Tutorials Session

PHM Society 2012, Hyatt Minneapolis, MN
September 24th, 2012

Introduction to Improved Real-time Mechanical Systems Diagnostics and Prognostics

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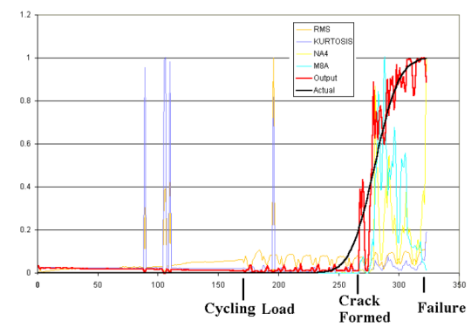

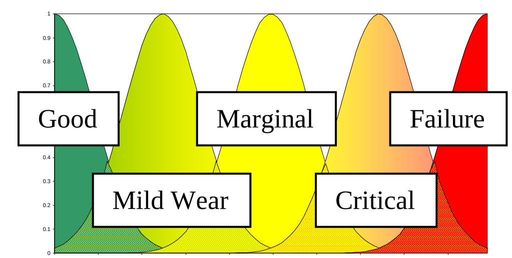

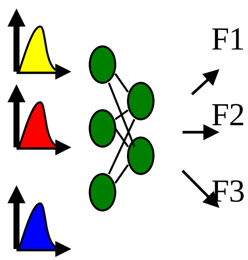

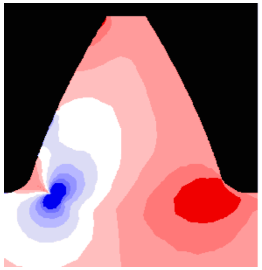

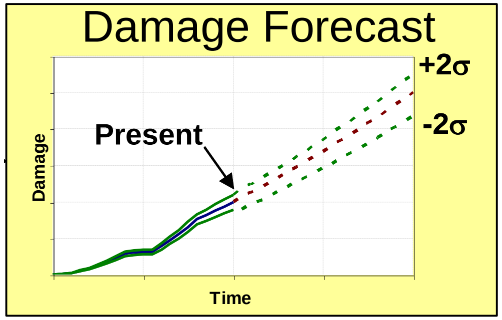

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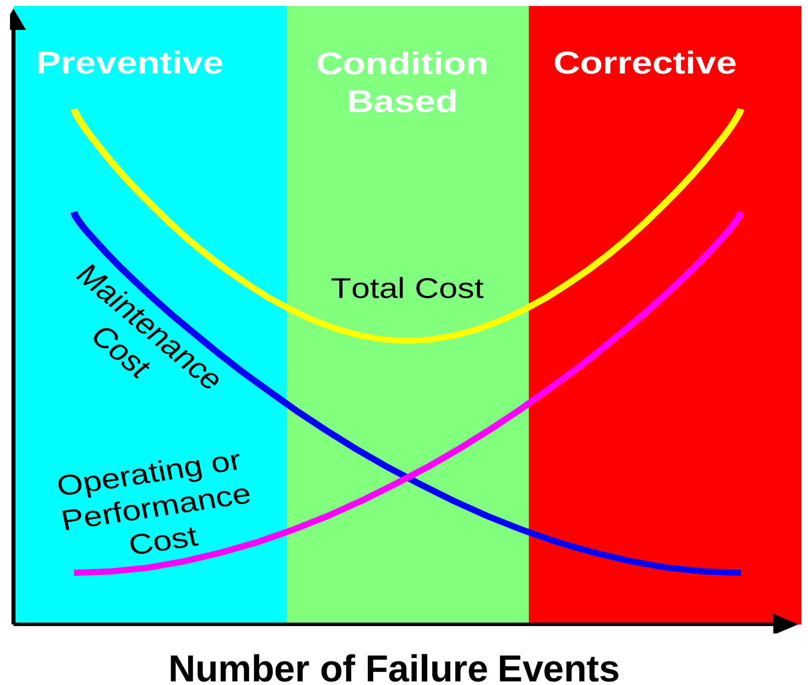
Why are we discussing these technologies?

- Engineered applications require high reliability and availability
- Strategies are needed to optimize Operation and Maintenance (O&M) costs
- Condition Based Maintenance (CBM) approaches are key
  - Enable early fault detection/low false alarm
  - Perform maintenance as necessary
  - Maintain high equipment reliability
  - Achieve lowest total ownership cost
  - Optimize maintenance man hours and actions



Balancing predictive maintenance actions with operational availability consideration should yield lowest total cost of ownership

What do we mean by Detection and Isolation?

- Anomaly or Fault Detection
  - One or more monitored parameters has departed a “normal” operating envelope.
  - Change can be related to some degradation in the machine.
  - Otherwise may be anomaly (unknown) or sensor problem
- Fault Isolation or Diagnosis
  - A statement of the nature of a condition made after observing symptoms or indicators.
  - Localize the problem to the component level of repair.
  - Identification of the most probable root cause or failure mode.
  - Assessment of current severity.
- These last three can really help in prognostics if we know how to use them.

What do we mean by Prognostics?

- Has many different definitions – but here's the basic premise:
  - Can detect or predict risk in advance of functional failure
  - If diagnosed failure modes are associated with "trajectories" (based on data-driven events or mathematical models), then tracked rate of change of trajectory represents failure evolution and character
  - When tracked change is extrapolated or forecast it provides prediction of remaining life or time to reach some event/risk level
- Uncertainty depends upon many factors
  - Accuracy of the baseline model used to define a failure mode
  - Accuracy, noise, and stability characteristics of sensor and features extracted
  - Amount of corroboration available and sensitivity/degree of correlation of tracked features to failure mode
  - Fidelity and model correlation of equipment use and environmental variables to specific degradation
  - Future load conditions, random events, and material condition changes
- It's still predicting a future event and that's hard to do

General Prognostics Classes

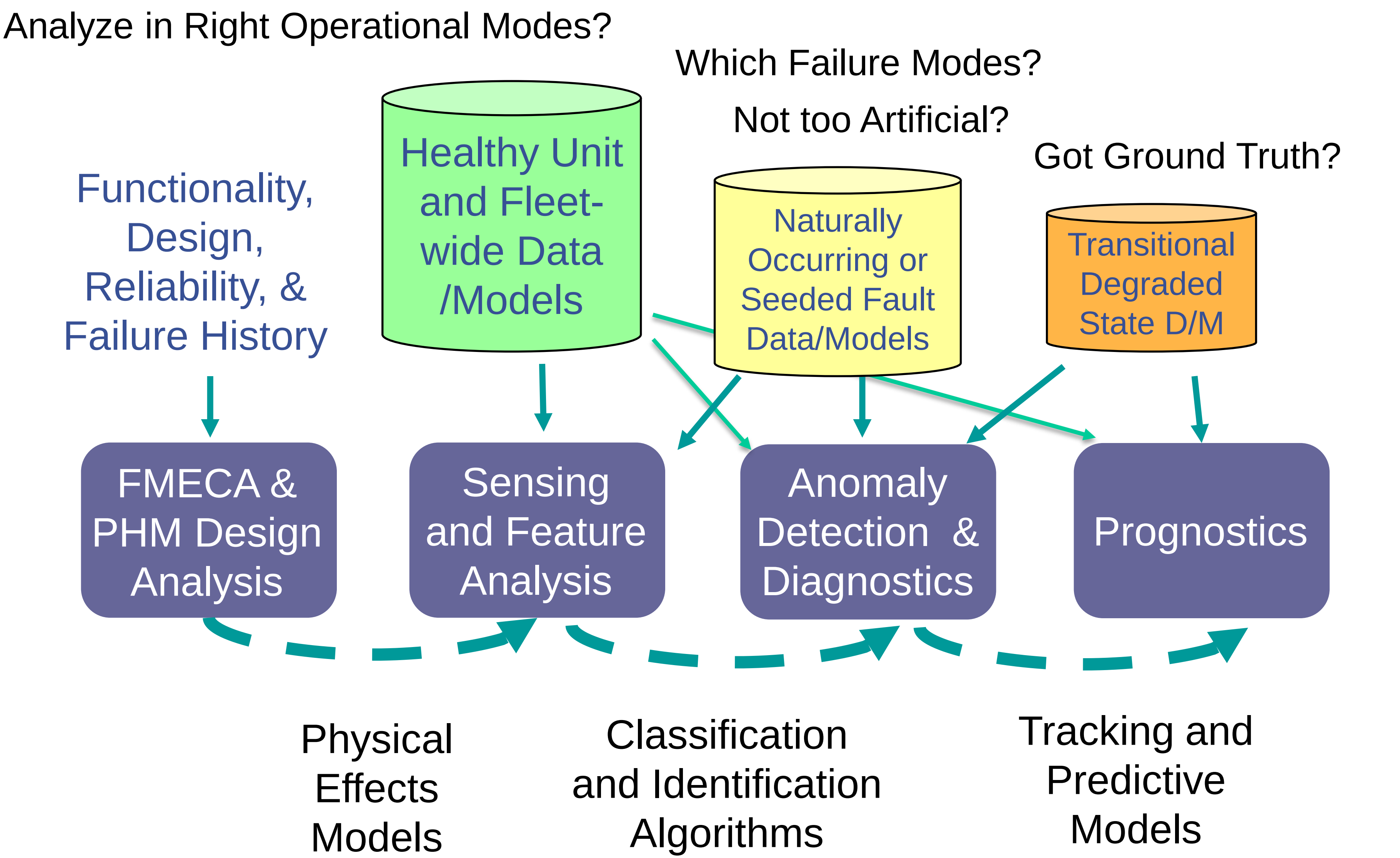
Usage-based Prognostics

This approach incorporates reliability data, life usage models and varying degrees of measured or proxy data. Forecast based on actual usage when possible. Incipient fault detection may not be available due to sensor or fault mode coverage limitations.

Condition (Health)-based Prognostics

This approach involves utilizing the assessed health or diagnostic fault classifier output to predict a failure evolution. Feature trending or physics-of-failure based prediction may then be used. Incipient fault detection and diagnostic isolation is absolutely necessary.

Processing and Data Feeding our Design



Data, Data, Data

Evaluate range of normal and dominant fault effects in controlled (ground-truth) laboratory and operational environments

("What does the machine say under different health conditions?")

- Normal and off-performance, multi-mode
- Seeded (artificial and natural)
  - Record measurements under known damage states for detection and discriminating diagnosis
- Transitional (good to failed state in continuous process)
  - Record along failure mode trajectories to understand progression and prognostics

Challenge: How to control and know conditions sufficiently and use lab and operational data?

Sensors and Signals

Translate physical phenomena and fault symptoms
into measurable quantities

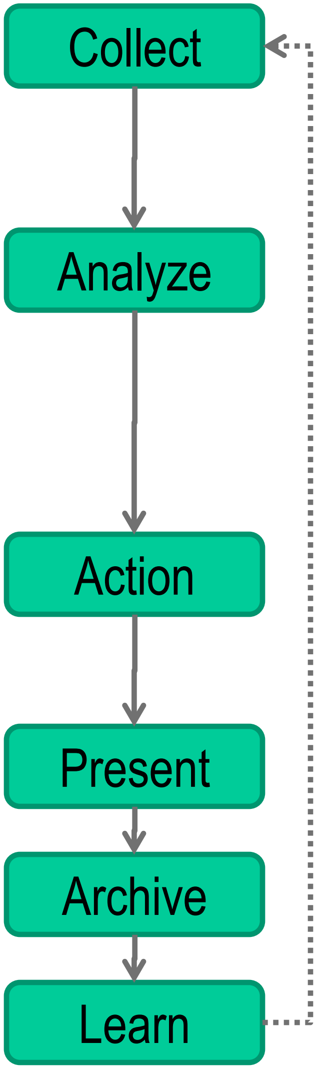
("The machine is trying to tell us something.")

