Probabilistic Method to predict Remaining Usage Life of Aircraft Structures

Mudit Rastogi

Honeywell International, Brno 62700, Czech Republic
Mudit.Rastogi@honeywell.com

ABSTRACT

Current trends in the design of new aircraft components and high level innovations in the older type of aircraft are clearly pointing to automation and integration of all aircraft systems to give increased cost efficiency in the aircraft operation. The same trend can be observed in the design, operation and maintenance of aircraft structures where advanced Structure Health Monitoring (SHM) systems are about to enter into service. These advanced systems are designed to provide both diagnostic and prognostic information enabling application of Condition Based Maintenance (CBM) or even Prognostics Maintenance (PM) concepts into the maintenance of the aircraft structures. To make this CBM/PM concept a reality, an accurate, reliable and robust method to predict the Remaining Usage Life (RUL) of the structure is the foremost step.

This paper presents a probabilistic method for RUL prediction. A hybrid approach is used, comprising of two different algorithms. The first algorithm adopts fracture-mechanics based fatigue crack growth model. This approach uses physics of failure to predict the crack growth curve and underlying degradation process. It calculates the accurate value of Stress Intensity Factor (SIF) to calculate the crack growth curve. The second algorithm is a mathematical model which quantify various sources of uncertainty such as future loading, crack length, model parameters etc. The process described in this paper results in enhanced remaining usage life estimation by compensating for the aforementioned modeling uncertainties. The model results were verified and validated on a typical aero structure with experimental, FEA simulation and fractography data.

1. INTRODUCTION

Structural Health Monitoring (SHM) is an approach to assess the current state of engineering structures (aerospace, & mechanical) by automatically detecting or diagnosing damage. In aerospace structures, fatigue or structural damage can be expected anytime during its operational life. To account for this problem, in modern aerospace vehicle structural design, two philosophies are frequently used to achieve a minimum satisfactory operational life; safe life and damage tolerance. The presented research study is proposed mainly for damage tolerant structures. The damage tolerance philosophy states that during the service life of a structure, any fatigue crack or damage will not progress to a catastrophic condition prior to detection during regular inspection intervals. In other words it assumes that readily detectable damage due to fatigue or any accidental occurrence will remain in somewhat stable condition till the next maintenance check. In modern aircraft maintenance, this concept covers a majority of primary structures, and is increasingly becoming popular. For aircraft structures, the current crack size estimation can be in future provided by a SHM system, alternatively this information can also come from NDT and visual inspection methods. This when combined with a robust structure prognostics RUL model can predict the crack growth in the due time of its operation and therefore help scheduling the maintenance when the need arises. This maintenance is performed when there is an indication of a structure fail or fast deterioration than the fixed scheduled maintenance checks. This is known as the Condition Based Monitoring (CBM). It would allow the maintenance personnel to minimize spare part cost, system downtime and time spent on maintenance leading to huge cost benefits. However uncertainty always exist in the RUL estimates due to uncertainty in the structure defect (crack size), material and geometric properties, crack growth model, environmental effects and most importantly future loading. This offer major challenge to any CBM/PHM system designer because of the fact that it entails large uncertainty which needs to be quantified. Hence a robust uncertainty quantification method in prognostics holds the key for a successful application of PHM as key enabler in industrial applications. Inappropriate and inefficient approaches to solve this problem will result in high false alarm rates, inaccurate predictions leading to wrong decisions and an overall PHM system that is not very reliable.

Past research studies tried to solve this problem by focusing mainly on natural variability in geometry and material properties. Some of them accounted for future loading uncertainty too. Additionally they used either physics based or data driven models, which have their own shortcomings when applied to practical applications. Physics based method (Newman 1984, Ray et al., 2001) includes physical understanding of the fatigue process. It is governed by series of dynamic equations defining relationships between damage at a given time or load cycle. They are usually computationally expensive to run requiring complete knowledge of physical processes. Data driven models (Gebraeel et al., 2004, Goebel et al., 2007, Amin et al., 2005) on the other hand use pattern recognition and machine learning techniques to detect and forecast damage in a structure. They require large amount of correct training data which can be challenging at times. This makes the applicability of both the models in real-time and practical scenarios somewhat limited, if not impossible. This paper describes a hybrid approach (combination of physics based and statistical model) to predict the RUL using three different algorithms. The first algorithm adopts fracture- mechanics based fatigue crack growth model. This approach uses physics of failure to predict the crack growth curve and underlying degradation process. It calculates the accurate value of Stress Intensity Factor (SIF) with every crack increment and uses PREFFAS model to calculate the crack growth curve.

The second algorithm manages the "Aleatoric" uncertainty which is inherent statistical variability in the process that may be characterized by experiments. A mathematical model based on Bayesian Statistics quantifies the input data uncertainties i.e. initial state (damage) estimate, variability in the material, manufacturing variability, crack growth model uncertainty.

