

A Method for Generalized Prognostics of a Component Using Paris Law

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Abstract—Vibration based Health and Usage Monitoring Systems (HUMS) can provide good information as to the condition of a component, (e.g. health), but other than trending, have not yet yield an estimated of the remaining useful life (RUL). Three fundamental problems need to be address to accurately estimate RUL. First, component health data is noisy. Even with filtering, the HI can be difficult to trend. Second, no generalized damage model has yet been proposed to address component degradation. Finally, the relationship between physical damage and measured component health is difficult to be established.

This paper explores methodologies to de-noise vibration data, model damage propagation using Paris Law, and address inferred damage via health indicators by using maintenance policy vs. a safety of flight criteria to initiate repair activities.¹

The RUL prognostic is validated on established crack data, and testing on HUMS derived fault data.

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1. INTRODUCTION

The Goodrich IMD HUMS and the next generation IVHMU have been equipped on a number of rotor aircraft. The installed fleet is over 40 S-92a aircraft, and over 200 H-60 derivatives. Further, there are a smaller number of CH-53e, CH-47, and UH-1 installations. These systems have increased operational readiness by improving the quality of information needed to perform maintenance. Additionally, by improving usage calculation and automating the yellow sheet process, maintenance cost per flight hour has been reduced [1].

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The mechanical diagnostics (MD) functionality has a proven capability to identifying anomalous components: upon inspection of high health indicator (HI), it was found that maintenance was appropriate. However, the full capability of the system (reduction in unscheduled maintenance) has not been realized. While opportunistic maintenance has been performed based on HI or on HIs that show a consistent upward trend, the ability to plan maintenance activities fifty or one hundred hours in the future remains elusive.

In short, the current trending/diagnostics capability has not fully negated the need for unscheduled maintenance. Nor does the current capability significantly reduce the logistic footprint by allowing maintenance to be planed tens even hundreds of hours in the future. Such a capability would allow better management of the aircraft fleet and reduce the chance of unscheduled maintenance occurring.

The ability to predict the RUL tens or hundreds of hours in the future requires three technical issues to be resolved.

- (1) Vibration based prognostics/diagnostics measure a signature on which an algorithm operates. The output of the algorithm is a condition indicator (CI), which is a descriptive statistic of the component health. In some cases, the measure is a direct metric, such as shaft order 1, 2 or 3 vibration in inches per second (IPS). At other times, the metric has no physical meaning, such as residual kurtosis for a gear. In all cases, the CIs are noisy, due to the interaction of component stiffness, torque, airspeed, aircraft attitude, and random vibration. These interactions can makes even simple trending difficult.
- (2) The relationship between a vibration based CI and damage is not well established. Even in a relatively direct metric CI such as shaft order 2 or 3, which are indicative a cracked coupling or bent shaft, it is not clear what level of damage is present on the shaft when these indicators are elevated. For bearings or gears, the CI relationship to damage is more indistinct. Service history and test stand data suggests that elevated CIs are indicative of damage, but how much damage, and how much RUL is unclear.
- (3) It is not clear, once a component is in a fault propagation mode, how to model RUL. In most

cases the components material properties are not entirely known. This makes detailed, physics based models difficult and/or impracticable. Even if all of the inputs to the model were known, it would be difficult to compute RUL for every component on the limited computational resources available on the aircraft or a ground station.

Presumably, if these technical obstacles can be surmounted, it should be possible to estimate a RUL with some small bound on error. Given the technical difficulty of these problems (particularly in (2) and (3)), it is necessary to simplify and bound the problem to make it more tractable.

2. LOGISTICS VS. CRITICAL SAFETY ITEM

It is proposed that (2) be approached from a logistics perspective instead of a critical safety item (CSI) or safety of flight (SOF) issue. Simply stated, instead of implying the absolute level of damage on a component, maintenance is performed when the component is deemed significantly anomalous.

This is because using non-destructive inspection (e.g. HUMS data) for inspection of CSI requires a high standard of information. It is implied that failure of a CSI could result in loss of aircraft and crew. Thus, gaining maintenance credit (using HUMS instead of inspection) implies an explicit relationship of damage to CI/HI.

Alternatively, if HUMS CI/HI information is used for logistics, there is no change concerning airworthiness directives. Using HUMS to supplement existing inspection and to schedule maintenance on components that are thought to require maintenance can greatly reduce unscheduled maintenance events. Changing to this logistics paradigm relaxes the requirement for an explicit relationship between damage and CI/HI value. This in turn allows maintenance to be planned when components are identified as anomalous.

