A Process for Real-Time Performance Monitoring of a Turboshaft Engine

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ABSTRACT

For helicopters engaged in sling loads or heavy lift, there is a need to report current turboshaft engine health (e.g., margin) and contingency power available from the engine in real-time. Displaying this information allows the pilot in command of the aircraft to make more informed decisions about the safety of continuing a mission. For engine margin, when aircraft parameter data is recorded by a health and usage monitoring system (HUMS) or flight data monitoring system (FDM), this functionality allows maintainers to be notified of the engines' degraded performance to initiate an inspection/maintenance action to restore the engine to its designed performance. However, this does not help the pilot make mission-critical decisions during the flight. The paper covers the method to use HUMS/FDM data to calculate, in real-time, the power available to the pilot.

1. SOME BACKGROUND ON HELICOPTERS AND TURBOSHAFT ENGINES

Turboshaft engines are ubiquitous in aerospace applications where high power and reliability are needed in a low-weight package. Most 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 provide information during an actual mission (flight) to indicate current engine health or power available. In many cases, the check looks at the engines' measured gas temperature (MGT) vs. an idealized MGT model to determine if the engine is operating properly.

Engines degrade over time, and assessing when maintenance is required is essential for the safe and efficient operation of the aircraft. For many operational missions, knowing the current engine performance will allow the pilot in command to make a go/no-go decision about continuing with the mission.

Turboshaft engines are for their weight and power and 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 273 lbs., can provide a continuous 804 horsepower (HP) of power. The engine has an overhaul period on the turbine of 2000 hours, while the compressor and gearbox are essentially on condition.

As noted, helicopters perform periodic tests to ensure the engine, compared to a nominal healthy condition, is operating at its design specification. For example, for the Bell 407, the flight manual (BHT-407-FM-3, 2018) states that periodically, power assurance checks need to be performed and that if the measured MGT is greater than or equal to some nominal temperature value, then maintenance is required. In this case, the modeled MGT is a function of pressure altitude (PA), outside air temperature (OAT), and the measured torque. However, this check does not determine the power available, e.g., torque, in real-time.

In the case of power assurance checks, which compare the operational MGT to the notional/modeled MGT. This is a go/no-go criterion. That is, if the HIT check MGT is greater than the notional MGT, maintenance is performed. Often, to make this trendable over time, an engine factor is calculated.

$$engine\ factor = \frac{nMGT - MGT}{nMGT} x\ 100 \tag{1}$$

Where *nMGT* is the notional MGT.

A positive temperature factor indicates the engine is operating as designed. Often, an engine fresh out of rework will have a 5 to 7 percent positive engine factor. Other power assurance checks for different engines may compare engine performance metrics such as torque or expected compressor RPM (Ng). In any case, the ratio of the difference of measured to expected performance indicator can be considered a margin, where a positive margin is indicative of the engine meeting its design parameters. In contrast, a negative margin would indicate engine performance degradation and the need for maintenance.

There are several causes for engine performance degradation. For example, accessories (barrier filters) will reduce performance stepwise by restricting airflow to the compressor. A barrier filter 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 restore safety and performance. A step change in engine performance during a flight cannot be detected with a power assurance check prior to the operation. This is another reason for the need for real-time monitoring.

Long-term changes in performance are a function of fouling, corrosion, erosion, and excess heat. Heat may cause turbine blade creep, or facilitate dry partials in the airflow to fuse to the hot blade.

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 debris/contamination builds up on the turbine/compressor blade. By altering the shape/roughness of the blade, the airflow is reduced, and more fuel is needed 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, like fouling, increases surface roughness and impedes airflow.

Finally, foreign object debris (FOD), or any object found in an inappropriate location, can be ingested by the engine and cause damage to it. While fowling, erosion, or corrosion degradation can accrue over time, FOD damage can be sudden (step change), resulting in a reduction in engine performance.

