National Aeronautics and Space Administration

Flying Fatigue Laboratory for Reducing Uncertainty in Predicted Remaining Useful Life

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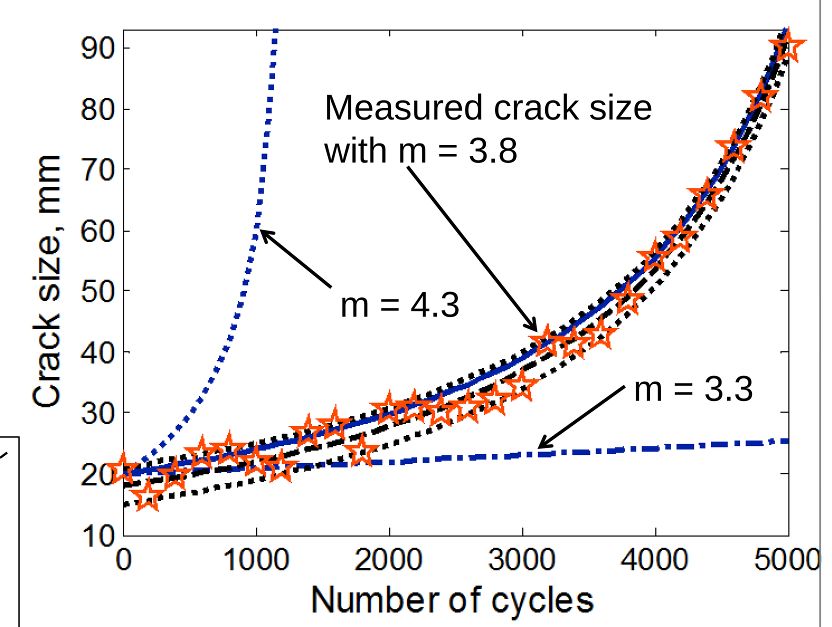
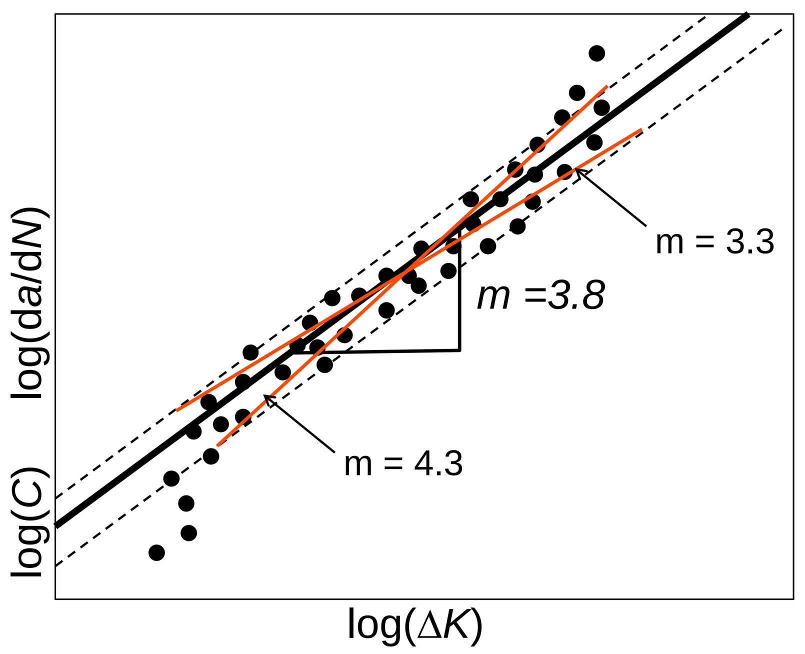
Introduction

- Wide distribution of damage parameters for a fleet of airplanes
- Single airplane or plate may have much narrower distribution
- Structural health monitoring data can be used to identify damage parameters for a specific panel