A number of studies have shown that there exists a relationship between physical damage and measured vibration signatures. Goodrich, under funding of the Center for Rotorcraft Innovation [2], [3] observed that there is an 87% correlation between measured vibration (a CI) to physical damage length, and over 95% correlation between an HI (weighted sum of CIs) with physical damage. This is important for three reasons:

1. It suggests that crack length (a - physical damage) can use a surrogate, the HI,
2. That the HI can model crack length with a simple linear model:

$$HI = \beta_0 + \beta_1 a \quad (1)$$

3. The exact relationship between HI/CI and damage is unimportant.

As noted, using HUMS for logistic support requires no explicit relationship between damage and HI level. Logistics only requires that when maintenance is recommended, the component be degraded enough for maintenance to be *appropriate* (e.g. the component has damage, yet is serviceable and did not put the aircraft at unreasonable risk of failure). This allows a maintenance policy to govern when repairs are conducted. For example, a policy is set that maintenance is performed when the HI reaches a value of "1". The maintainer is assured that when a component is at an HI of "1", it has damage, and that it is appropriate for maintenance to be performed (e.g. low probability of a component at 1 of not requiring maintenance). Given more service history, the scaling of the HI can be made such that the explicit relationship between crack/physical damage and HI is known (eq. 1), but at this time, it is only important to know that the relationship exists.

In allowing the HI to only assure that the component is damaged, the problem reverts to one of identifying components which are thought to be anomalous. A number of algorithms have been proposed and tested for anomaly detection [4], [5], [6], and [7]. In anomaly detection, the HI is posed as a formal hypothesis:

- H_0 : component is nominal vs.
 H_1 : component is *not* nominal

By approaching component health in this way, well-established statistical techniques can be employed in determining when the HI is anomalous, and HI performance metrics, such as HI expectation, variance, false alarm rate, probability of fault detection, can be calculated. Further, it allows a mathematically robust method that can be standardized across components, and across platforms.

In establishing a standard work process for threshold setting, Goodrich has collaborated with its customers in establishing a health paradigm in which:

1. Nominal aircraft are between an HI of 0 and 0.5 (Normal Low),
2. Between 0.5 and 0.75 is Normal High (serviceable, but out of limits),
3. Between 0.75 and 0.99 is out of limits: schedule maintenance: Warning
4. HI of 1: perform maintenance: Alarm.

Service history from a number of mechanical diagnostics "finds" suggests that these rules for health are appropriate. For this paper, the HI is based on a statistical approach of multi-dimensional hypothesis testing using the Nakagami

probability distribution [8], where the threshold of 0.5 is set with a probability of false alarm of 10^{-6} .

For shaft and bearing CIs, the general form of the HI function is:

$$HI = \sqrt{\mathbf{CI}^T \Sigma^{-1} \mathbf{CI}} * 0.5/\nu \quad (2)$$

where

- CI** is a vector of CI values
- Σ** is the covariance of the CI Values and
- ν** is the critical value for a Nakagami with n degrees of freedom.

For $n = 3$ (shaft HI: shaft order 1, shaft order 2 and shaft order 3), with a probability of false alarm of 10^{-6} , $\nu = 9.44$. For $n = 5$ (bearing HI: cage envelope, ball envelope, inner race envelope, outer race envelope and envelope RMS), with a probability of false alarm of 10^{-6} , $\nu = 10.45$ (Figure 1). The mean HI value and variance can now be calculated for the nominal components, and is:

- $E[\text{Shaft HI}] = .19$, $V[\text{Shaft HI}] = 0.0031$
- $E[\text{Bearing HI}] = 0.22$, $V[\text{Bearing HI}] = 0.0026$

The validity of this methodology is based on the CI probability distribution function, such that the HI is a function of distributions. This method of threshold setting based on functions of distributions is patent pending.

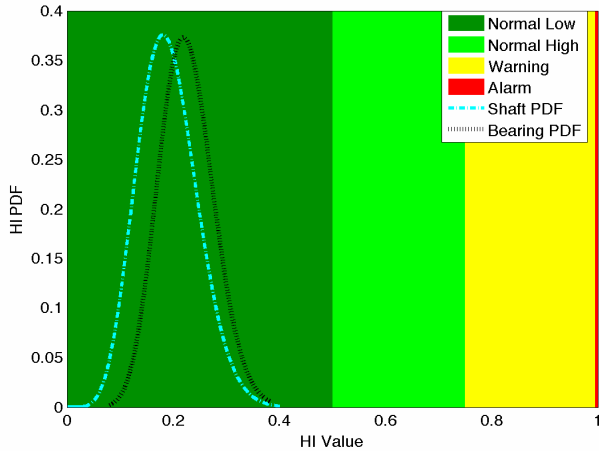


Figure 1 HI PDF and Health Paradigm

3. CRACK PROPAGATION MODEL

For metallic components, if the cyclic stress level is significantly high, micro cracks will spread across the surface. These cracks will penetrate into the body of the material and continue to grow. The growth behavior of the

crack has been the subject of numerous experiment studies. These studies have attempted to derive a theoretical relationship between rate of crack growth and the number of stress cycles.