The engine itself will have exceedances-based turbine RPM, Ng RPM, MGT limitation, and torque limitation. For example, at takeoff, a helicopter with a heavy gross weight (due to fuel) can run for a limited period of time at an MGT or Ng higher than it could continuously. For multi-engine aircraft, such as the EC-135, UH-60A, and Bell 429, the torque and MGT for one engine inoperative (OEI) are higher than in normal operation. These contingency cases allow the pilot in command to make decisions in real-time on how the aircraft is operated to complete its mission safely.

ANALYSIS: ENGINE HEATH

The performance of turboshaft engines is subject to thermodynamic analysis (see Hill, 1992). In general, turboshaft engines in helicopters have an inlet, a compressor (which is driven by the high-pressure turbine, HPT), a burner, and a low-pressure (or free) turbine (LPT). The HPT's RPM is governed, typically 100%, and provides torque to the load, which drives the rotors to supply thrust.

Using real-world data from the RR M250C47 engine as an example, it is possible to build a simplified, physics-informed model to estimate the turbine's max continuous power, contingency power, and current power. The ratio of the difference in measured power to the modeled power, divided by model power, is the margin. If the margin is negative, sustained, and significantly below the error in the model, the aircraft may not have the power available to complete the mission, and the pilot in command may decide to change their mission profile.

1.1. Building the Power Assurance Check

Environmental parameters 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.

For the M250C47 engine, the measurements available to determine engine turbine health are OAT, MGT, PA, and TQ. The power check procedure uses these parameters to indicate the maximum allowable MGT. However, in this paper, the inverse problem is solved using MGT, OAT, and PA to estimate the modeled torque (see Figure 1).

As seen in Figure 1, the relationship between engine MGT PA, OAT, and TQ is complex and not easily derived due to turbulence in the burner and other non-idealized metrics of the engine itself.

That said, there is some function of MGT, PA, and OAT that estimate TQ:

$$TQ = f(MGT, OAT, PA) \tag{2}$$

The function could be defined by several machine learning algorithms. However, training data based on real-world data would bias the results to the sampled engines' health. To better model a zero-margin (idealized) engine, the inverse problem could be solved in that for a range of OAT, PA, and MGT, the estimated zero-margin torque could be found. Then, with this dataset, in real-time, a machine-learning model could be built and referenced to the ideal engine.