- System State Observables
  - Process variables (Flow, Temp, Press, Speed, Torque,etc)
- Energy Event Observables
  - Acoustic and Vibration (Accelerometers, Velocity & Proximity Probes, Microphones)
  - High Frequency (Ultrasonics, Acoustic Emission)
  - Electrical and Magnetics
- Physical Observables
  - Oil properties and debris
  - Human perceptible

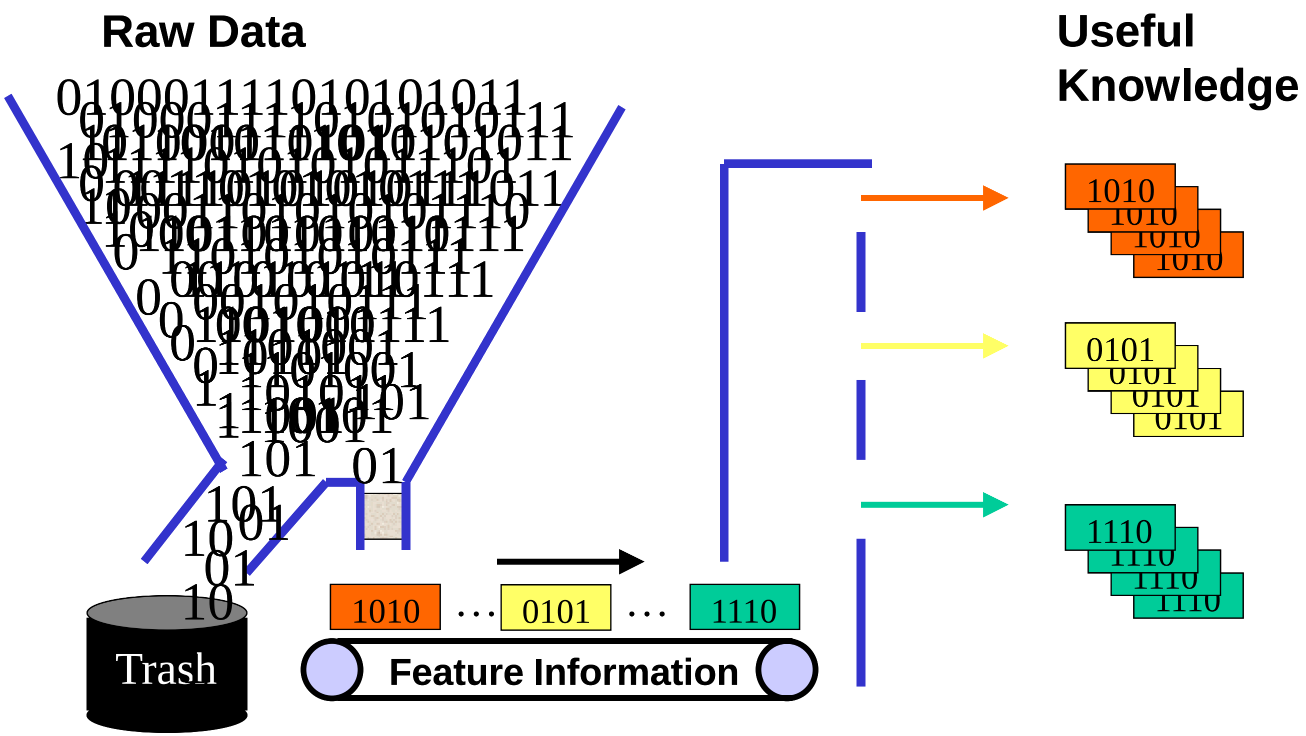
Challenge: How to choose, locate and process all the sensors?

Enabling Technologies

- Sensors and data acquisition
  - Correct sensors to observe/cover failure modes
  - Reliable data collection during appropriate conditions
- "Real time" analysis: insight into current & future equipment health
  - Automated diagnostics & prognostics
  - Component health management techniques
- Automated reasoning: provide reliable, accurate actionable information
  - Suggest unambiguous corrective actions
- Remote monitoring
  - Real-time access to machinery health information
- Site database: archive data for future analysis
- Updateable system to adapt to new info



Feature Extraction Motivation



We usually can't afford to and really shouldn't need to save everything, all the time!!
But we can be smart about what we do save and where we "find" data.

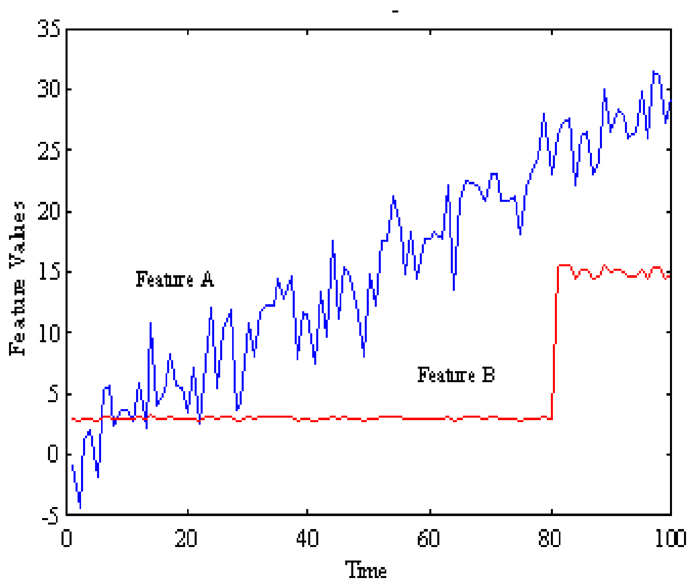
Not all Features are Created Equal
What are we looking for?

Feature A

- Exhibits a predictable trend and is therefore useful for both diagnostics and prognostics

Feature B

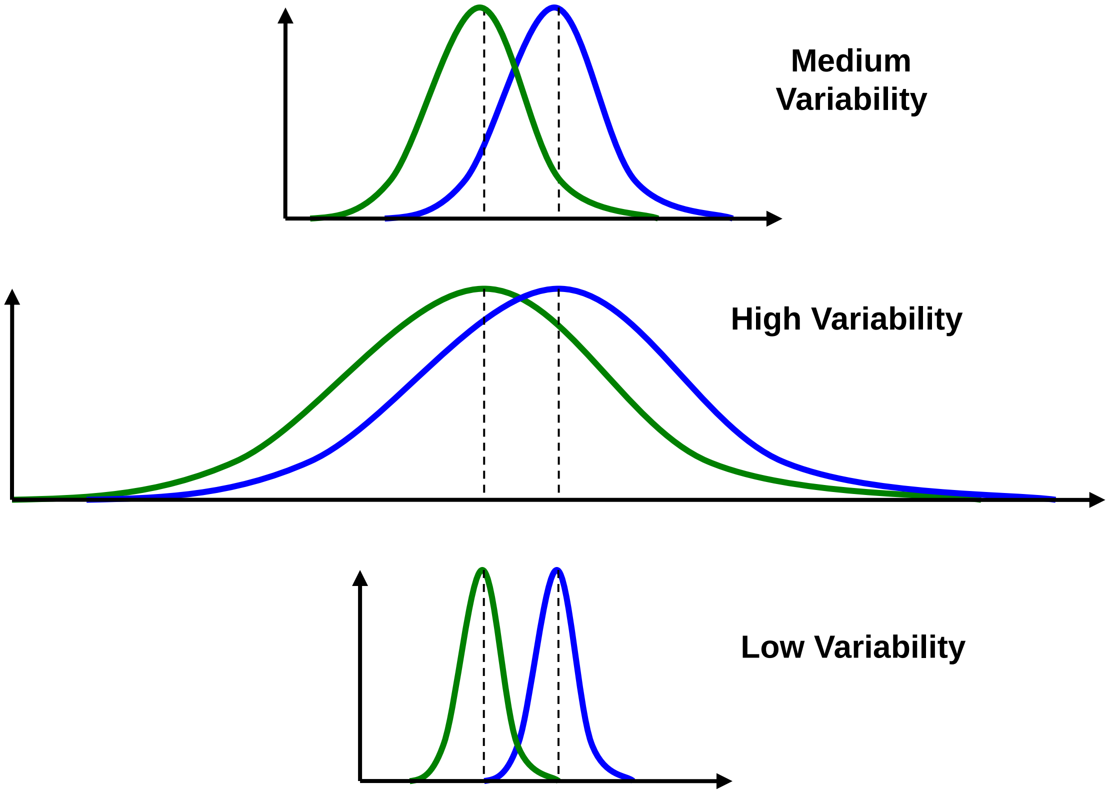
- Useful for diagnostics since it provides wide separation in feature space
- Difficult to predict the drastic maneuver, therefore not very useful for prognostics alone



Feature Selection and Evaluation

- Sensor validation is performed first
- Feature selection is performed based on the goal of PHM operation (i.e. diagnostics/prognostics)
- Feature extraction is accomplished using range of digital processing and statistical features
- Further evaluation and selection is accomplished using clustering, principal component, and other reduction techniques

Feature Selection and Evaluation

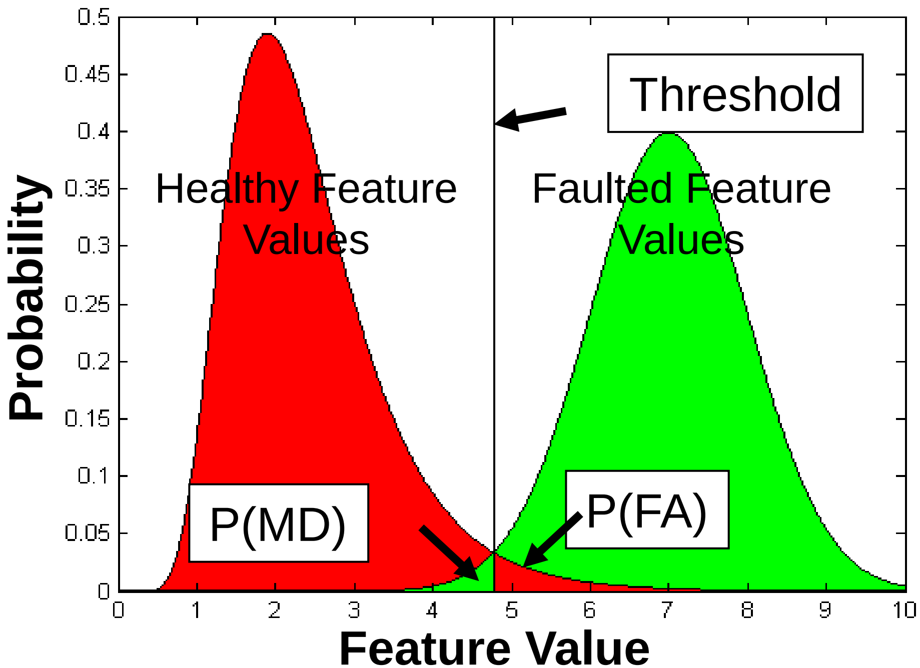


$$z = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_{X_1}^2}{n_1} + \frac{s_{X2}^2}{n_2}}}$$

where s_X^2 and $\overline{X}$ are the variance and mean of the distribution

Feature Statistical Analysis

- Analysis of healthy and faulted features' separation or overlap
- Ideally features' distributions would not overlap
- Overlap leads to missed fault detections and false alarms
- Set threshold (limit) based on P(MD) and P(FA) requirements
- Increased threshold = decreased P(FA) but increased P(MD)