Since 1953, a number of crack growth theories have been presented:

1. Head's Theory
2. The Geometrical Similarity hypothesis
3. Net area stress theories,
4. Accumulated strain hypothesis
5. Dislocation theories
6. Energy Theories
7. Frost and Dixon's theory
8. Fracture-mechanics crack growth theory

This list is not exhaustive [9]. On inspection, these theories can be generalized by the Paris Law

$$da/dN = D(\Delta K)^m \quad (3)$$

which governs the rate of crack growth, where

- da/dN is the rate of change of the half crack length
- D is a material constant of the crack growth equation
- ΔK is the range of the K during a fatigue cycle
- m is the exponent of the crack growth equation

The range of strain, ΔK is given as:

$$\Delta K = 2\sigma\alpha(\pi a)^{1/2} \quad (4)$$

here

- σ is gross strain
- α is a geometric correction factor
- a is the half crack length

Most of these variables are specific to a given material and test article. For components encountered in a drive train, they are unknown. As such, some simplifying assumptions can be made to facilitate analysis. For many components/material, the crack growth exponent is 2, which will be used as a default value. The geometric correction factor α , is set to 1. Equation (4) simplifies to:

$$da/dN = D(4\sigma^2\pi a) \quad (5)$$

The goal is to determine the number of cycles, N , remaining until a crack length a is reached. Taking the reciprocal of (5) gives:

$$dN/da = \frac{1}{D(4\sigma^2\pi a)} \quad (6)$$

Integrating gives the number of cycles (N) remaining. Note that N for synchronous systems (e.g. constant RPM) is equivalent to time by multiplying with a constant.

$$\begin{aligned} N &= \int_{a_o}^{a_f} dN/da \\ &= \int \frac{1}{D(4\sigma^2\pi a)} da \\ &= \frac{1}{D(4\sigma^2\pi)} (\ln(a_f) - \ln(a_o)) \end{aligned} \quad (7)$$

Equation (7) gives the number of cycles N from the current measured crack a_o to the final crack length a_f . As noted previously, the measured component health (HI) will be used as a surrogate for crack length a , in keeping with the logistics paradigm. The only remaining unknown is D , the material constant of the crack growth equation.

4. FILTERING, ESTIMATION OF DA/DN AND D

It was stated that vibration based CI/HI are noisy. From equation (5), it is evident that in addition to a filtered/denoised HI, the rate of change of the HI (dHI/dt) and an estimate of D is needed. One method for filter and state reconstruction (e.g. reconstructing an unknown parameter, such as rates, from observed data) is the Kalman filter [10].

The Kalman filter is a kinematic model in which a filter gain is set optimally based on the measurement and system variance. The batch process for a state is:

$X_{t t-1} = F X_{t-1 t-1}$	State Propagation
$P_{t t-1} = F P_{t-1 t-1} F' + Q$	Predicted Covariance
$K = P_{t t-1} H' [H P_{t t-1} H' + R]^{-1}$	Kalman Gain
$P_{t t} = (I - KH) P_{t t-1}$	State Covariance
$X_{t t} = X_{t t-1} + K(Y - H X_{t t-1})$	State Update

Where:

$t|t-1$ is the condition statement (e.g. t given the information at $t-1$)

X is the state information ($x, dx/dt$)
 P is the state covariance matrix
 Q is the process noise model
 H is the measurement matrix
 R is the measurement variance, and
 F is the state transition matrix. For this case, where the states are health, and the rate of change of health (dHI/dt), F is an integrator.

Two Kalman filters are run: one filters the measured HI, and calculated dHI/dt (rate of crack growth) and one estimates the unknown parameter D . The unknown D can be found via an extended Kalman filter, where an estimate

of HI (e.g. a) and strain σ is derived from the current estimate of D . The state prediction of σ and a are:

$$\hat{a} = \frac{da/dN}{\hat{D}(4\sigma^2\pi a)} \quad (8)$$

and

$$\hat{\sigma} = \sqrt{\frac{da/dN}{\hat{D}(4\pi a)}} \quad (9)$$

where \hat{D} is the state estimator for D .

The measurement matrix H , which is the Jacobian of equation (8) and (9) is:

$$H = \begin{bmatrix} -da/dN / \sqrt{4D^2\pi a \frac{da/dN}{\hat{D}(4\pi a)}} & 0 \\ -da/dN / 4D^2\pi\sigma^2 & 0 \end{bmatrix} \quad (10)$$

Model Validation

In order to validate the assumption used in estimating the number of cycles remaining, a crack growth data set from [11] was used. The data set contains crack length vs. number of cycles in austenitic steel, where the cyclic loading was 62 MN/m².