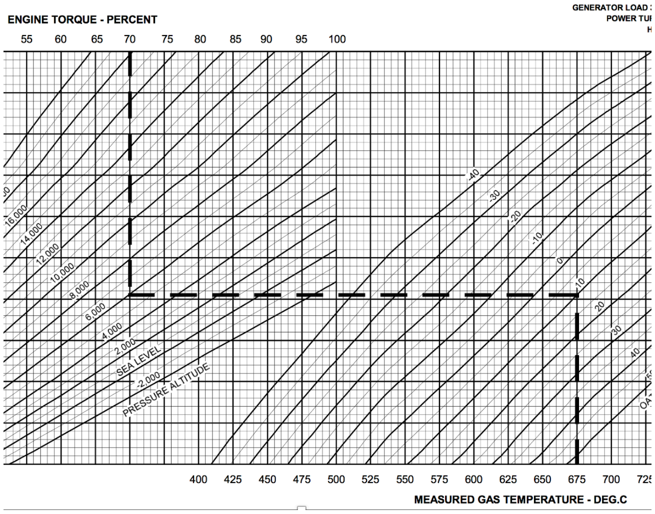

Figure 1 Engine Performance Table for Bell 407GX

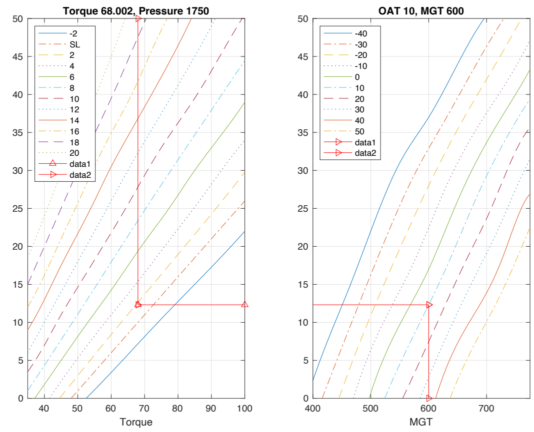

Figure 2 Using the Bicubic Spline to Solve the Inverse Problem

1.2. Building the Test Dataset

To automate the process required to build the dataset, for each curve in Figure 1, points on the x-axis were selected to build a spline. This spline output data is then used to build a second spline in the y-axis, known as a bicubic spline. In the model, two bicubic splines were used to solve the inverse problem in Figure 1. That is, of the output *y*, for, say, MGT of 600F, as given an OAT of 10, is:

$$y = Ay_j + By_{j+1} + Cy_j'' + Dy_{j+1}'' \tag{3}$$

Where:

$$A = {x_{j+1} - x} / {x_{j+1} - x_j} \tag{4}$$

$$B = {x - x_{j+1}} / {x_{j+1} - x_j} \tag{5}$$

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

$$D = {1}/{6}\,(B^3 - B)\left(x_{j+1} - x_j\right)^2 \tag{7}$$

See Press et al. (1992) for more details on bicubic splines. In solving the inverse problem, the "Righthand Side" (RS), the input is MGT and OAT, and the output is a ***y*** value, which is then the input to the "Lefthand Side" (LS). The LS then enters with PA (say 1750). The RS was designed with *y* to return 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:

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

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

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

The bicubic spline for the RS takes the measured MGT parameter data and builds a series of interpolated *y* values for each OAT, then interpolates those *y's* for the measured OAT. The inverse process occurs on the LS using PA to output the zero margin/minimum allowable TQ (Figure 2, 68.002% Torque).

To build the dataset, a range of MGT, OAT, and PA were used to define the zero-margin torque output TQ:

- MGT = 400 to 740, every 20 degrees
- OAT = 0 to 35, every 5 degrees.
- PA = 0 to 15000 feet, every 1000 ft.

This gave a relatively small training dataset of 724 test cases.

1.3. Selecting a Machine Learning Algorithm

One question is, given the ability to solve the inverse problem for TQ, based on MGT, PA, and OAT, why not implement the two bicubic spline models to run in real-time on an embedded processor? This was not a consideration, as most embedded processors for avionics have finite computational resources. Hammering away on the problem for an 8Hz display would likely tax the ability of the embedded to keep up with the display. Instead, a more straightforward, linear regression model was trained for ***b***, giving the inputs from the bicubic spline model for OAT, PA, and MGT as:

$$X = \left[1, \sqrt{PA}, PA, \sqrt{OAT + 273}, \sqrt{OAT + 273} \times \sqrt{MGT}\ \right] \tag{8}$$

This allows for a low computation model to estimate TQ as:

$$\widehat{TQ} = \boldsymbol{X} \times \boldsymbol{b} \tag{9}$$

Where ***b*** is the regression coefficient, and TQ (hat) is an estimator for TQ. Solving for ***b*** is easily performed using the pseudo inverse, giving a least square error solution:

$$\boldsymbol{b} = (X' \times X)^{-1} \times X' \times TQ \qquad (10)$$

The computational requirement for the inverse is small, as the inner product of the *Xs* is only a 6x6 matrix.

We can evaluate the fit by looking at the standard deviation of the residual (the difference between the model TQ and the regression TQ), which was 0.67%, and the correlation coefficient, R^2, of 0.998 (Figure 3). For more information on the evaluation of regression fit, see Wackerly (2008).

