Sensor/Model Fusion for Adaptive Prognosis of Structural Corrosion Damage

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Abstract— Corrosion, stress-corrosion cracking or corrosion-initiated fatigue significantly impact maintenance downtime and structural life limitations of aging aircraft. Both legacy and new air platforms such as the Joint Strike Fighter (JSF), realize that corrosion will likely continue to be a structural challenge that warrants a structural health management system to provide accurate, cost effective assessments of a platform's current (diagnosis) and future (prognosis) readiness. Corrosion/fatigue models exist that can reasonably predict failure progression in laboratory environments with controlled materials, usage profiles and environmental conditions. The prognostic challenge however, is to employ such models in the field where *a priori* factors and loading are far less certain and damage state awareness much more imprecise. With the goal of improving the accuracy of useful life estimates or time to inspection, an approach is presented in this paper for fusing imperfect state information such as global/local environmental measurements with physics of failure models to enable adaptive prognosis. Under the support of DARPA's Structural Integrity Prognosis System (SIPS) program, a corrosion/fatigue growth model developed by Wei and Harlow of Lehigh University is adapted though calibration of initial conditions as well as internal state variables given measurements of temperature and periodic local damage estimates, using a technique known as Kalman filtering. When coupled with a stochastic wrapper, the prognostic model output provides time to a given structural damage level with confidence bounds from which informed operational and maintenance decisions can be made.

1. INTRODUCTION

Since primary purpose of this paper is to introduce the concept of adaptive prognosis via model/sensor fusion, the author's have chosen to utilize a very straightforward corrosion/fatigue model which will be described herein. After a brief description of the adaptive prognosis concept, the Wei/Harlow model will be introduced followed by a Monte Carlo analysis of the model so that estimates on fatigue transition and fatigue failure are available as probability density functions (PDFs). Next, "hooks" between the model and observable parameters will be described. Finally, a generic approach for current state sensor/model fusion known as a Kalman Filter will be described and illustrated in application.

2. ADAPTIVE PROGNOSIS

In the context of structural health management (SHM), diagnosis is essentially classification of a current material damage state. Prognosis is the prediction of a future damage state (preferably with confidence bounds) and does not necessarily require a diagnosis. Adaptive prognosis, however, entails that information available at the current time (which may or may not be diagnostic in nature) are used to modify future predictions. This concept is illustrated in Figure 1 and Figure 2 [1,2] and described next.

Consider point *d0* in Figure 1 to be the mean initial damage condition for a prognostic model. A prognosis of life, from time k to predetermined damage level is found to be represented by RUL_0 or Remaining Useful Life. Suppose that some imperfect measurement $z(k)$ regarding the damage state becomes available at time $k=k+p\Delta T$. The challenge is to find optimal current damage state to re-initialize the model and/or adjust model parameters so that a calibrated and more accurate prognosis can be established[1].

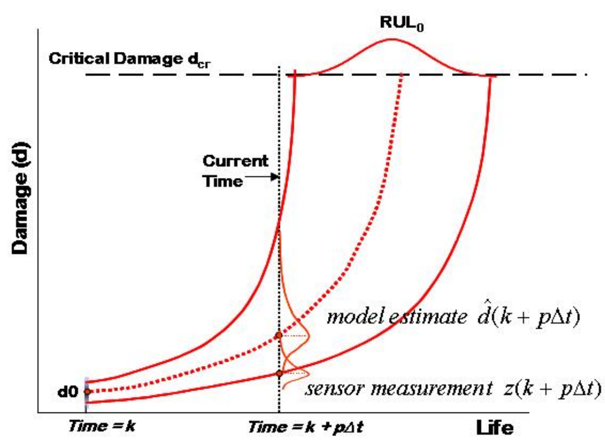

Figure 1: Adaptive Prognosis 1

Though utilization of a new initial condition, $\tilde{\boldsymbol{d}}(\boldsymbol{k})$ at time $k=k+p\Delta T$ as shown in Figure 2, it is apparent that the prediction mean has shifted and the confidence bounds on the resulting *RUL* has less variance than the original. The prediction accuracy improvement would generally mean that a decision to take action based on failure probability

[1] The decision to take this action is one that must be carefully considered. One criteria may be based on a statistical hypothesis test of the measurement and model prediction PDFs.