A sequential extended Kalman filter was used to filter the crack length (figure 2) and to calculate da/dN (figure 3). Equations 8, 9 and 10 were used to estimate D (figure 4). Cycles remaining were calculated using (7) (figure 5).

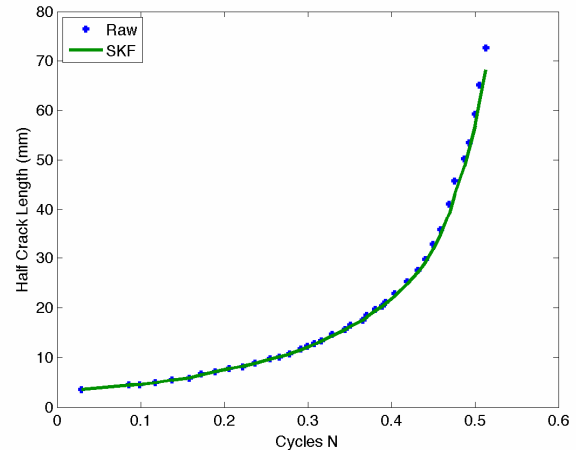


Figure 2 Crack Length vs. Cycles

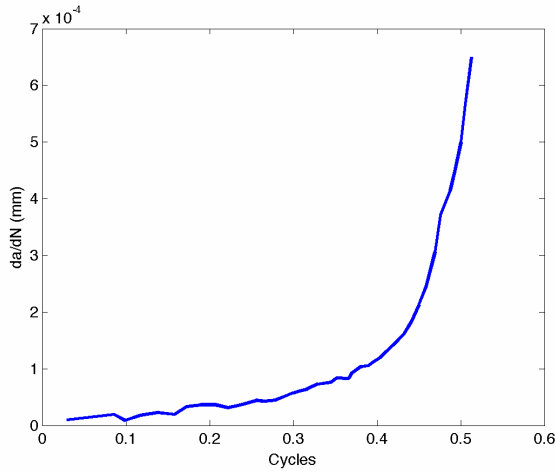


Figure 3 Derived da/dN from Kalman Filter

While it is assumed that D is constant, it is seen to vary a small amount, likely due to a model violation. Since the Kalman filter is an iterative estimate of D , it requires some small number of updates to converge (figure 4).

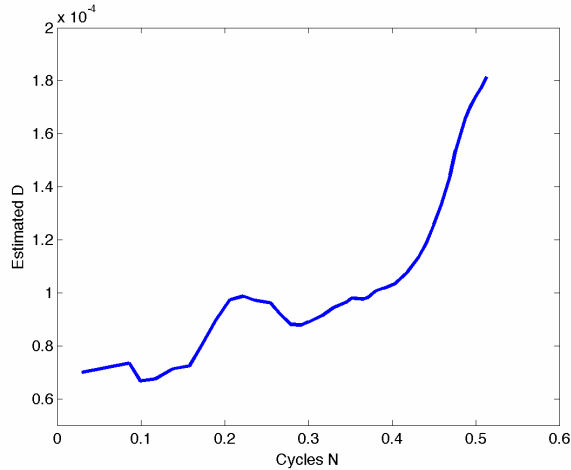


Figure 4 Estimate of D , Material Constant

The number of cycles remaining converges to the experiment results quickly (about 3 measurements). It is noted that the number of cycles remaining is a function of D and da/dN . Note that the estimated RUL converges to the observed remaining life quickly, and is remarkable accurate predictor of the cycles remaining

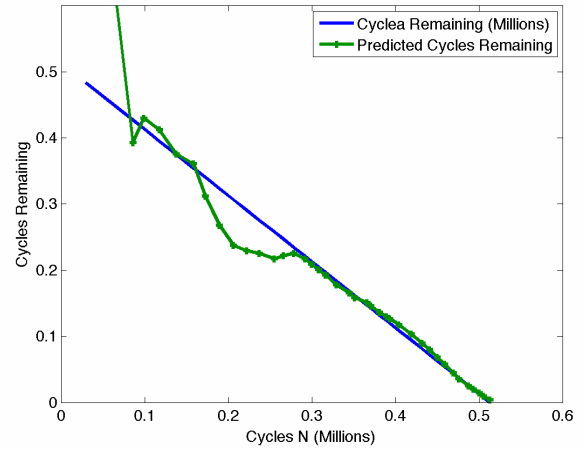


Figure 5 Cycles Remaining

Given this validation, the same algorithmic procedure was used against real world data acquired from test stand data and a utility helicopter.