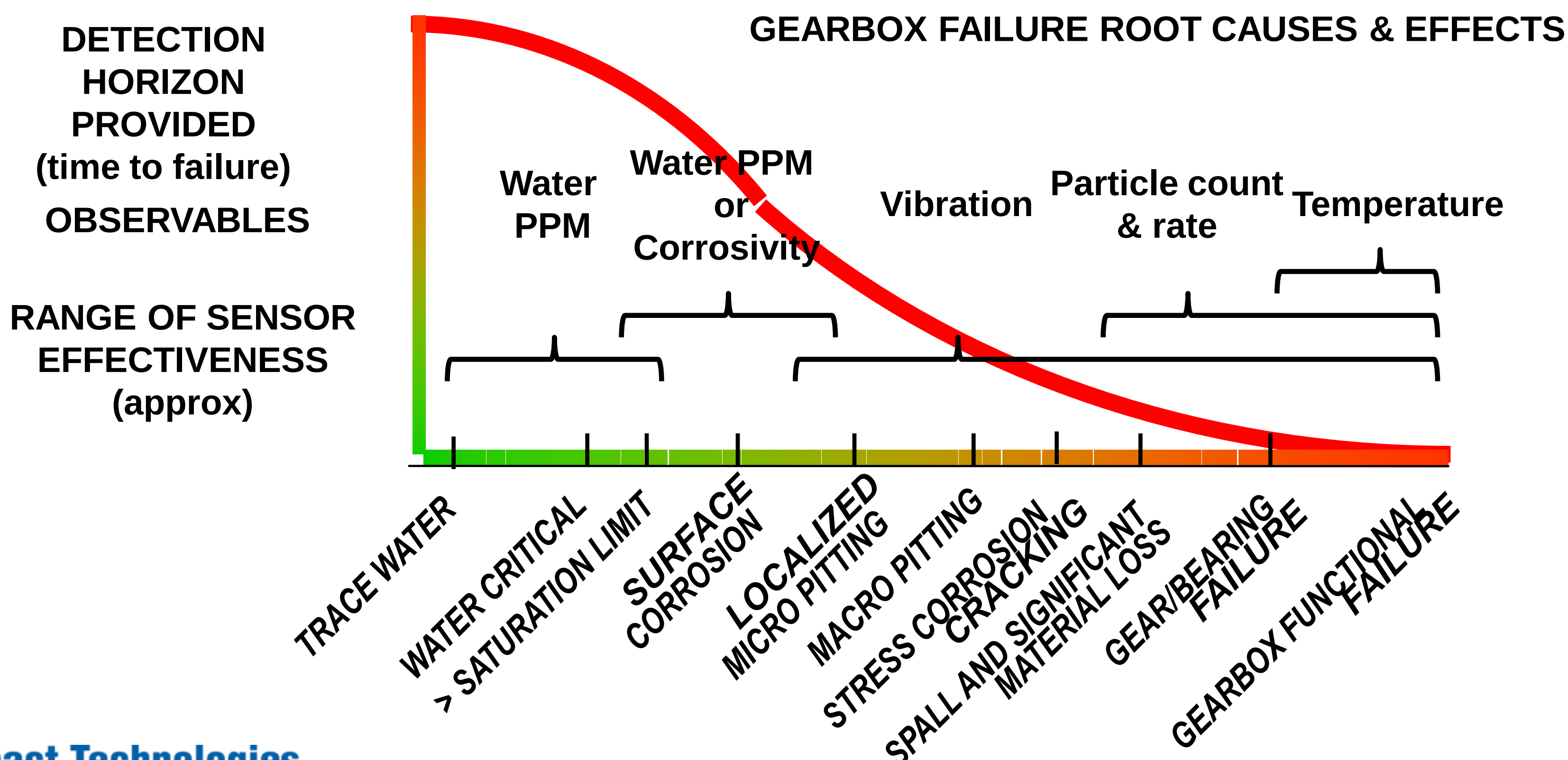


P(MD) = Probability of missed detection

P(FA) = Probability of false alarm

PHM Observables and Considerations

- Early detection is critical to maximizing CBM benefit
  - Should strive to provide longest detection horizon possible
  - Multiple sensing technologies required to provide full coverage
- Example water ingestion example



Engine/Drivetrain CBM Sensor Tradeoffs

- **Temperature** – low-cost and may work for end of life in controlled ambient conditions but:
  - Little incipient, isolation, or prognostic value
  - Very difficult to reliably use in practice
- **Velocity/Proximity Probe**– provides good shaft coverage and maybe end of life indication but:
  - Low sensitivity to incipient fault – little detection horizon
  - Limited component coverage
- **Lubricant Debris Monitoring** – can provide early indication and predictive trending value but:
  - Localization and coverage problems
  - Debris size and type sensitivity limitations
  - Nuisance indications and normal wear accumulations vs. real incipient faults
  - Non metallic issues in hybrid bearings, Corrosion and non surface fatigue failure modes??
- **Lubricant Condition Monitoring** – provides condition trending & contamination warnings before problems but:
  - Difficult to impossible to infer mechanical component health
  - Useful to extend equipment life, TBO, and reduce risk of mechanical component damage

Engine/Drivetrain CBM Sensor Tradeoffs

- **Acoustic Emission Detection** – is responsive to material failure stress wave release but:
  - High frequency wave transmission issues
  - Potentially high computational resources
  - Limited fault isolation capabilities
- **High Frequency Accelerometer** – may provide earliest incipient detection and good fault localization but:
  - High sampling and processing requirements
  - May require sensor validation, mode detection, and false alarm mitigation
  - Maybe difficult to directly infer damage levels in complex systems
  - Structural transmissibility may be an issue for small incipient damage detection

Fusion of multiple non-commensurate or commensurate sensor types can take best advantage of each capability while mitigating shortcomings

(increase detection rate and decrease false alarms)

Engine/Drivetrain PHM
Indicators and Detection Horizon

Increasing Detection Horizon

Functional Failure

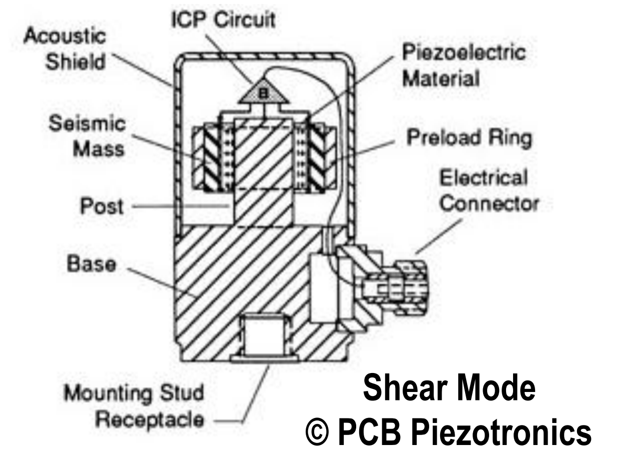
High Frequency Vibe/AE	Oil Debris	Low Frequency Vibe	Temperature Indicators	Control System Shutdown

- Bearings
  - Acceleration with or without tachometer and demodulation-based, ImpactEnergy™ analysis
  - **Requires high sampling rates if performed digitally**
  - **Mechanical transmissibility and sensor location are key**
- Gears
  - Acceleration and tachometers with time synchronous averaging and residual vibration signal analysis
  - GearMod™, Wavelets, Interstitial Enveloping
  - **Requires medium sampling and good stationarity in time**

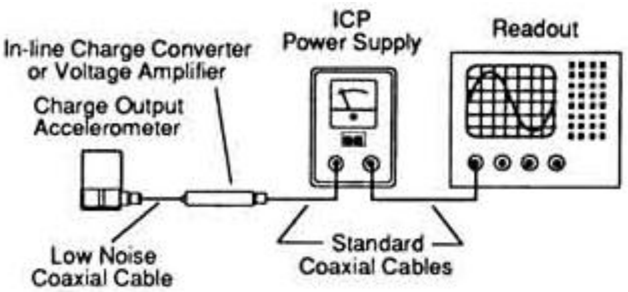
Acceleration

- "It is easy to get an accelerometer to measure acceleration. The problem is to keep it from measuring everything else!"
  – Walter Kistler

- Acceleration can be measured with a few methods but typically a piezoelectric/ceramic
- These sensors are designed to be sensitive to specific spatial directions and integrate to a voltage directly proportional to g-force within a linear range
- An AE transducer is similar in design to an accelerometer but without much to zero proof mass which provides for a higher mounted resonance
- Linearity regions and Resonance depends on sensor design, mass, mounting method, and signal conditioning/filtering



Shear Mode
© PCB Piezotronics



Typical Signal Conditioning
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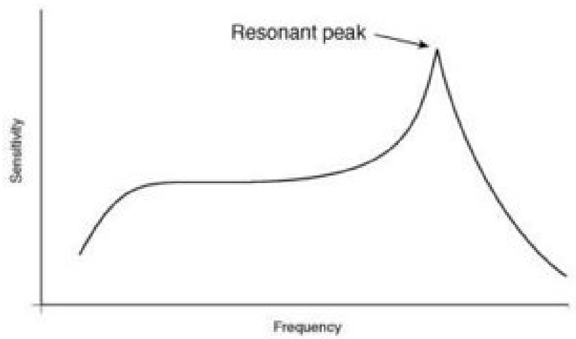
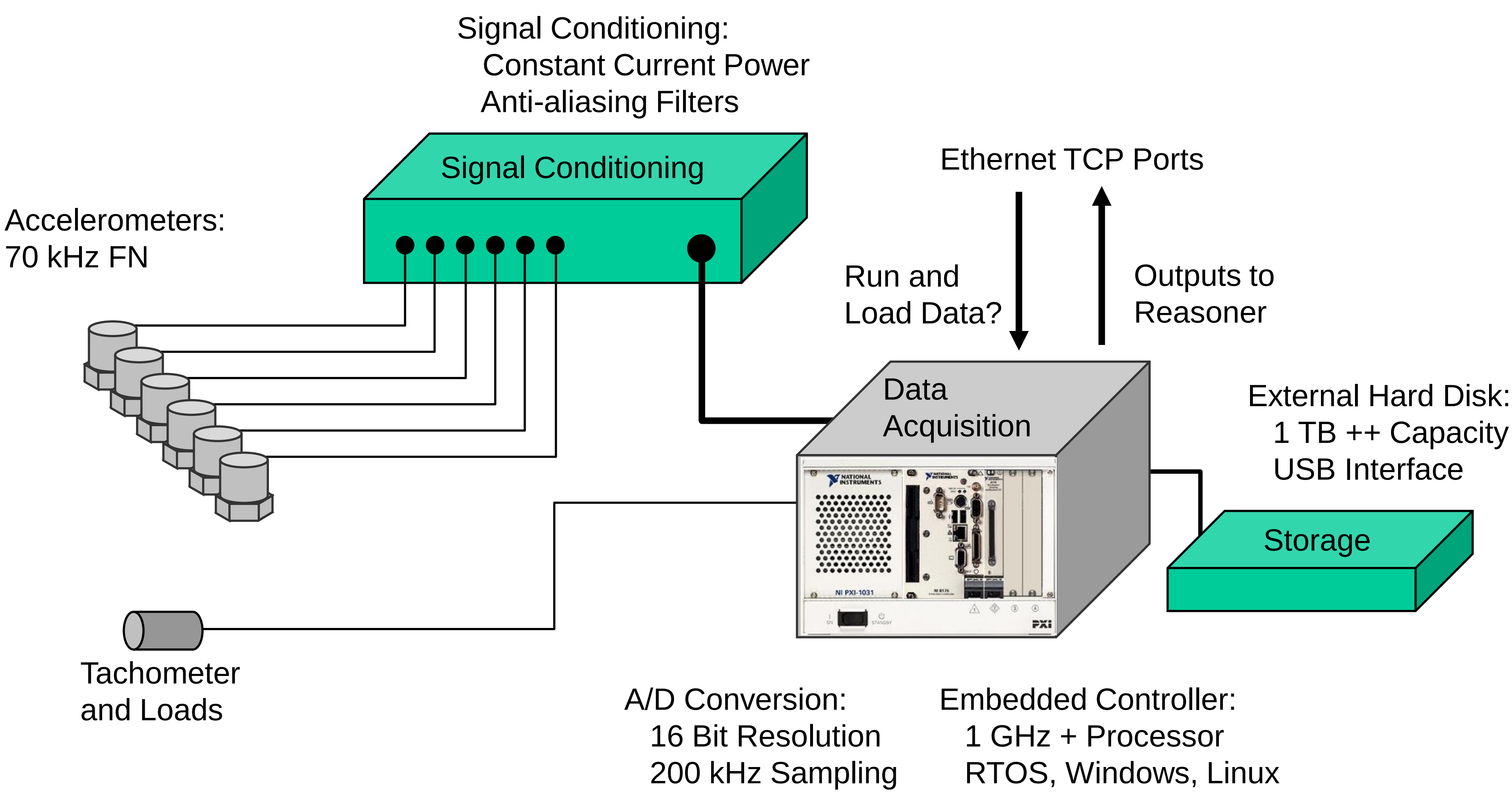


