Recent Case Studies in Bearing Fault Detection and Prognosis

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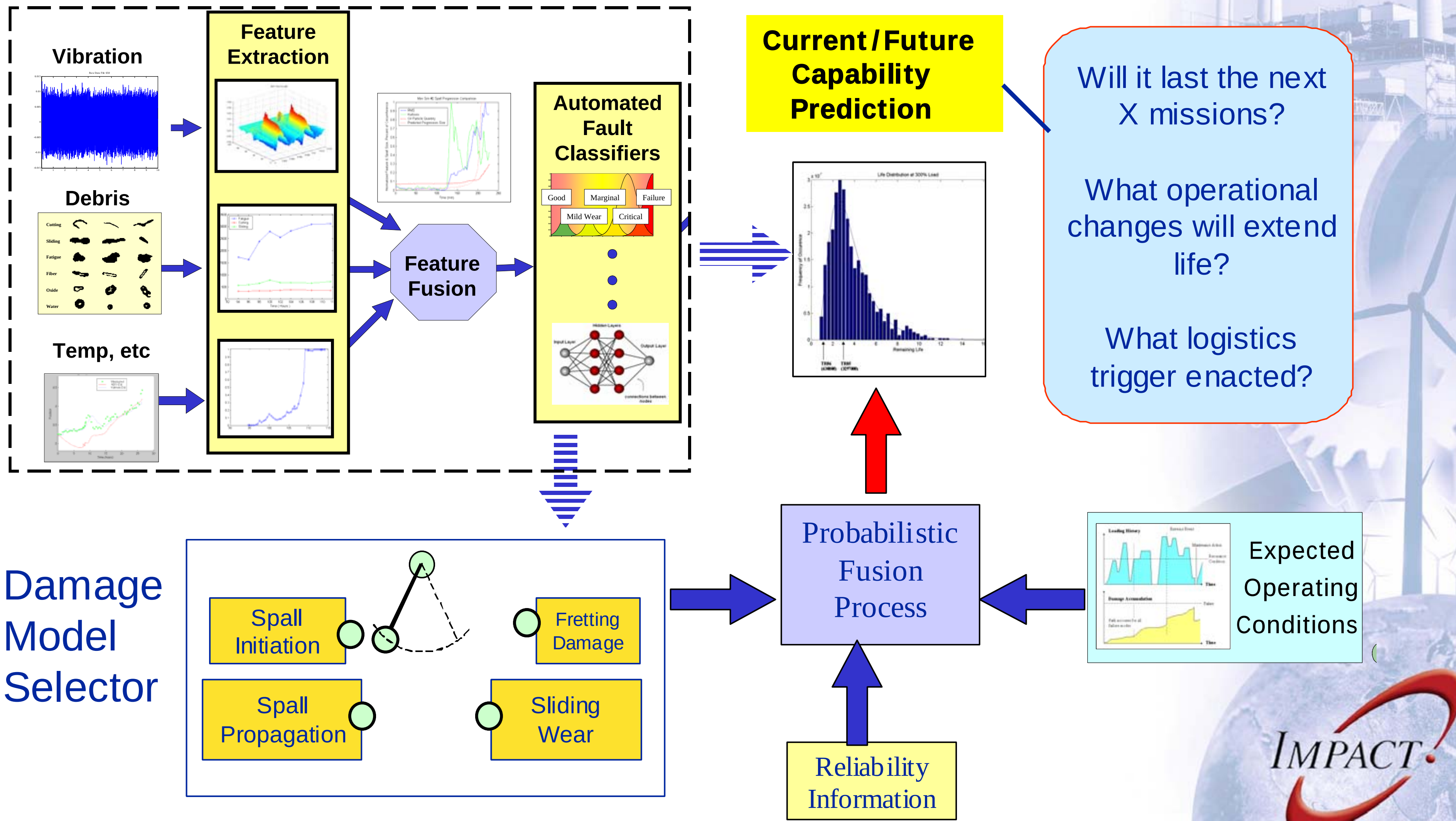
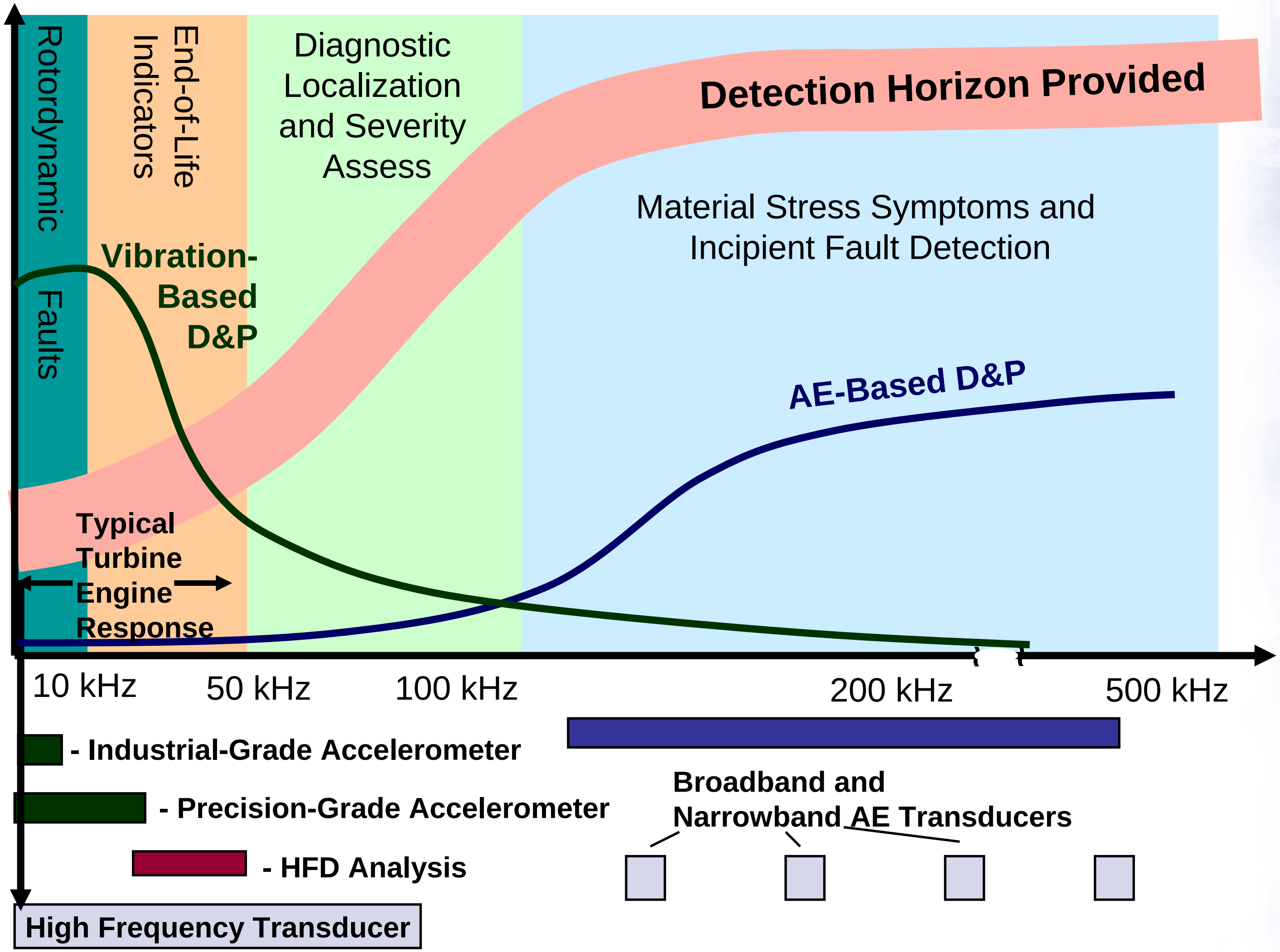
Outline

