Process for Turboshaft Engine Performance Trending

Eric Bechhhoefer[1], and Fatemeh Hajimohammadali[2]

[1]*GPMS Int. Inc., Waterbury, VT,05675, USA*
eric@gpms-vt.com

[2]*Department of Energy, Systems, Territory and Constructions Engineering*
University of Pisa, Pisa, Tuscany, Italy
fatemeh.hajimohammadali@phd.unipi.it

ABSTRACT

Turboshaft engines are ubiquitous in aerospace applications where high power and reliability are needed in a low-weight package. Most all helicopters incorporate turboshaft engines. All turboshaft-equipped aircraft have power assurance checks to ensure the engine can achieve the minimum specification for power. However, these checks seldom are automatically collected, nor do they trend the engine health over time to better assess vehicle health. Engines degrade over time, and the ability to assess when maintenance is required is accentual for the safe and efficient operation of the aircraft. This paper covers a process to evaluate a turboshaft engine's state of health using a model-based assessment of the engine's performance margin over time.

1. THE NEED FOR ENGINE PERFORMANCE ASSESSMENT.

Turboshaft engines, for their weight and power outputs, are remarkably reliable. For example, the M250C47B engine on the Bell 407 aircraft (from which this data was measured as part of a Health and Usage Monitoring System – HUMS), weighing a mere 124 kg, can provide a continuous 600 kW of power. The engine has an overhaul period on the turbine of 2000 hours, while the compressor and gearbox are essentially on condition.

However (BHT-407-FM-3, 2018) states that periodically, power assurance checks need to be performed and that a negative margin requires maintenance as soon as practical. This periodic check ensures the pilot and maintainer that the engine is able to generate the specification power. Operationally, a positive margin (good engine health) allows the aircraft to be deployable for commercial missions. Perhaps as important, a reduced engine margin or negative margin means that more fuel is needed to generate the same amount of power. Over time this reduces commercial aircraft profitability and increases the aircraft's carbon footprint.

There are a number of causes for engine performance degradation. For example, accessories (barrier filters) will reduce performance in a stepwise manner as they restrict airflow to the compressor. This may be an operational necessity that needs to be accepted. Improper maintenance or failure/leaking of lines, such as bleed air, will also decrease performance. Detection of a step change in performance necessitates an inspection to resort safety and performance.

Long-term changes in performance are a function of fouling, corrosion, erosion, and excess heat. Heat may cause turbine blade creep, or dry partials in the airflow could fusion to the hot blade. In general, the flight manual has requirements for inspections if the engine. Some aircraft are equipped with HUMS (health and usage monitoring systems), which automatically alert the maintainer when engine exceedance occurs. Some exceedances are:

- Greater than 5 minutes when the engine is operated between 727 and 799c, or
- Not to exceed 843c for 10 seconds, or
- Not to exceed 927c for 1 second.

Corrosion occurs when chemical reactions of the internal parts and contaminants are introduced into the flow. The risk of corrosion is higher at extreme temperatures.

Fouling occurs when particular debris/contamination builds up on the turbine/compressor blade. By altering the shape/roughness of the blade, the airflow is reduced, and more need is required for the same amount of work. Typically, 70 to 85% of loss in engine performance can be attributed to compressor fouling, which can be corrected with an engine wash. Barrier filters and particle separators are often installed to reduce fouling. Erosion occurs again when particles enter the airflow. Erosion is an abrasive removal of material that, similar to fouling, increase surface roughness and impedes airflow.

While turboshaft engines have been the subject of many books and papers (Kurlikov, 2010, Wilson, 2014), few have approached engine performance margin/engine health as a vehicle health monitoring exercise. Chait and Balakrishnan (2013) used flight data recorder (FDR) parameter information to evaluate fuel burn vs engine performance. This was in the context of evaluating aircraft emissions. Using fuel flow and thrust, the paper highlights that the ICAO (International Civil Aviation Organization) Landing Takeoff Cycle (LTO) vs the actual FDR data differ, affecting emission inventories. This paper did not look at modeling engine health as a function of engine margin and did not use the data to trigger maintenance events.