5. REAL WORLD EXAMPLES

Three real world examples are presented, the first two being shaft examples, the third being a bearing example. The first shaft example is a destructive test of a shaft on a test stand. The second shaft case is a high-speed input shaft driving the helicopter main module. It present challenges in that the cyclic loading is not constant. The third example is a generator drive ball bearing. While the load is relatively constant, it was found that it required a different crack growth exponent. All three examples show encouraging results.

High Speed Shaft: Test Stand

This high-speed shaft is used as a power takeoff from a turbine accessory gearbox. The shaft uses a flexible coupling rated at infinite life. In order to propagate a fault on a test stand, the shaft was run at 6800 RPM at 1000% load (e.g. 10 times design limit). As such, it ran 10 million cycles prior to fault propagation. From the commencement of fault propagation until the test stand was shut down (due to high shaft order 3) was no more than 400 seconds (figure 6).

In the validation example, known crack values and strain where used. In the shaft example, there is no direct measure of physical damage. Instead, as previously noted in addressing problem (2), the shaft health (HI) was used as a surrogate for damage.

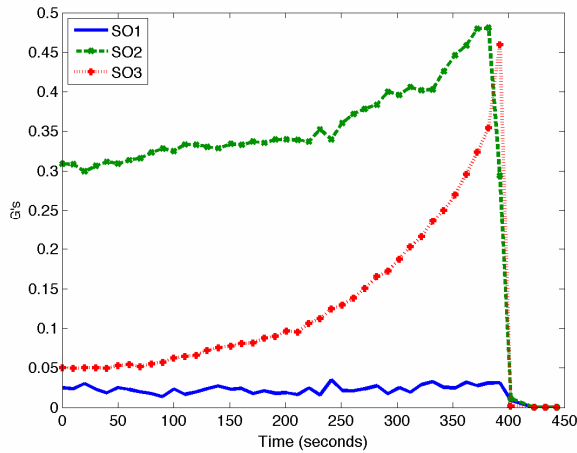


Figure 6 High Speed Shaft Failure

The shaft health was calculated with eq 2. The covariance was calculated using shaft order 1, 2 and 3 from the previous day. The HI, Kalman filtered HI, dHI/dt and estimate of D are given in figures 7 and 8. At the end of the test run, the shaft coupling was found to have a 2 cm crack traversing the outer rim of the coupling.

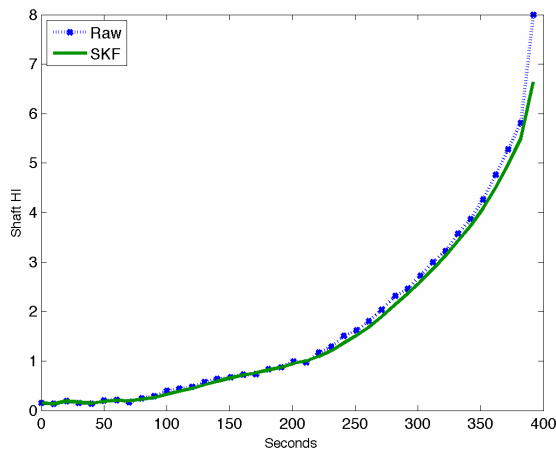


Figure 7 High Speed Shaft Raw and Filtered Health

Note that the health moves from 0.22 to 8. Normally, 1 is the truncated limit, which is reached after only 200 seconds from the start of the fault propagation. For this example, the RUL is calculated to an HI of 8 instead of the nominal 1.

For this shaft, there was no measure of cyclic strain. Normally, some relationship between cyclic strain and torque must exist. This relationship is unknown. For that reason, a nominal value of 10 (1000%, based on the accelerated life testing load) was used.

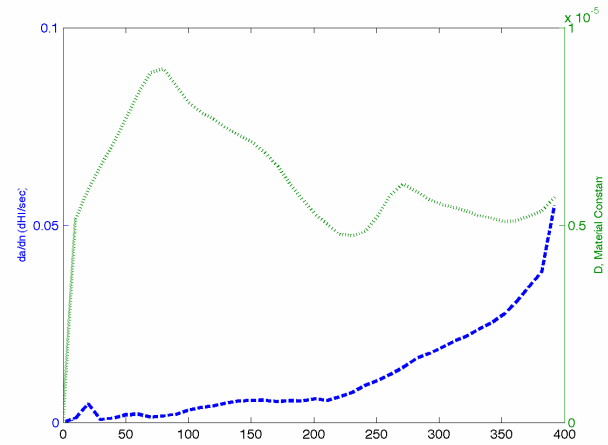


Figure 8 Rate of Change in HI and Estimate of D

This data consisted of 40 measurements, a comparatively short number of acquisitions relative to the time scale. In figure 9, it is seen that the prognostics converges with approximately 200 seconds remaining.