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

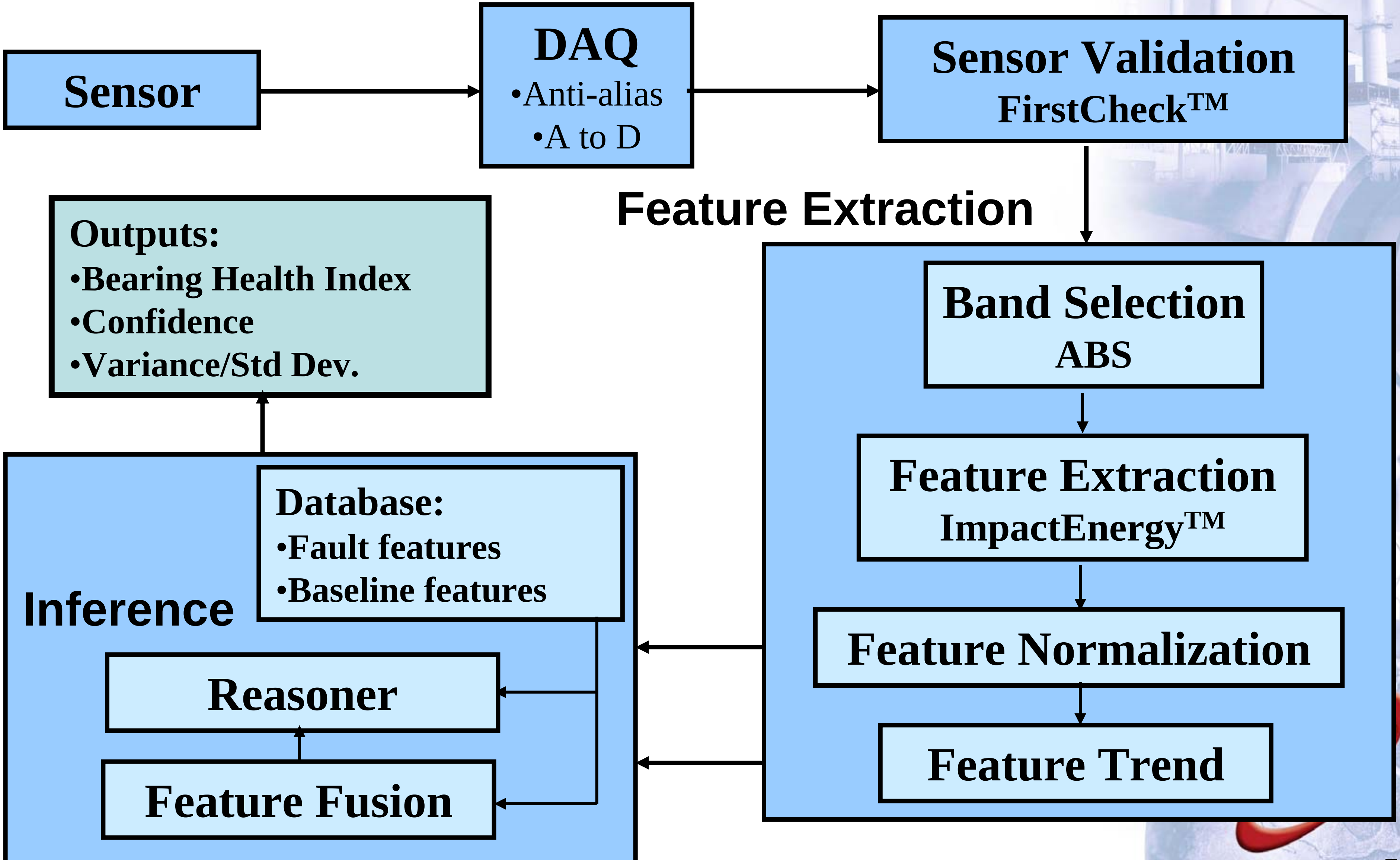
Bearing Prognostic Architecture



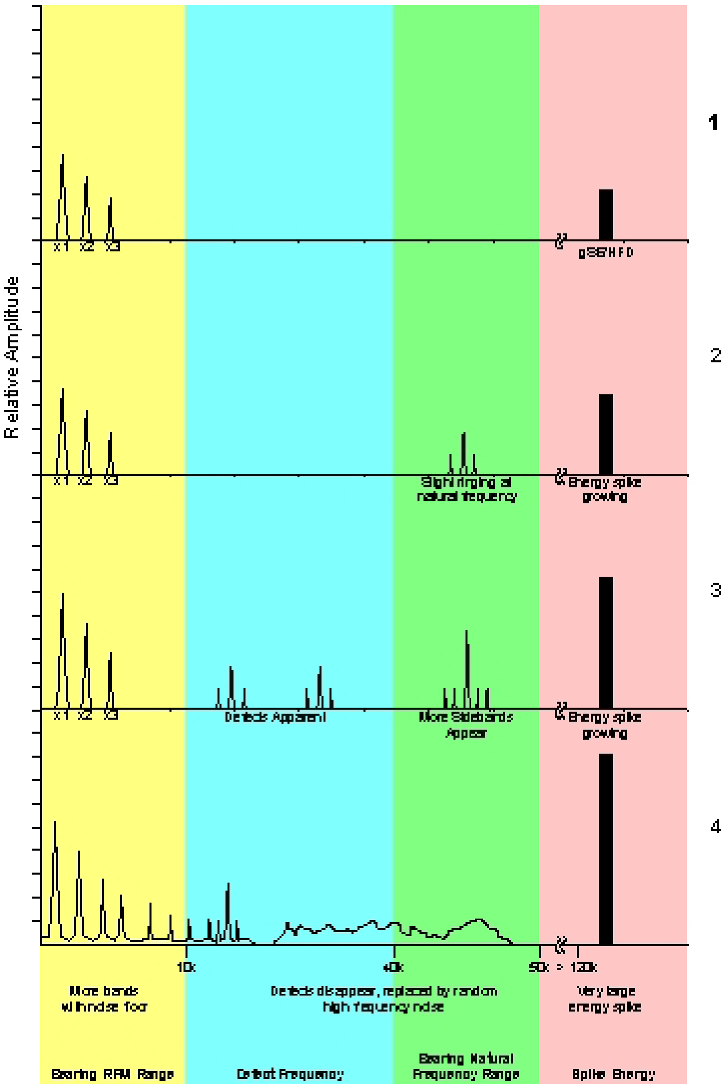
Vibro-Acoustic Monitoring

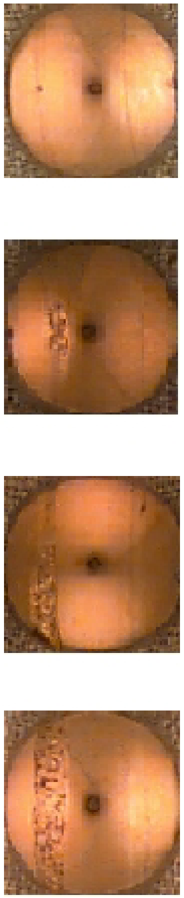


Bearing Incipient Fault Detection Elements and Process



Bearing Failure Mechanism Progression

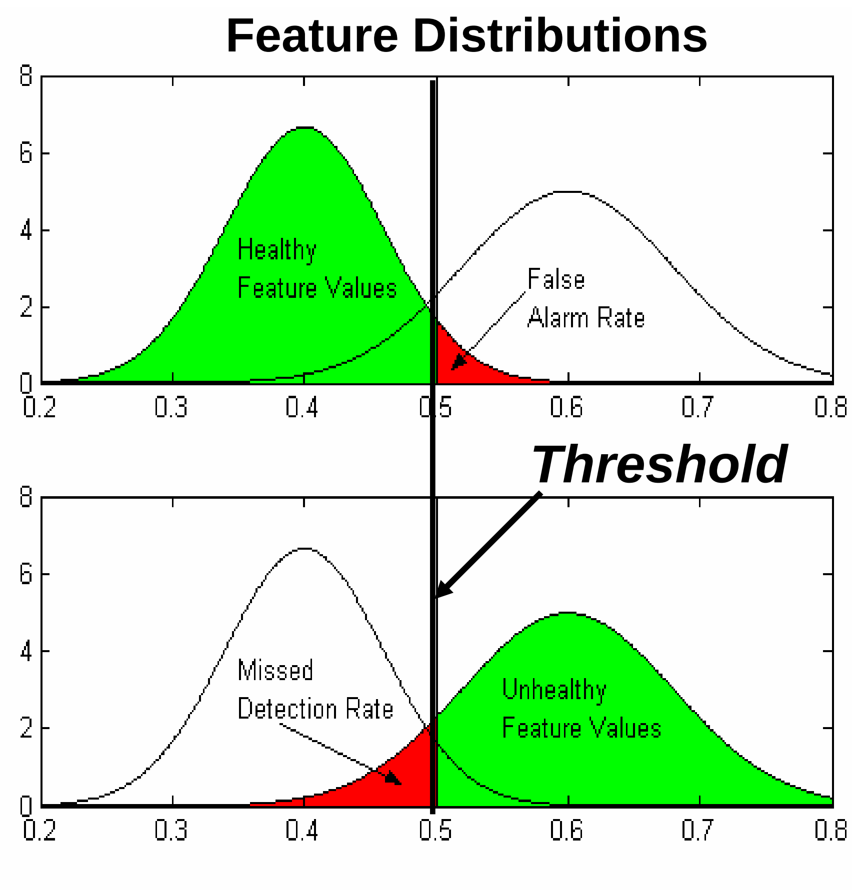




- Failure occurs in stages
- Symptoms start at high frequency excitation and move toward lower frequencies as damage progresses
- Coupling high frequency vibration techniques with models can provide best confidence in predictions

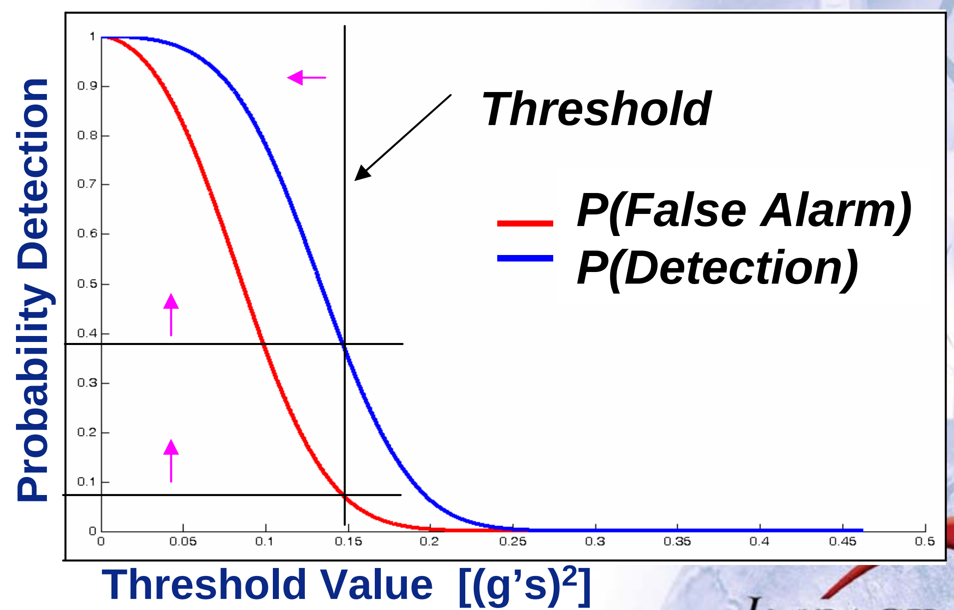
Statistical Feature Detection

Detection Theory, Uncertainty and Threshold Settings



P(FA) = 1-P(CR)

P(D) = 1-P(MD)



