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Change Detection for Improved Maintenance Notification and Remaining Useful Life Calculation

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Abstract

The Defence Science and Technology Group (DTSG) Data Challenge provides an opportunity to demonstrate essential HUMS (Health and Usage Monitoring Systems) technologies. In general, HUMS aims to improve the safety and reliability of critical helicopter components. However, widespread technology adoption requires HUMS to provide a return on investment (ROI) by adding functionality and actionable maintenance information to improve asset management. Providing an estimate of remaining useful life (RUL) enhances safety and allows better control of assets, providing greater opportunities for revenue and improving ROI.

RUL estimation is an end-to-end process of feature extraction, threshold setting, extrapolation of damage propagation, and validation. Feature extraction is the generation of condition indicators (CI) that are representative of damage. Threshold setting triggers an alert as to when it is appropriate to do maintenance. In this application, it defines the health indicator (HI). A high cycle fatigue model can then be used to estimate the remaining cycles from the current HI to the HI at which an alert is generated. As important as the estimate in the RUL is some indicator of the confidence in the RUL. A high confidence RUL validates that the asset should be removed from service and maintenance performed.

This paper describes the CIs used, the HI function, and the development of a configuration process to support threshold setting. A subcritical crack growth model, based on a power law, uses the HI time series to estimate the RUL and both the first and second derivatives of the RUL. It is hypothesized that a well-modeled RUL estimation will have a first derivate of - 1 (that is, for each hour of usage, the RUL decrements by -1), and the second derivative of near 0 (the model is stable)..

Keywords: Condition indicator, Fatigue failure, Health indicator, RUL, Threshold setting.

Introduction

Helicopter drive systems play a signification role in the safety of rotorcraft. Vibration monitoring systems have been developed to improve the safety and maintainability of these drive systems. Because of their compact size and efficiency, the planetary transmission is used in many rotorcrafts in the final stage of the drive. Planetary drive systems have posed a challenge for vibration-based gear fault detection because the load is shared by multiple planets operating synchronously, such that the other health gears may mask a gear fault.

Helicopter planetary gearbox faults are rare. Further, there are even fewer publicly available data sets to develop new or test existing algorithms against. From an end-to-end perspective, vibration-based component fault detection is part of a health and usage monitoring system (HUMS) chain of events needed to trigger a maintenance event responsive to a potential fault. As with any safety system, HUMS provides a balance between production/operations and safety. The goal of HUMS can then be seen to provide actionable information in a timely way. That is, to maximize operational availability while maintaining the safety of the aircraft.

As such, the Defence Science and Technology Group (DTSG) Data Challenge provides a rare opportunity to test the chain of processing for HUMS (for details on the dataset, see [1]). That includes condition indicator/feature extraction, threshold setting (when it is appropriate to perform maintenance), and remaining useful life (RUL). Operationally, RUL allows operators to schedule maintenance opportunistically. Given that the aircraft typically has 50 or 100-hour inspections, a valid RUL will enable maintainers to move unscheduled maintenance (something broke) to scheduled maintenance events. This improves operational availability, lower logistic cost, and improves safety.

Condition Indicator Algorithms

Modern gear fault algorithms are based on using the Time Synchronous Average (TSA) for signal separation. The TSA is then operated on using algorithms that are sensitive to gear tooth damage [2]. The dataset consisted of hunting-tooth (HT) TSA relative to the planet/ring gear. Each TSA was 405405 data points. This corresponds to 11583 * 35 planet teeth. To recover the TSA for the planet shaft, HT TSA can be reshaped to a 4095 x 99 matrix, with the TSA being along the 99 columns. While the generalized techniques from [2] were tested, they did not perform as well as expected, likely due to low signal-to-noise from the nominal planets.

Instead, two algorithms based on the HT TSA were developed. The TSA based on the HT is based on the concept that a damaged gear tooth will cause contact data on another tooth. The period at which these two now damaged teeth mesh is the hunting tooth frequency (*HTF*),

$$HTF = {}^{Gear\ Mesh\ Freq}\!\Big/_{(\#Teeth\ Pinion\ \times \#Teeth\ Gear)} \tag{1}$$

For the OH-58 gearbox, the HTF is a relatively low frequency of 567.7/(99*35) = 0.1638 Hz. However, as we assumed, one tooth on a planet is damaged once per planet revolution; one can expect that the cracked tooth will have a reduced stiffness. This, in turn, this meshing will cause the gear mesh acceleration to be non-sinusoidal. As the damage increases (gear tooth stiffness reduces), the gear mesh acceleration will become more non-sinusoidal, or perhaps even impacts will be generated. In the Fourier domain, the result will be multiple harmonics spaced every 35 indexes.