The third algorithm manages the "Epistemic" uncertainty which is unknown level of uncertainties arising due to lack of knowledge information. Estimating future loading and quantification of this immense uncertainty falls in this domain. We used Dempster-Shafer Theory, based on subjective probability model, which are simply considered to be degrees of belief and quantify the extent to which the statement is supported by existing knowledge and available evidence.

1.1. Proposed Integrated SHM & PHM Model Concept

The PHM model discussed here can either be used as a standalone system or can be integrated with Structural Health Monitoring (SHM) system (Tinga et al.) as shown in Figure 1. The difference in the two approaches being that while in the former case the current crack size estimation will come from NDT methods, the latter uses SHM algorithms to do the same.

Once the damage reaches a detectable size, various SHM/NDT techniques can be employed to evaluate the current state of structural health by estimating the crack size. This together with the loading profile information would serve as input to the PHM model. The final output would be a probabilistic RUL range.

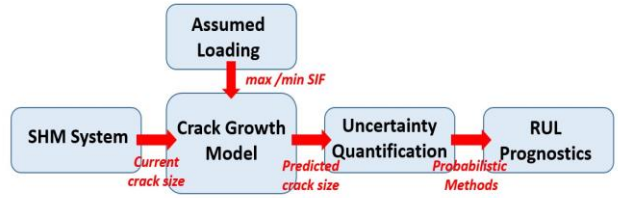

Figure 1. SHM/PHM Model Concept

1.2. Formulation of the Problem

The Figure 2 below shows the bottom flange of wing main beam stiffened by stringers of uniform space and sizing on both the sides. The stringers are attached to the flange with equally spaced rivets. This represents one of the most common aero structures found in real life i.e. riveted structures with unequal cross section thickness and therefore is used for PHM model results demonstration.

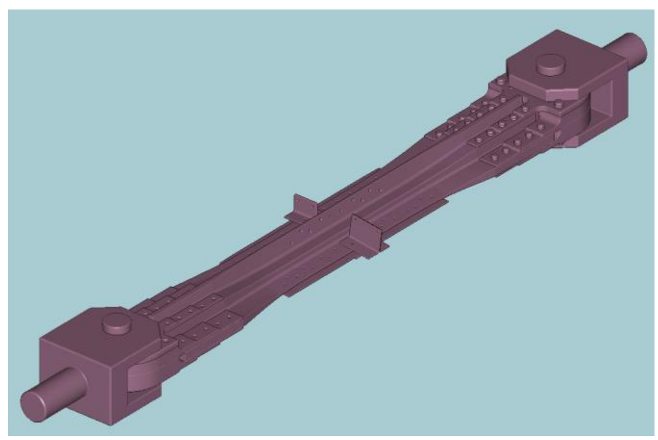

Figure 2. Specimen Geometry

The loading sequence used represents a series of loading cycles affecting the structure. Duration of the loading cycle is constant for all the sequence, i.e. 1/3s. Each cycle is described by its maximal and minimal stress levels [σ_{min}, σ_{max}]. The maximal and minimal stress levels are expressed as multiples of a nominal stress σ0. Thus, we have a pair of numbers {n_{min}, n_{max}} so called load factors for single loading cycle. The whole sequence of the loading cycles is defined by series of minimal and maximal load factors

A typical flight spectrum for particular aircraft is used in order to define typical flight loading sequence. The typical flight spectrum was defined according to FAA AC 23-13A.

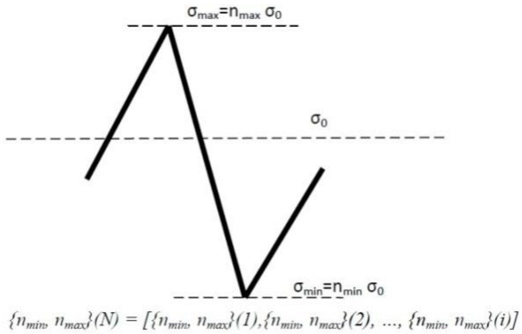

Figure 3. Loading Cycle

The program block from the full-scale fatigue test of the wing was applied in the simulation. One program block consists of 199 basic program cycles followed by one extended program cycle, (Figure 4). Basic program cycle representing one flight contains 6 constant amplitude (CA) cycles of ground loads followed by 9 CA cycles of vertical gusts on two load levels and 6 CA horizontal gust cycles. Extended program cycle contains also one extra 7.5 m/s vertical gust cycle.

