Recent Case Studies in Bearing Fault Detection and Prognosis

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Outline

1. Introduction and Prognosis Architecture
2. Incipient Fault Detection System and Algorithms
3. Data Collection and Analysis
   - T-63 Engine Test Cell
   - Engine OEM Rig Testing
   - Bearing OEM Test Cell
   - CH-47 Swashplate Bearing
4. Conclusions
Bearing Prognostic Architecture

Current/Future Capability Prediction

Will it last the next X missions?
What operational changes will extend life?
What logistics trigger enacted?

Probabilistic Fusion Process

Expected Operating Conditions

Reliability Information

Feature Fusion

Automated Fault Classifiers

Feature Extraction

Vibration

Debris

Temp, etc

Damage Model Selector

Spall Initiation

Fretting Damage

Spall Propagation

Sliding Wear

Feature

Expected Operating Conditions

0
-0.015
-0.01
-0.005
0
0.005
0.01
0.015
-0.015
-0.01
-0.005
0
0.005
0.01
0.015

Failure
Good
Marginal
Mild Wear
Critical

Failure
Good
Marginal
Mild Wear
Critical

0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Will it last the next X missions?
What operational changes will extend life?
What logistics trigger enacted?

Expected Operating Conditions

Reliability Information
Vibro-Acoustic Monitoring

- Rotodynamic Faults
- Vibration-Based D&P
- AE-Based D&P
- High Frequency Transducer
- Broadband and Narrowband AE Transducers

Material Stress Symptoms and Incipient Fault Detection
Detection Horizon Provided

- Rotodynamic Indicators
- End-of-Life Indicators
- Diagnostic Localization and Severity Assess

- Typical Turbine Engine Response

- Industrial-Grade Accelerometer
- Precision-Grade Accelerometer
- HFD Analysis

10 kHz 50 kHz 100 kHz 200 kHz 500 kHz
Bearing Incipient Fault Detection
Elements and Process

Sensor

DAQ
- Anti-alias
- A to D

Sensor Validation
FirstCheck™

Feature Extraction

Outputs:
- Bearing Health Index
- Confidence
- Variance/Std Dev.

Inference

Database:
- Fault features
- Baseline features

Reasoner

Feature Fusion

Band Selection
ABS

Feature Extraction
ImpactEnergy™

Feature Normalization

Feature Trend
Bearing Failure Mechanism Progression

- Failure occurs in stages
- Symptoms start at high frequency excitation and move toward lower frequencies as damage progresses
- Coupling high frequency vibration techniques with models can provide best confidence in predictions
Statistical Feature Detection

Detection Theory, Uncertainty and Threshold Settings

\[ P(FA) = 1 - P(CR) \]
\[ P(D) = 1 - P(MD) \]
T63 Engine Bearing #2

Incipient Fault Testing
Overview

- Tests conducted at Wright-Patterson Air Force Base in June 2005
- Rolls Royce T63 turboshaft helicopter engine test cell
- Two different independent seeded faults: dent and spall on inner race of Bearing #2
- Vibration data collected for fault detection analysis
Test Bearing Conditions

Three Bearing Conditions:

- **Healthy**
  - Used but in good condition

- **Dented**
  - Two Brinell Hardness Indents on inner race
  - Inner raceway wear path

- **Spalled**
  - Spall initiated in Minisimulator from a Brinell mark on inner race
  - Dimensions 0.3 in x 0.25 in
  - ~8 hrs at 12,000 RPM
Engine Operating Conditions

Typical Test Cycle

<table>
<thead>
<tr>
<th>Bearing Condition</th>
<th>Cycle Numbers</th>
<th>Total Cycles</th>
<th>Operating Hours (approximately)</th>
<th>Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>3-4</td>
<td>2</td>
<td>1.1</td>
<td>6/10/05</td>
</tr>
<tr>
<td>Spalled</td>
<td>14-17</td>
<td>4</td>
<td>2.25</td>
<td>6/16/05</td>
</tr>
<tr>
<td>Dented</td>
<td>18-74</td>
<td>66 (Three Runs)</td>
<td>43</td>
<td>6/14/2005; 6/20/05-6/30/05</td>
</tr>
</tbody>
</table>
Broadband Analysis: False Alarms?