In Nkoi, Pililisa, and Nikolaidis (2013), the authors model gas turbine engines to estimate design points. These were tradeoff studies to establish limits on thermal efficiencies. This is interesting as it may allow for more accurate modeling of a turboshaft engine to establish real-world performance margin and is more in keeping with the aforementioned books on turboshaft engine design.

In “Estimation of Performance Parameter of Turbine Engine Components Using Experimental Data in Parametric Uncertainty Conditions” (Khustochka et al, 2020), fuzzy sets theory was used for engine model identification using a small set of data. The paper points out that small measurement errors can result in high variational results. Using least squares methods was shown to have low stability. To improve results, a priori knowledge of the physical system was used to improve the stability and precision of the estimation. Again, this paper did not approach the identification problem as a way to calculate engine performance margin or to support health monitoring, but it does give insight into the complexity of accurately modeling engine performance.

Simon and Litt (2008) presented an automated power assurance test for the Blackhawk helicopter. This paper is interested in calculating the power available in supporting helicopter mission planning. The paper automates the Maximum Power check (MPC) procedure which is performed by a maintenance pilot by using data collected by the helicopter’s Health and Usage Monitoring System (HUMS). The automation concept did not extend to condition monitoring of the engine or establish a procedure for engine performance trending.

The paper is focused on a process of automating the collection of engine performance data and using this data to assess the engine’s margin. Using the margin, the health of the engine will be calculated, trended, and used to direct a maintenance action. This system was implemented on a HUMS (Foresight MX) to improve safety and availability for helicopters.

2. A PROCESS FOR MODELING ENGINE MARGIN

Helicopter manufacturers, such as Bell Fight, work with the engine suppliers to design power assurance checks a part of the Type Certificate (TC, see BHT-407-FM-3, 2018). This document allows the pilot or maintainer to record the measured engine torque (TQ), pressure altitude (PA), and outside air temperature (OAT) to calculate the maximum allowed measured gas temperature (MGT). The test is conducted when the aircraft in hover or level flight of 85 to 105 knots.

If the MGT is greater than that from the power assurance model, the engine requires maintenance as soon as practical. Note that the test is valid only under certain regimes. For a test to be conducted, the HUMS must be able to identify when it the aircraft is in an appropriate state. The HUMS function is called regime recognition. For a further description, see Bechhoefer and Kessler, 2022.

As noted, there are a number of environmental parameters that affect the power produced by the turbine engine, including Fouling, Corrosion, Erosion, and others such as

- Airflow from forward flight
- Fuel Mixture
- Governor Setting
- Fuel Injector atomization

to name just a few. The measurements which are available to determine engine turbine health, as previously noted: are OAT, MGT, PA, and TQ. These parameters are used by the power check procedure to indicate the maximum MGT. In this paper, MGT is converted to percent margin by normalizing using the modeled MGT for those measured conditions (see Figure 1).

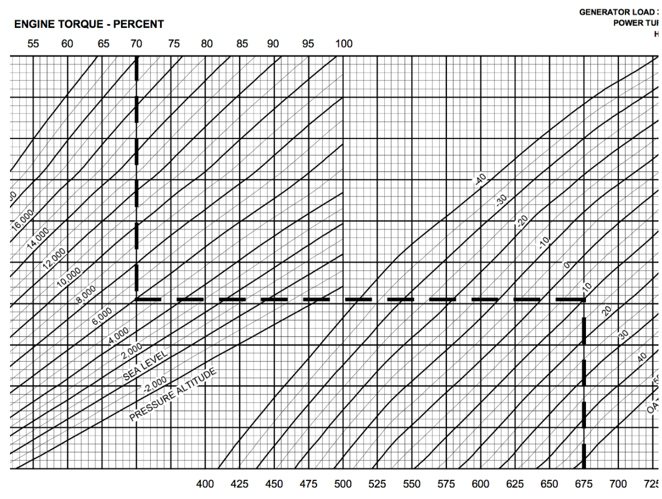

Figure 1 Engine Performance Table for Bell 407GX

As seen in Figure 1, the relationship between engine TQ, PA, OAT, and MGT is complex and not easily derived. As such, the manufacturer provides a table that allows one to, for a given TQ and PA, normalized by OAT, to derive the maximum allowed MGT for those operating conditions.