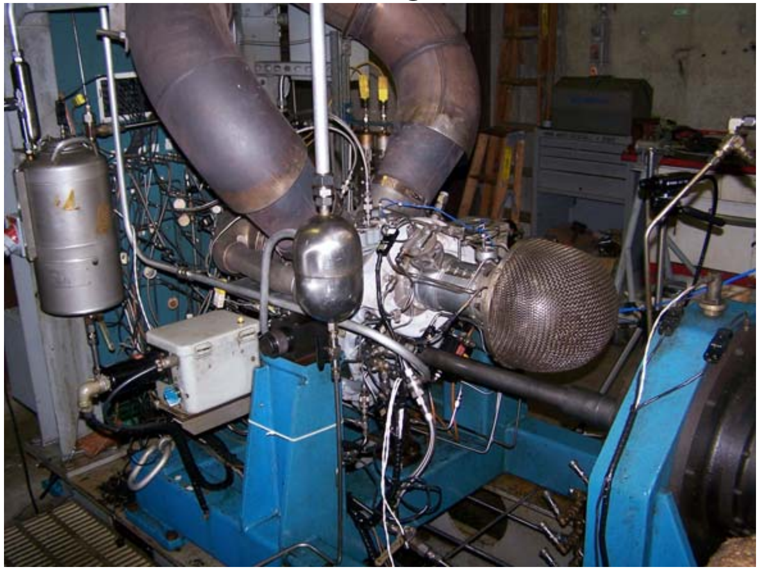
T63 Engine Bearing #2

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

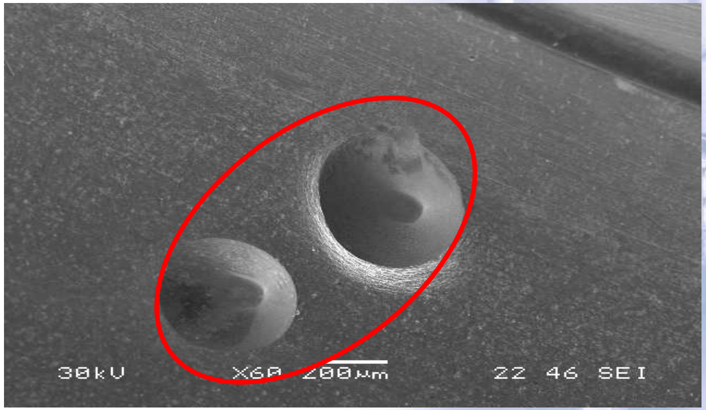
T63 Turboshaft Engine Test Cell



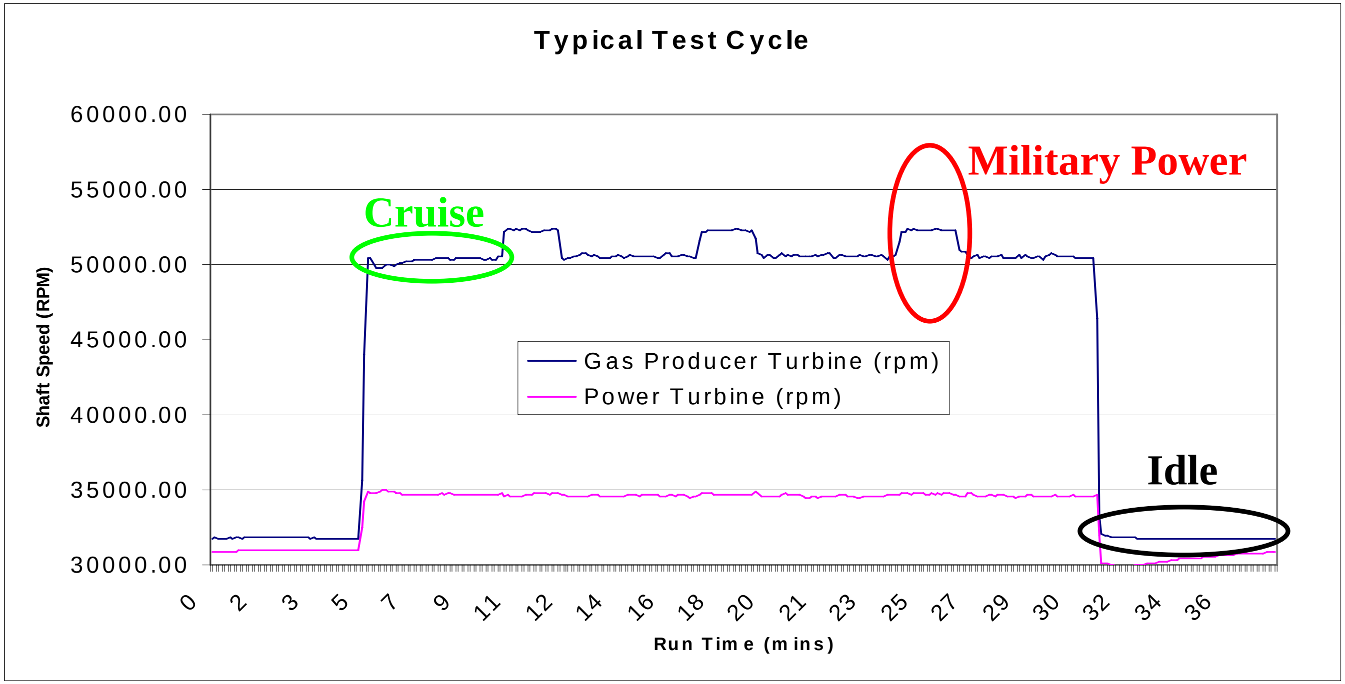
Test Bearing Conditions

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

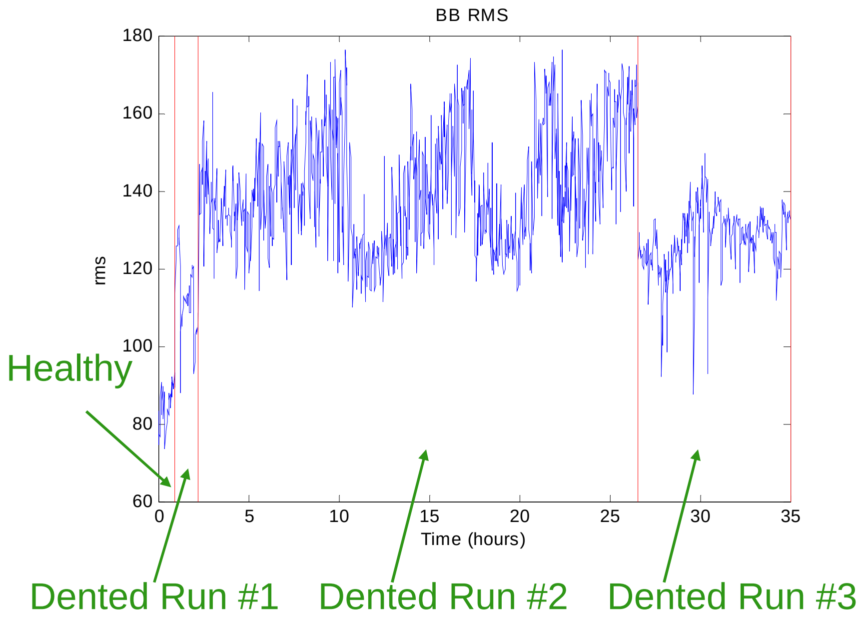


Engine Operating Conditions



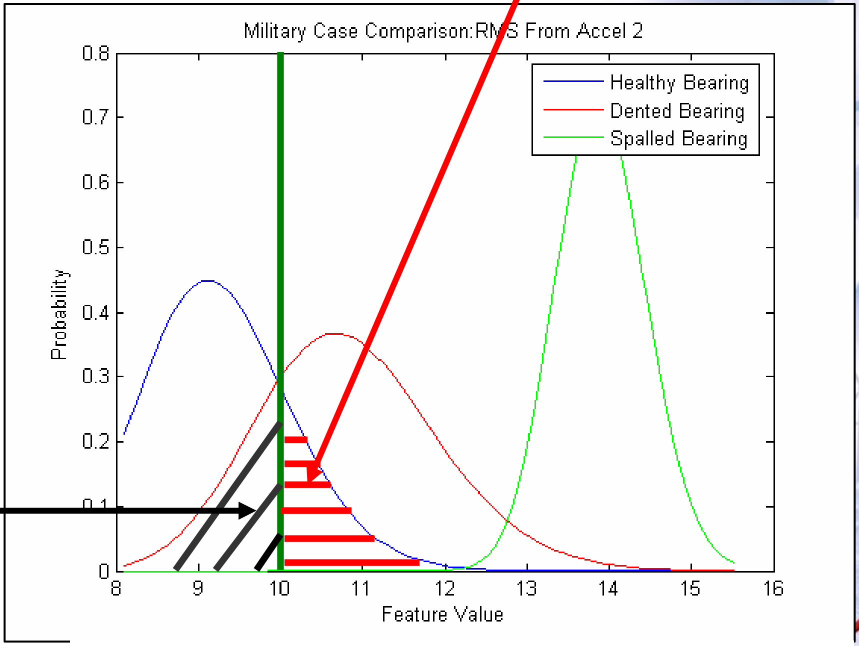
Bearing Condition	Cycle Numbers	Total Cycles	Operating Hours (approximately)	Dates
Healthy	**3-4**	**2**	**1.1**	**6/10/05**
Spalled	**14-17**	**4**	**2.25**	**6/16/05**
Dented	**18-74**	**66 (Three Runs)**	**43**	**6/14/2005; 6/20/05-6/30/05**

Broadband Analysis: False Alarms?



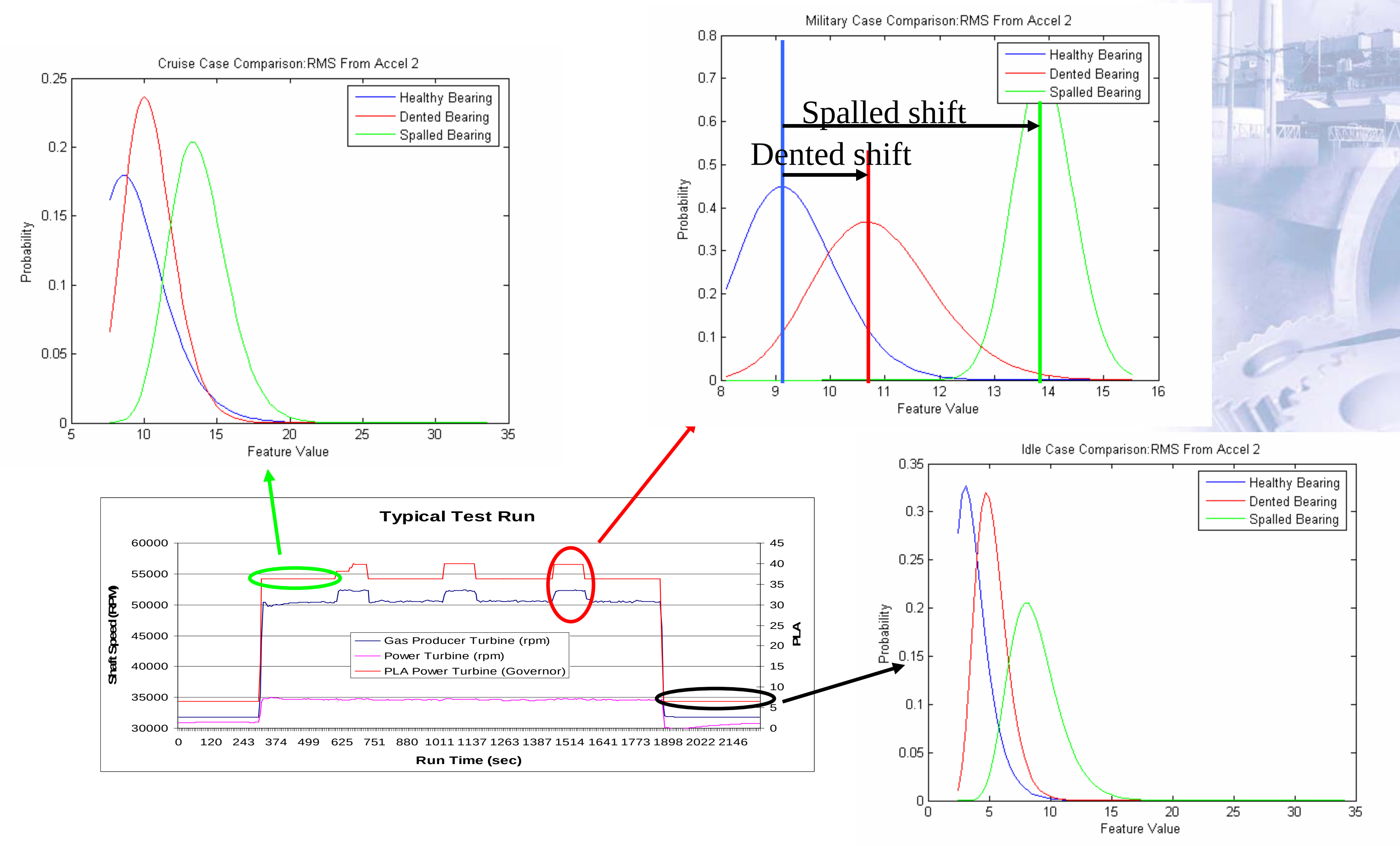
High False Alarm Level

High Missed Detection

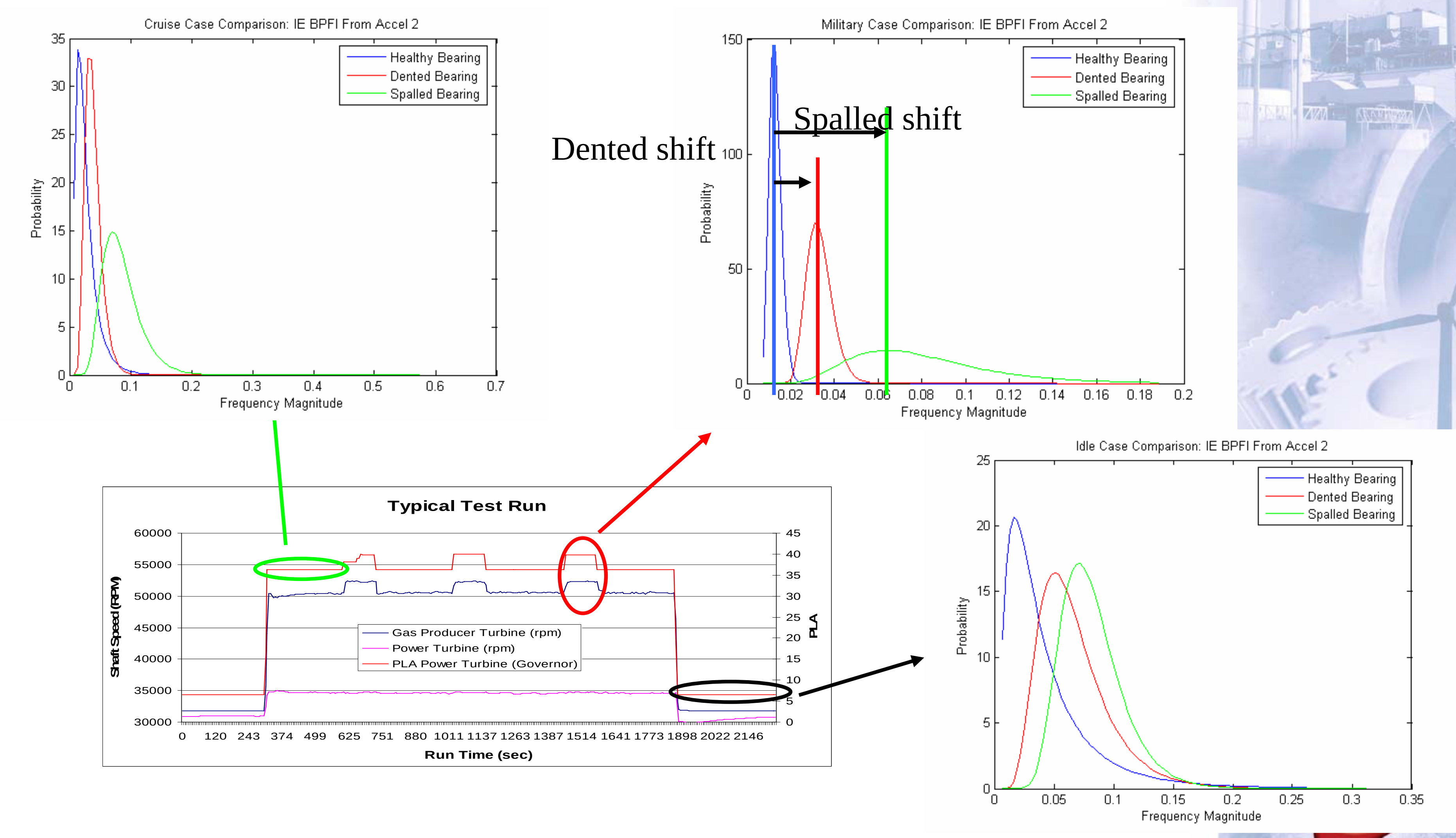


NOTE: The results presented here were taken from the military speed portion of the tests