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1. REPORT DATE **2006**	2. REPORT TYPE	3. DATES COVERED **00-00-2006 to 00-00-2006**

4. TITLE AND SUBTITLE **Sensor/Model Fusion for Adaptive Prognosis of Structural Corrrosion Damage**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Impact Technologies LLC,200 Canal View Blvd,Rochester,NY,14623**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
The original document contains color images.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**		**5**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

will likely reduce lost operational availability over a run-to-failure maintenance plan.

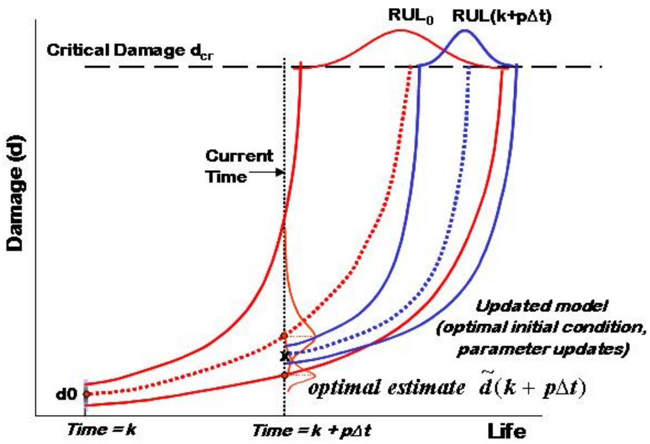

Figure 2 - Adaptive Prognosis – 2

3. Corrosion/Fatigue Model basis

A simplified model for pit growth proposed by Harlow and Wei [3] to estimate corrosion-initiated fatigue damage evolution for aircraft-grade aluminum was employed in this study. The model assumes the pit to be hemispherical in shape, with radius and volume, $V = (2/3)\pi a^3$. The rate of pit growth is given in terms of Faraday's law as shown in Equation 1, with it's solution determined from finite-difference integration for each timestep Δt.

$$\frac{a(k+1)-a(k)}{\Delta t} = \frac{MI_p}{2\pi n\rho F a(k)^2} \tag{1}$$

$$I_P = I_{P0}\exp\left[-\frac{\Delta H}{RT}\right] \tag{2}$$

Where in Eqn (1),

M = Molecular weight;
I_p = Pitting current [A];
n = Valency;
ρ = Density [kg/m$^{3]}$;
F = Faraday's constant [C/mol];
$a(k)_o$= Initial pit size, or the size of the initiating particle or particle cluster [m];
R= Universal gas constant [J/mol-K];
ΔH=Activation enthalpy [kJ/mol];
T=Temperature [K]

Note that Equation (2) contains environmental temperature and initial effective galvanic pitting current as key inputs. The resulting current density that can be supported by the particle (or cluster of particles) and its surface area is thus a function of both material properties and environmental conditions. Equation (1) can be linearized if expressed in terms of volume growth rate. This will become an important point regarding the Kalman Filter approach described later.

Wei and Harlow have linked the corrosion model to the Paris fatigue law [4] given as:

$$da/dN = C_c\left(\Delta K_{sc}\right)^{n_c} \tag{3}$$

Where:

N=Cumulative load cycles
a=Crack size
ΔK=Threshold intensity range
C_c ,n_c= linear elastic crack growth (Phase II) characteristics

The ΔK term is a function of both crack geometry and stress condition, details of which are omitted here. The corrosion and fatigue model descriptions provide the framework for transition from an initial corrosive state to a mechanistic crack growth failure mode. This transition is governed via the rate comparison (Figure 3, lower plot) of both models simultaneously [3], with the transition from corrosion to mechanistic surface crack (denoted "sc") given as:

$$\left(da/dt\right)_{SC} \geq \left(da/dt\right)_{PIT} \tag{4}$$

A deterministic simulation of this model is shown in upper plot of Figure 3, for an ambient temperature of 293 [K], initial pit size of 4.78 x 10^{-6} [m], and cyclic stress of 100 [MPa]. Transition to surface fatigue crack growth occurs at approximately 770 days in this case.