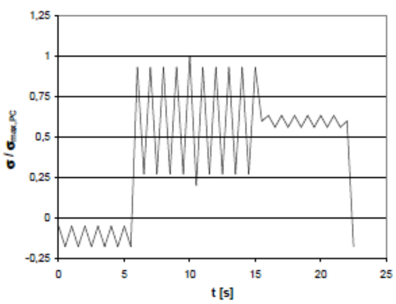

Figure 4. Variable loading sequence for typical flight

2. CRACK GROWTH MODEL

2.1. Calculation of rivet forces

Crack propagation in any structural components require calculation of stress intensity factors for cracks subjected to complex stress fields as accurate as possible. Its significance in the crack propagation can be estimated from the fact that it is present as exponential term in any crack model equation, and hence a small variation in its value can give absurd result. The variety of crack configurations and the complexity of stress fields occurring in engineering components require more versatile tools for calculating SIF than available handbook solutions. These empirical SIF formulae obtained are good for a limited geometry and load combinations but not for in service aero structures as shown here in Figure 2.
Finite Element Analysis can be used to calculate SIF of complex geometry with growing crack length. However this method is impractical because of huge time demand, in modeling and running the simulation.

Therefore an analytical method for calculating SIF for cracks subjected to nonlinear stress field and complex geometry is developed and discussed here in this section. The method is based on the use of the weight function technique developed by (Bueckner, 1970) and (Rice, 1972).
The SIF for mode I problems can be calculated by integration of the product of the weight function, m(x, a), and the stress distribution σ(x), normal to the potential crack plane.

$$K = \int_0^a \sigma(x) m(x, a) dx \qquad - (1)$$

There are numerous weight functions of different mathematical forms available in technical journals and handbooks. However it has been found that weight functions for crack in mode I can be represented by one general expression in the form of equation below

$$m = \frac{2}{\left[2\pi\left(1-\frac{x}{a}\right)\right]^{1/2}} \left[1 + M1\left(1-\frac{x}{a}\right)^{\frac{1}{2}} + M2\left(1-\frac{x}{a}\right) + M3\left(1-\frac{x}{a}\right)^{\frac{3}{2}} \right] \qquad - (2)$$

The parameters M1, M2, and M3 depend on the geometry of a cracked body (Shen et.al 1991, Zheng et.al 1996, Wang et. Al 1995). To calculate the SIF using the weight function technique the following tasks were carried out in steps:

1. Determine the stress distribution σ(x) in the prospective crack plane using the linear elastic analysis of uncracked body. The total nonlinear stress field is calculated by superimposing the stresses due to rivets in the crack vicinity and applied uniaxial stresses (Poe, 1971)

2. Apply the uncracked stress distribution σ(x), to the crack surface as tractions.

3. Choose an appropriate generic weight function as per the specimen geometry.

4. Integrate the product of the stress function σ(x) and the weight function m(x, a) over the entire crack length or crack surface.

Once the SIF is calculated for a particular crack length, PREFFAS model is used to find the crack increment. It is a simple model based on the Elber crack closure concept. The crack closure is calculated with a cycle-by-cycle approach. The model was developed for stationary variable amplitude loadings with a short recurrence period. However, it is difficult to include the negative loads in the model and therefore all the compressive stresses are truncated to zero. To evaluate the crack growth model effectiveness, we compared the results with experimental values and NASGRO simulation model as shown in Table 1 and Figure 5. The first crack of 5mm length as observed visually during the fatigue

test is used as initial crack length in the model. Whereas for NASGRO simulations, an initial crack length of 1.27 mm is used to forecast RUL.
The crack growth model was run in two steps. First as center crack originating from both the sides of loaded rivet till one crack reaches the flange end. After that, in the second step we assumed it to be as one single end crack.

Table 1. Crack Growth Model Results

Damage Model	No. of cycles to critical crack length	Percent difference to Exp. value
Experiment	166015	
NASGRO 3	48000	71.08 %
NASGRO 4.23	132500	20.18%
Current Model	**152500**	**8.2%**

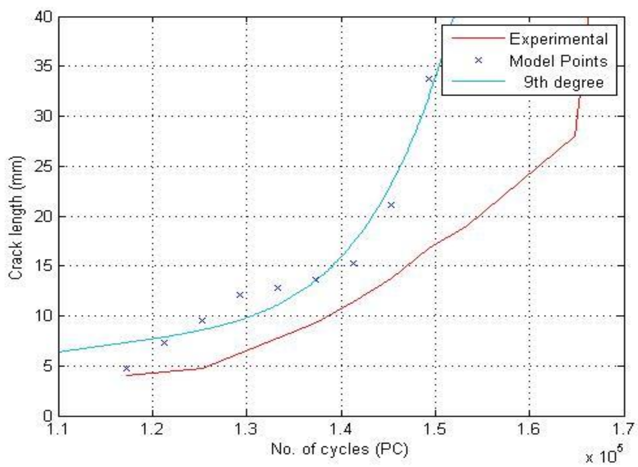

Figure 5. Crack Growth Model v/s Lab Test Results

Though the results from the developed crack model is quite impressive, the same has not been used for the uncertainty quantification as described in the next section. This is due to the fact that the computation time to generate "n" no. of curves is very demanding and hence a simpler version, "Paris Law" is used. However in future, the model would be made computationally less time consuming so that it could replace Paris Law model.