Mounted resonant frequency

Typical High End Data Acquisition Design



Acoustic Emission

- Transient high-frequency stress waves generated by the rapid release of strain energy due to crack initiation, plastic deformation, or phase transformation in composites
- Unstable discontinuities affected by loading emit acoustic energy
- AE inspection is a real-time test of active flaw during change of stress field around flaw
- AE inspection is non-directional

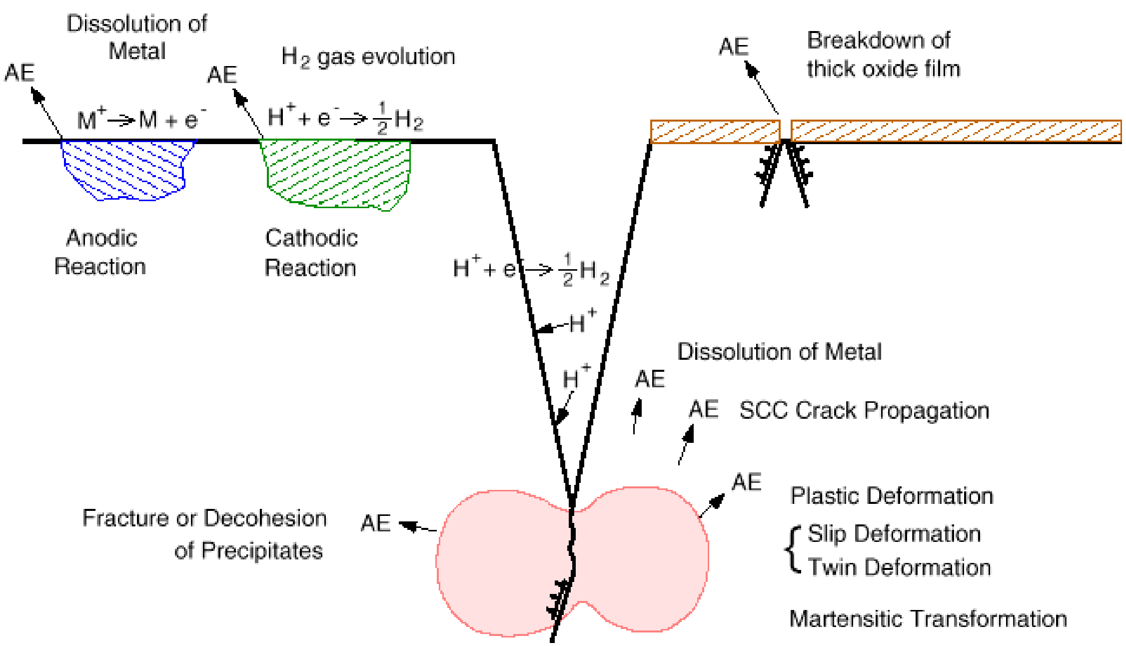
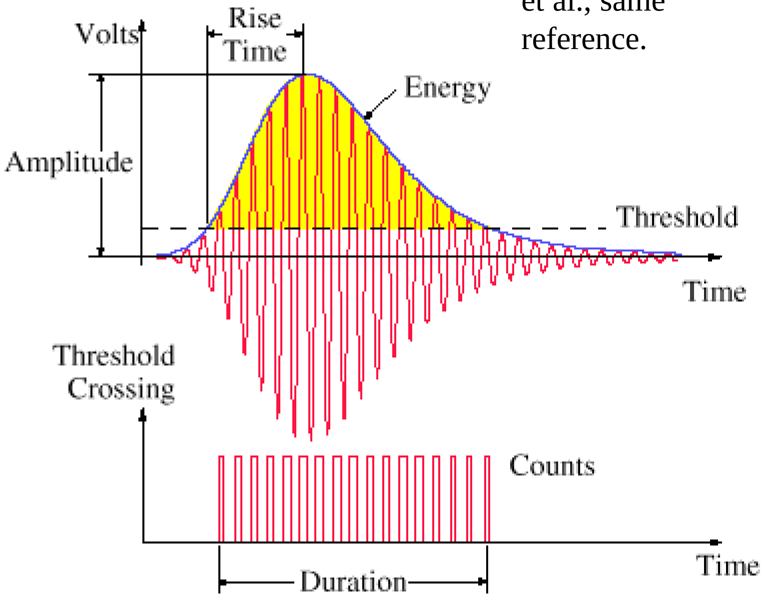


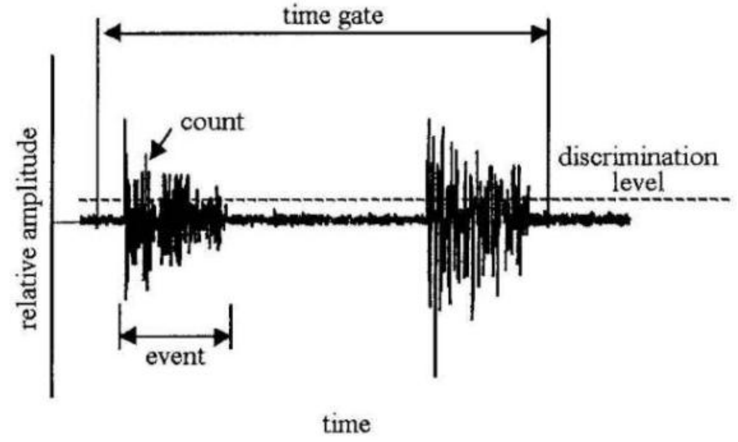
Image published in: Using Acoustic Emission in Fatigue and Fracture Materials Research November 1998 (vol. 50, no. 11) JOM.

Acoustic Emission (cont'd)

- AE can very sensitive with broadband or narrowband measurements with wide range 40kHz to 10MHz
  - Requires preamps and filters to condition
- Parametric and waveform data
  - Cumulative Number (Summation) of Counts or Events
  - Rate of Counts versus Parameter of Interest
  - Peak Detection (Threshold Detection)
  - Ringdown or Threshold Counting Number of Positive Crossings of a Preset Threshold
  - Energy of Transducer Output
  - Digitization of AE Waveform
  - Rise Time and Event Duration
  - Frequency (counts/event)

© Miinshiou Huang, et al., same reference.





AE Sensors

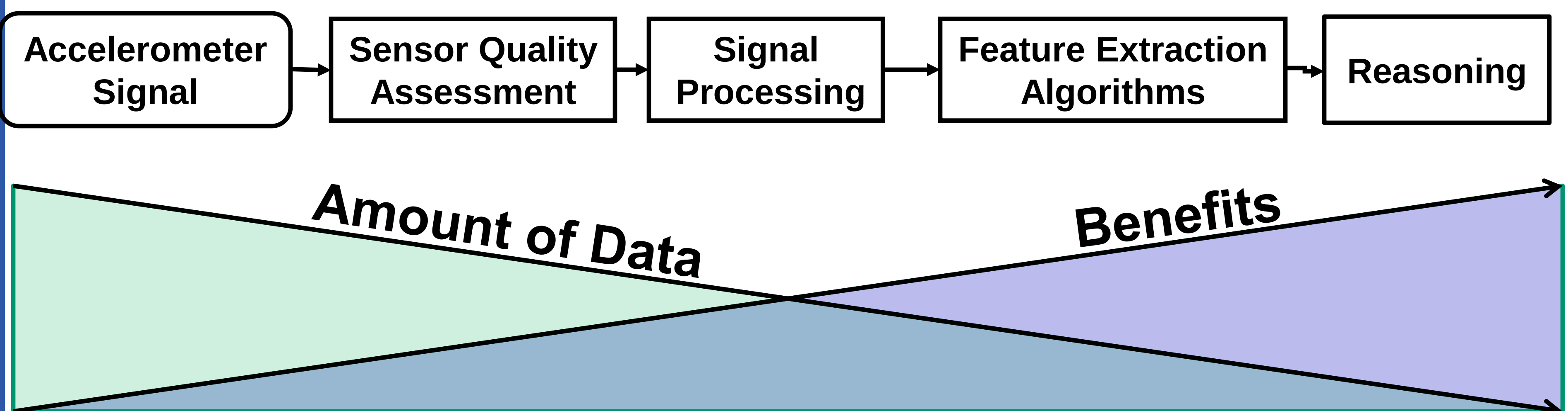
- Piezoelectric Ceramic Sensors
  - Lead zirconate titanate (PZT)
  - Lithium niobate
  - Barium titanate (Ba Ti O_3)
  - Lithium sulfate
  - Tourmaline
  - Quartz
  - Aluminum nitride
- Polymeric film transducers
  - Polyvinylidene fluoride (PVDF)
- Fiber-optic Sensors

© Physical Acoustics Corporation

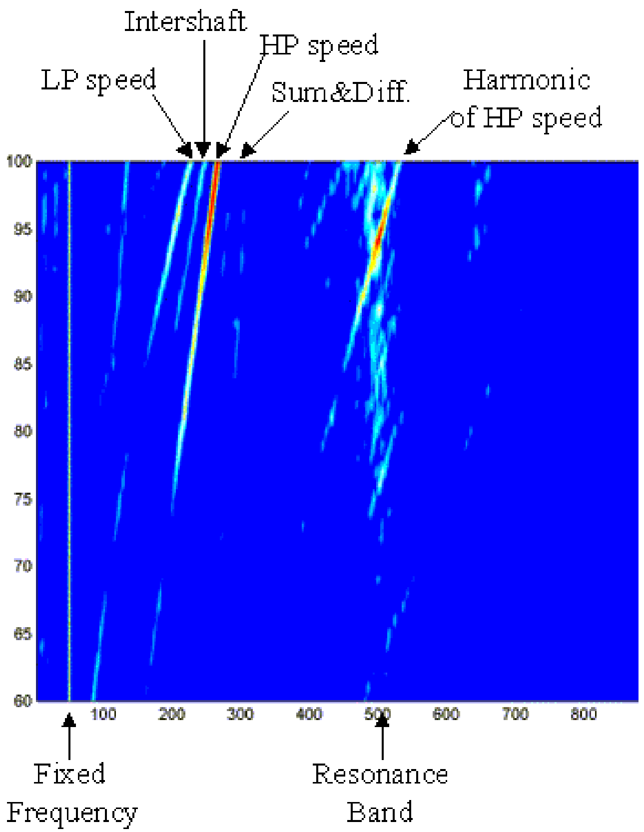
© McWade Monitoring Systems

Effectively Using Dynamic Signals

- Dynamic signals not typically used directly
  - Some **automated** analysis needs to be performed
- Appropriate analysis depends on sensor, system, and targeted components
  - Bearing, gear, shafts all require slightly different analysis
- Need to analyze the analysis to distill various features to actionable information



Example Features for Low Frequency Vibration Fault Diagnostics

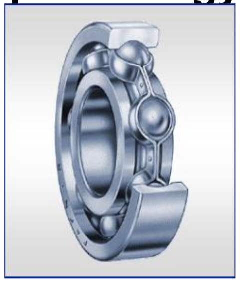


Spectral Plot Features	Unbalance	Shaft Interaction	Eccentricity	Squeeze film malfunction	Blade Rub	Rotor instability	Oil in rotor	Flange/joint slip	Looseness	Misalignment	Swashed track
1 EO without harminics	X	X	X	X							X
1 EO & 2 EO (first harmonic)										X	X
1 EO and multiple harmonics					X	X		X	X	X	
1/2,3/2, 5/2 EO				X	X				X		
Sub-harmonics (1/4,1/3,1/2 EO)	X			X	X						
Broad band (raised floor)						X			X		
Fixed frequency				X							
Side bands						X	X		X		
Sum & Diff frequencies	X	X									
Roughly 0.45 EO				X							
Roughly 0.9 EO							X				

Track Shape Features	Unbalance	Shaft Interaction	Eccentricity	Squeeze film malfunction	Blade Rub	Rotor instability	Oil in rotor	Flange/joint slip	Looseness	Misalignment	Swashed track
Const. 1 EO amplitude			X								
1 EO increase with RPM^2	X										
1 EO step change				X				X			