Statistical Feature Extraction (Broadband RMS)

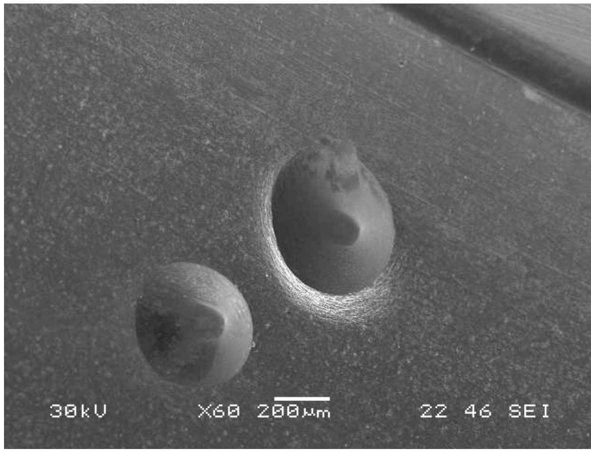


Frequency Feature Extraction (Narrowband IE BPFI)

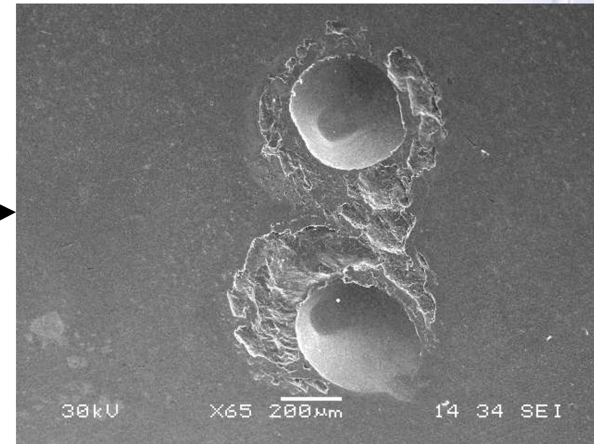


Dented Bearing Fault Progression

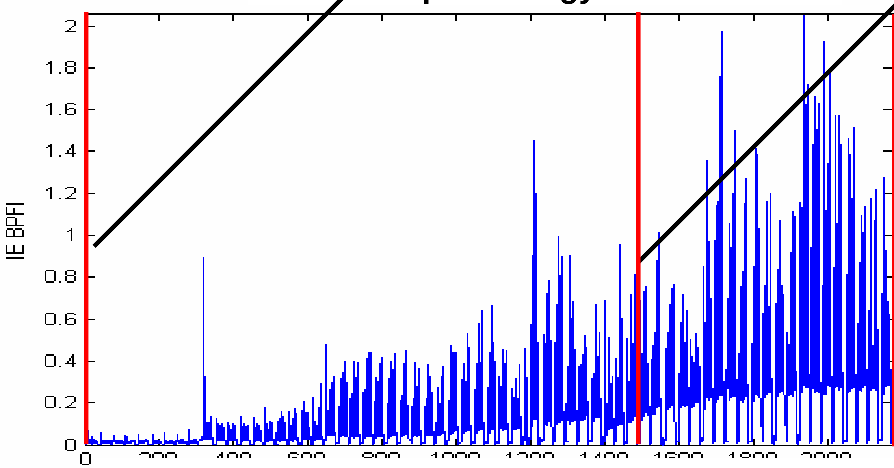
After 1st Dented Run

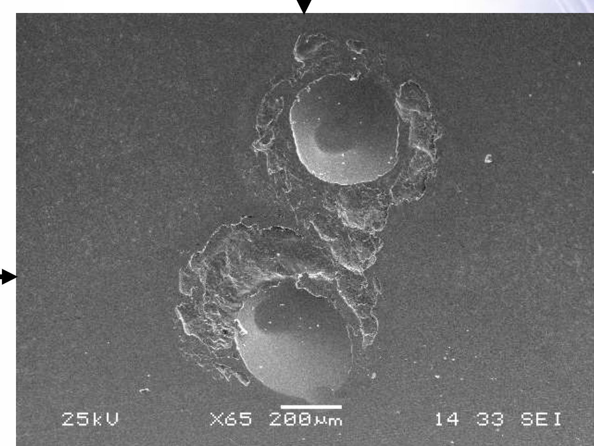


After 2nd Dented Run



ImpactEnergy™ BPFI

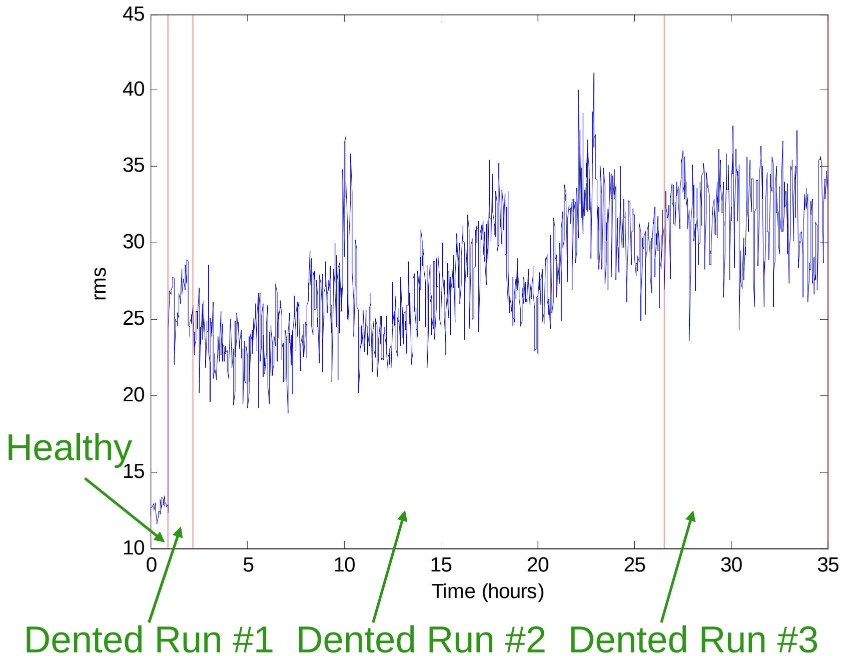


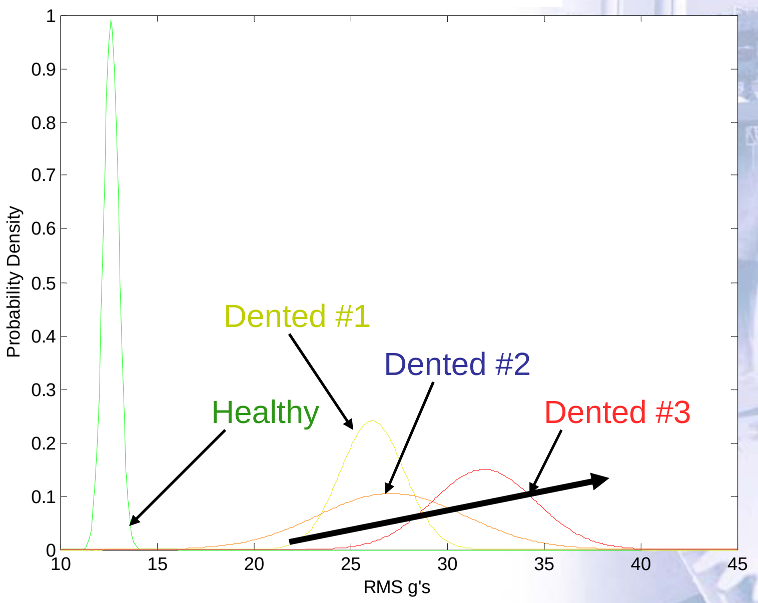


ImpactEnergy™ Analysis

After 3rd Dented Run

Narrowband Feature





Fault Progression

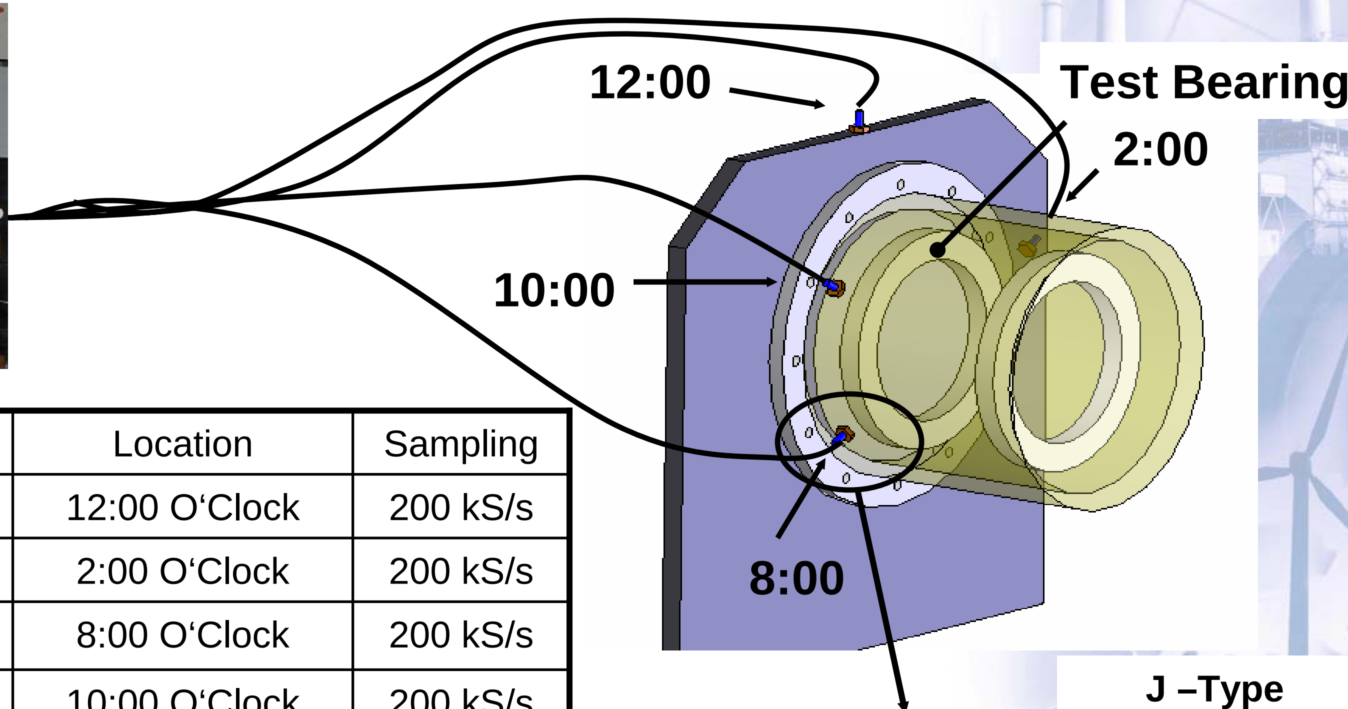
- Significant reduction in False Alarms
- Increase in Mean and Variance of faulted distributions