NOTE: The results presented here were taken from the military speed portion of the tests.

High False Alarm Level

High Missed Detection
Statistical Feature Extraction (Broadband RMS)
Frequency Feature Extraction
(Narrowband IE BPFI)

Typical Test Run

Run Time (sec)

Shaft Speed (RPM)

Gas Producer Turbine (rpm)

PLA Power Turbine (Governor)

Dented shift

Spalled shift
Dented Bearing Fault Progression

After 1st Dented Run

ImpactEnergy™ BPFI

ImpactEnergy™ Analysis

After 2nd Dented Run

After 3rd Dented Run
Narrowband Feature

- Significant reduction in False Alarms
- Increase in Mean and Variance of faulted distributions
T-63 Test Observations

- Broadband analysis is a mild (yet inconclusive) indicator of faults
- Preferential bands enable fault identification and progression
- Narrowband features provide good statistical separation of healthy and faulted cases
- Narrowband features compensate for effects of tear down and assembly
- Reduced false alarm and missed detection rates
Engine OEM Bearing Rig Testing: Hybrid Ceramic Bearing Fault Detection
## Monitoring System Hardware

<table>
<thead>
<tr>
<th>Channel</th>
<th>Type</th>
<th>Location</th>
<th>Sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Accelerometer</td>
<td>12:00 O’Clock</td>
<td>200 kS/s</td>
</tr>
<tr>
<td>2</td>
<td>Accelerometer</td>
<td>2:00 O’Clock</td>
<td>200 kS/s</td>
</tr>
<tr>
<td>3</td>
<td>Accelerometer</td>
<td>8:00 O’Clock</td>
<td>200 kS/s</td>
</tr>
<tr>
<td>4</td>
<td>Accelerometer</td>
<td>10:00 O’Clock</td>
<td>200 kS/s</td>
</tr>
<tr>
<td>5</td>
<td>Thermocouple</td>
<td>12:00 O’Clock</td>
<td>5 kS/s</td>
</tr>
<tr>
<td>6</td>
<td>Thermocouple</td>
<td>2:00 O’Clock</td>
<td>5 kS/s</td>
</tr>
<tr>
<td>7</td>
<td>Thermocouple</td>
<td>8:00 O’Clock</td>
<td>5 kS/s</td>
</tr>
<tr>
<td>8</td>
<td>Thermocouple</td>
<td>10:00 O’Clock</td>
<td>5 kS/s</td>
</tr>
<tr>
<td>9</td>
<td>Tachometer</td>
<td>Low Spd Shaft</td>
<td>5 kS/s</td>
</tr>
<tr>
<td>10</td>
<td>Tachometer</td>
<td>High Spd Shaft</td>
<td>5 kS/s</td>
</tr>
</tbody>
</table>

- **Test Bearing**: J-Type Thermocouples
- **PCB 357B14**: Accelerometers
Test Configuration

 Emerald Hybrid Test Bearing
 • Silicon nitride rolling elements
 • Metallic races
 • Angular contact geometry
 • Rolling Element Seeded Fault

 Speed and Load Profile
 • Stage 1 100% axial load 100% speed
 • Stage 2 48% axial load 93% speed

 Data Acquisition
 • 2 seconds of data every two minutes
 • Over 700 GB of data; over 1100 hrs of testing
Overview of Damage Progression

Incipient Anomaly Detection  
Run Time: 575 hrs

Accelerometer 2 Energy Feature 1

Severe Damage Propagation  
Run Time: 575 – 774 hrs

Quasi-Steady State Cyclic Fatigue Periods

Near End-Of-Life Damage Propagation  
Run Time: 1000 – 1100 hrs

*Note: Typical of Accelerometers 1-4
Failure Mode Identification

Accelerometer 2 Outer Race Feature

Ball Spall Propagation

Accelerometer 2 Ball Feature

Outer Race Spall Propagation
Statistical Detection Analysis

Accelerometer 2 Energy Feature 1

- False Alarm: 2.0%
- Incipient Detection: 97.0%
- Severe Fault Detection: 100%
- Incipient Fault Threshold: 20.3
Statistical Fault Detection Summary

- **False Alarm Seeded Fault**: 15.4%
- **Missed Detection Seeded Fault**: 5.5%
- **Threshold**: 0.1524