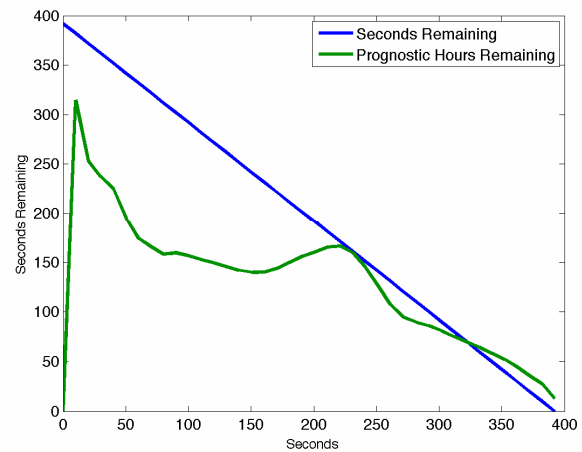


Figure 9 High Speed Shaft Time Remaining

Realistically, acquisitions should have been taking every two seconds vs. every ten seconds. Presumably, this additional information would allow a better prognostic. It should be noted that in this example the failure mode was shaft order 2 and shaft order 3: in the next example, the predominate failure mode is shaft order 1.

High Speed Input Shaft

The high-speed input shaft rotates at approximately 22,000 RPM and delivers a maximum of 700+ horse power and 300 ftlbs of torque to the main module. While shaft failures are exceedingly rare, at times shaft balances are required for maintenance. Additionally, there is a limited chance that the shaft coupling could crack or become loose.

The metric for RUL was hours until the HI was greater than 1 as per the proposed maintenance policy. The HI was derived from (2), where the CI's were magnitude of

vibration for shaft orders 1, 2 and 3. Note that for a constant RPM system, the only difference between cycles (N) and time is a scalar multiplier (which is captured in the calculation of D , eq. (7)).

The power transmitted to the main module is dependent on how the aircraft is flown. Ostensible there is a relationship between engine torque and cyclic strain – again, it is unclear what that relationship is. Given that, four measures of torque were tested to estimate cyclic loading between acquisitions. It is hypothesized that between two acquisitions, any change in component health is a function of torque: flight regimes requiring high torque are more damaging than benign regimes requiring low torque.

The shaft example encompasses approximately 371 hour of usage, over 304 operations (an operation in IMD-HUMS generates a raw data file), at the end of which maintenance was conducted. The time was calculated by measuring the cumulative time between acquisitions where torque was $> 10\%$. Approximately 60% of the time the aircraft a torque less than 30%, suggesting a ground turn. Raw and filter data are presented in figure 10.

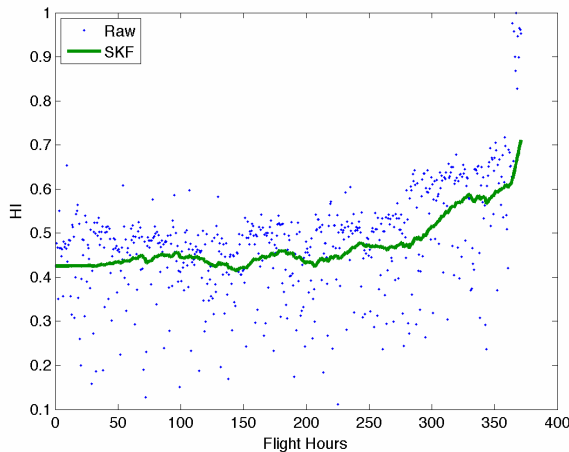


Figure 10 Raw and Filtered Input Shaft

The Kalman filter “filter factor” and ability to reconstruct and observables is based on configuration input variables for the plant noise and the measurement noise. The Kalman filter parameters for plant noise was set at 0.01 (e.g. maximum rate of change of health is .01/hour), while the measurement noise was 0.055 (expected standard deviation of the HI). The median % torque between acquisitions was found to have the highest correlation with the rate of change in health. This was then used for the strain metric at each update to N . At approximately time 150, torque and rate of change correlate reasonable well (figure 11). In figure 10, it appears that at time 150, the shaft starts to propagate the fault, which is supported by figure 11.