Automation of the process requires a mathematical way to map TQ, PA, and OAT to MGT. As the relationship is clearly nonlinear (see Figure 1), two bicubic splines were used to interpolate between given points from Figure 1. The construct of the output y, for, say, TQ x at given a PA, is:

$$y = Ay_j + By_{j+1} + Cy_j'' + Dy_{j+1}'' \tag{1}$$

Where:

$$A = {}^{x_{j+1} - x}\!/_{x_{j+1} - x_j} \tag{2}$$

$$B = {}^{x - x_{j+1}}\!/_{x_{j+1} - x_j} \tag{3}$$

$$C = {}^{1}\!/_{6}\,(A^3 - A)\left(x_{j+1} - x_j\right)^2 \tag{4}$$

$$D = {}^{1}\!/_{6}\,(B^3 - B)\left(x_{j+1} - x_j\right)^2 \tag{5}$$

For example, for the "Lefthand Side" (LS), the input is TQ and PA, and the output is a ***y*** value which is then the input to the "Righthand Side" (RS). The RS is then entered with OAT. The LS was designed with y values for TQ, for a given PA. There were 12 PA tables for -2000ft PA to 20,000ft PA. Example for the 4000 ft PA:

```
TQ = [44.5 53.7 63 72.5 82 91.4 100]
     Y = [0 5 10 15 20 25 30 34]
```

For the RS, there are ten OAT tables for MGT and the input y value from the LS. For 10C, as an example:

```
MGT = [524 585 635 680 725 780]
    Y = [0 10 18 26 33 40]
```

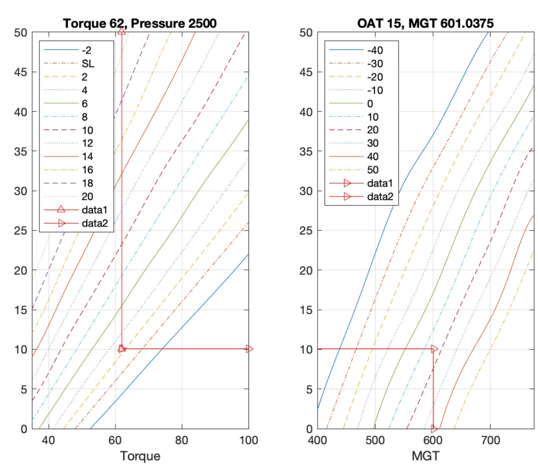

Figure 2 Bicubic Interpolation to Calculate Maximum Allow MGT

The bicubic spline for the LS takes the measured TQ parameter data and builds a series of interpolated y values for each PA, the interpolates those y's for the measured PA. The inverse process occurs on the RS using OAT to output the zero margin/minimum allowable MGT (Figure 2).

The input measurement for this example was 62% TQ, at 2500ft PA, with an OAT of 15. The output maximum MGT was 601.04C.

2.1. Conversion of MGT to Margin

As noted, the output of the analysis is the maximum allowed MGT. If the measured MGT is less than the model, the engine is running with a positive margin, which is good (eq. 6)

$$margin = (MGT_{modeled} - MGT)/MGT \times 100 \tag{6}$$

The margin for a typical Bell407GX is given in Figure 3. This HUMS data was approximately 5000 automated acquisitions over four years. Note that acquisitions were taken only in appropriate regimes of hover and between 85 and 105 knots. This period covered roughly 2000 flight hours.