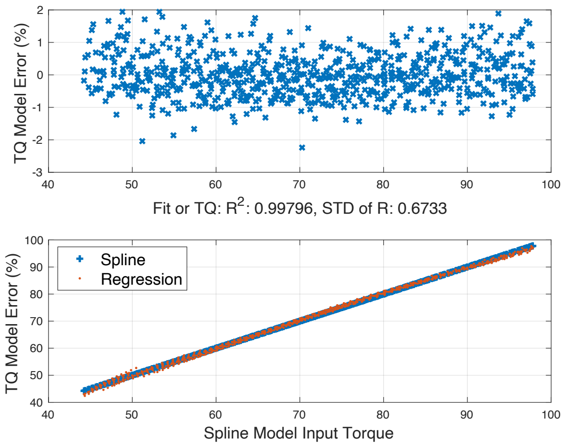

Figure 3 Regression Residual and Model Fit for using Eq 8

For the residual, it is seen that the model fits well and has variance relatively independent of TQ.

The selection of the model in eq 8, particularly the product of OAT (reference to absolute zero) and MGT, takes into account the non-linear relationship between them and pressure altitude.

1.4. Test Cases

The Bell 407 was installed with a HUMS, which, among other functions, performs flight data monitoring (FDM, recording of aircraft parameter data) and automates the power assurance check (Fig 1). In the example, the aircraft is performing a typical inspection mission. This includes a transit on-site, patrol, and return to base. On landing, the pilot reported that the aircraft seemed to lack power. The HUMS, after automatically downloading the mission data, triggered an alert for an engine power assurance check. The MGT margin was -6.29%, requiring an inspection. However, the power margin, calculated using (8) was -17% (mean value, Figure 4). This indicates that the power available was much less than expected. If the mission success was dependent on being able to complete a heavy lift, such as a sling load, knowing that the engine was not making its expected power would be important information for the pilot.

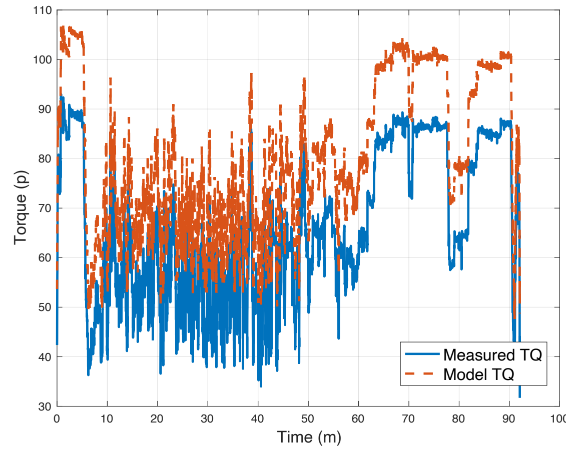

Figure 4 Failed Power Assurance Check with Mean Power Margin of -17%

The post-flight inspection revealed that the engine bleed air valve was leaking. The valve was repaired, and the aircraft returned to service. These types of events are rare. In fact, in monitoring over 50,000 operational hours, we have only observed this type of event 23 times.

In general, we see that the engine runs a positive MGT margin. The margin is typically 2 to 5%, depending on the age of the engine, when the last compressor wash was performed, and other environmental considerations. Figure 5 shows a typical mission with a power assurance check for MGT of +2.2% and a mean power (TQ) margin of 10.3%.

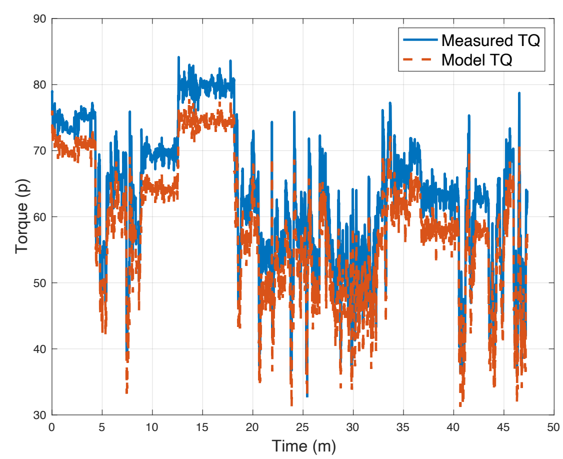

Figure 5 Typical Positive Margin Mission

2. OTHER CONSIDERATIONS: POWER AVAILABLE

The pilot/flight crew, at any time, may want to know what power is available from the engine. Power available is a function of limits of other engine parameters, such as compressor RPM (Ng), MGT, and TQ itself. As an example, an engine may have (as per the flight manual) a maximum continuous operating MGT of 810F. What TQ can be produced at 810F for the current OAT and PA? Additionally, this engine has a 30-minute limit of 851F and a 12-second limit of 878F. Other operating limits might are Ng (102p for 12 seconds). Finally, the gearbox itself has a limit for TQ, of 110%.