Two gear CIs based on the HTF were developed. $CI1$ was based on the sums of the absolute value of the TSA Fourier transform (*fTSA*) for gear tooth order for the planet (35) to (35*99*4), which is the HT order * 4. The factor of 4 was chosen as there are four planets.

$$CI1 = \sum_{i=1}^{396} fTSA_{i\times 35} \tag{2}$$

The second analysis, $CI2$, is similar but normalized by the HTF spectral energy. Nominally, the planet gear mesh should have little modulation (as three other planet gears are synchronous to it), so the ratio should be proportional to the change in gear tooth stiffness.

$$CI2 = \sum_{i=1}^{396} {}^{fTSA_{i\times 35}}\!\Big/_{HFT} \tag{3}$$

Health Indicator/Thresholding

The CI data was normalized and fused into the health indicator (HI). The HI provides a common nomenclature/threshold across all components in the gearbox. This also facilitates a common remaining useful life (RUL) algorithm. The HI also provides process gain from data fusion, improving fault detection. Since the fault is initially unknown in this application, the HI algorithm performs a hypothesis test.

In the context of a hypothesis test, one assumes condition indicators (CIs) have a know PDF. This then allows the HI to be a function of the CI distribution. The HI function in the application is the weighted norm of *n* CIs (e.g., the normalized energy of *n* CIs), where the weights are determined by the Jacobian (the inverse covariance):

$$HI = {}^{0.35}\!/_{critPFA} \sqrt{\boldsymbol{Y}^T \boldsymbol{Y}} \tag{4}$$

Where $\boldsymbol{Y}$ is the whitened, normalized array of CIs, and *critFPA*, is the critical value of the test for some probability of false alarm (set at 1e-6). A hypothesis test calculates the critical value from the inverse cumulative distribution function (ICDF) for a given probability of a false alarm. For (4), the ICDF is the Nakagami where η is the number of CIs in the array and = *n*, and $\omega = \eta/(2-\pi/2)*2$; see [4]. A normalized HI > 0.35 for a component indicates that the null hypothesis is rejected. However, maintenance is not recommended until the HI > 1.

Whitening the CIs was done using a Cholesky decomposition [2]. The Cholesky decomposition of a Hermitian positive definite matrix results in $\mathbf{A} = \boldsymbol{LL}^*$, where $\boldsymbol{L}$ is a lower triangular, and $\boldsymbol{L}^*$ is its conjugate transpose. Because the inverse covariance is positive definite Hermitian, it follows that:

$$\boldsymbol{LL}^* = \boldsymbol{\Sigma}^{-1}\text{, then } \boldsymbol{Y} = \boldsymbol{L} \times \boldsymbol{CI}^{\mathrm{T}} \tag{5}$$

The matrix $\boldsymbol{CI}$ is the CIs from the first 146 acquisitions from the data set. The transformed vector $\boldsymbol{Y}$ is 1 to *146,* now uncorrelated CIs with unit variance. The Cholesky decomposition, in effect, creates the square root of the inverse covariance. This, in turn, is analogous to dividing the CI by its standard deviation (as in the case of one CI). It can be shown that $\boldsymbol{Y} = \boldsymbol{L} \times \boldsymbol{CI}^{\mathrm{T}}$ creates the necessary independent and identical distributions required to calculate the critical values for a function of distributions.

Trending and RUL Calculation

The study of material strength and fatigue has resulted in several contending theories on how components degrade due to high cycle fatigue [5]. After some testing of the fault propagation of the HI, it was found that the best RUL model was based on dislocation theory. In the model, the crack loading is in the anti-plan strain (Mode 3), and the plastic zone of the crack tip can be represented as a continuously distributed array of small dislocations on the crack plane. It is assumed that crack growth occurs when the accumulated plastic strain distribution at the crack tip exceeds some critical value and continues as this value is exceeded at the crack tip. The rate at which the crack grows per stress cycle in terms of displacement leads to the following:

$$^{da}\!/_{dN} = \frac{a^2 \sigma_{max}^4}{DE\sigma^3} \tag{6}$$

Where *da/dN* is the rate of change of the crack length, *D* is a material constant, σ is the gross stress, and *E* is Young's modulus. The assumption is that the gear HI is proportional to crack length *a*, so by inverting (6) and integrating and substituting HI for *a,* the RUL is:

$$RUL = {}^{dt}\!/_{dHI} \times HI_i \times \left(2 - 2\sqrt{HI_i}\right) \tag{7}$$