Mechanical Component Specific Modules

ImpactEnergy™



Bearing Module

Firstcheck™

Sensor Module

GearMod™

Gear Module

GearMod™ Shaft

Shaft Module

Extensive Successful Field Application Experience

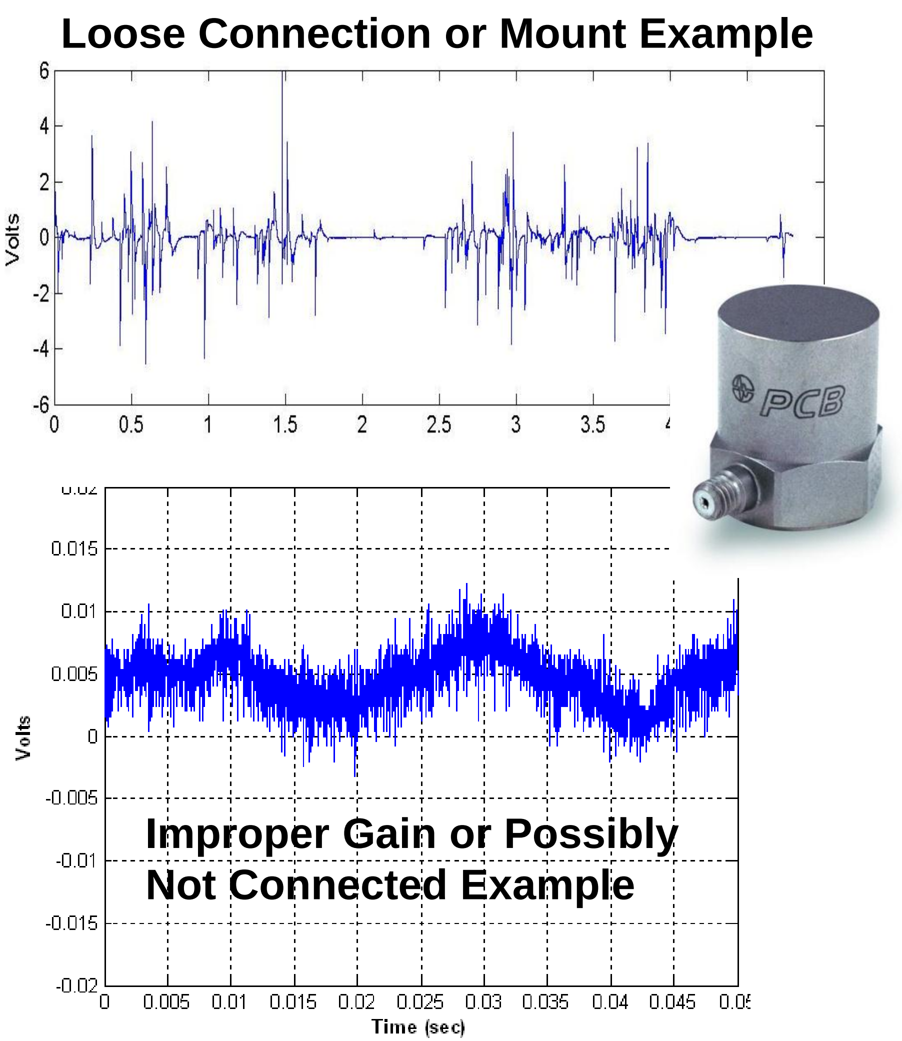
- Aircraft Engine OEM Test Cell
- Engine OEM Onboard PHM
- Bearing and Power Transmission Component OEM
- Various DoD and Industrial Applications

Data Validation (FirstCheck™)

Objective: to automatically validate accelerometer data in real time in preparation for fault detection

- Improper amplification or gain settings
- Sensor clipping
- Extreme signal bias
- Loose or complete loss of connection
- Loose/improper mounting
- Random signal anomalies primarily related to internal sensor damage and leading to signal corruption

High Bandwidth/Vibration Sensor Faults



Loose Connection/ Loose Mount

Misleading magnitude & frequency content of signal depending on level of severity affecting many algorithms

Dis-Connected or Dis-Mounted

Complete loss of information, worst case scenario, but easily identifiable

Improper Gain Settings

If to high can lead to clipping and signal saturation, if set to low poor A/D converter resolution

Damaged Sensing Hardware

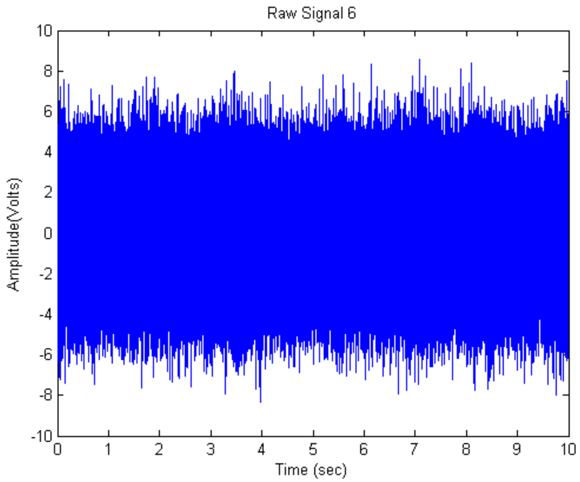
DC offset, clipping, resembles closely to a mechanical fault vibration signature

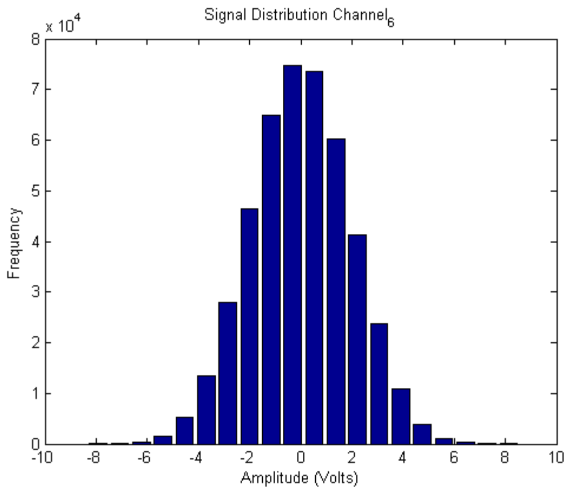
Extreme Operating Conditions

Situations involving high load, temperatures, rotating speeds, shaft misalignment, exploiting sensors original performance design intent

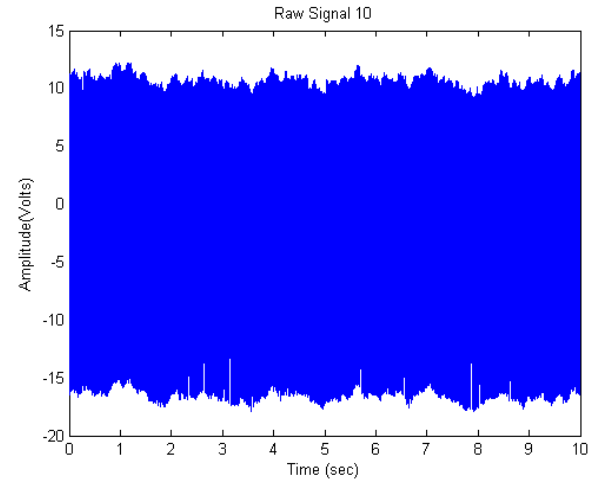
Vibration Sensor Fault Example

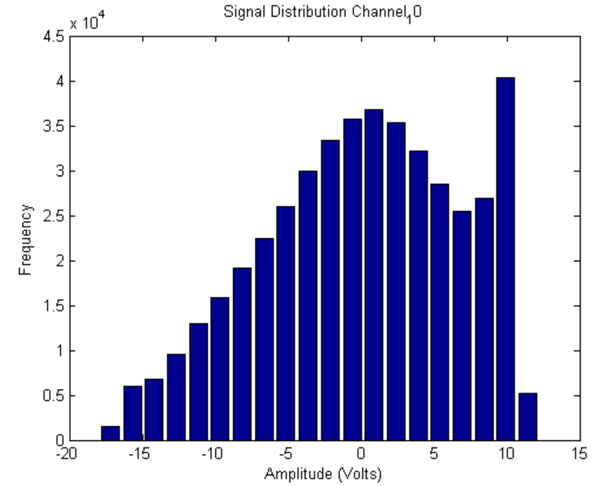
Good Signal





Bad Signal



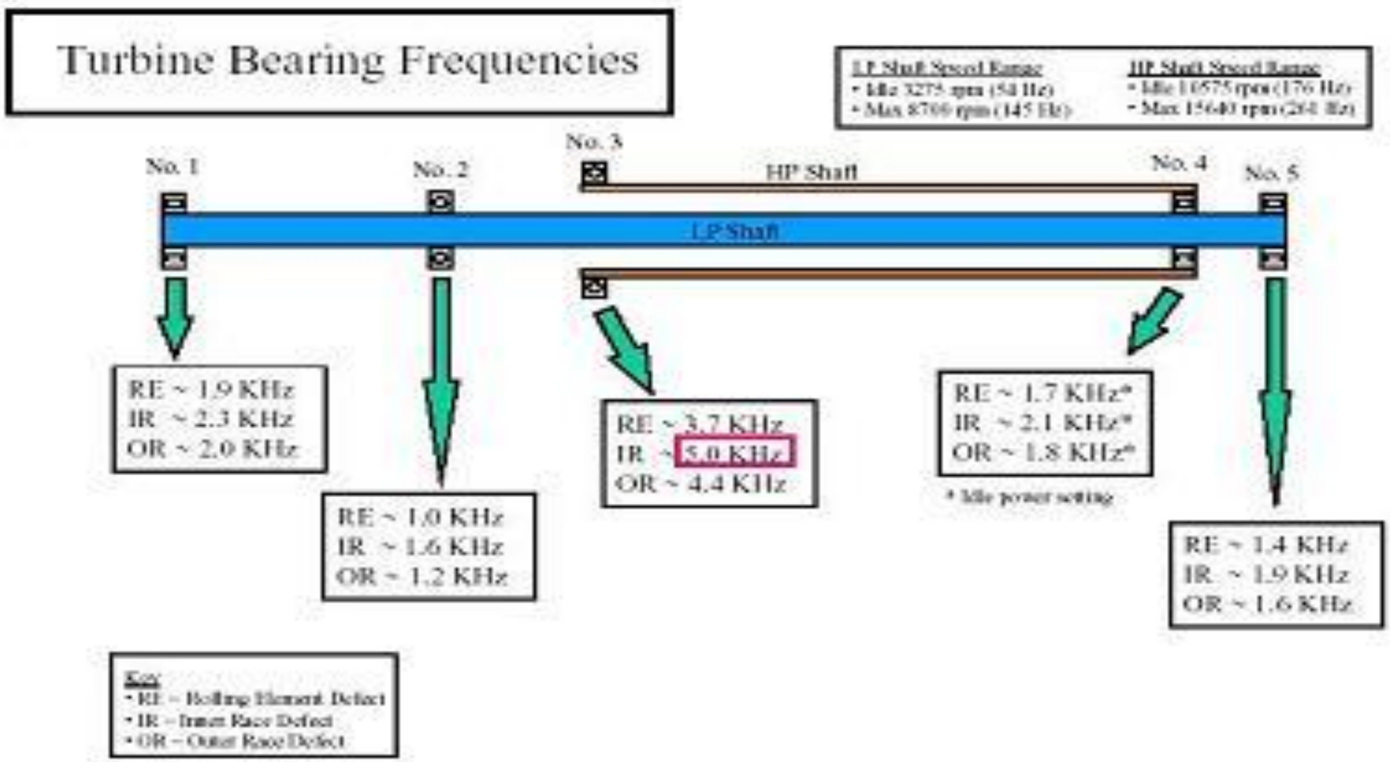


Quick look of raw time-signal of a faulty accelerometer can often be misleading (top)

Viewing the signal from a statistical standpoint, histogram plot (bottom) reveals likely corrupt nature

Some Engine/Drivetrain PHM Challenges

- Broad bandwidth “noise”
- High speed operation
- Multiple shaft frequencies
- Extreme operating environment
- Fault signal transmissibility
- Speed and load variation



Understanding Vibration

- Component specific signal processing and feature extraction
- Numerous well established diagnostic algorithms exist

Bearing analysis:

- **Spectral Analysis**: Frequency analysis based on bearing geometry and known fault frequencies
- **Enveloped-based Demodulation**: used to extract bearing defect information from higher frequencies regions

Gear/shaft analysis:

- **Time Synchronous Averaging (TSA):** Amplifies shaft synchronous vibrations
- **Residual Analysis**: Provides localized fault detection by evaluating modulation of tooth meshing vibration & harmonics (appears as sidebands in FFT)
- **Difference Analysis**: Detects distribution of energy over wide range of frequencies as fault progresses

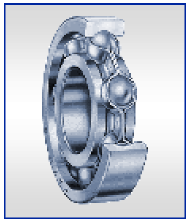
Joint Time-Frequency Analysis (JTFA):

- transforms 2-D time domain or frequency domain signal into 3-D time-frequency domain signal

Advanced Vibration PHM

- **ImpactEnergy™**: Novel enhancements to traditional bearing analysis (i.e., narrowband time-domain, enveloped-based demodulation, etc.)
  - Automated selection of optimal demodulation band (ABS)
  - Novel feature extraction and fusion of analysis from multiple bands
  - Optimized FFT for more accurate fault frequency tracking

ImpactEnergy™



Bearing Module

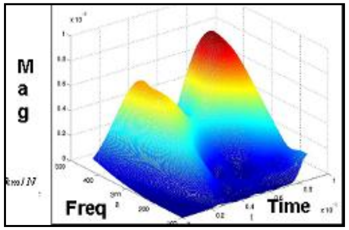
- **GearMod™/GearMod-Shaft™**: Accepted gear/shaft analysis (TSA-based) plus novel signal processing enhancements
  - Novel TSA that optimizes FFT Resolution
  - Improved feature/CI extraction methods
  - Advanced "No Tach" processing capability

GearMod™

Gear Module

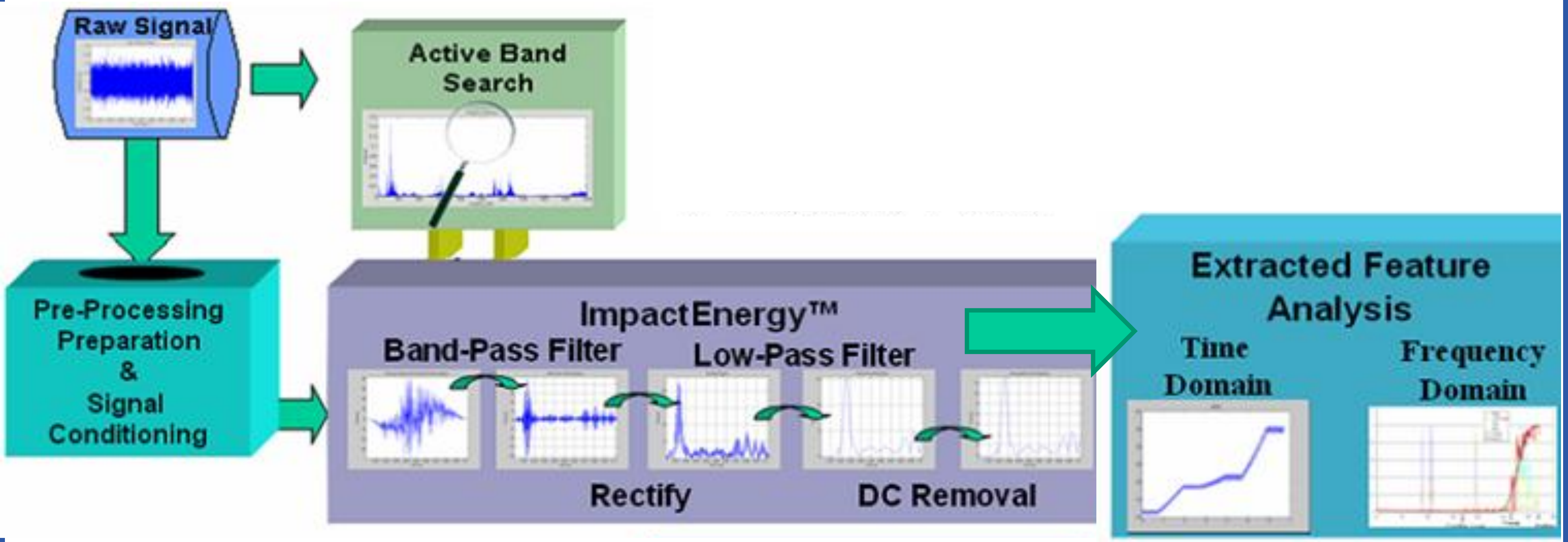
- **Joint Time-Frequency Analysis (JTFA)**: transforms 2-D time domain or frequency domain signal into 3-D time-frequency domain signal
  - Allows analysis during transients/start-up – especially important for components highly loaded during start-up

JTFA



ImpactEnergy™: Overview

- Step 1: Automated Band Selection: Identifies best regions of spectrum for analysis/demodulation
- Step 2: Demodulation
- Step 3: Feature Extraction: Various time and frequency domain features with feature-level fusion (when appropriate)



Leveraged Bearing Data Sets and Rig Experience

- F404, T-55 Engine Test Cells
- TF-39 Test Cells – Dover, Travis
- Engine and Drivetrain Test Cells
  - F100 AEDC
  - JSF LiftFan, F-135, F-136
- JSF F-100 Seeded Engine Tests
- AFRL T-63 Engine, Minisimulator, and Fatigue Initiation Rigs
- Dedicated Engine Bearing Test Rigs
- Accessory Gearbox and Generators

Over 100 TeraBytes of Engine/High Speed Gearbox Bearing Vibration Data!

Tutorials Session

PHM Society 2012, Hyatt Minneapolis, MN
September 24th, 2012

T63 Engine Bearing #2

Incipient Fault Test

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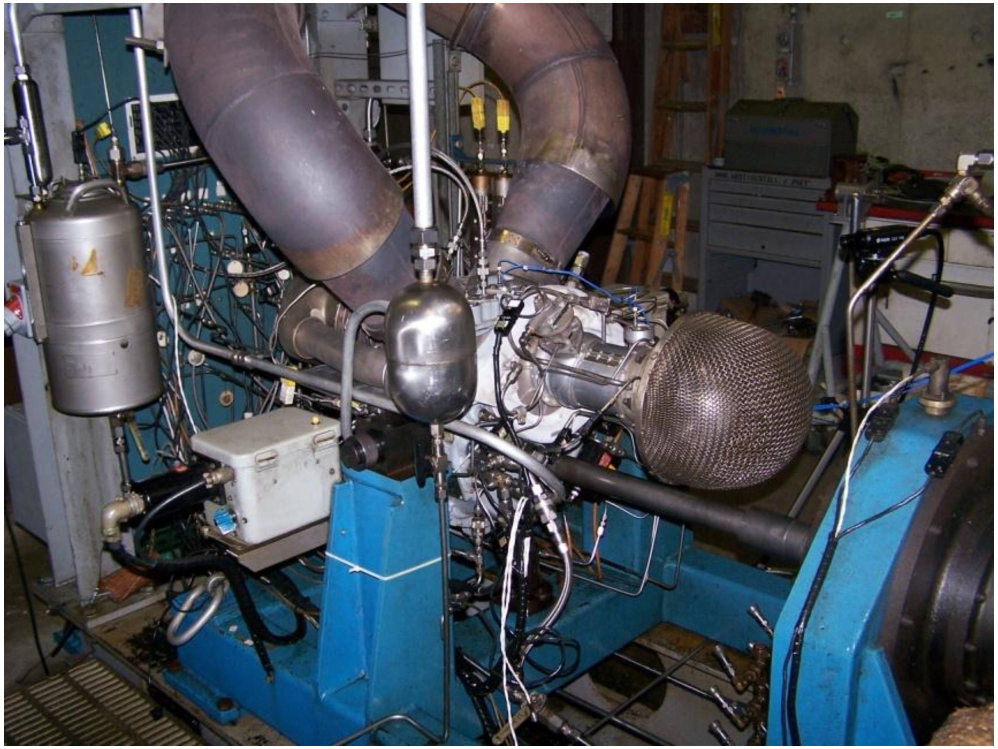
Overview

- 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



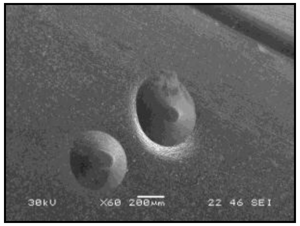
Operational Engine Test

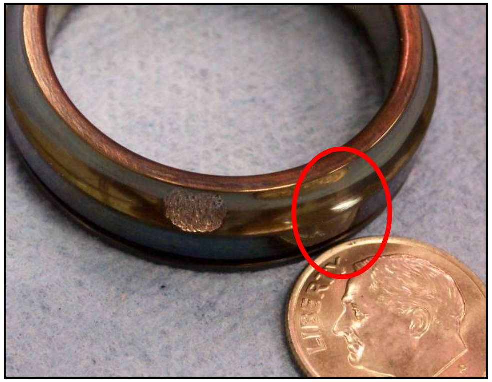
<u>Helicopter gas turbine engine</u>

- High speed (>20,000 RPM)
- Dynamometer loaded

<u>Bearing conditions:</u>

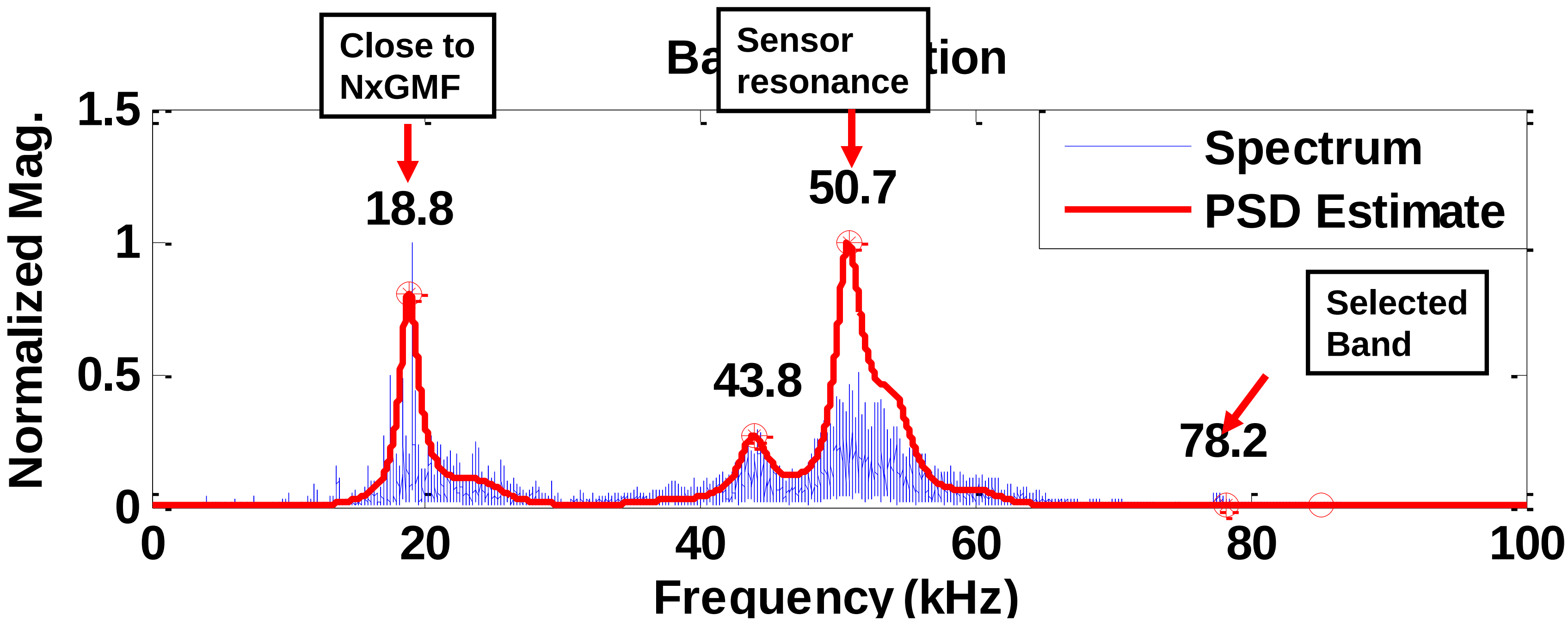
- Healthy
- Dented
  - Two Brinell hardness indents
  - Inner raceway wear path
- Spalled
  - Spall initiated in another test rig from Brinell mark on inner race
  - Initial dimension= 0.3 in x 0.25 in





