

After a period of 18 month of work and several meetings with the NRC Canada and with Juan Ocampo a solid basis and supporting tools for the first applications of PRA for RUAG has been established.

The determination of POD is also a difficult task since the POD distribution is not only dependent from the material, geometry and method, but also from environmental effects and the inspection results. The detectable crack size is defined from case to case and a POD can then be approximated based on engineering judgment. The sensitivity study was performed with the data based on this case study. It was not possible to establish the influence of each input in detail, since the inputs are interconnected and dependent from each other. However, the spectrum, EPS distribution and POD show a pattern of being the most sensible inputs when the distribution is varied.

The performance of PRA is not yet state of the art to maintain the structural integrity of a fleet. The SFPOF calculations are complicated and very small probability calculations are involved which needs experience and time. Using the three different tools (SMART|DT, PROF3.2, and ProDTA) which were used in this case study confidence in the SFPOF results could be gained. Further case studies must be done in collaboration with different organizations for future applications for safety in structural integrity.

SMART|DT is an opportunity for RUAG and other companies to start thinking about PRA and its role on future systems. If the PRA shall be a central part of risk assessments, it is important to start gathering relevant data as soon as possible and to put together a good database. International collaborations might lead to a reliable data pool.

ACKNOWLEDGEMENTS

Special thanks to armasuisse for providing the data and RUAG for the support given in order to be able to publish at ICAF 2023. The authors would also like to thank the PROF3.2 developer, UDRI, and USAF A-10 ASIP management for permitting the use of PROF3.2 results in this paper. A big thanks also to Juan Ocampo for the support given during the master thesis and for the insightful discussions concerning SMART|DT.

REFERENCES

[1] SMall Aircraft Risk Technology. [Online] [09. 07 2022.] https://smartdtsoftware.wixsite.com/smart.
[2] DoD. Aircraft Structural Integrity Program (ASIP). 2016.
[3] Ocampo, Juan, 2021, PROBABILISTIC DAMAGE TOLERANCE WITH BAYESIAN UPDATING, ASIP 2021
[4] Skinn, D.A., et al., 1994, Damage Tolerant Design Handbook
[5] V. Ferrari, 2022, Preliminary Structural Risk Assessment
[6] P. White, L. Molent, S. Barter, 2005, Interpreting fatigue test results, International Journal of Fatigue
[7] L. Molent, Q. Sun, A.J. Green, 2006, Characterisation of equivalent initial flaw sizes in 7050
[8] S. Barter, 1998, Fractographic Inspection of the. s.l. : DSTO
[9] S. Barter, 2003, Fatigue Crack Growth in several 7050T7451 Al alloy thick section plates DSTO
[10] N. Crosby, H. Millwater, Efficient Probabilistic Damage Tolerance Analysis using adaptive multiple importance sampling, SMall Aircraft Technology.
[11] RUAG internal structural assessment
[12] M. Liao, G. Renaud and Y. Bombardier, Application of Quantitative Risk Analysis in Support of Continuing Airworthiness Management, ICAF 2015.
[13] M. Liao, Comparison of Different Single Flight Probability of Failure (SFPOF) Calculations for Aircraft Structural Risk Analysis, AA&S 2012
[14] L. Domyancic Hunt, J, McFarland, J. Cardinal, Review of Methods for Single Flight Probability of Failure