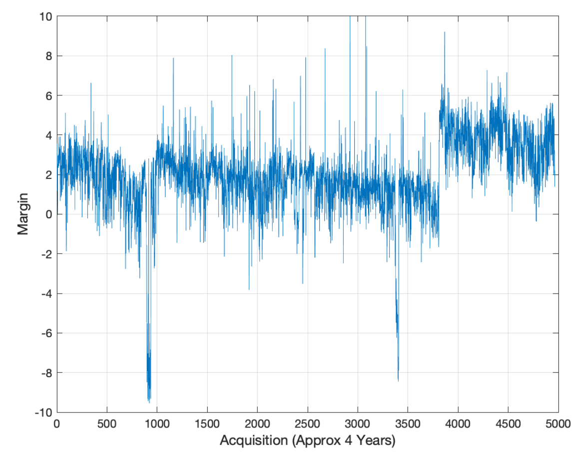

Figure 3 Calculated M250C47 Engine Margin

A couple of things to note. There are periods where the margin was negative, resulting in maintenance being performed (acquisition 896 and 3373). Additionally, the engine was replaced at acquisition 3811. The standard deviation of the margin is 0.94%. Of course, there is a general decrease in the margin, over time, probably due to fouling and wear of the engine. The first step change decrease was due to a bad bleed air value, while the second maintenance action was due to filter barrier damage. The HUMS detected the change in the margin as was used to initiate the maintenance action.

CHANGE POINT DETECTION, TRENDING, AND ENGINE HEALTH

In HUMS, there is a concept of component health. The health index (HI) should result in a maintenance action that restores the component to be fully mission capable. The HI uses condition indicators (CIs) with a clear correlation to a fault, in this case, the engine margin. That is, the decreased margin is a fault. Thus, the appropriateness of repairing the faulty engine can be seen as an action to restore the designed reliability of the system, driven by exceeding a HI threshold, typically set at 1.0.

A component with a high HI value does not define a probability of failure for the component, nor that the component fails when the HI is 1.0. Instead, defining maintenance at an HI of 1 initiates a proactive policy to change operator behavior. The desire is to reduce the cost and time associated with engine failure by performing maintenance prior to an unacceptable reduction in reliability, which would impact the safety of flight.

Given the relatively large standard deviation of the margin, it would improve the accuracy of HUMS if the margin and then the resulting engine health (HI) were trended. This is usually done with a low-pass filter. Trending takes into account the relatively low bandwidth of changes in engine health over time. It will, as a result, filter out step changes due to faults that are not associated with fouling/erosion, such as the bad bleed air value. For this reason, an automated method for step-change detection is needed. Once the step changes are identified, then it is a simple thing to trend between those identified step changes.

A step-change in component health occurs when an event, such as maintenance or damage/FOD, results in degradation or improvement to the HI value that is not associated with high cycle fatigue, fouling, or other low bandwidth degradation. That is, the HI trend does not adequately model events that are not associated with high cycle fatigue.

There are several statical procedures for detecting a change in process, such as a Shewart control chart or CUSUM (a sequential method for detecting a change in the mean value). However, we have found that in cases with high or time-varying standard deviations, neither method can capture the step change consistently. This suggests that for a generalized change detection algorithm, a more robust calculation of σ_d (time-varying over some length of window) is needed or that techniques other than CUSUM or Shewart may be more appropriate. For this reason, PELT was evaluated.

2.2. PELT for Change Detection

The Pruned Exact Linear Time method, as outlined in Haynes et. al. 2017, approaches change detection in a very different way than CUSUM or Shewart. In PELT, the approach is to identify multiple change points by minimizing a cost function, C, for a segment of the data along a penalty function, $Bf(m)$, to guard against overfitting:

$$\sum_{i=1}^{m+1}[C(y_{ti-1}+1):ti]+Bf(m)\ ] \qquad (7)$$

Algorithmically, PELT inputs are:

- A set of data, $y_1, y_2, \ldots y_n$
- A measure of the fit $C(.)$, which is dependent on the data,
- A penalty constant B, which is not dependent on the number or location of the change points

And a constant K, which satisfies:

$$F(t) + C(y_{(\tau+1):s}) + K > F(s) \qquad (8)$$

The algorithm is initialized by:

- n = length of the dataset,
- $F(0) = -B$
- $cp(0) = NULL$, and
- $R_1 = \{0\}$

Then for $\tau^* = 1, 2, \ldots, n$

- Calculate $F(\tau^*) = \min_{\tau^*} [F(\tau) + C(y_{(\tau+1):\tau^*}) + B]$
- Let $\tau^1 = \arg\{\min_{\tau^*} [F(\tau) + C(y_{(\tau+1):\tau^*}) + B]$
- Set $cp(\tau^*) = [cp(\tau^1), \tau^1]$
- Set $R_{\tau^*+1} = \{\ \tau \in R_{\tau^*} \cup \{\tau^*\}: F(\tau) + C(y_{(\tau+1):\tau^*}) + K < F(\tau^*)\}$

The output is the index of the change point.