3. CRACK DETECTION AND CRACK SIZE EVALUATION

For diagnostics and estimating the crack size we used the SHM algorithms (Hedl et al. 2012) developed during the scope of previous projects. PZT sensors were placed strategically on the structure to get the data. Sensors are excited by 3 cycles of sinusoidal wave weighted by Gaussian window. Frequency of the wave is 200 kHz.
The obtained signals are the values of voltage on the sensors recorded with respect to time. The algorithm is based on mainly two methods namely artificial neural network and linear regression. The results of the crack estimation in time have shown really good conformity with real crack growth curves, because 40% of measured signal of this test was used for ANN training and all data for Linear Regression coefficient calculation. Damage indices are computed for all measured signals by comparing to the baseline signals. The observed variability represent the structural damage and is computed as overall energy extracted from Short Time Fourier Transform. The visualization of the damage is consequently based on the computed damage indices and processed by adjusted version of, Weighted Spatial Mapping of Signal Difference Coefficients using Triangulation (WEMAT) algorithm (Hedl et al. 2012).
The Figure 6 below shows the broken specimen after 166973 flight cycles with installed sensors used for diagnostics.

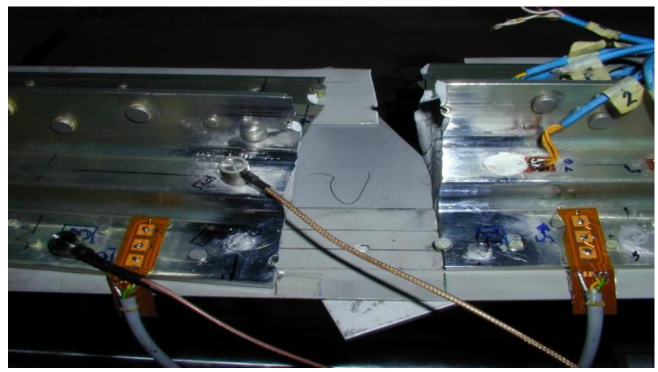

Figure 6. Cracked Specimen

For input to our PHM model a crack of length 18 mm as detected by SHM system after 1.5 X 10^5 Program Cycle (PC), is used. SHM system detection uncertainties is included in the formulation of likelihood function as described in later section.

4. UNCERTAINTY QUANTIFICATION

There are two broad categories of probability interpretations which are referred as "physical" and "subjective" probabilities. Physical probabilities are associated with the random physical systems such as rolling the dice. Each trial of an experiment will lead to an event which is nothing but a subset of the sample space. In the long run of repeated trials or when no. of trials, "n" tends to infinity, each event will occur at a persistent rate calculated merely by dividing the no. of favorable events by total events. Thus physical probabilities can be defined only in the context of random experiments. Subjective probabilities on the other hand can be assigned to any statement in the absence of random experiments. Bayesian and Dempster Shafer Theory are based on subjective probabilities, which are simply considered to be the degrees of belief and quantify the extent to which the statement is supported by existing knowledge and available evidence. Both methods can be used for different probability problems. However in the present context of SHM, there is only one structure which is being monitored, and so at any time instant, there is no physical randomness in the SHM result associated with the structure from a frequentist or physical point of view. As a result it is not appropriate to represent any system quantity, no matter how uncertain it is with a probability distribution, using the physical interpretation of probability. We therefore use subjective probability method to quantify the major uncertainties in the RUL prediction. While Bayesian Statistics is used for uncertainty in crack size & model parameters, Dempster Shafer theory is used to tackle the future loading.

4.1. Bayesian Inference

Bayesian Inference is a normative and rational method of updating beliefs when new information in the form of SHM system crack estimation is made available (Karandikar et. al, 2012).In this method, initial crack size and model parameters are treated as uncertain random variable, which can be easily characterized by a uniform probability distribution. The next step is to generate n no. of crack growth curves from the joint distribution of initial crack length (a_0) and model parameters (m, C). The probability that one of this n curves represent the true crack growth curve is equally likely and hence can be written as 1/n. These sample curve simulations are used as the prior when applying Bayesian Inference.