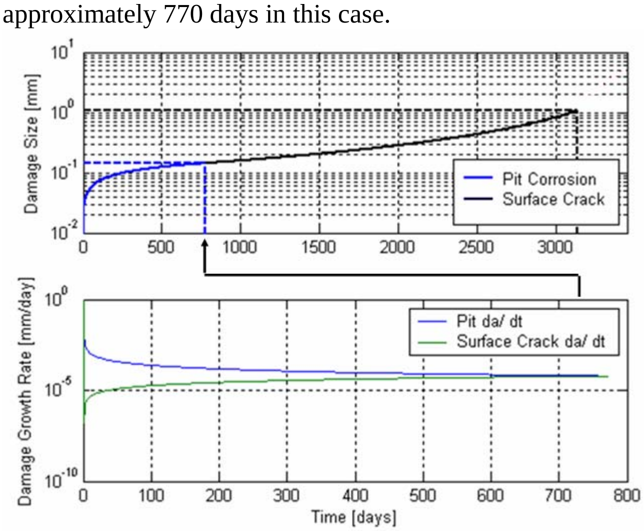

Figure 3 - Deterministic simulation

For prognosis, deterministic life estimates are inadequate for risk-based decision making. Therefore a Monte-Carlo simulation was run on the model. 300 simulations were performed with the initial pit size, temperature and stress used as random variables. The resulting PDFs were best approximated by lognormal distributions with normal means and standard deviations provided in Table 1 for the time to fatigue transition and to a crack of size of 1 mm.

Table 1 - Simulation results

	Mean	Stand. Dev.
Mean Pit/Surface Crack Transition Time [days]	1008	355
Remaining Useful Life Prediction [days]	4245	1730

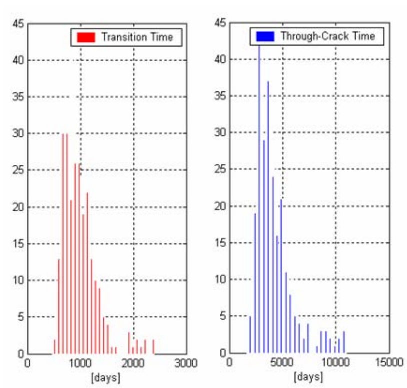

Figure 4- Histograms of results

If maintenance decisions, such as when to initiate inspections, where based solely on this analysis, a considerable amount of cost and operational availability would be sacrificed to maintain an acceptable failure risk. If additional parameters in the model were defined as random variables the variability in the result would be even greater! There are simply too many unknowns in this simple model to have a prognosis from a virgin material be of practical use. Information that can be used to update the model, no matter how imperfect, must be used calibrate (shift mean) or reduce the variability in the predictions.

4. SENSOR/MODEL "HOOKS"

In reality, there are generally very few, if any, model parameters that can be obtained directly from fielded sensors, let alone in a laboratory environment. For this model, let us assume that two parameters can be inferred: the local surface temp and the volumetric material loss at discrete points in time. If we use ambient temperature as a direct input to the pitting current calculation in the model, it is no longer required it to be a random variable input. Note that utilizing a temperature vs. time history will certainly reduce the variability in the current damage state estimate. In addition, statistics of the model-sensor residuals e(k) can be used for prognosis.

Using a temperature measurement to estimate the pitting current is an input parameter substitution. A different situation arises when the measured parameter is a state or output of the model such as when a pit damage estimate can be obtained. While the many methods for assessing corrosion damage are beyond the scope of this paper, let us consider a micro-electro mechanical (MEM) sensor application to estimate damage state. MEM sensors for corrosion are sacrificial and fabricated out of the same material as the substrate material that is to be monitored [5]. The resistance of the sacrificial material can be related to the free corrosion potential and the current density to the rate of corrosion. Hence, given calibrated initial conditions a material loss estimate of a substrate material can be provided at a desired sampling rate.