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



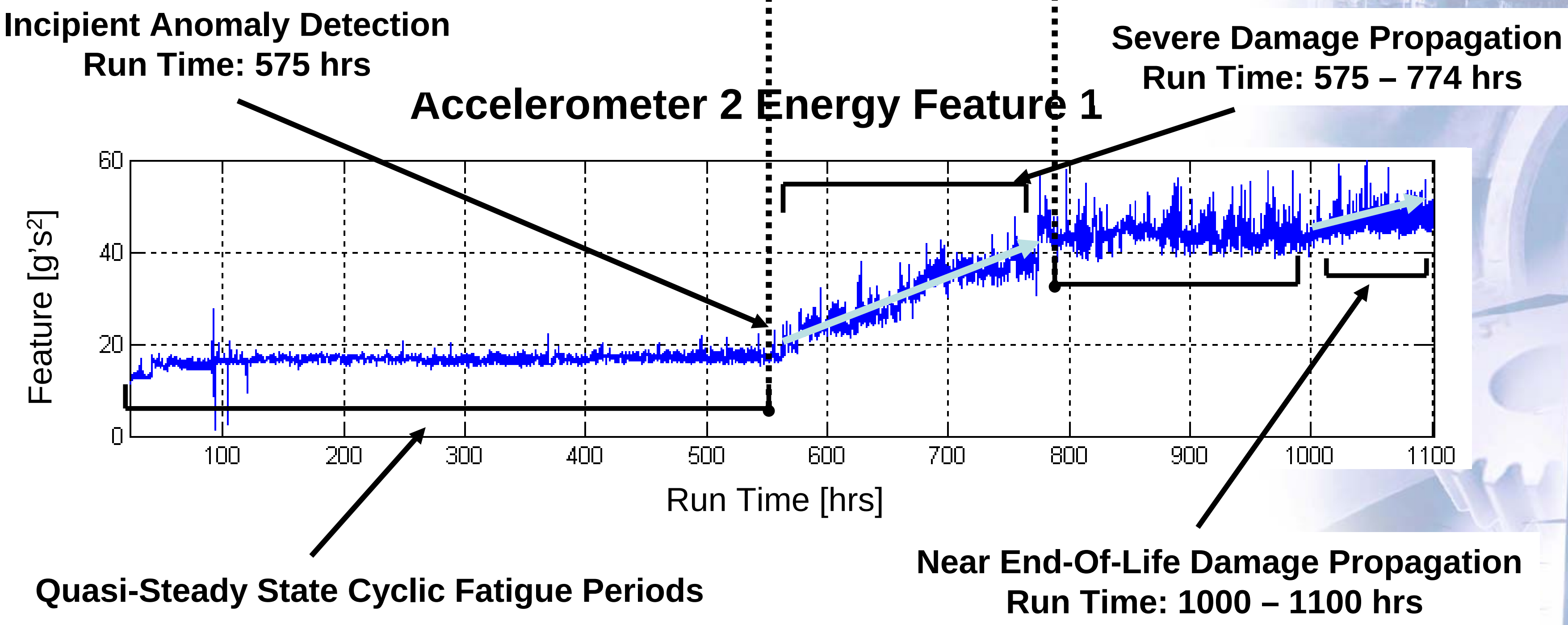
Channel	Type	Location	Sampling
1	Accelerometer	12:00 O'Clock	200 kS/s
2	Accelerometer	2:00 O'Clock	200 kS/s
3	Accelerometer	8:00 O'Clock	200 kS/s
4	Accelerometer	10:00 O'Clock	200 kS/s
5	Thermocouple	12:00 O'Clock	5 kS/s
6	Thermocouple	2:00 O'Clock	5 kS/s
7	Thermocouple	8:00 O'Clock	5 kS/s
8	Thermocouple	10:00 O'Clock	5 kS/s
9	Tachometer	Low Spd Shaft	5 kS/s
10	Tachometer	High Spd Shaft	5 kS/s

Test Configuration

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

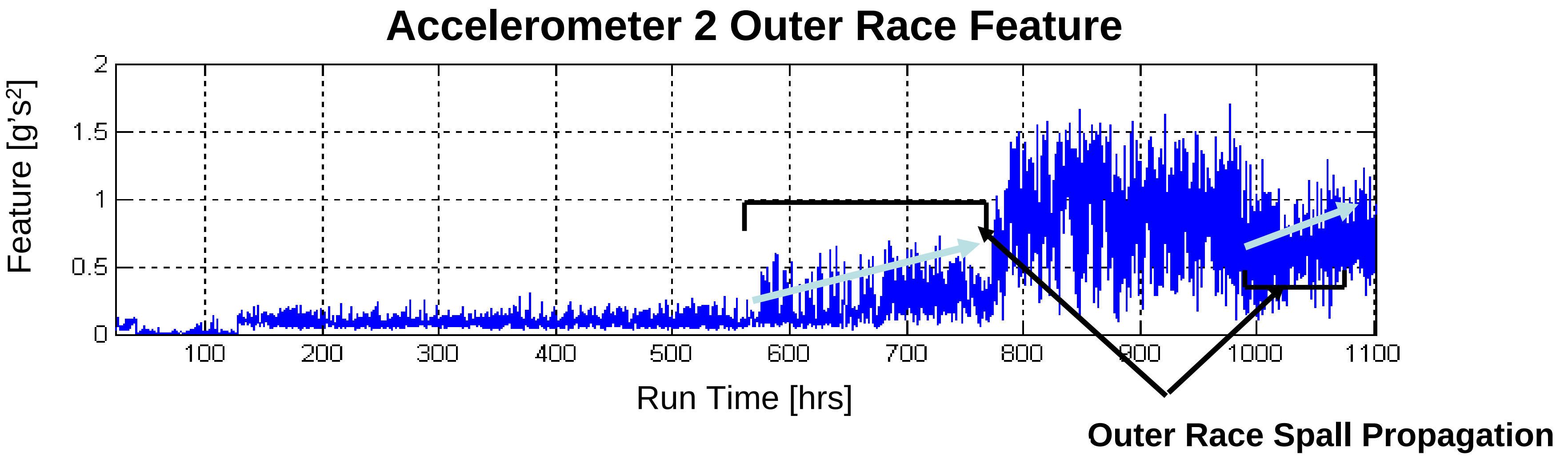
- Speed and Load Profile
  - Stage 1 100% axial load 100% speed
  - Stage 2 48% axial load 93% speed
- Data Acquisition
  - 2 seconds of data every two minutes
  - Over 700 GB of data; over 1100 hrs of testing