2.3. The Trend Model

For trending, it was assumed that the rate of change in HI was bandwidth-limited, piecewise linear, and stationary. That is, the measurement noise, plant noise, and update rate are constant. As such, a forward/backward α-β tracker was used. This is a two-state filter of the HI, and its derivative.

Given the assumption of stationarity, the α-β tracker is treated as a steady-state Kalman filter. The filter coefficients for the α-β tracker (used for HI and dHI/dt) can be calculated as:

$$\lambda = \frac{\sigma_w dt^2}{\sigma_v}, \qquad (9)$$

$$r = \frac{4+\lambda-\sqrt{8\lambda+\lambda^2}}{4}, \qquad (10)$$

Where the process variance is σ_w^2, and plant noise variance is σ_v^2. The filter gains are:

$$\alpha_1 = 1 - r^2, \qquad (11)$$

$$\beta_1 = 2(2-\alpha) - 4\sqrt{1-\alpha}. \qquad (12)$$

The filter is then:

```
For i = 1:n,
       fCI = fCI + dCI x dt;
       rk = CI(i) - fCI
       fCI = fCI + α₁*rk;
       dCI = dCI + (β₁*rk)/dt;
```

Integration of change detection with trending greatly improves the ability of a maintainer to determine the degradation in the performance of the engine (Figure 4).

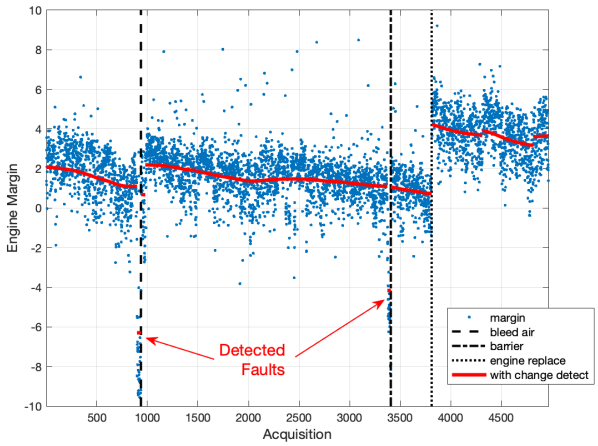

Figure 4 Engine Margin with Change Detection and Trending

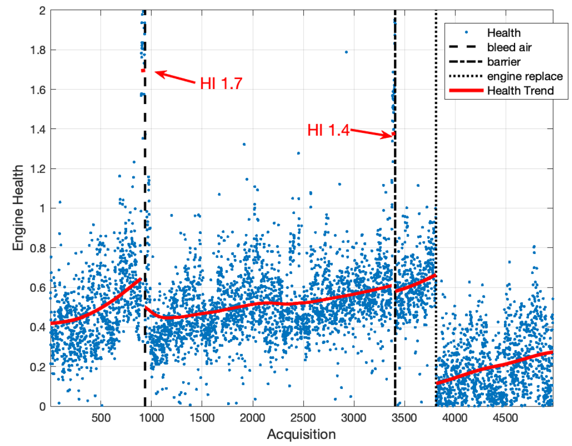

Figure 5 Engine Health with Change Detection and Trend

2.4. Engine Health

In the HUMS community, analysis of components results in condition indicators (CIs). As noted, the CI is typically some descriptive statistic of a fault feature. For a shaft, a CI might be Shaft Order 1 (SO1) magnitude, which is a measure of imbalance. Or, for a bearing, the CI might be relative to the envelope energy associated with the inner race. Conversely, the CI for Engine performance was the margin.

However, these various CIs have no common meaning other than some threshold. To improve human factors, the concept of Health Indicators (HI, See Jinks, 2016), as previously mentioned, is defined as "An indicator of the need for maintenance action for a component from either a single CI value or a combination of two or more CI values." The concept of the HI is such that the CI is mapped to the HI in such a way that all component indicators have a common threshold. From a maintainer perspective:

- The HI reflects the current component's damage.
- A warning (yellow) alert is generated when the HI is greater than or equal to 0.75: maintenance should be planned.
- An alarm (red) alert is generated when the HI is greater than or equal to 1.0. Continued operations could cause collateral damage.