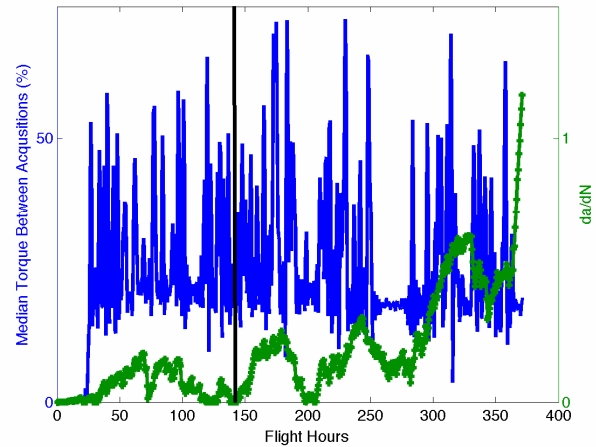


Figure 11 dH/dt and Median % Torque vs. Time

Some assumptions were made with the Kalman filter model, for both filtering the shaft health and for estimation of the material constant D . First, it is assumed *a priori* that components do not “heal” themselves (that is, dH/dt is zero or positive). Thus, in the filtering operations, if dH/dt was negative, it was set to zero. Second, from equation (7), it is apparent that D must be greater than zero. A test for this condition was made as well, with D being set to $1e-7$ if negative or zero (figure 12).

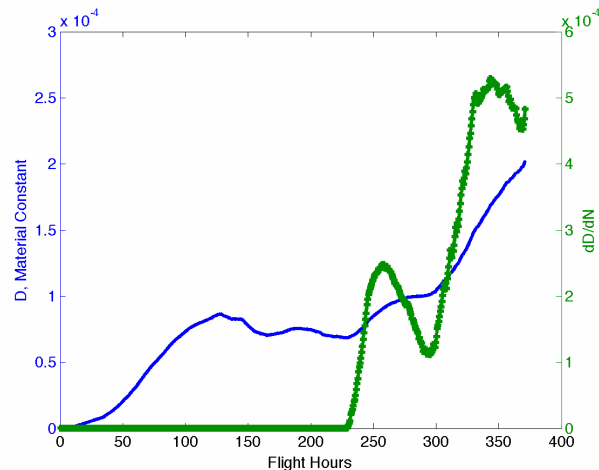


Figure 12 D (Material Constant) and dD/dN

Note that dD/dN is effectively zero until time 230. This corresponds well with when the prognostic for RUL tracks well with the actual RUL (figure 13)

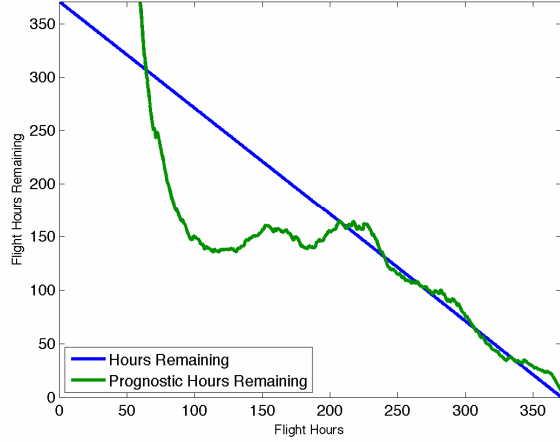


Figure 13 RUL and Prognostics Hours Remaining

At approximately 220 hours, the predicted RUL prognostic is within a few percent of the actual hours remaining until maintenance (e.g. HI = 1). This suggests a prognostic of 150 operational hours.

Generator Shaft Drive Ball Bearing

The generator shaft drive ball bearing showed elevated HI/CIs and was removed for operation. The HI was derived from (2) where the CI's were the envelope cage, ball, inner and outer race values and envelope RMS. For a full description of the CI algorithms for bearing, see reference [2]. On inspection, it was found that the ball elements were pitted and was in need of maintenance [12]. For this component, the Paris Law model crack growth exponent was 1/2 (vs. 2 for the shaft example). This gives the following model for crack propagation

$$da/dN = D(4\sigma^2 \pi a)^{1/2} \quad (11)$$

Rearranging (11) in terms of N gives:

$$dN/da = \frac{1}{D(4\sigma^2 \pi a)^{1/2}} \quad (12)$$

Integrating gives the number of cycles (N) remaining.

$$N = \int_{a_o}^{a_f} dN/da = \frac{2a}{3} \sqrt{2\sigma} D(\pi a)^{1/4} \Big|_{a_o}^{a_f} \quad (13)$$

Similarly to previous example, D is found using an extended Kalman filter, state prediction of σ and a are:

$$\hat{a} = \frac{da/dN}{\left(\hat{D}\sqrt{2\sigma}\pi^{1/4}\right)^4} \quad (14)$$

and

$$\hat{\sigma} = \left(\frac{da/dN}{\hat{D}\left(\sqrt{2}(\pi a)^{1/4}\right)^2} \right) \quad (15)$$

The measurement matrix H , which is the Jacobian for equation (14) and (15) is:

$$H = \begin{bmatrix} -0.318 da/dN^2 / D^3 \sigma^2 & 0 \\ -0.318 da/dN^4 / D^5 \sqrt{a} & 0 \end{bmatrix} \quad (16)$$

Given that the torque for a generator is a function of power required, and that it is likely that electrical power would remain fairly constant throughout the operating regimes of the helicopter, the mean torque was used for strain (26%). The HI for the generator drive ball is calculated from (2) (figure 14).