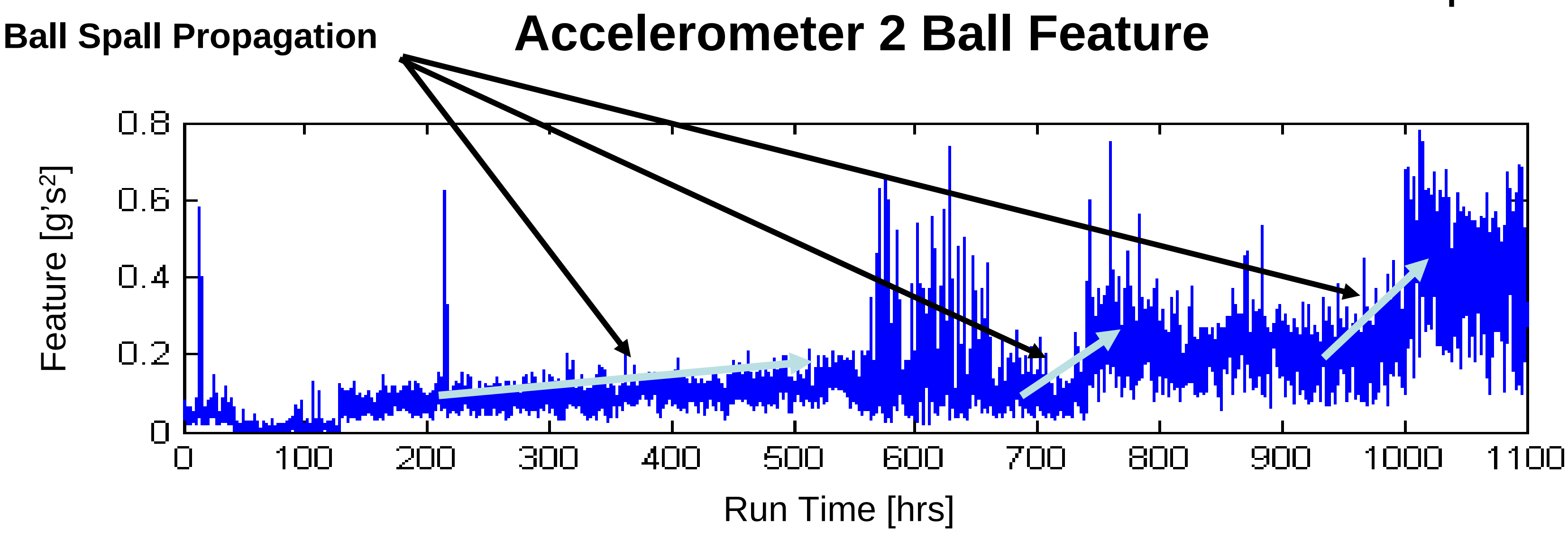
Overview of Damage Progression



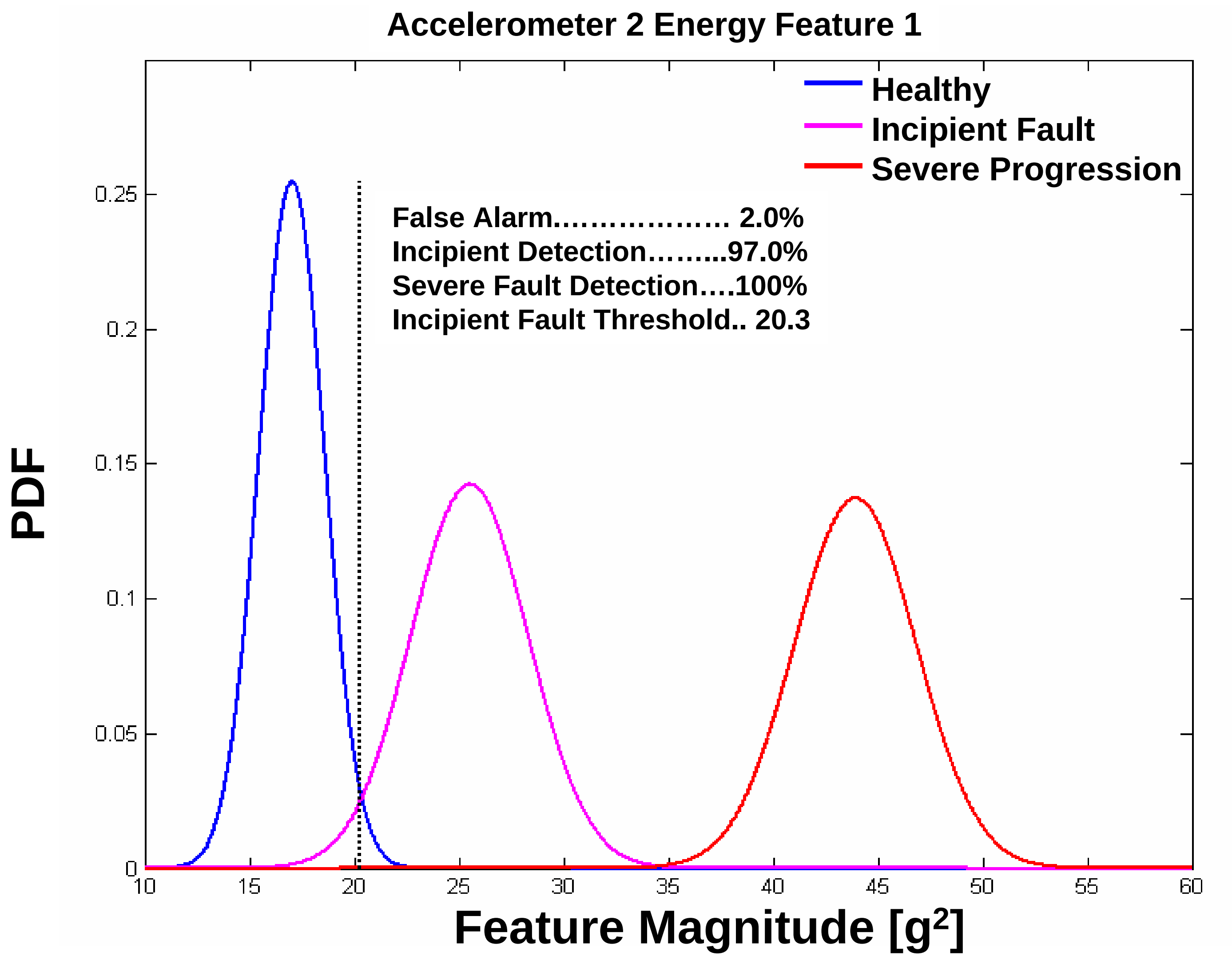
*Note: Typical of Accelerometers 1-4

Failure Mode Identification

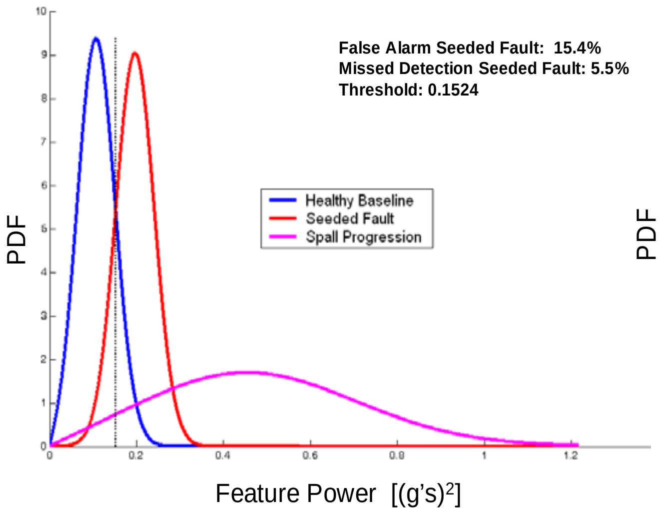


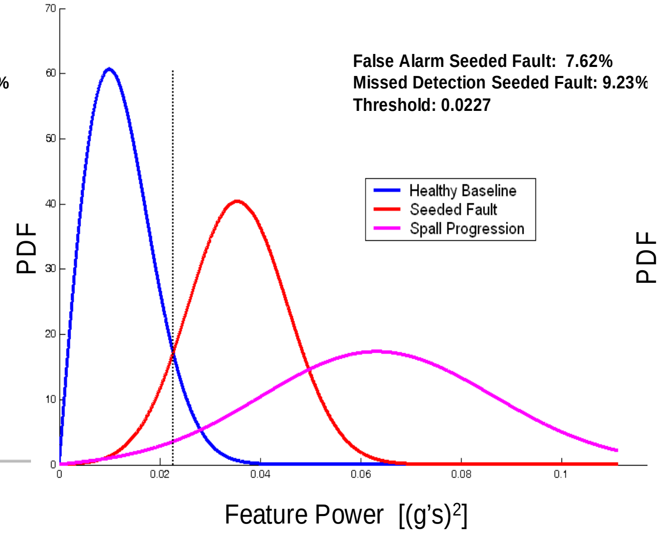


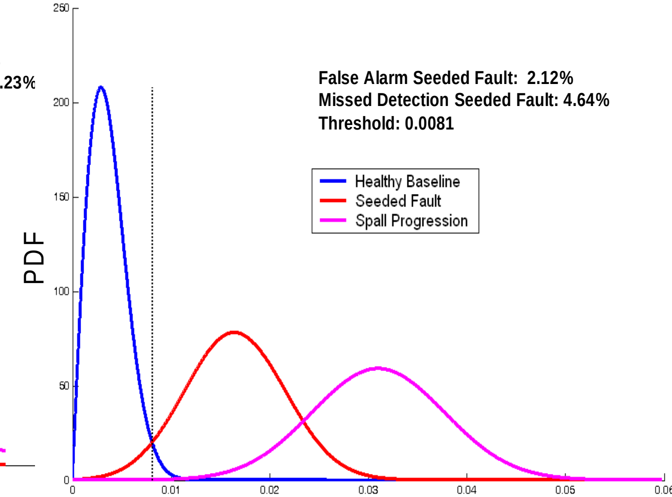
Statistical Detection Analysis

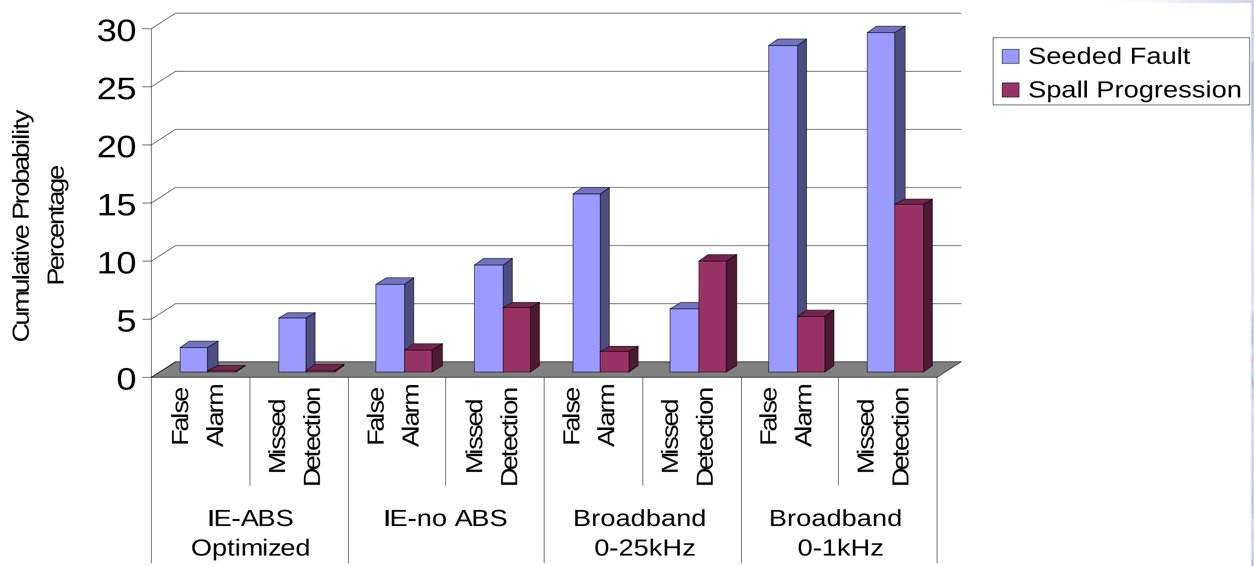


Statistical Fault Detection Summary









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

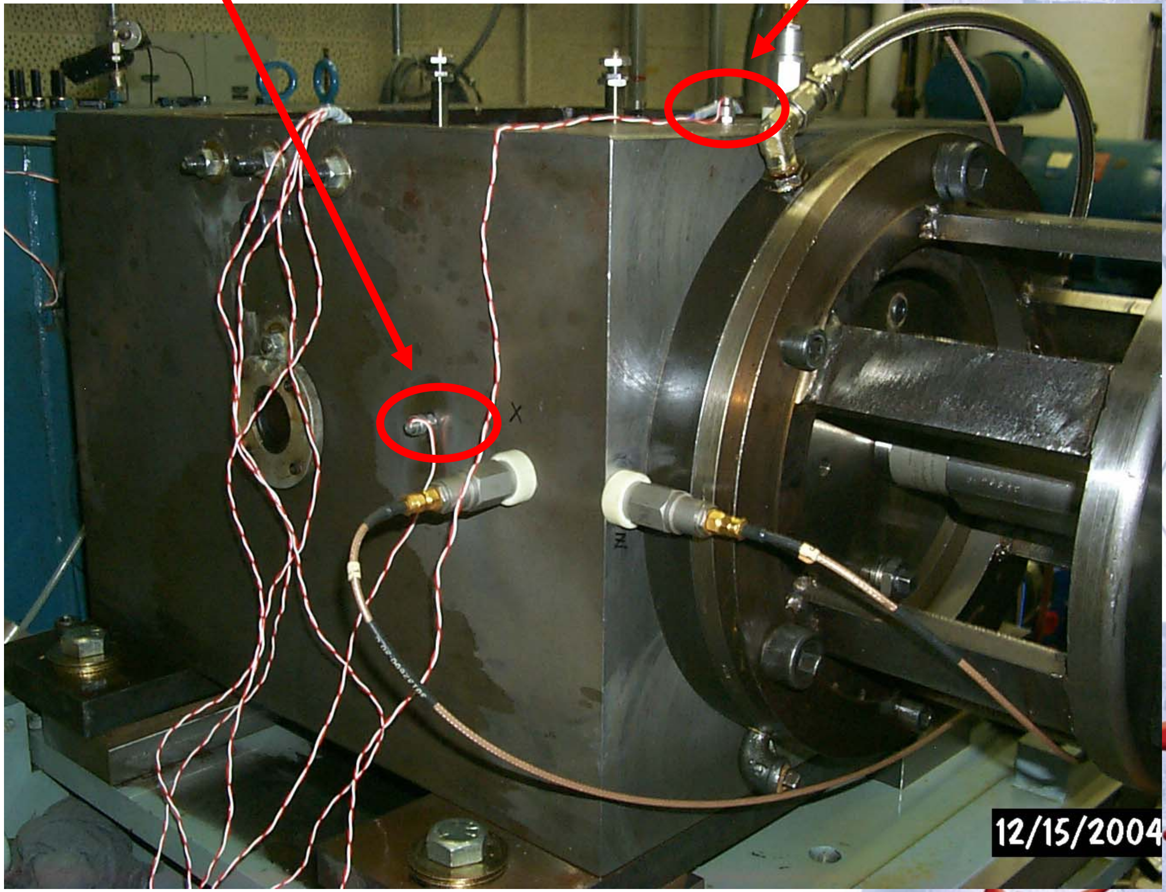
Seeded Fault Detection and Progression

Monitoring System Hardware

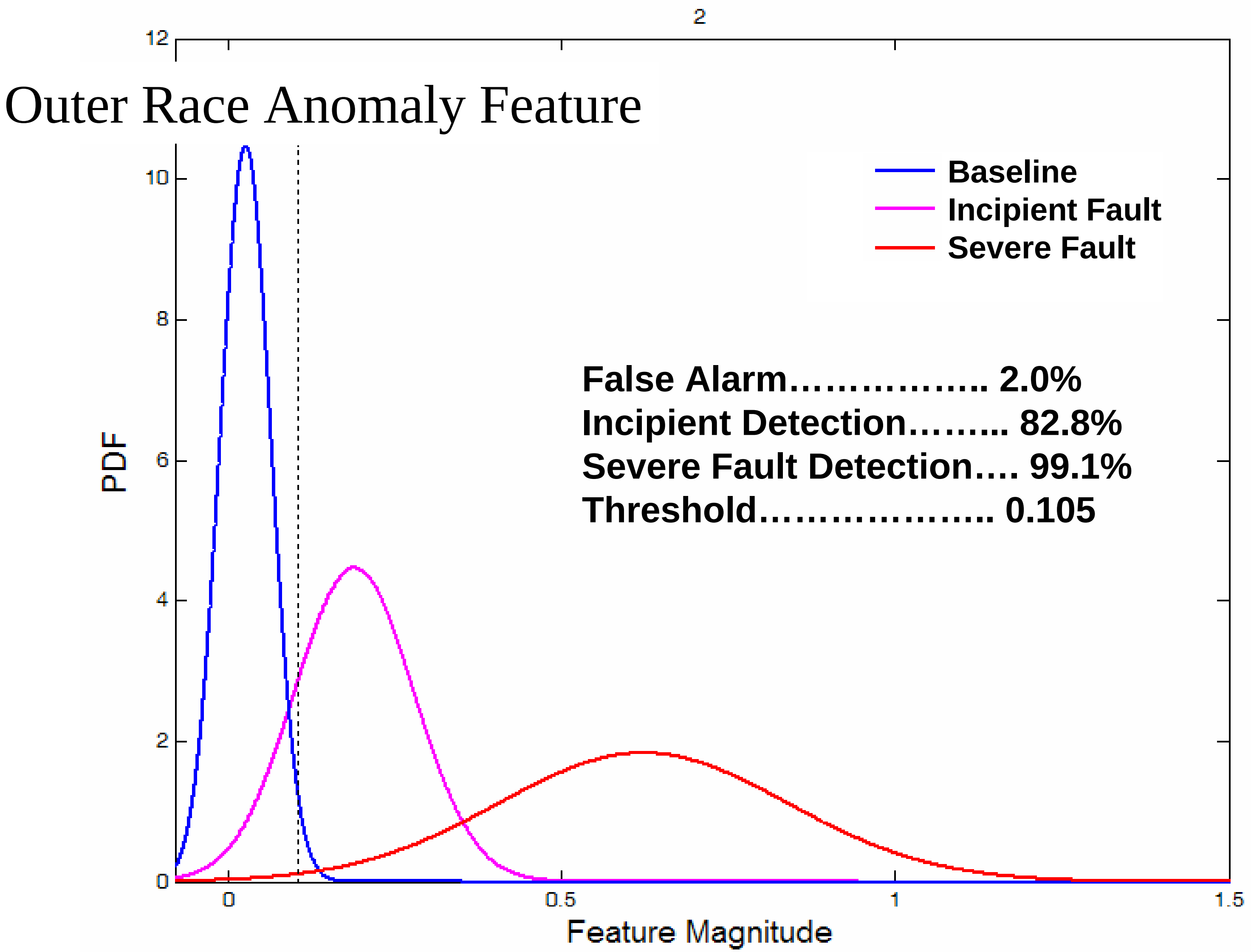
DAQ Hardware

Exterior Accelerometer Location G

Exterior Accelerometer Location H

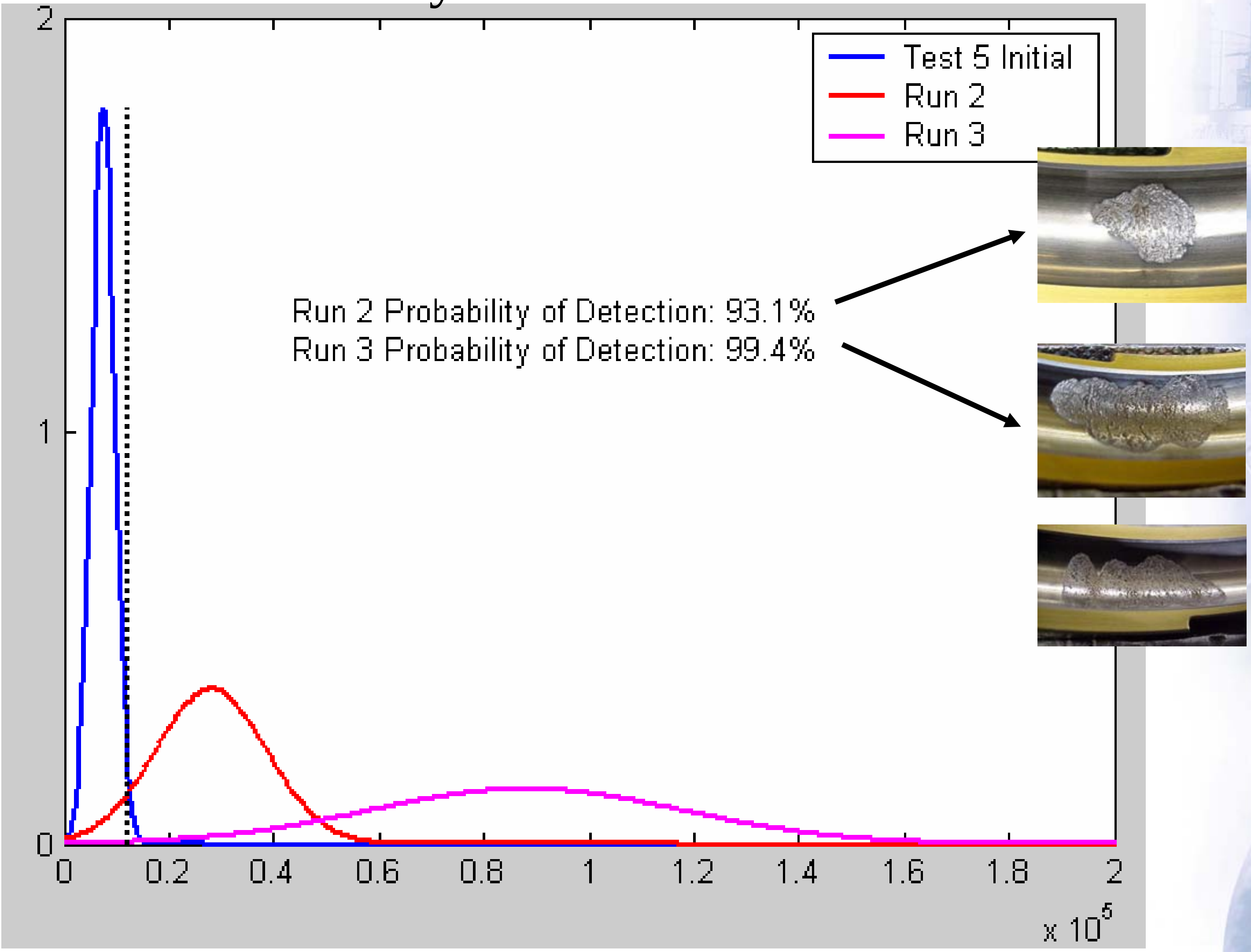


Test 2: Statistical Detection



Test 5: Statistical Detection

Outer Race Anomaly Feature

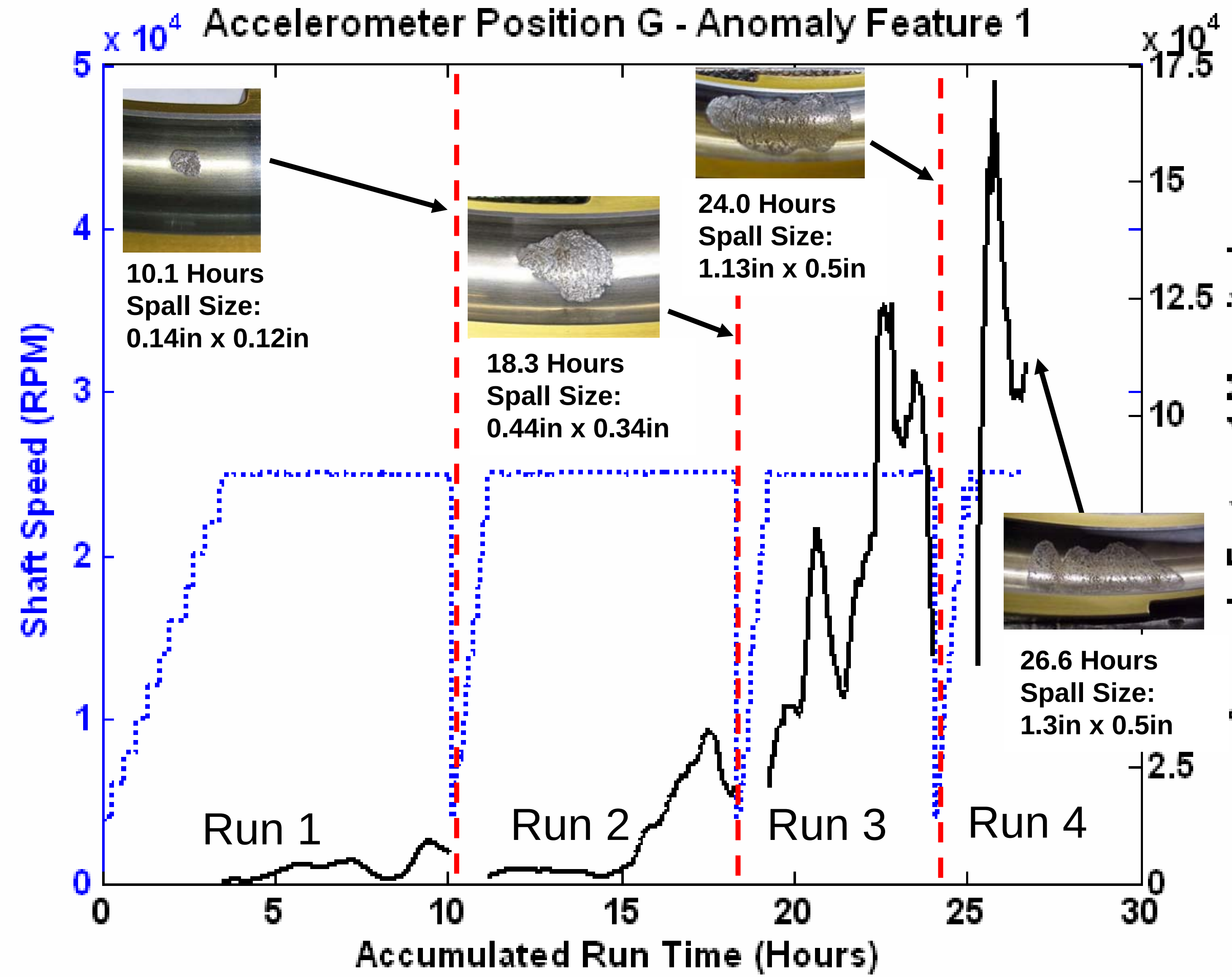


18.3 Hours
Spall Size:
0.44in x 0.34in

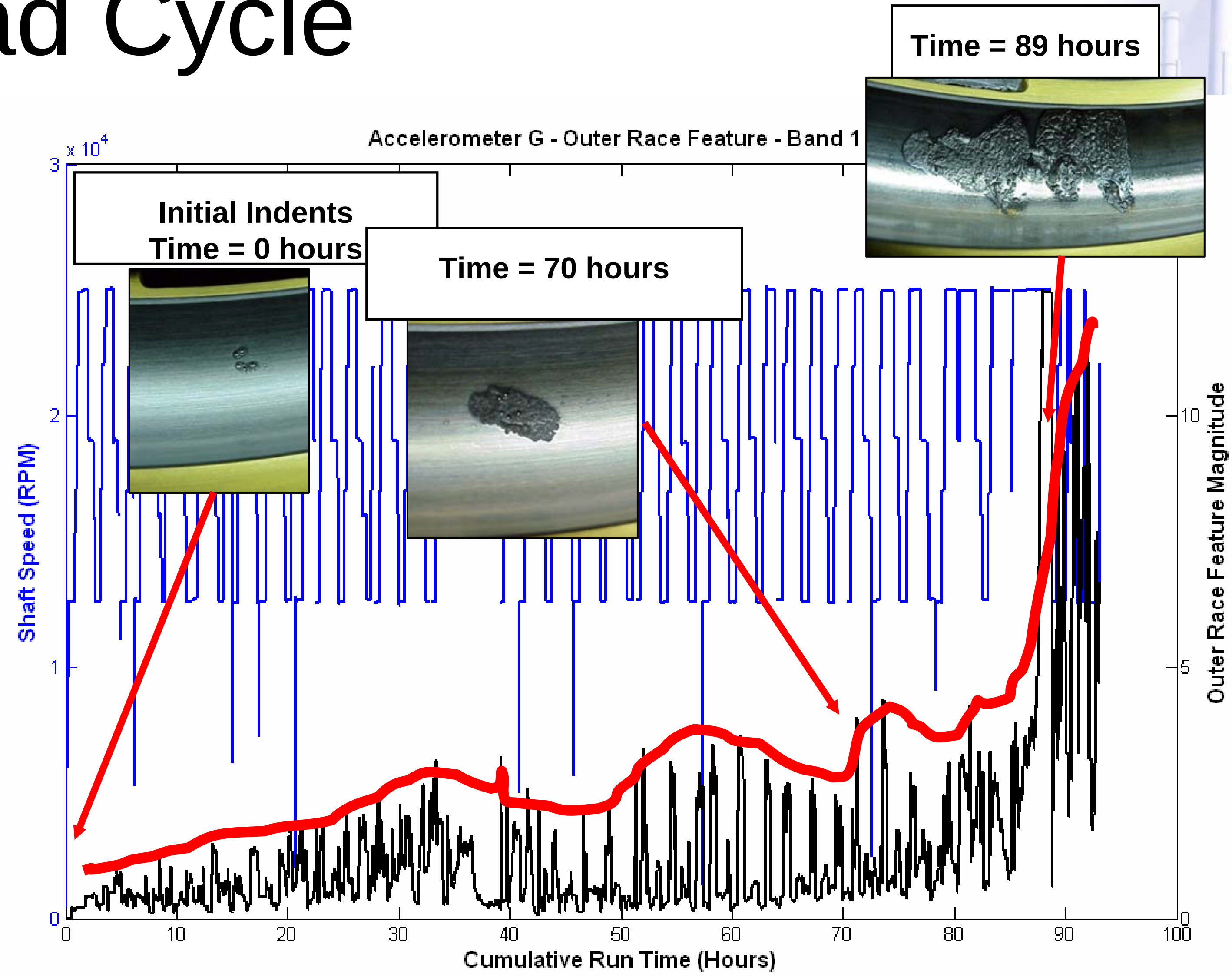
24.0 Hours
Spall Size:
1.13in x 0.5in

26.6 Hours