Following the logic of Eq 2., we built a relationship between Ng and MGT. That is, there is some function where:

$$Ng = f(MGT) \tag{11}$$

Again, there are any number of potential solutions to the Ng function based on machine learning, either regression, artificial neural network (ANN), or some other approach. As an example, using regression, a potential model is:

$$\boldsymbol{X} = \left[1 \;\; PA \sqrt{MGT_i} \;\; MGT_i \right] \tag{12}$$

where:

$$\widehat{Ng} = \boldsymbol{X} \times \boldsymbol{b} \tag{13}$$

Figure 10 shows the relationship between MGT and Ng and the estimate of the regression model. Again, other ANN/ML techniques could be used to estimate Ng from MGT or other aircraft parameters.

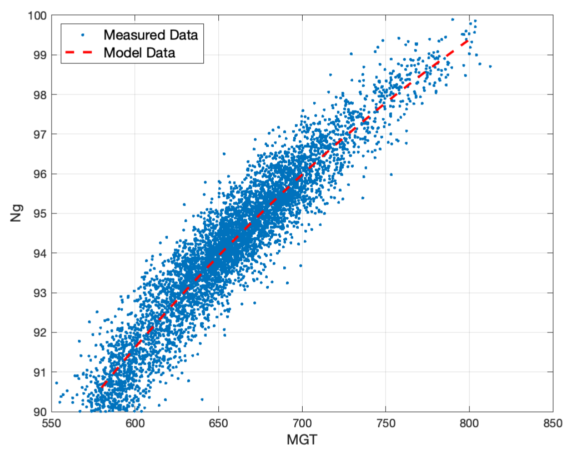

Figure 6 Relationship Between MGT and Ng

Of course, this requires a separate model for predicting an estimate of TQ based on Ng. Again, we will rely on regression. NOTE: The measurement error for the acquisition system is approximately 0.5%, which can explain some of the scatter in the data.

Given an estimate from MGT for Ng and using Ng to estimate TQ in real-time, the contingency power limits can be calculated to estimate their respective values and limits for display to the flight crew. In this example, in real-time, the estimated Ng is calculated for MGT for, say, 810F, using max continuous MGT, for a pressure altitude of 1514 ft, at time *i*, is then:

$$99.6 = \left[1 \; 1514 \; \sqrt{810} \;\; 810\right] \times \boldsymbol{b\widehat{Ng}} \tag{14}$$

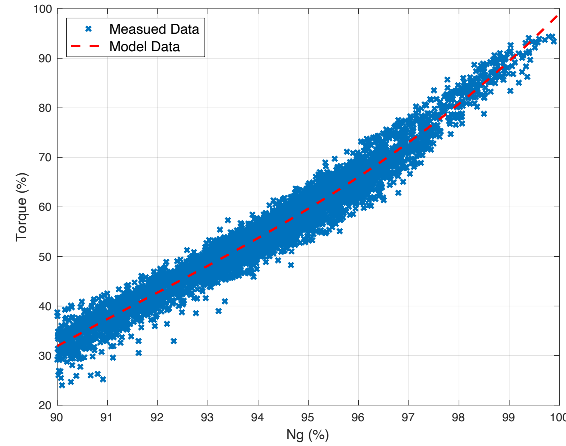

Figure 7 Relationship Between Ng and TQ

Then, a test is performed to ensure that Ng, at the current time, does not exceed its limit of 102%. With these estimated Ng values, the estimated normalized contingency power can be calculated for max continuous power for the current PA and OAT (using a regression model):

$$94.5 = \left[1 \;\; \sqrt{99.6} \;\; 99.6 \; 99.6^2\right] \times \boldsymbol{b} \tag{15}$$

This would indicate that the max continuous TQ for the current PA, OAT, and Ng is 94.5%.