Effect of scatter in *m* on damage growth with one set of simulated measurements

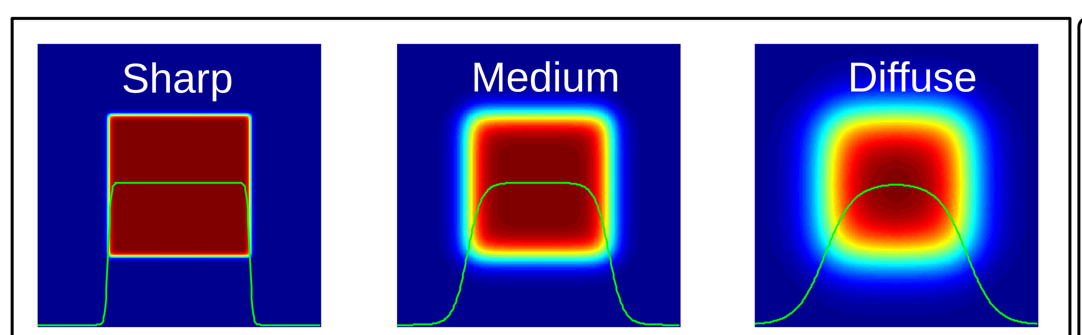


Scatter of laboratory damage growth measurements

Objective

Noisy SHM inspection data are used in **Bayesian updating** to identify **damage growth parameters**. More accurate parameters lead to better **remaining useful life estimation**.

Image-Based Uncertainty



Step 1: Equally spacing sampling → **Step 2**: Histogram generation → **Step 3**: Probability density function conversion

- **SHM Response Model**

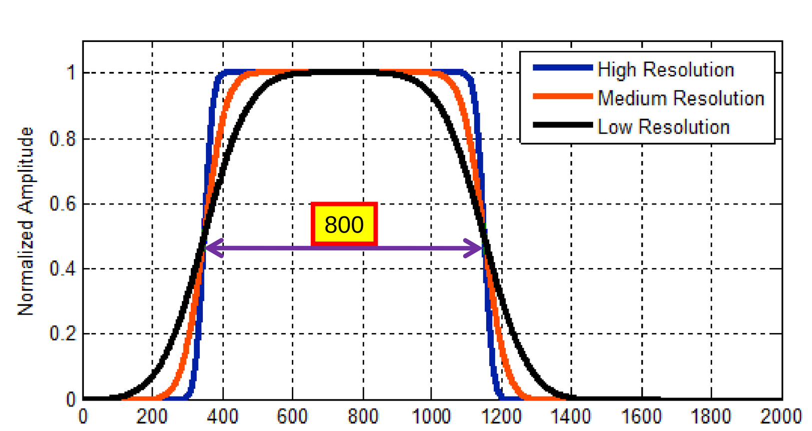
$$R(n) = S(n) \otimes D(n)$$

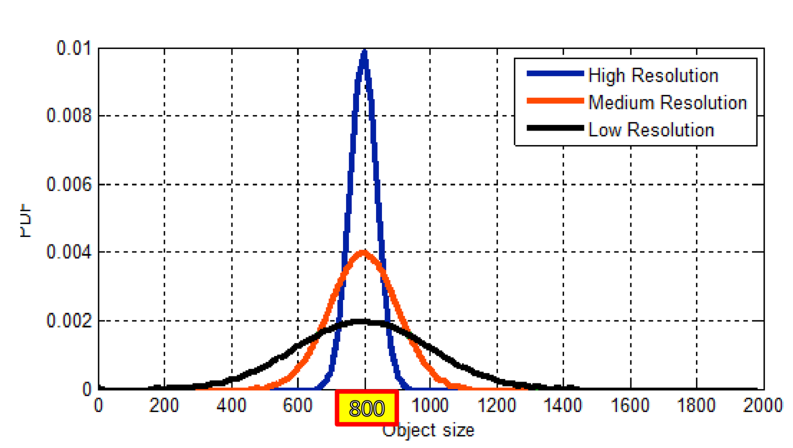
- **Measure Model**

$$M[\Psi(n)] = \Delta x = x_{max}[\Psi(n)] - x_{min}[\Psi(n)]$$

- **PDF Conversion**

$$f(a) = \frac{d\left\{\xi\left[\int_{-\infty}^{a} H(a)da\right]\right\}}{da}$$





- Online/Offline SHM results (detected responses or imaging results) continually reflect probabilistic information of the damage in the airframe structures
- The 3-step explicit method extracts probabilistic damage quantification, providing indispensible initiation for the following Bayesian based damage prognosis

Fatigue Crack Growth and Measurement Model

- Through-the-thickness crack of a fuselage panel (Al 7075-T651)
- Paris model with repeated pressurization cycles

$$\frac{da}{dN} = C(\Delta K)^m \qquad \Delta K = \sigma\sqrt{\pi a} \quad \sigma = \frac{pr}{t}$$