Spall Size:
1.3in x 0.5in

Test 5: Prognosis



Test 14 Results Under Speed & Load Cycle



Outer Race Incipient Fault Tests

Statistical Performance Results

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

- 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**

Images: (L) Keller, J., Grabill, P., "Inserted Fault Vibration Monitoring Tests For a CH-47D Aft Swashplate Bearing," **American Helicoptor Society 61st Annual Forum**, June 1-3, 2005. (R) http://www.chinook-helicopter.com

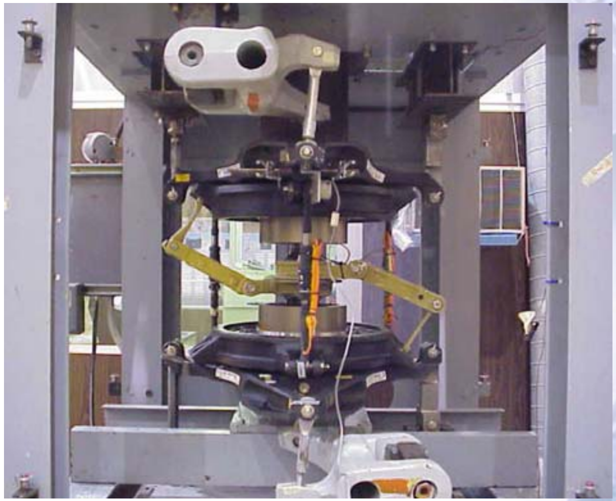
CH-47D Swashplate Bearing

- 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

Corrosion

Spalling

Cage "Pop" Fault

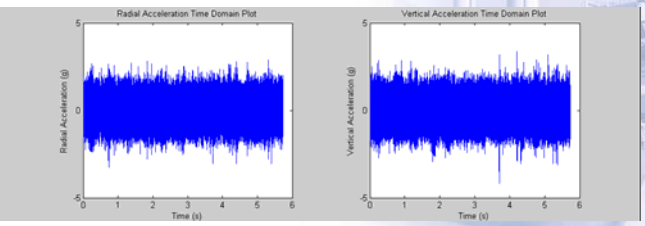


Images: Keller, J., Grabill, P., "Inserted Fault Vibration Monitoring Tests For a CH-47D Aft Swashplate Bearing," **American Helicoptor Society 61st Annual Forum**, June 1-3, 2005.

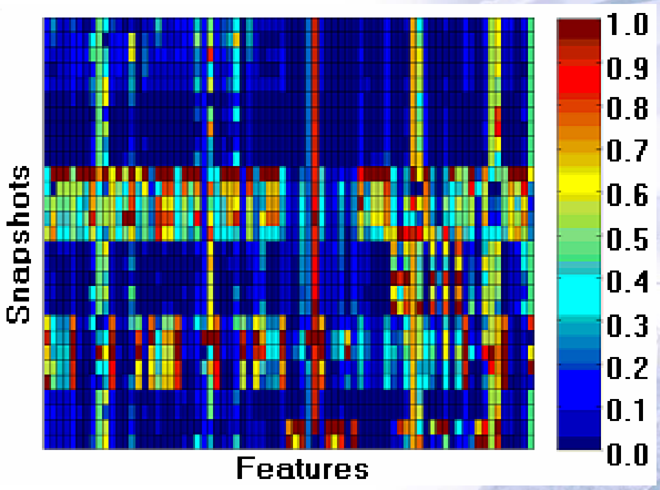
ImpactEnergy™ Feature Extraction

- 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

Vibration Data