Baye's rule in this context can be written as

$$\text{P (curve= true crack growth curve | SHM output)} = \frac{\text{P (SHM output | curve = true crack growth curve)}}{\text{P (SHM output)}} \text{ x P(curve = true crack growth curve)} \quad - (3)$$

Here, P (curve = true crack growth curve) is the prior probability, which as described above is simply 1/n for each sample curve. P (SHM output | curve = true crack growth curve) is referred to as the likelihood. P (curve= true crack growth curve | SHM output) is the posterior probability that the given curve is true crack growth curve given a SHM output at any time. P (SHM output) is the normalization constant for the posterior distribution. It is nothing but the summation of the non-normalized posterior values. This step is needed because from the axioms of probability theory, the area under a probability density function in a continuous case should be equal to unity. In this way, Baye's rule can be used to update the probability that a sample curve is the true crack growth curve each time after SHM/NDT detection results are provided to the model. Eventually the posterior calculated at a given time becomes the prior for the next time step.

The uncertainty in the SHM system detection capabilities is incorporated in the model, by calculating the likelihood function. The user estimate the uncertainties in the crack size measurement based on his/her belief about the robustness of the SHM system. This value is subjective and changes with the diagnostics algorithm, senor layout and specimen. The likelihood function takes into account the above information and is expressed as following

$$l = e^{\frac{-(a-a_{meas})^2}{k}} \quad - (4)$$

where l is the likelihood function, a_{meas} is the measured crack size, a is the crack size for a sample fatigue crack growth curve at measurement N, and k is a parameter that describes the function spread. The likelihood function is expressed as a non-normalized normal distribution, where the parameter k = $2\sigma^2$ and σ is the standard deviation of crack size (due to measurement, material, and model uncertainty). The value of k is estimated by the user based on his/her beliefs. Based on the assumptions on the robustness and reliability of our SHM system, we took k = 2, in this paper for demonstration purposes. This assumption comes from the preliminary lab tests done on metallic structures.

Our SHM system detected damage after 1.5 X 10^5 PC and estimated a crack length of 18 mm. This is considered as the triggering point, and the RUL value is estimated hereafter at this point. The posterior distribution is calculated by the multiplication of the prior and likelihood functions as described in Eq. (3). Figure 8 below shows the posterior cdf of crack size at 1.5 X 10^5 PC.

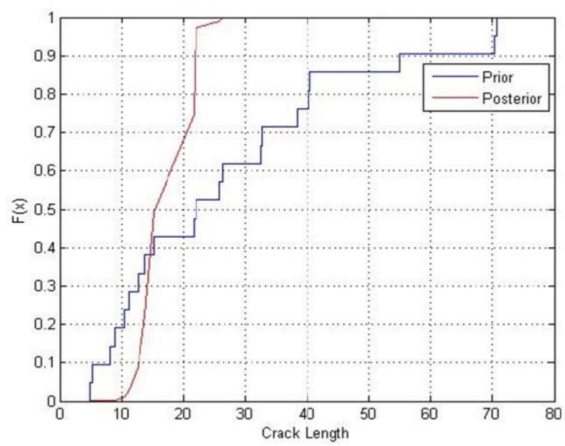

Figure 8. Prior & Posterior cdf at 1.5 X 10^5 PC

From the Figure 8 above it can be seen that it is highly likely that the crack length is less than the critical crack length of 38mm. Likewise, the posterior cdf is updated for each cycle interval of 1 X 10^5 PC and consolidated to give the Probabilistic RUL graph.

Figure 9 shows the posterior probability that the crack size will be less than the critical crack length as a function of PC (no. of cycles)

This gives us the probabilistic value of RUL while including the initial crack length, SHM system and model parameters uncertainty. The y- axis signifies the probability that the crack length is less than critical crack length, while the x- axis depicts the loading cycle.

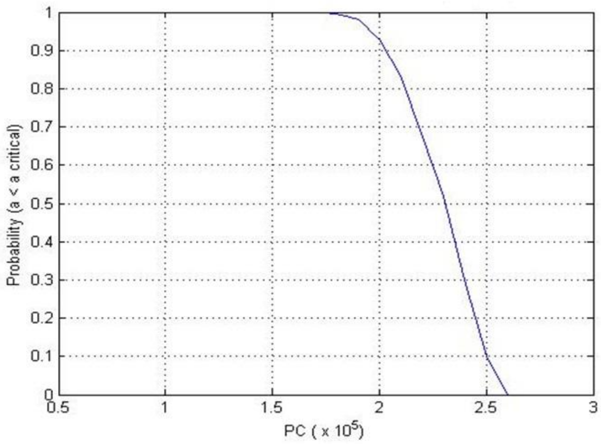

Figure 9. RUL Probabilistic Curve

To get a definite RUL value, user can fix the probability value as per his needs. In our paper, we used a conservative approach and define the RUL value for the 99% probability i.e. 1.75 x 10^5 PC. This RUL value would now be used in Dempster Shafer model to account for loading uncertainties, which will give us the final RUL estimation.