C, *m*: damage parameters

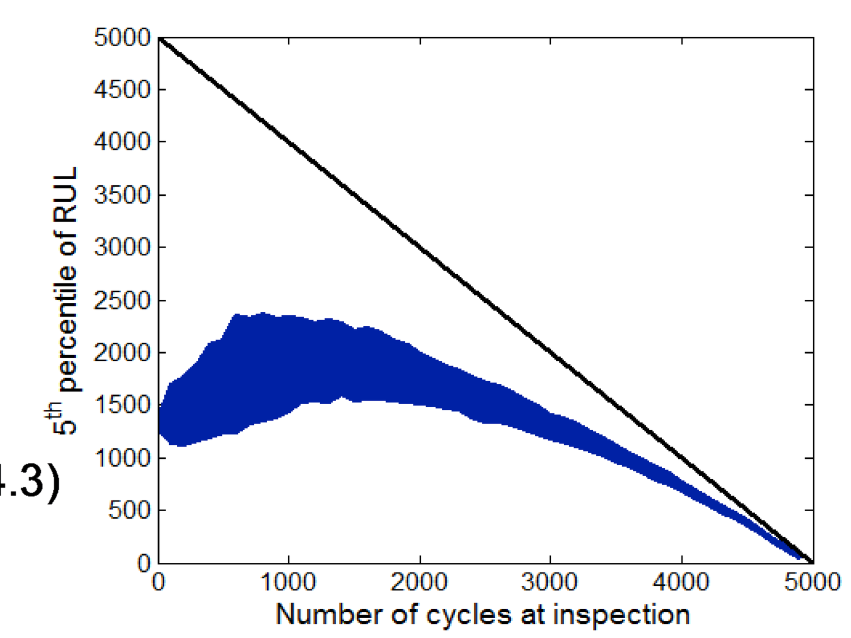
- Crack size after *N* cycles a_N^{true}
- Simulated SHM data: random readings from a model that includes **unknown (but single valued) bias** *b* $\quad b = [-2, +2]$ mm
- and **random noise** from equipment and environment, *v* $\quad v \sim U(-V, V)$ mm
- Measured crack size after *N* cycles: $a_N^{meas} = a_N^{true} + b + v$

Bayesian Updating for Parameter Distribution

- Updating damage growth parameter distribution using Bayes' theorem and SHM data:

$$f_{updt}(m) = \frac{L_{test}(m) f_{init}(m)}{\int_{-\infty}^{+\infty} L_{test}(m) f_{init}(m) dm}$$

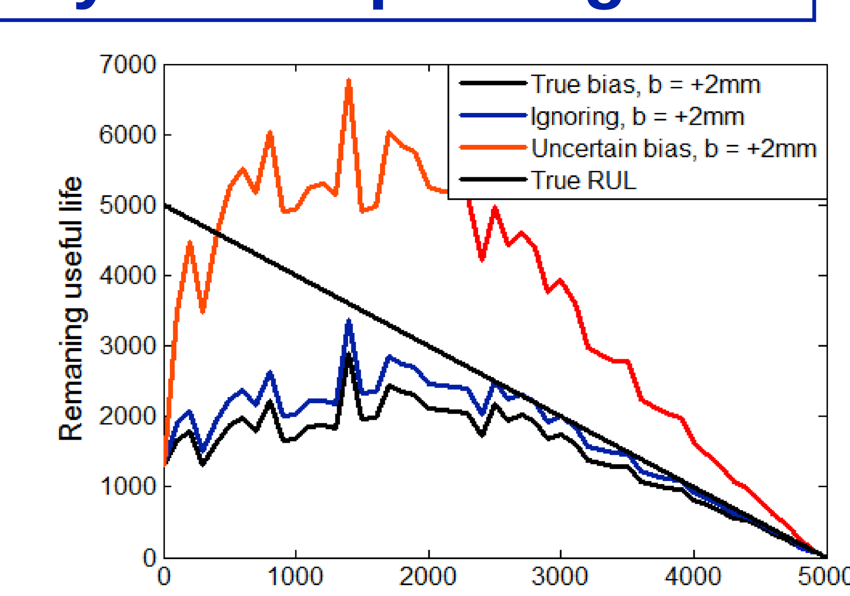
- f_{init} : assumed (or prior) probability density function, initial distribution from the range of test data: $f_{init}(m) \sim U(3.3, 4.3)$
- L_{test} : likelihood function, likelihood to have the observed crack growth between two inspections for a given *m* (includes uncertainty in noise and applied pressure)
- Progressive reduction of uncertainty in damage growth parameter



Distribution of 5th percentile of RUL using Bayesian updating (mean ± 1STD) (*b* = -2mm and *V* = 1 mm)