- **False Alarm Seeded Fault**: 7.62%
- **Missed Detection Seeded Fault**: 9.23%
- **Threshold**: 0.0227

- **False Alarm Seeded Fault**: 2.12%
- **Missed Detection Seeded Fault**: 4.64%
- **Threshold**: 0.0081

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**Cumulative Probability Percentage**

- **False Alarm**: 0%
- **Missed Detection**: 0%

**IE-ABS Optimized**

- **False Alarm**: 0%
- **Missed Detection**: 0%

**IE-no ABS**

- **False Alarm**: 0%
- **Missed Detection**: 0%

**Broadband 0-1kHz**

- **False Alarm**: 0%
- **Missed Detection**: 0%

**Broadband 0-25kHz**

- **False Alarm**: 0%
- **Missed Detection**: 0%
Ceramic Bearing Test Observations

- Vibration-based ImpactEnergy™ processing provides clear race spall detection with high confidence
  - Corroborated by estimate of ground truth and debris measurements
- Current vibration technology is extensible to hybrid ceramic bearings
- Technology validated and verified with full scale engine bearing rig through successful detection of a both incipient and severe faults
Bearing OEM Test Cell

Seeded Fault Detection and Progression
Monitoring System Hardware

DAQ Hardware

Exterior Accelerometer Location G

Exterior Accelerometer Location H
Test 2: Statistical Detection

Outer Race Anomaly Feature

False Alarm.................. 2.0%
Incipient Detection........... 82.8%
Severe Fault Detection.... 99.1%
Threshold....................... 0.105
Test 5: Statistical Detection

Outer Race Anomaly Feature

Run 2 Probability of Detection: 93.1%
Run 3 Probability of Detection: 99.4%

18.3 Hours
Spall Size: 0.44in x 0.34in

24.0 Hours
Spall Size: 1.13in x 0.5in

26.6 Hours
Spall Size: 1.3in x 0.5in
Test 5: Prognosis

![Graph showing the accumulated run time and spall sizes for different runs.]

- **Run 1**: 10.1 Hours, Spall Size: 0.14in x 0.12in
- **Run 2**: 18.3 Hours, Spall Size: 0.44in x 0.34in
- **Run 3**: 24.0 Hours, Spall Size: 1.13in x 0.5in
- **Run 4**: 26.6 Hours, Spall Size: 1.3in x 0.5in
Test 14 Results Under Speed & Load Cycle

Initial Indents
Time = 0 hours

Time = 70 hours

Time = 89 hours
Outer Race Incipient Fault Tests

Statistical Performance Results

<table>
<thead>
<tr>
<th>TEST NUMBER</th>
<th>SENSOR</th>
<th>FALSE ALARM</th>
<th>INCIPIENT DETECTION</th>
<th>INCIPIENT DETECTION TIME [HRS]</th>
<th>SPALL DETECTION</th>
<th>SPALL DETECTION TIME [HRS]</th>
<th>TOTAL RUNTIME [HRS]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Accel: G</td>
<td>2.0%</td>
<td>82.8%</td>
<td>33.4</td>
<td>99.1%</td>
<td>86.7</td>
<td>174.4</td>
</tr>
<tr>
<td>3</td>
<td>Accel: H</td>
<td>2.0%</td>
<td>99.3%</td>
<td>46.7</td>
<td>99.7%</td>
<td>93.3</td>
<td>117.1</td>
</tr>
<tr>
<td>4</td>
<td>Accel: H</td>
<td>2.0%</td>
<td>97.4%</td>
<td>8.2</td>
<td>100.0%</td>
<td>9.4</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>Accel: G</td>
<td>2.0%</td>
<td>66.8%</td>
<td>5.7</td>
<td>97.2%</td>
<td>20</td>
<td>24.8</td>
</tr>
<tr>
<td>6</td>
<td>Accel: G</td>
<td>2.0%</td>
<td>96.1%</td>
<td>33.4</td>
<td>100.0%</td>
<td>82</td>
<td>116.5</td>
</tr>
<tr>
<td>7</td>
<td>Accel: H</td>
<td>2.0%</td>
<td>90.9%</td>
<td>25</td>
<td>99.7%</td>
<td>84.2</td>
<td>101.6</td>
</tr>
<tr>
<td>10</td>
<td>Accel: H</td>
<td>2.0%</td>
<td>95.6%</td>
<td>23.4</td>
<td>100.0%</td>
<td>93.3</td>
<td>101.6</td>
</tr>
<tr>
<td>12</td>
<td>Accel: G</td>
<td>2.0%</td>
<td>97.6%</td>
<td>4.2</td>
<td>97.6%</td>
<td>7.9</td>
<td>8.8</td>
</tr>
<tr>
<td>14</td>
<td>Accel: G (Exterior)</td>
<td>2.0%</td>
<td>89.2%</td>
<td>16.7</td>
<td>99.0%</td>
<td>166.7</td>
<td>185.6</td>
</tr>
<tr>
<td>14</td>
<td>Accel: F (Interior)</td>
<td>2.0%</td>
<td>96.7%</td>
<td>16.7</td>
<td>100.0%</td>
<td>167.8</td>
<td>185.6</td>
</tr>
</tbody>
</table>