4.2. Dempster-Shafer Theory

Future loading uncertainty has a significant impact on prognostics and the RUL estimation. Future loading conditions, flight maneuvers, operating conditions etc. are highly uncertain and impossible to predict, which put the estimated RUL value in jeopardy. We included uncertainties associated with model parameters in section 4.1 for the given variable amplitude loading (Figure 4). This loading profile is calculated by the OEM and is quite conservative. However in reality we don't know, how the future loading will look like, which give rise to the uncertainty in future loading. Dempster-Shafer Theory (DST) is a powerful mathematical theory to handle this kind of uncertainty which contains incomplete information. The primary object of this theory is the primitive function called the Basic Probability Assignment (bpa). This is usually calculated by the empirical data or experts' belief. In this paper bpa is calculated using the triangular fuzzy number concept. Contrary to the classical crisp sets, fuzzy sets do not have any sharp boundaries, which mean being a member of a fuzzy set is not a simple matter of being definitely in or definitely out. In the given context, this concept can be used to say, that at a given time there can be different RUL values, each compatible with a future loading scenario. Each of these RUL values are calculated from three different loading profiles.

We assume three RUL values; most likely, worst and best case. The most likely RUL value comes from the section 4.1 above as 1.75 X 10^5 PC. Calculation of these worst and best case loading profiles and subsequently their RUL values need comprehensive study and research, which is not included in the scope of this paper. For demonstration purposes, in order to find maximum and minimum RUL values we multiplied the most likely RUL with a factor of +/- 25% to get 2.1875 X 10^5 and 1.3125 X 10^5 PC respectively. The present index of +/- 25% comes after the discussion and assumption by OEM. However this value is highly subjective and cannot be claimed as a benchmark. In future, these values should be calculated by studying the load spectrum, flight frequency, airplane usage etc.

Now we can express the RUL parameter as a triangular fuzzy number with [max, min] as the support with the most likely value in the center. We now assume n no. of equally spaced α cuts which will give us n nested intervals. These nested intervals are nothing but the focal elements with each interval having a bpa of 1/n. The focal elements are given by the alpha-cut as ${}^{\alpha}A_i$ = {x: $\mu(x) \geq \alpha_i\}$ =[${}^{\alpha}A_{ilower}$, ${}^{\alpha}A_{iupper}$], (i=1,2,3…..,n), where α Є [0,1]. If we now consider a finite number and discretize the fuzzy number, the bpa can be calculated by first integrating the membership function between different α cuts

$$\int_{A^{\alpha}_{\text{ilower}}}^{A^{\alpha}_{\text{iupper}}} \mu(x)dx \qquad - (5)$$

Then, by normalizing procedure the BPA for ${}^{\alpha}A_i$ is defined as

$$M({}^{\alpha}A_i) = \frac{\int_{A^{\alpha}_{\text{ilower}}}^{A^{\alpha}_{\text{iupper}}} \mu(x)dx}{\Sigma i \int_{A^{\alpha}_{\text{ilower}}}^{A^{\alpha}_{\text{iupper}}} \mu(x)dx} \quad - (6)$$

We now consider our RUL fuzzy number A= [1.3125, 1.75, 2.1875] X 10^5. We can define this fuzzy set by assigning to each value a number between 0 and 1, which indicates the degree or grade of membership in the set. The assignment of 0 to a particular value means that this value definitely does not belong to the set; the assignment of 1 means that the value definitely does belong to the set. The following membership function is used to describe the concept.

$$\mu(x) = \begin{cases} (x - 1.3125)/.4375; & 1.3125 < x < 1.75 \\ (2.1875 - x)/.4375; & 1.75 < x < 2.1875 \end{cases}$$

BPA is then calculated using the method described above with corresponding alpha cuts chosen as α0 = 1, α1= 0.8, α2= 0.6, α3=0.4, α4=0.2, α5 =0, as shown in Table 2

Table 2. BPA obtained from triangular fuzzy number

Focal Elements	[1.7175, 1.7875]	[1.6325, 1.8675]	[1.5525, 1.9475]	[1.4725, 2.0275]	[1.3925, 2.1075]	[1.3125, 2.1875]
BPA	0.039	0.111	0.168	0.208	0.232	0.240

From these mass assignments, the upper and lower bounds of a probability interval can be defined. This interval contains the precise probability of a set of interest and is bounded by two non- additive continuous measures called belief and plauibility:

$$\mathrm{Bel(A)} \leq \mathrm{P(A)} \leq \mathrm{pl(A)}$$

The belief bel (A) for a set A is defined as the sum of all the masses of subsets of the set of interest:

$$\mathrm{bel}(A) = \sum_{B|B\subseteq A} m(B).$$

The plausibility pl (*A*) is the sum of all the masses of the sets *B* that intersect the set of interest *A*:

$$\mathrm{pl}(A) = \sum_{B|B\cap A\neq\emptyset} m(B).$$

Figure 10 below depicts the calculated cumulative Plausibility and Belief measures.