Limitations on Bayesian Updating

- Although bias is deterministic, it is unknown to the user (uncertain)
- Bayesian updating ignored the bias in likelihood calculation because it does not affect much the RUL estimation
- Bayesian updating gives satisfactory results but it did not handle well **uncertainty in bias**



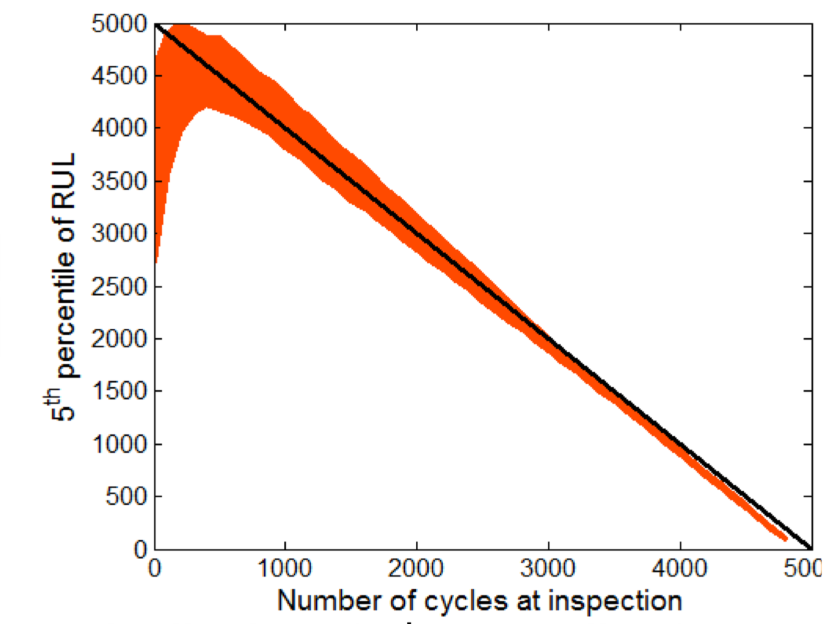
Effect of the bias in the calculation of the likelihood on the 5th percentile of RUL distribution using one set of measurements

Identification Using Least Square Method

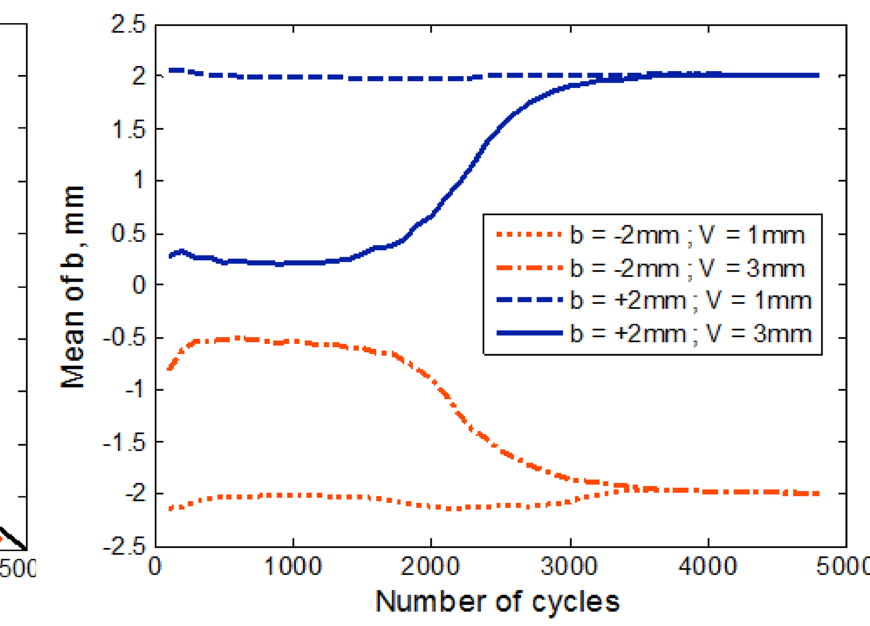
- Reduced the uncertainty in bias by identifying it $\quad \min_{a_0, b, m} \sum_i \left(\left(a_i^{meas} - b\right) - a_i \right)$

with $a_i = \left[N_i C \left(1 - \frac{m}{2}\right) \left(\sigma\sqrt{\pi}\right)^m - a_0^{1-\frac{m}{2}} \right]^{\frac{2}{2-m}}$