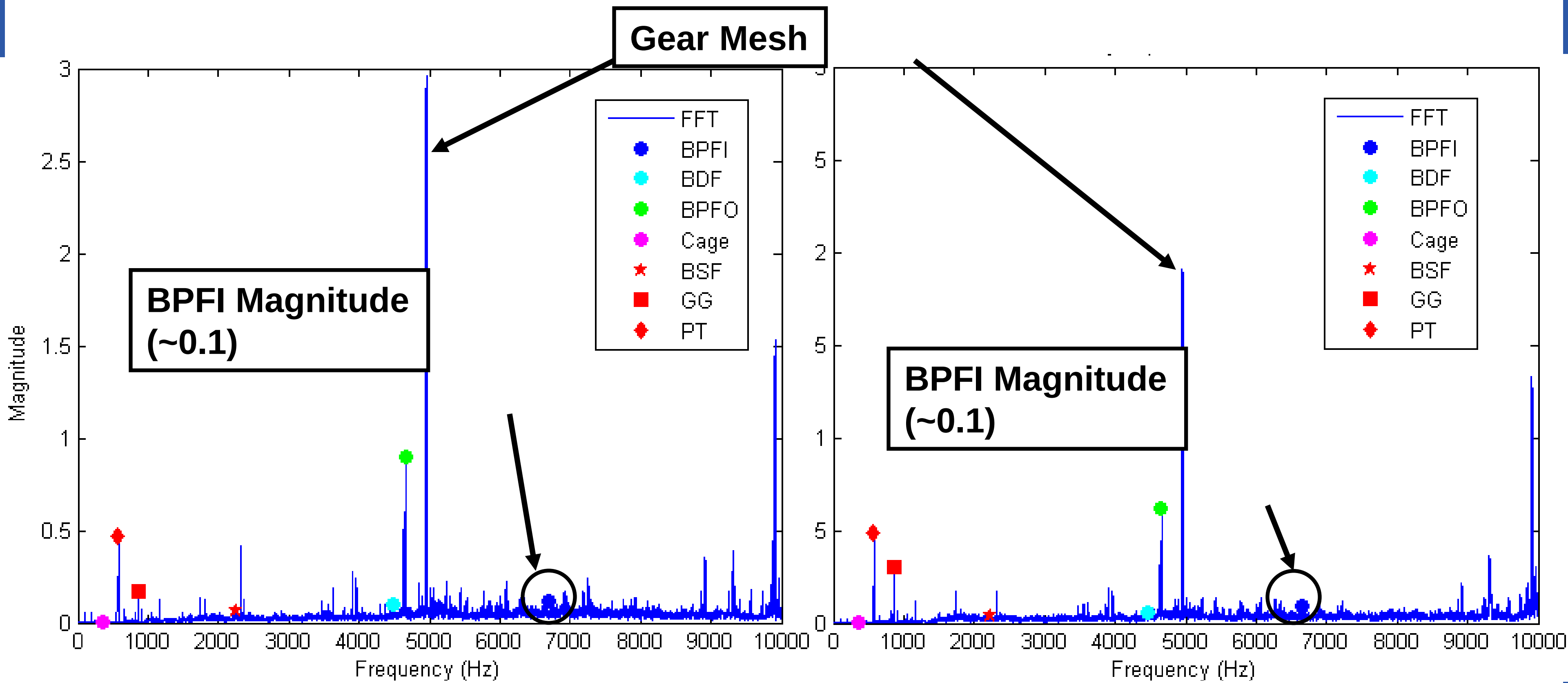
Advanced Band Selection Analysis

- Applied to several data segments
- Identified frequencies compared to known system frequencies, avoid certain ones
- Analysis used ~70 kHz center frequency



Conventional Bearing Features

- Conventional spectrum + bearing fault frequencies
- No significant difference from healthy to dented

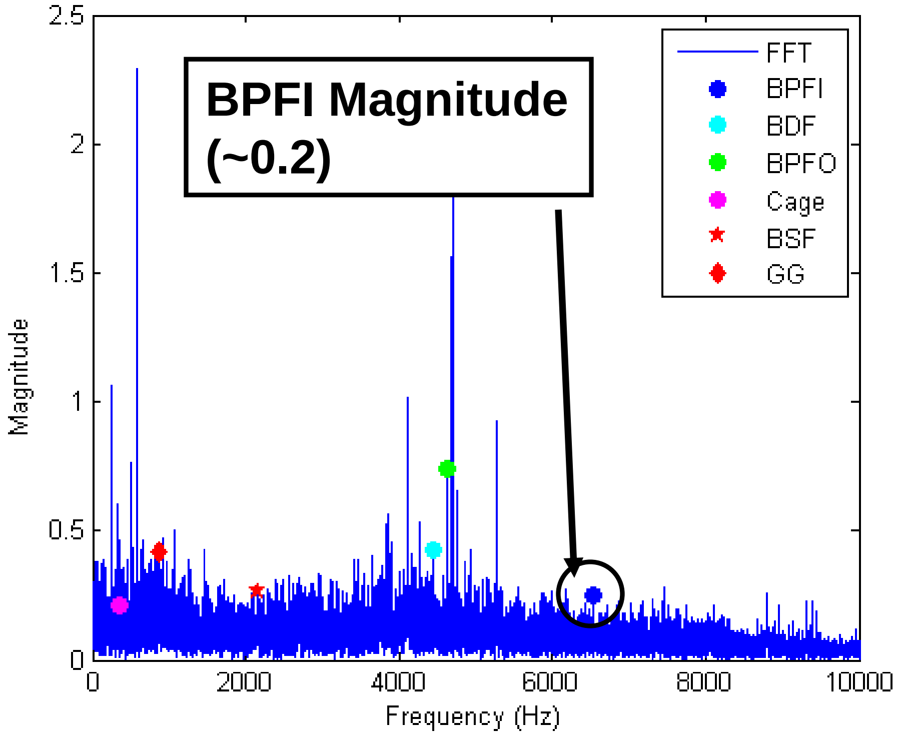


Healthy Bearing

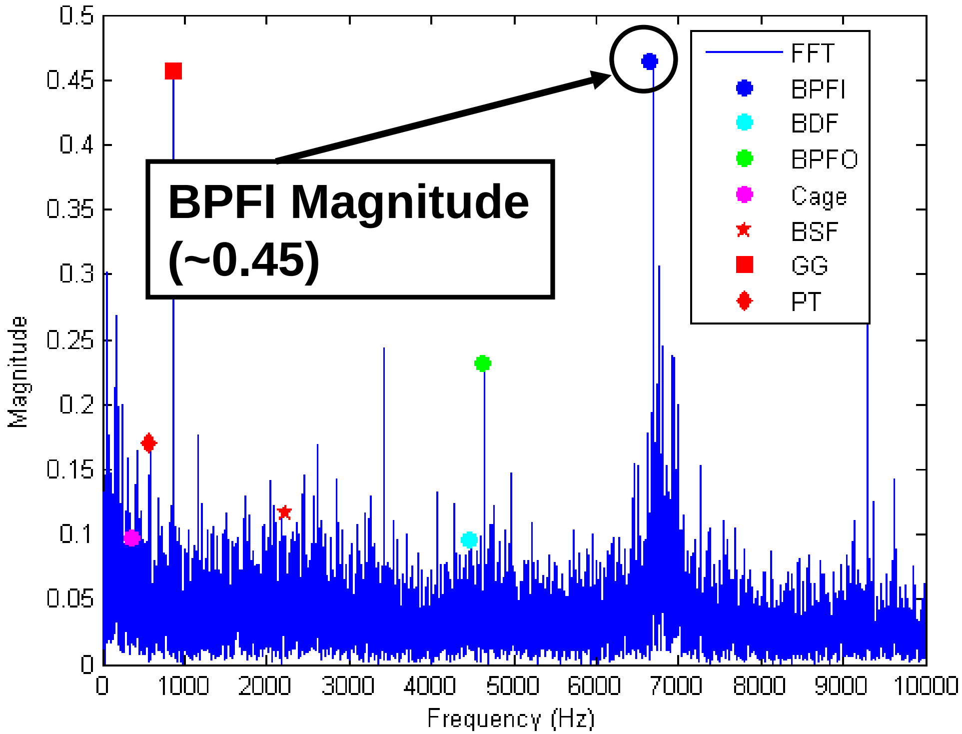
Dented Bearing

ImpactEnergy Analysis

- Using same dented dataset, 50 and 70 kHz carrier frequencies
- BPFI peak above noise floor for 70 kHz, not for 50 kHz



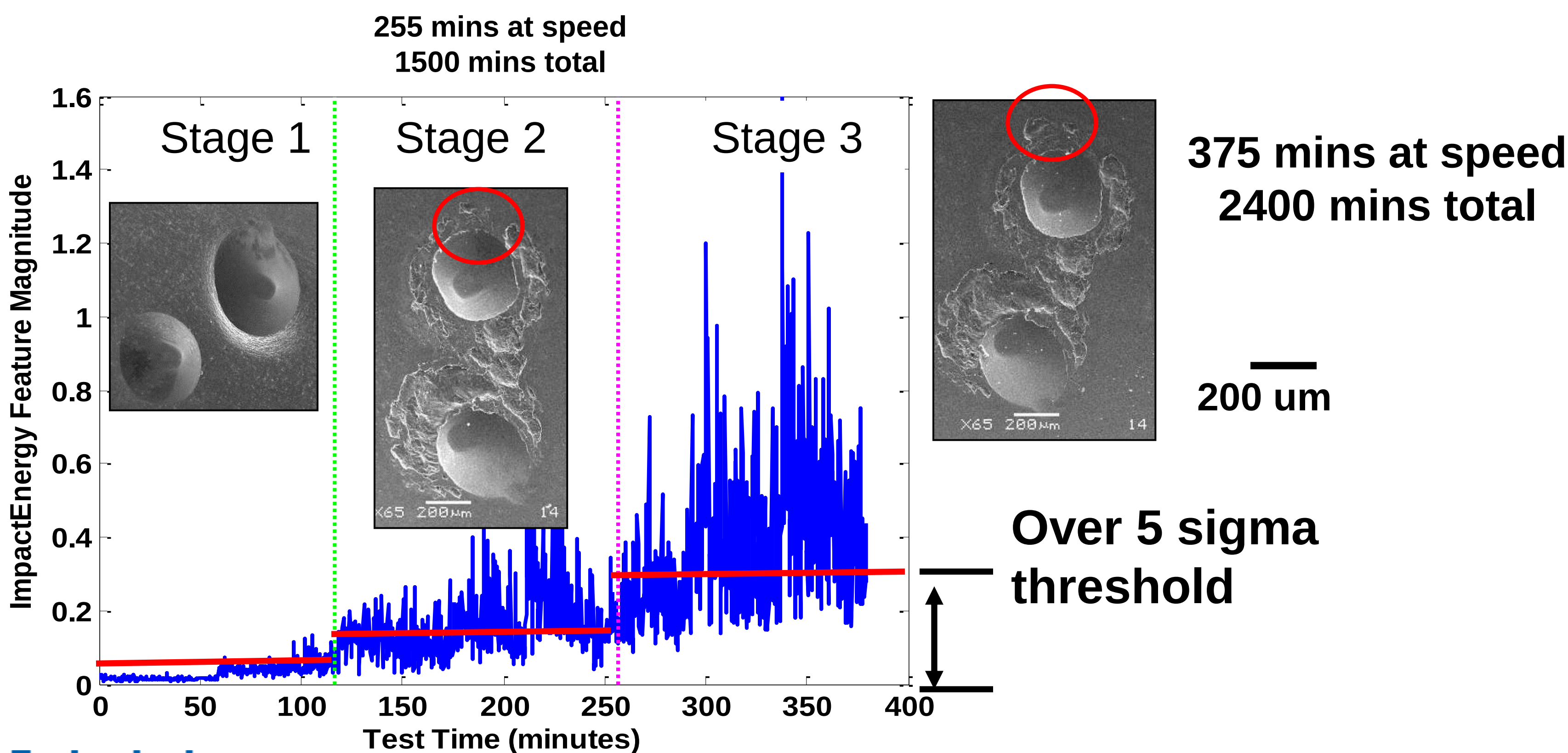
Dented Bearing, 50 kHz



Dented Bearing, 70 kHz

Incipient Detection and Tracking

- Raceway spall detection at < 200 micrometers damage
- Spall propagated and tracked throughout
- All measurements and assessments made in operating gas turbine with case accelerometers