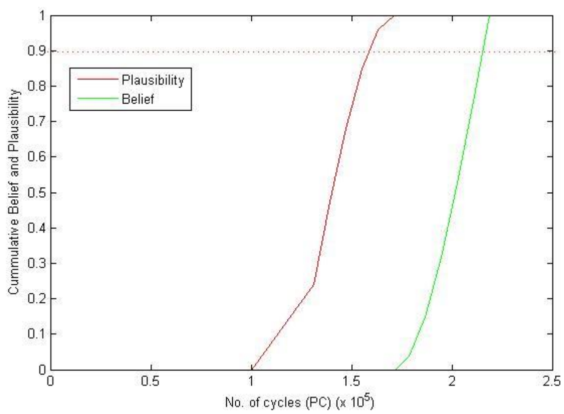

Figure 10. Cumulative Belief and Plausibility

5. VERIFICATION AND VALIDATION

For our RUL model comparison we used three different methods:

Lab Tests

The fatigue test experiment, with the described loading (section 1.2) was conducted on INOVA fatigue testing machine with a hydraulic motor SAVAD 2-200-100 having max force of 200 KN and max. stroke length of 100mm.

Figure 11. Fatigue Test

Fractrography

The fractography analysis was also done on the flange specimen. The specimen was adjusted according to the JSM 840A electron microscope chamber size. Internal and external crack were analyzed separately and measurement lines were marked in the directions of cracks growth. Crack surfaces were observed by an electron microscope, and all overloading markers were identified. Next, coordinates of a marker intersection with the measurement line and surfaces were measured. All intersections of each marker are interspersed with Bezier curves, (Figure 12). The position of each marker is measured from the edge of the rivet hole.

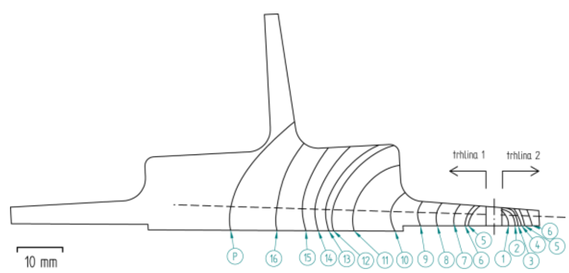

Figure 12. Crack Growth Marks (Fractogrpahy)

FEA Analysis

It is based on the boundary element model prepared and solved in the FRANC3D/BES code and on the NASGRO crack growth rate equation. The computational model of the bottom flange crack was prepared using the software FRANC3D developed at the Cornell University. FRANC3D calculates the stress intensity factors using the displacement correlation technique. NASGRO version 4.23 and 3 is used to analyze the crack propagation thereafter. The initial crack length of 1.27 mm is used to calculate the RUL for NASGRO simulations.

The Table 3 below summarizes the result using different models and techniques to estimate RUL.

Table 3. Results Table

RUL Methods	RUL Value (X 10^5)
Experimental Lab	1.66015
NASGRO 3	.48000
NASGRO 4.23	1.32500
Fractography	1.65828 – 1.66270
Current Model (90% Prob.)	1.58 – 2.11

6. CONCLUSION

The contributions of this research study can be summarized in two points: the first is the crack growth model (section2).The model is able to find unique SIF for complex aero structures and uses PREFFAS model to calculate crack increment. The results from this model was compared to the lab tests for a flange. Although, the computation time is quite demanding, but accurate crack growth with less than 10 % difference in the end life from lab test values can be achieved.

The second is the RUL value predicted by the model. The paper describes a new and simple way to quantify all the major uncertainties in the model. The RUL value as predicted by the model matches quite well with the experimental and fractography tests. It also proved to be a better estimation than the commercial software NASGRO values, which is commonly used in industries.

However, the model needs to be verified and validated on other specimens and loading scenarios, before anything can be said on its credibility and robustness. Future work also includes methods to reduce the computation time of the crack growth model.

ACKNOWLEDGEMENT

The presented work has been supported by the TACR, Technology Agency of Czech Republic grant project no. TA03010140. The author would also like to thank Brno University of Technology for significant help with lab experiments and NASGRO simulations.