5. OPTIMAL MODEL/SENSOR FUSION

The means with which to minimize the variance, *e(k)*, between a sensor and model-based *state* estimates is a classic control problem. For linear systems and with the assumption of zero mean Gaussian noise, a technique called a Kalman filter [6,7] can be used to estimate a time-varying optimal gain that minimizes the variance in *e(k)* as depicted in Figure 5.

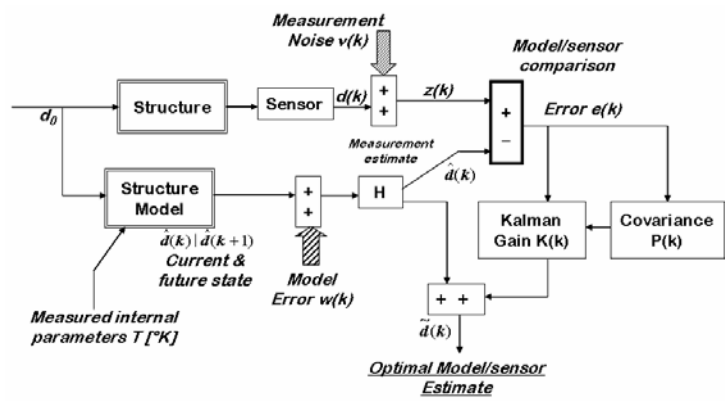

Figure 5 - Process with Feedback Gain

Consider the linear corrosion-only model in the volume form of Eq.1 with Gaussian model (process) noise w_k as shown in Equation (5). In addition, consider a measurement z_k with measurement noise υ_k as given in Equation (5).

$$\hat{d}_{k+1} = A\hat{d}_k + w_k, \qquad A = \frac{MI_P}{nF\rho} \tag{5}$$

$$z_k = H_k d_k + v_k \tag{6}$$

Define Q_k, R_k as the covariance matrices of process and sensor noise sequences ω_k, υ_k.

$$E[w_k w_i^T] = Q_k \qquad E[v_k v_i^T] = R_k \tag{7}$$

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Define $\hat{d}_k^-$ to be the a priori state estimate (prediction) at step k given knowledge of the process prior to step k, and $\hat{d}_k$ to be the a posteriori state estimate at step k given measurement z_k. We can then define a priori and a posteriori estimate errors as,

$e_k^- \equiv d_k - \hat{d}_k^-$

and $e_k \equiv d_k - \hat{d}_k$.

The a priori estimate error covariance is then,

$$P_k^- = E[e_k^- e_k^{-T}] = E[(d_k - \hat{d}_k^-)(d_k - \hat{d}_k^-)^T] \qquad (8)$$

and the a posteriori estimate error covariance is,

$$P_k = E[e_k e_k^T] = E[(d_k - \hat{d}_k)(d_k - \hat{d}_k)^T] \qquad (9)$$

The Kalman Gain K_k is chosen to minimize the a posteriori error covariance P_k.

With

$$P^-{}_k = A_k P_{k-1} A_k^T + Q_k \qquad (10)$$

and $P_k = (I - K_k H_k) P_k^-$ (11)

the Kalman Gain (K) is found to be:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \qquad (12)$$

Therefore, new optimal damage estimate can be found to be:

$$\hat{d}_k = (I - H_k K_k)\hat{d}_k^- + K_k z_k \qquad (13)$$

$$\hat{d}_k^- = A\hat{d}_{k-1} \qquad (14)$$

In this case, $H_k = 1$.

With the assumption of constant model and measurement noise, both error covariance and Kalman gain will converge to a constant value. The final effect of the Kalman filter is shown in the subplot of Figure 6, where we simulated a noisy sensor signal that was 'filtered' via combination with a model estimate. The optimal Kalman estimate at current time then becomes the initial conditions for an estimate of when fatigue crack initiation should occur, as shown in Figure 6. Note that transformation back to a pit radius (damage) has already been applied. The use of the Kalman filter, in this case, not only resulted in a mean shift in the prediction (bold lines) but also a variance reduction due to the fact that the model prediction now stems from a new initialization point.