- **Unconservative** estimate of RUL distribution



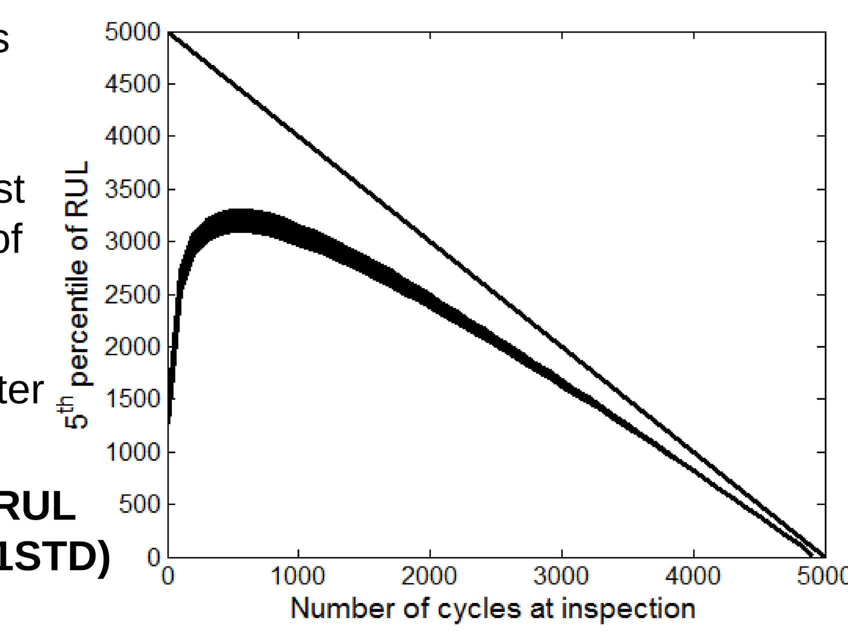
Distribution of 5th percentile of RUL using least square fit (mean ± 1STD) (*b* = -2mm and *V* = 1 mm)



Mean of identified *b*

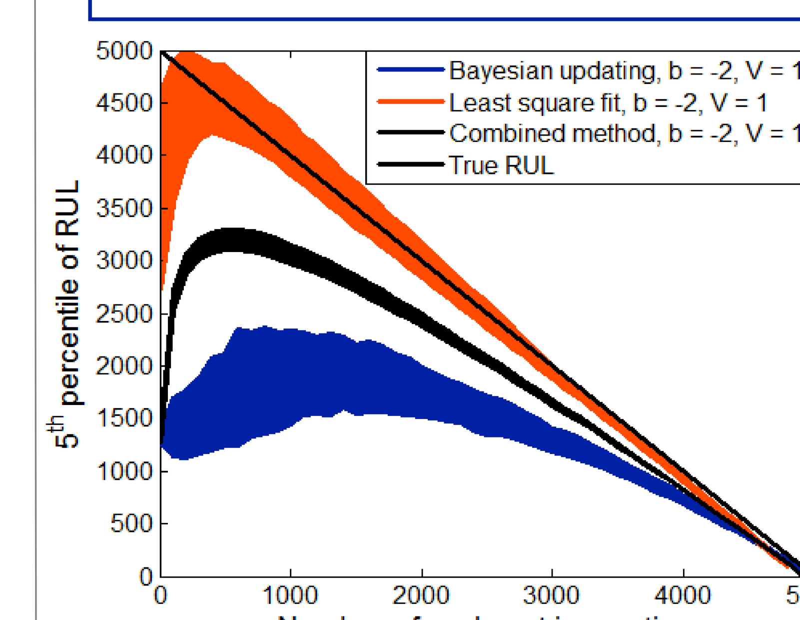
Least Square-Based Bayesian Method

- Uses **least square fit as a pre-processor** to reduce the effect of bias and noise
- Applies Bayesian updating on the least square fit to estimate the distribution of RUL
- More stable estimate, converges faster remaining on the conservative side



Distribution of 5th percentile of RUL using least square fit (mean ± 1STD) (*b* = -2mm and *V* = 1 mm)

Conclusions and Future Work



Comparison of the 3 methods, Distribution of 5th percentile of RUL using least square fit (mean ± 1STD) (*b* = -2mm and *V* = 1 mm)

- Substantial **narrowing of the uncertainty** in damage growth parameters using **noisy SHM data**
- Combining Bayesian updating and least square fit gives better results than either of them alone
- Allows much better prediction of the future behavior of other panels on the same aircraft

- Apply this work to more complicated model
- Apply to multiple panels case
- Looking for actual inspection data