Normalized Feature Spectrum



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

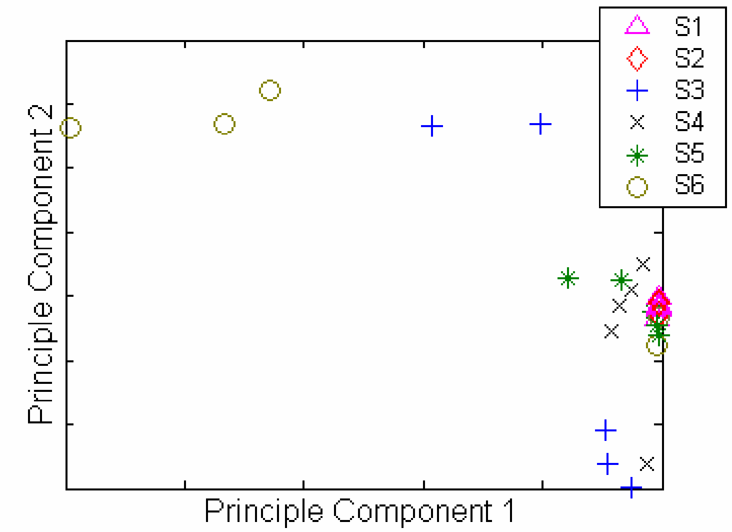
$$\mathrm{cov}(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{(n-1)}$$

- Solve eigenvalue problem for matrix C
- Determine the p largest eigenvalues – project data on coresponding eignvectors

$$F_{pca} = F_{raw} \cdot v$$

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

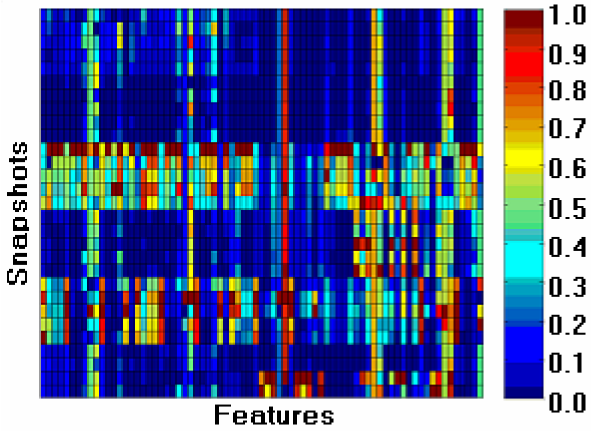


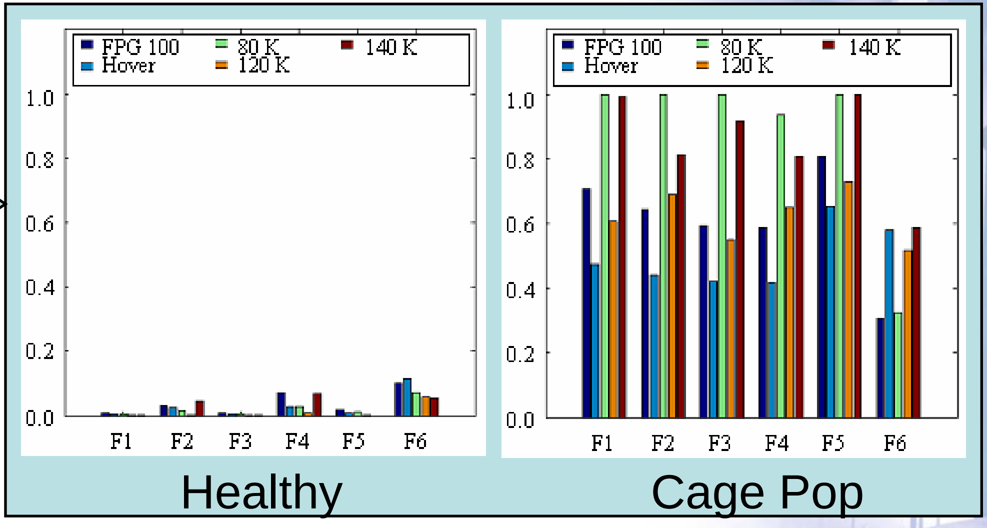
A classifier is required that will separate all fault classes while remaining invariant to load condition

Modified Hierarchical Approach

Hierarchal PCA

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





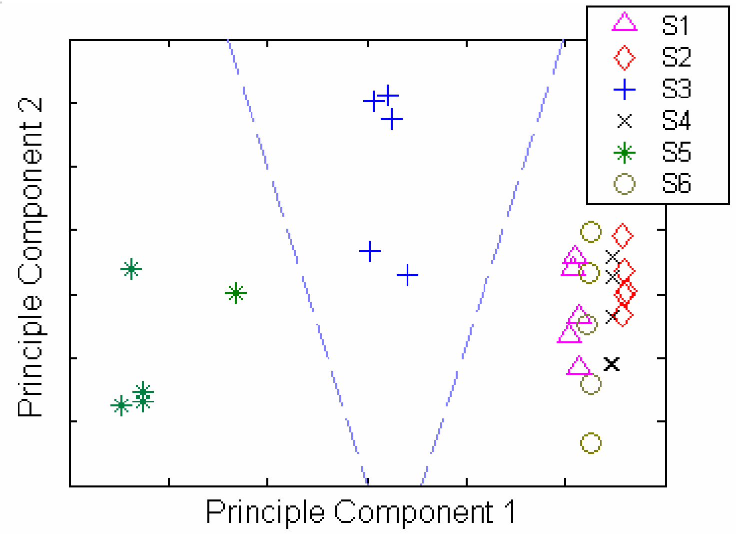
- Iterative application of PCA can identify feature groups that separate specific faults for all load conditions

Separable Classes Resulting

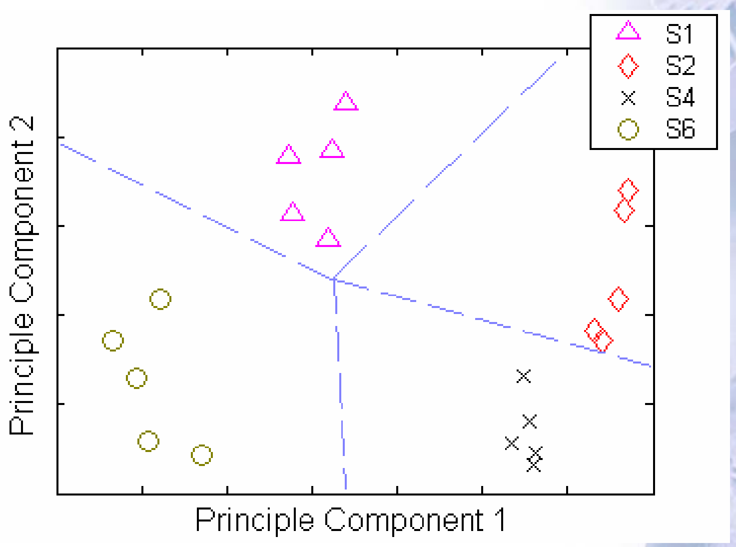
Hierarchal PCA - Layers of classification

- 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