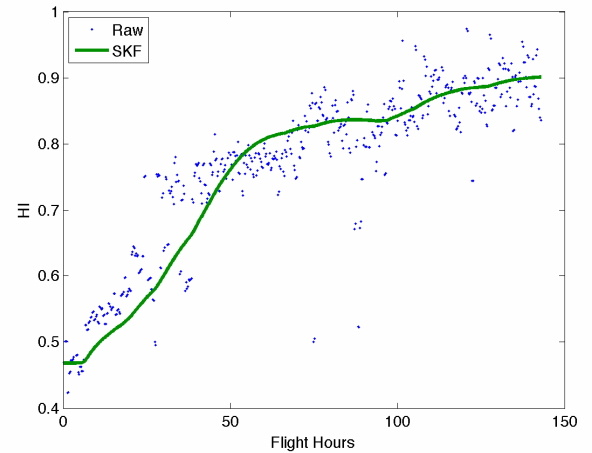


Figure 14 Raw and Filter HI for Generator Drive Ball Bearing

Over the past two years, IMD-HUMS has captured a number of generator related faults, such as the generator drive shaft. The trend of shaft order 1, 2 and 3 are similar to the trend observed in figure 14. This may suggest that the failure model is not a function of component type (bearing vs. shaft), but location. Figure 15 displays the RUL and the predicted RUL using this model. It is likely that the accuracy is limited to the resolution of measuring cyclic strain. There is no parametric data to measure current or torque on the generator.

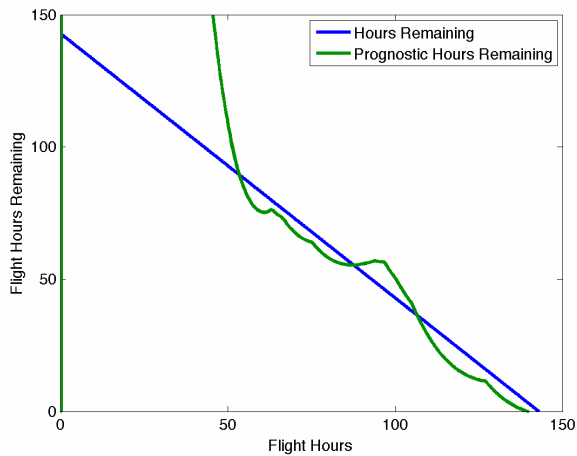


Figure 15 RUL and Prognostics Hours Remaining for Bearing

Note that the prognostics converges to approximately the true RUL at 50 hours, or almost 100 hours prior to replacement.

6. DISCUSSION

In the short term, it is unlikely that any HUMS algorithm will be able to quantify physical damage based on a vibration based sensor. This in of itself will limit the ability for maintenance credits to be applied to HUMS equipped aircraft. However, this does not limited a reduction in aircraft operating cost that could be achieve by using MD information to reduce unscheduled maintenance and reduce the logistics foot print required to operate a fleet of aircraft.

As demonstrated, techniques for prognostics could be available for operators use.

Prognostics techniques based on probabilistic models [13], [14], such as Hidden Semi-Markov Models, based repair activity on the cumulative probabilities that the component will last n units of time. This is a difficult concept to articulate and hard to make maintenance decisions on. The technique presented here could simplify the decision process of maintainers by giving a rough estimate of the time remaining until a maintenance action is taken. This is a policy decision and as such does not impact safety of flight (e.g. we are not suggesting reducing the requirement for inspection).

Three examples of component failures where presented. This generalized method of prognostics produced acceptable estimates of RUL on three different failure modes (shaft order 2 and 3 failures, shaft order 1 failures, and bearing failures). This is encouraging. However, additional worked required, such as:

1. For a class of components, is the material constant D the same between components? Across Aircraft?
2. Does the application of a geometric correction factor improve performance?
3. Are there better measures of cyclic strain than torque?
4. The Kalman filter is used for filtering, are other methodologies, such as particle filter or kernel smoothing, more appropriate?
5. In smoothing the data, could curve fitting techniques be applied with better results
6. When is the RUL prognostic accurate?
7. How best can this information be displayed to the maintainer?

Given the increased service history of HUMS equipped aircraft, it is likely that additional faulted components will be found and tested. It is hoped that this Paris Law model will provide useful indication of the RUL and eventually be incorporated into a maintenance support tool.

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