To solve (7) for an acquisition index, *i*, an estimate of the *HI* and *dHI/dt* is needed. For this, an α-β tracker was constructed [6], where the filter gains were calculated using the process variance is σ_w^2, plant noise variance is σ_v^2, and time from the last measurement (*dt*) to give:

$$\lambda = \frac{\sigma_w dt^2}{\sigma_v}, \text{ and } r = \frac{4+\lambda-\sqrt{8\lambda+\lambda^2}}{4}, \tag{7}$$

Then:

$$\alpha = 1 - r^2, \text{ and } \beta = 2(2-\alpha) - 4\sqrt{1-\alpha}. \tag{8}$$

Using these filter gains, α, β, the estimated HI and dHI/dt in [7] are calculated with each updated acquisition, where the filtered HI is *fHI*:

```
For each HIi update:
  fHIi = fHIi-1 + dHI/dti-1 * dt;    //Updated the Model
  rk = HIi - fHIi;
  fHIi = fHIi + α * rk;
  dHI/dti = dHI/dti-1 + (β*rk)/dt;
```

Reliability of the RUL

Conceptually, if the RUL algorithm returns 100 hours, and one hour of life is consumed, the RUL for a good model should be 99 hours. Intuitively, the derivative of the RUL should be -1, and for a stable model, the second derivative should be near zero. For this reason, the RUL from 7 is filtered using an α-β-g tracker.

Planetary Gear Fault Detection Results

The decision to trigger an alarm (e.g., HI > 1) is based on the filtered HI and was found to be acquisition 465 (record Day026_Hunting_SSA_20220114_132407). As this is a detection problem, it is depended on the probability of false alarm (set at 1e-6). A false alarm rate of 1e-3 would allow sooner reporting of the fault. From [1], the mean performance of the HI can be quantified for the nominal, the crack initiation, and propagation (Figure 1, 2, Table 1).

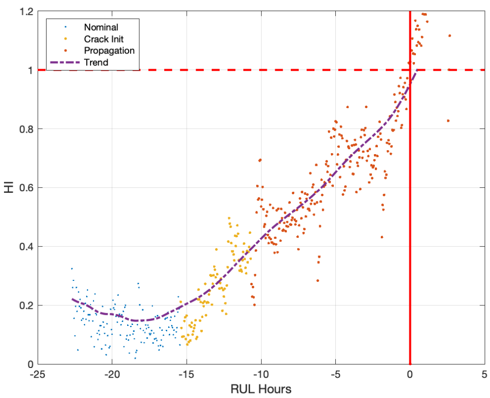

Figure 1 Planet Gear HI 1, RUL 0

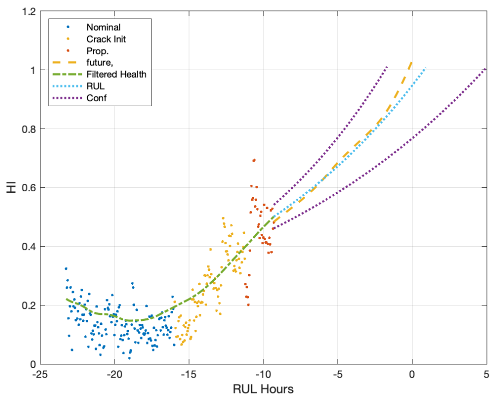

Figure 2 Planet Gear HI, with RUL of 10 Hours

Note that in Figure 1, the HI is at 1, alarm, with an RUL of 0. Figure 2 displays the HI at approximately 0.5, with an RUL of 10 hours. The confidence bounds are 90%. Note that the RUL matches the future HI trajectory as well. At this time, the *dRUL/dt* is -0.99, with the d^2RUL/dt^2 of 0.15. This would indicate that the confidence in the RUL is high. The damage rate grows exponentially after index 465, HI of 1.0. The time to reach an HI of 2 from HI 1 is acquisition 466 to 508, while for HI 2 to HI 3 is 509 to 524. The last two acquisition's HIs were 56 and 58!