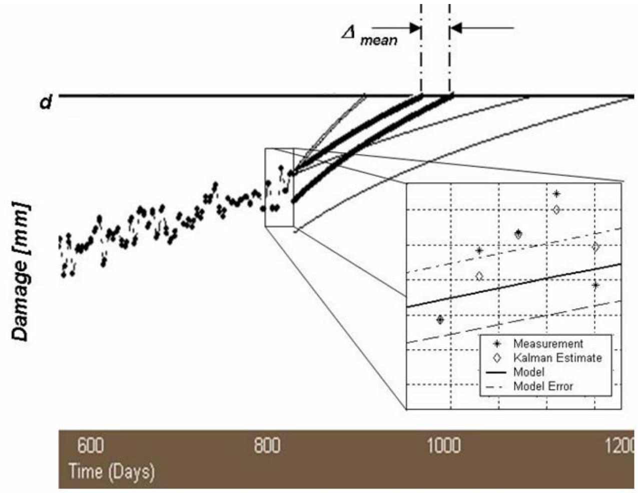

Figure 6: Kalman Enhancement to Prognosis

6. SUMMARY

Prognosis is inherently a statistical process in which the aggregate of many unknowns can result considerable prediction variability. The concept of adaptive prognosis was introduced in this paper whereby available, albeit imperfect, information is used to update elements of the prognostic model. Only one of many approaches for accomplishing this was introduced as Kalman Filtering applied to a corrosion model and material loss estimates. Other techniques include Bayesian updating, constrained optimization and particle filtering.

The process by which features and models are integrated is vital to the success of future corrosion health management programs and there are many remaining challenges. It is a significant challenge to design systems so that data such as pitting current, material loss, time-of wetness, etc. estimates can be fused and used in conjunction with corrosion life models to estimate current and future damage states. Furthermore, in the case of corrosion fatigue or stress corrosion cracking, multiple models will be required that may or may not use various feature inputs. Finally, feedback mechanism in the system design cannot be ignored. Specifically, the system must be capable of intelligently calibrating a-priori initial conditions (i.e. humidity, strain and temperature have changed), random variable characteristics or switching prognostic models in an automated yet lucid process to empower better operational and logistical decisions for air platforms.

7. ACKNOWLEDGMENTS

The authors would like to thank Steve Engel at Northrop Grumman, George Vachtsevanos at Georgia Tech and Bob Wei and Gary Harlow of Lehigh University for contributing to various aspects of this study in adaptive prognosis.

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Finally, we thank DARPA and specifically Dr. Leo Christodoulou, for continuing to fund programs such as SIPS which progress technology and integrate many diverse engineering disciplines.

8. REFERENCES

[1] Steve Engel et al, *Reasoning and Prediction*, Northrop-Grumman Doc. SIPS-RAP-01132004, May 2004

[2] Engel, S., Gilmartin, B., et al. "Prognostics, the Real Issues With Predicting Life Remaining", Proceedings of the 2000 IEEE Aerospace conference; 0-7803-5846-5

[3] Harlow, D.G., Wei, R.P., "Probability Modeling and Statistical Analysis of Damage in the Lower Wing Skins of Two Retired B-707 Aircraft", Fatigue Fract Mater Struct, 24, 523-535, 2001

[4] Bannantine, J., *et al*., Fundamentals of Metals Fatigue Analysis, Prentice Hall, 1980

[5] Analatom Inc., http://www.analatom.com/products.html

[6] Kalman, R. E., "A new approach to Linear Filtering and Prediction Problems," Transactions of the ASME – Journal of Basic Engineering, pp 35-45 (1960)

[7] Welch, Bishop, "An Introduction to the Kalman Filter", http://www.cs.unc.edu/~welch/media/pdf/kalman_intro.pdf

9. BIOGRAPHIES

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