With this in mind, the HI function for margin is given as:

- a new engine has a margin of 5%, and
- warning is defined at a margin of 0, then:

$$HI = \sqrt{((-margine + offset)/offset \times 0.75)^2} \quad (13)$$

Figure 5 is the HI, using eq (13) with the change point detection and trend.

Note that with change detection, it is easy to alert on the two events where the HI was greater than one: the leaking bleed air valve and the block barrier filter. This triggers the maintenance event and restores the engine to its design performance. With the change detection segmenting the trend, the degradation due to fouling (most likely cause) is easily seen. It is interesting to note that the engine replacement occurs when the HI is approximately 0.75, which is in keeping with the HI paradigm of planning maintenance when the HI is greater than 0.75. Again, the engine was pulled from service as 2000 hours of usage, per the manufacturer's scheduled time between overhauls.

CONCLUSION

Engine performance checks are a normal part of helicopter operations. They are required to ensure that the aircraft engine is meeting its design performance. The automation of engine performance checks gives a record that allows operators to enact maintenance better when required and enhances safety. However, the engine performance check as designed is more of a go, no-go indicator. Knowledge creation from a trend can better allow maintenance decisions to be made. This is facilitated by modeling engine performance as an engine margin calculation.

The automation of the process of calculating engine margin was done through two bicubic spline interpolations. This is enabled through the use of regime recognition in order to collect data only when the performance calculation is appropriate, at hover and between 85 and 105 knots. It was found that interpolation of engine performance using the bicubic spline resulted in a margin calculation was a standard deviation of 0.94%.

To help improve the decision-making process (e.g., when maintenance is needed), both change point detection and trending were incorporated. Change point detection reacts to high bandwidth step changes in engine margin, whereas trending reveals low bandwidth degradation in performance due to fouling or other types of slow engine degradation.

Finally, the engine margin was transformed into an engine health index, HI. This gives a common maintenance decision: plan maintenance when the HI is greater than 0.75 and do maintenance when the HI is greater than 1.0. The automation of engine health ensures: the reliability of the helicopter, enhances safety, and reduces cost (through reduced fuel consumption). The was implanted on a commercial HUMS system (Foresight MX). The data for this paper was from a Bell 407GX, connected over a period of five years. It is likely that trending of the HI will also allow estimation or remaining useful life (RUL). RUL allows operators to plan asset availability and utilization better by moving unscheduled maintenance to planned maintenance.

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BIOGRAPHIES

Eric Bechhoefer received his BS in Biology from the University of Michigan, his MS in Operations Research from the Naval Postgraduate School, and a Ph.D. in General Engineering from Kennedy Western University. He is a former Naval Aviator who has worked extensively on condition-based maintenance, rotor track and balance, vibration analysis of rotating machinery, and fault detection in electronic systems. Dr. Bechhoefer is a Fellow of the Prognostics Health Management Society, a Fellow of the Society for Machinery Fault Prevention Technology, and a senior member of the IEEE Reliability Society. Additionally, Dr Bechhoefer is also a member of the SAE committee covering Integrated Vehicle Health Management and a member of the MSG-3 Rotorcraft Maintenance Programs Industry Group. Dr. Bechhoefer is Helicopter Association International's "Salute to Excellence for Safety" for his work to introduce a low-cost/lightweight Health and Usage Monitoring System (HUMS) to the light single helicopter market.

Fateme Hajimohammad Ali graduated from Shariaty University- Iran with a degree in Electrical Engineering in 2014. Due to her interest in intelligent systems and control systems, she pursued a Master's degree in the field of Intelligent Control and graduated from KNT university in 2019. During her Master's studies, she conducted research on control systems and fault detection systems in the industry using data analysis, signal processing, artificial intelligence, machine learning, and other techniques. Currently, she works as a Ph.D. researcher in the DESTEC department at the University of Pisa. Her main field of activity is the implementation of fault detection systems in various industrial sectors using artificial intelligence especially deep learning concepts. She is currently responsible for launching a project to set up intelligent systems for fault detection in hydroelectric power plants.