- Incipient detection time horizon was about 75% of total run time (on average)
- Significant spall detection time horizon was about 25% of total run time (on average)
CH-47 Swashplate Bearing Fault Classification
CH-47 Bearing Case Study

- Case study: Catastrophic failure of CH-47D aft swashplate bearing
  - Class A mishap: Destroyed aircraft—serious safety concerns
  - Motivated an extensive manual inspection of entire 47D/E fleet—significant increases to maintenance workload providing only incomplete results

- Proposed solution: On-board monitoring of bearing health
  - Determine health of bearing and presence of faults without manual physical system inspection
  - Promote safety while reducing maintenance requirements

CH-47D Swashplate Bearing

Test Cell data to demonstrate the feasibility and benefits of bearing health monitoring

- Six inserted (field used) bearings of known condition
  - Two healthy bearings—baseline
  - Four faulted bearings (1 corroded, 1 spalled, 2 cage faults)
- Five operating conditions: ground, hover, and speeds of 80, 100, 140 forward knots

ImpactEnergy™ Feature Extraction

- Statistical Anomaly Features
  - Fault detection capabilities
  - Limited computational overhead
  - Sensitive to higher levels of fault
  - Calculated for: broadband, narrowband and demod signal

- Frequency domain bearing and shaft features
  - Fault detection & isolation capabilities
  - Signal processing & filtering to eliminate noise
  - Incipient fault sensitivity

- Large set of potential condition indicators
Separation and Clustering

Principle Component Analysis (PCA)
- Reduction of high dimension data using linear algebra: n features to p principle components
- Identify directions of highest variance in the data and project data on those vectors
- Dimension of data is reduced with a minimum of lost information

PCA Process
- Calculate covariance matrix of data, C
  \[
  \text{cov}(X, Y) = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}
  \]
- Solve eigenvalue problem for matrix C
- Determine the p largest eigenvalues – project data on corresponding eigenvectors
  \[
  F_{pca} = F_{raw} \cdot \nu
  \]
Single Level PCA Attempt

- PCA performed on entire data set
  - Several classes with no clear separation
  - Some classes cluster for a few of the load conditions

A classifier is required that will separate all fault classes while remaining invariant to load condition.
Modified Hierarchical Approach

Hierarchal PCA

- It is possible to identify feature groups targeted at specific classes

- Iterative application of PCA can identify feature groups that separate specific faults for all load conditions
Separable Classes Resulting

Hierarchal PCA - Layers of classification

- First level: most separable classes - corroded (S3), spalled (S5)
- Remove classified faults from analysis
- Second level: refined classifier for cage faults – cage pop (S4), cage overlap (S6) from healthy specimens (S1) & (S2)

Level 1 Classifier

Level 2 Classifier
Case Studies Conclusions

- Successful incipient fault detection and incipient fault-to-failure trending on a variety of test platforms
- In general, all vibration features susceptible to load and speed variations
  - Adds “noise” to statistical based analysis
  - Effect is mitigated somewhat by preferential band selection
  - Normalization and fusion can also aid in reduced noise but care must be taken
- Overall, demodulated features react better to incipient faults and reduce false alarms
- More sophisticated classification schemes may be required to:
  - Differentiate failure modes
  - Reduce flight load sensitivity