2.1. Display Considerations

In practice, this information would be displayed in real-time on an accessory display (not on the primary). This is because there are software certification issues with using the primary display (DO-178C, DAL A). Additionally, the likely deployment is a retrofit application into an existing helicopter, where the HUMS would drive the display directly. Considering that it is not often that new helicopters or aircraft are produced, retrofitting a system is a common practice via a supplemental type certificate (STC).

Another consideration is that all models have errors, and developers must be concerned with false alarms. That is, saying maintenance is required when, in fact, the engine is good. Therefore, a real-time display would indicate an acceptable range of margin so that the pilot in command, in real-time, can be informed of the power available and engine health. For example, in Figure 8, the measured torque is 63%, the model estimates the max continue torque as 94.5%, and the 30-minute limit is 106%. The 12-second limit is greater than the 110% limit of the transmission – so the limit is just 110%. Note that the model's estimated torque for this condition is 66.7%. That is, the engine is running at -3.7% (negative) margin. The error in the model is 2% (3 standard deviations of the residual error), which gives a range of "within limits" error of 64.7% to 68.7% TQ (although running a positive margin is not bad, a significant positive margin could indicate a model failure or measurement error).

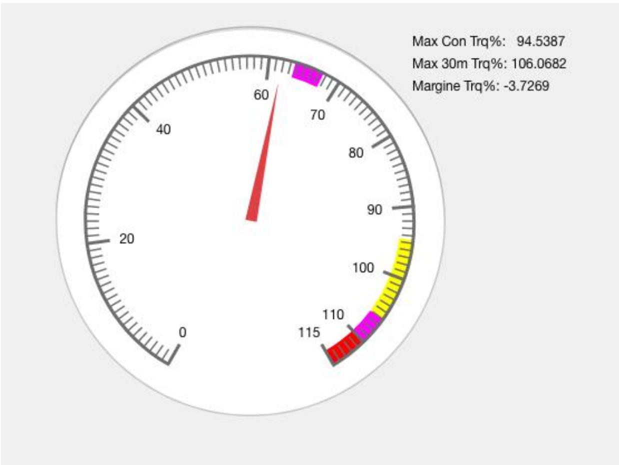

Figure 8 Example of Torque Margin and Power Available Cockpit Display

A prolonged and persistent negative margin would indicate degraded engine performance. In this case, the gauge indicator would be changed to red. A HUMS/FDM would then report this as an inflight exceedance. The report of an exceedance by the pilot, flight crew, or the HUMS would initiate an engine inspection to restore the engine to its design performance.

3. CONCLUSION

The paper is concerned with estimating, in real-time, a turboshaft engine margin (e.g., performance) and power available. While all engine manufacturers have power assurance tests, these are conducted at the beginning of the flight for one operating condition. Most power assurance checks measure performance based on measured gas temperature (MGT), not torque (TQ). As turboshaft engines run at 100%, TQ is proportional to power.

Using the bicubic splines, the inverse of the power assurance check is used to estimate TQ based on MGT, pressure altitude (PA), and outside air temperature (OAT). While machine learning approaches could build a relationship between MGT and TQ, it would only be for the engine on which the data was collected. What if the engine is running below margin? Using the standard power assurance test as a model allows for an absolute performance measure.

A real-time model can also provide other aircraft safety information, such as the available contingency power. Turboshaft engines have RPM limits for the compressor (Ng), temperature, and torque limits. Both the Ng and MGT limits directly affect the torque that can be generated by the engine. Providing real-time power available for max continuous, 30-minute, or 5-minute (as per the flight manual) gives information that the aircrew will use in executing their mission.

This model is for predicting torque margin and contingency power but is built using linear regression. These models have low error and are computationally easy to implement in a real-time system.

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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.

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.