Table 1 HI Statistics for the Planet Gear

Stage	Mean	Std Dev	Max	Slope (HI/dt)
Prior to Crack	0.18	0.28	2.4	0.012
Crack Init	0.28	0.17	1.5	0.032
Propagation	0.65	0.17	1.2	0.046

The estimated RUL is given in Figure 3. Note that the idealized RUL is just the time remaining until the HI is one, while the dislocation RUL is the filtered, data-driven RUL calculated from (7). In figure 1, there is no fault propagation until approximately -15 hours, so the estimated RUL is large. Once the fault starts to propagate, the estimated RUL quickly converges to the idealized RUL (approximately time, -10).

In Figure 4, the first derivative is approximately -1.0 from -13 to -2 hours, with the second derivative being near 0.0 from -9 to -2 hours. This indicates that there is high confidence in the RUL. Note that at time -2, there are a few HI measurements that are recorded at 0.6 to 0.8 HI (acquisition 417), which pulled the HI trend below 1.0 and increased the RUL value. The uses of the first and second derivatives indicate that confidence in the RUL is low. However, within two hours, 20 acquisitions later, the HI is greater than 1, indicating that maintenance should be performed.

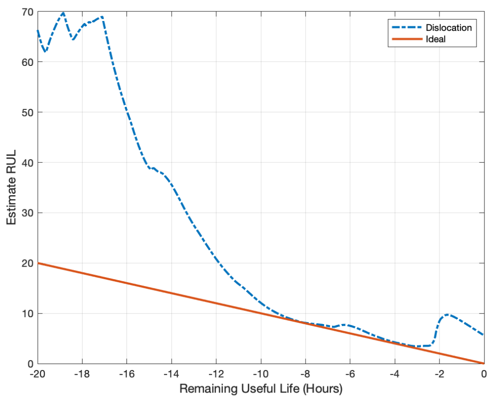

Figure 3 Planet Gear RUL

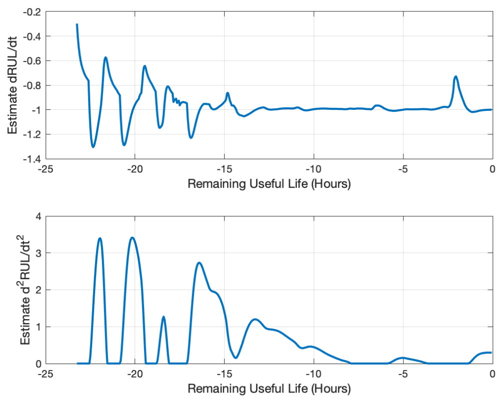

Figure 4 Planet Gear dRUL/dt and d^2RUL/dt^2

Conclusion

The hunting tooth frequency can be calculated from the gear mesh, divided by the product of the pinion and gear tooth count. Because of the low frequency (0.164 Hz), one period is long (about 6.1 seconds) and requires a long acquisition. For a planet gear fault, the TSA of the hunting tooth provided much improved signal to noise for feature extraction over the typical TSA of the plant shaft. It was hypothesized that the cracked planet tooth would produce non-sinusoidal acceleration that would be measured by the TSA. The Fourier transform of the TSA would reconstruct those features as multiple gear harmonics associated with the planet gear tooth. The energy associated with the harmonics was then used as a condition indicator (2,3).

The two CIs were then fused into a health indicator (HI). The HI was designed to have a probability of false alarm of 1e-6. The HI provided a common nomenclator across all monitored components: an HI > 0.75 is in warning, and maintenance should be planned. A HI > 1.0 is in alarm, and it is recommended that maintenance be performed. The HI trend and the first derivative of the HI were used to estimate the remaining useful life of the component using a dislocation theory equation (7). The best estimate of the HI and its derivative was calculated with an α-β tracker. A measure of the confidence in the RUL was calculated using the first and second derivative of the RUL, as intuitively, a well-modeled RUL should have a *dRUL/dt* of -1.0. That is, for each component usage, the RUL should be reduced by one hour.

The result of the system indicated that the planet gear should be removed from service at the 465 acquisition, where the HI was first greater than 1.0. The HI increased exponentially until an HI value of 58 was calculated at acquisition 526 (the end of the trial). The trend HI was used to calculate the RUL. The RUL with high confidence was calculated between -10 and -2 hours which was within 5% of ground truth.

The success of HUMS is dependent on the integration of signal processing for feature extraction, statics for fault detection, and modeling for predicting RUL. These functions, added together, allow HUMS to improve safety and reduce unscheduled maintenance. The demonstration of fault detection of a planet gear, a known difficult program, helps validate the effectiveness and value of HUMS of rotorcraft.

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