NOMENCLATURE

σ_{min}	Minimal stress level
σ_{max}	Maximal stress level
n_{min}	Cycle minimal load factor
n_{max}	Cycle maximal load factor
RUL	Remaining Usage Life
SHM	Structural Health Monitoring
PC	Program Cycle
SIF	Stress Intensity Factor
BPA	Basic Probability Assignment
cdf	Cumulative Density Function
CBM	Condition Based Monitoring
a	Crack Length
x	Variable distance along x- axis
N	No. of cycles
m,C	Paris law model constants
OEM	Original Equipment Manufacturer

REFERENCES

Amin, S., Byington, C., Watson, M. (2005). Fuzzy Inference and Fusion for Health State Diagnosis of Hydraulic Pumps and Motors. Proceedings of the Annual Meeting of the North American Fuzzy Information Processing Society.

Ali, T., Dutta, P. (2012). Methods to obtain Basic Probability Assignment in Evidence Theory. *International Journal of Computer Applications*, vol. 38(4), pp. 46-51

Bueckner, H. F. (1970). A novel principle for the computation of stress intensity factors. *Z Angew Math Mech 50*, pp 529-546

Gebraeel, N., Lawley, M., Liu, R., and Parmeshwaran, V. (2004). Life Distributions from Component Degradation Signals: A Neural Net Approach. *IEEE Transactions on Industrial Electronics*, vol. 51, no 3

Goebel, K., Eklund, N (2007). Prognostic Fusion for Uncertainty Reduction. Proceedings of AIAA InfoTech@ Aerospace Conference. Reston, VA: American Institute for Aeronautics and Astronautics, Inc.

Hedl, R., Finda, J., Adamek, K. (2012). Structural Damage index mapping system and method. Patent US 20120330570A1.

Karandikar, J. M., Kim, N. H., Schmitz, T. L., (2012). Prediction of remaining useful life for fatigue-damaged structures using Bayesian Inference. *Engineering Fracture Mechanics*, vol. 96, pp. 588-605

Newman Jr, J. C. (1982). Prediction of fatigue crack growth under variable-amplitude and spectrum loading using a closure model. *Am Soc Test Mater STP*, vol. 761, pp. 255-277

Poe Jr, C. C., (1971). *Stress-Intensity Factor for a cracked sheet with riveted and uniformly spaced stringers*. NASA Technical Report. NASA Langley Research Center.

Ray, A., Patankar R.P. (2001). Fatigue crack growth under variable amplitude loading. Part1 &2 *Applied Mathematics Model Journal*, vol. 25 (11), pp. 979-1013

Rice, J. R., (1972). Some remarks on elastic crack tip stress field. *International Journal of Solid Structures*, vol. 8, pp. 751-758

Shen, G., Glinka, G. (1991). Determination of weight functions from reference stress intensity factors. *Theoretical and Applied Fracture Mechanics*, vol. 15(3), pp. 237-245

Shen, G., Glinka, G. (1991). Weight functions for a surface semi-elliptical crack in a finite thickness plate. *Theoretical and Applied Fracture Mechanics*, vol. 15, pp. 247-255

Tinga, Tiedo and Loendersloot, Richard (2014) *Aligning PHM, SHM and CBM by understanding the physical system failure behaviour.* In: European Conference of the Prognostic and Health Management Society, 08-07-2014 - 11-07-2014, Nantes (pp. 162 - 171).

Wei, H., Williard, N., Osterman, M., Pecht, M. (2011). Prognostics of lithium-ion batteries based on Dempster - Shafer theory and the Bayesian Monte Carlo method. *Journal of Power Sources*, vol. 196, pp. 10314-10321

Wang, X., Lambert, S. B. (1995). Stress Intensity Factors for low aspect ratio semi-elliptical surface cracks in finite thickness plates subjected to non-uniform stress. *Engineering Fracture Mechanics*, vol. 51, pp. 517-532

Zheng, X. J., Glinka, G., Dubey, R. (1995). Calculation of stress intensity factors for semi-elliptical cracks in a thick wall cylinder. *International Journal of Pressure Vessel & Piping*, vol. 62, pp. 249-258

Zheng, X. J., Glinka, G., Dubey, R. (1996). Stress Intensity Factors and Weight Functions for a corner crack in a finite thickness plate. *Engineering Fracture Mechanics*, vol. 54, pp. 49-62

Zheng, X. J., Glinka, G., Dubey, R. (1996). Stress Intensity Factors and Weight Functions for a corner crack in a finite thickness plate. *Engineering Fracture Mechanics*, vol. 54, pp. 49-62

BIOGRAPHIES

Mudit Rastogi earned his Master of Science in Mechanical Engineering from University of Michigan, Ann Arbor, USA in 2013 and his Bachelor of Engineering from University of Pune, India in 2008. He has been a R&D scientist with Honeywell focusing on Vehicle Health Management projects since 2013. His work is aimed on the SHM system development (Prognostics of the damage growth, Sensor System Optimization, SHM integration into aircraft maintenance plan). His interests include Structural Health Monitoring, Structural Analysis, Composites, and Design Optimization & Fatigue Design.