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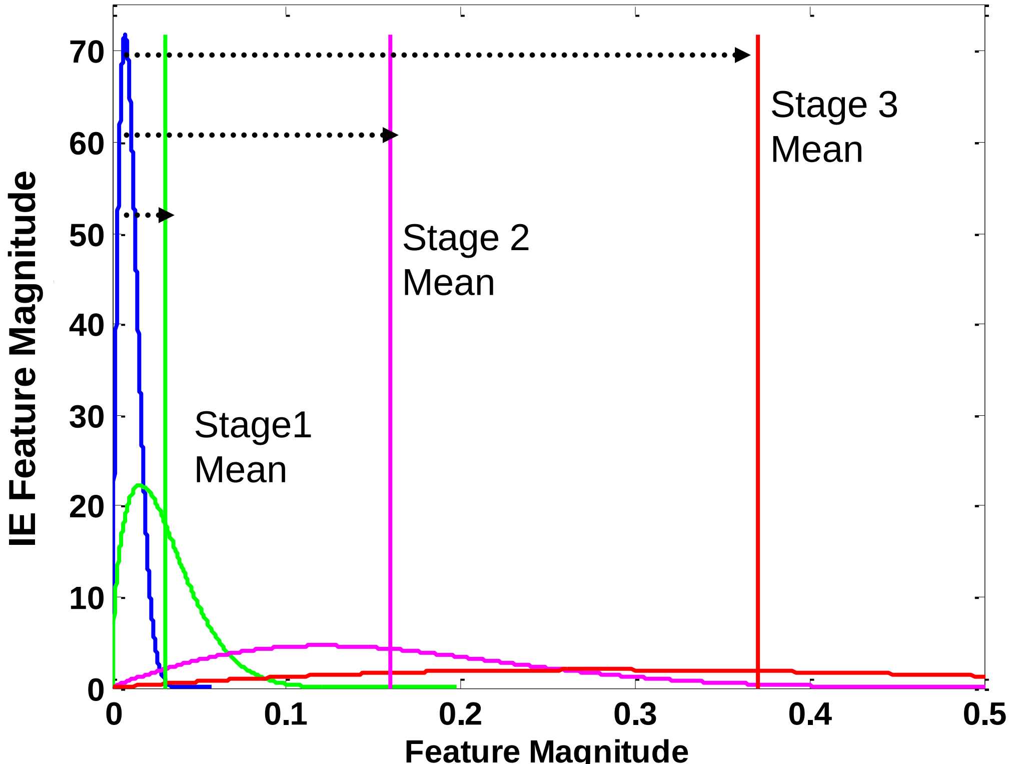
www.impact-tek.com

Feature Distributions and Metrics

- Calculated healthy and faulted distributions using best fit methods
- Set threshold based on 2% P(FA)
- Calculated P(MD) for each stage



Threshold = 0.024
P(MD) 1 = 45.12
P(MD) 2 = 2.30
P(MD) 3 = 0.49

As fault size increased P(MD) decreased

Tutorials Session

PHM Society 2012, Hyatt Minneapolis, MN

September 24th, 2012

Engine OEM Bearing Rig Testing: Hybrid Ceramic Bearing Fault Detection

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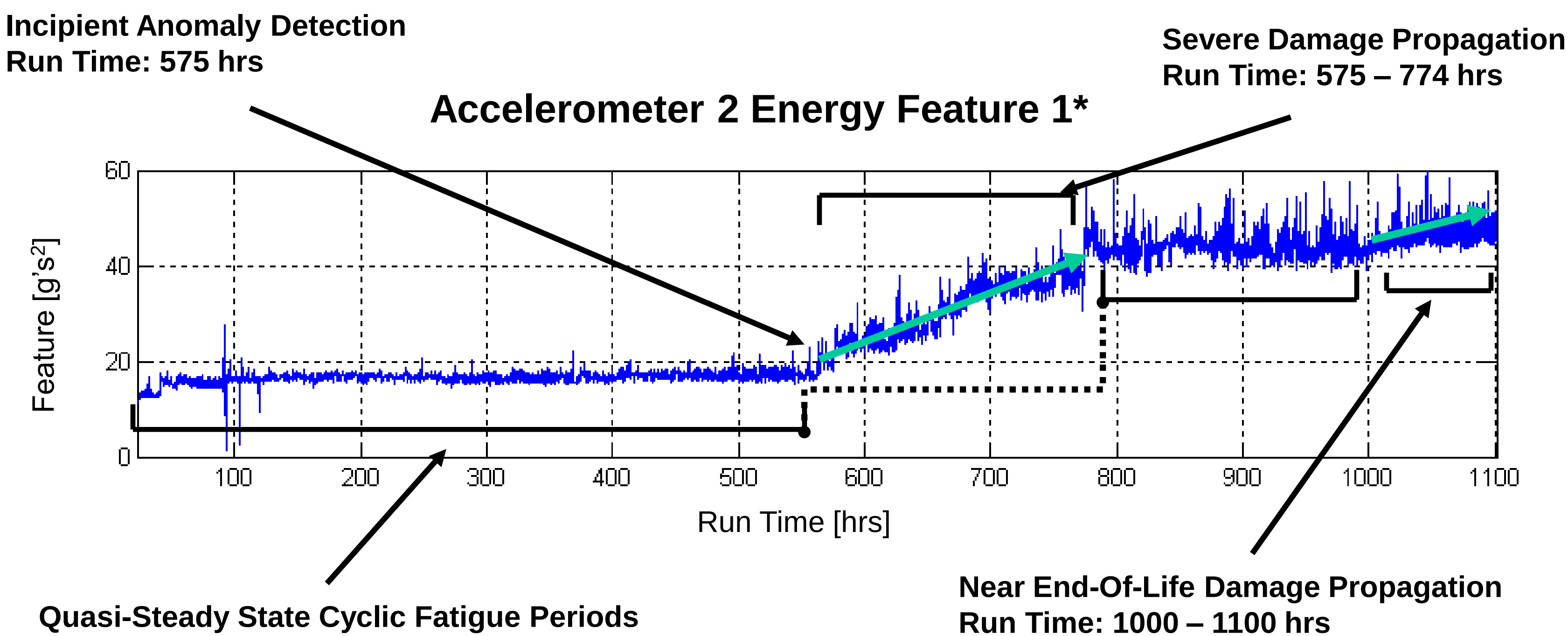
Test Configuration

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

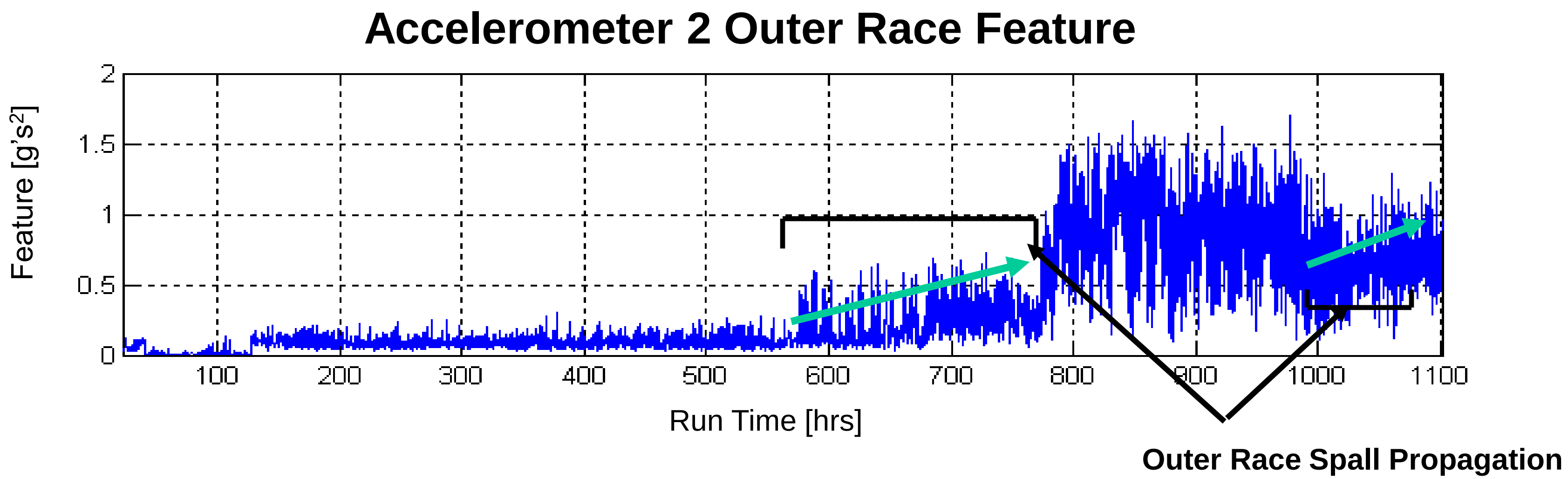
- Speed and Load Profile
  - Stage 1 100% axial load 100% speed
  - Stage 2 48% axial load 93% speed
- Data Acquisition
  - 2 seconds of data every two minutes
  - Over 700 GB of data; over 1100 hrs of testing

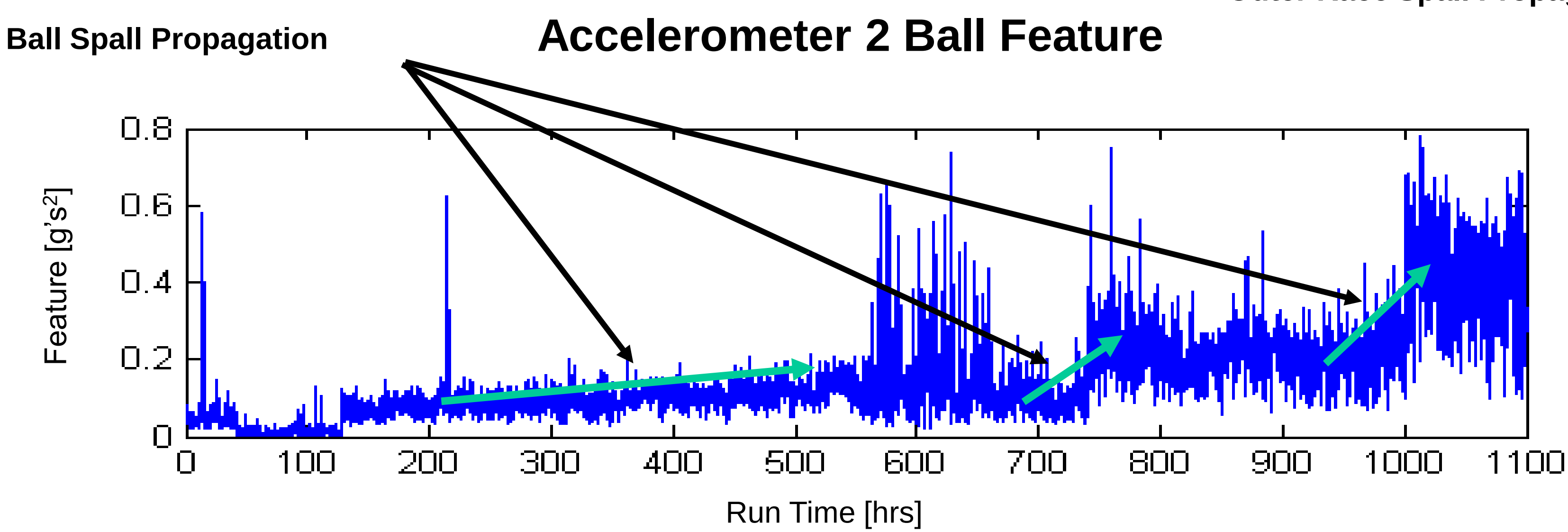
Overview of Damage Progression



***Note: Typical of Accelerometers 1-4**

Unique Failure Mode Identification





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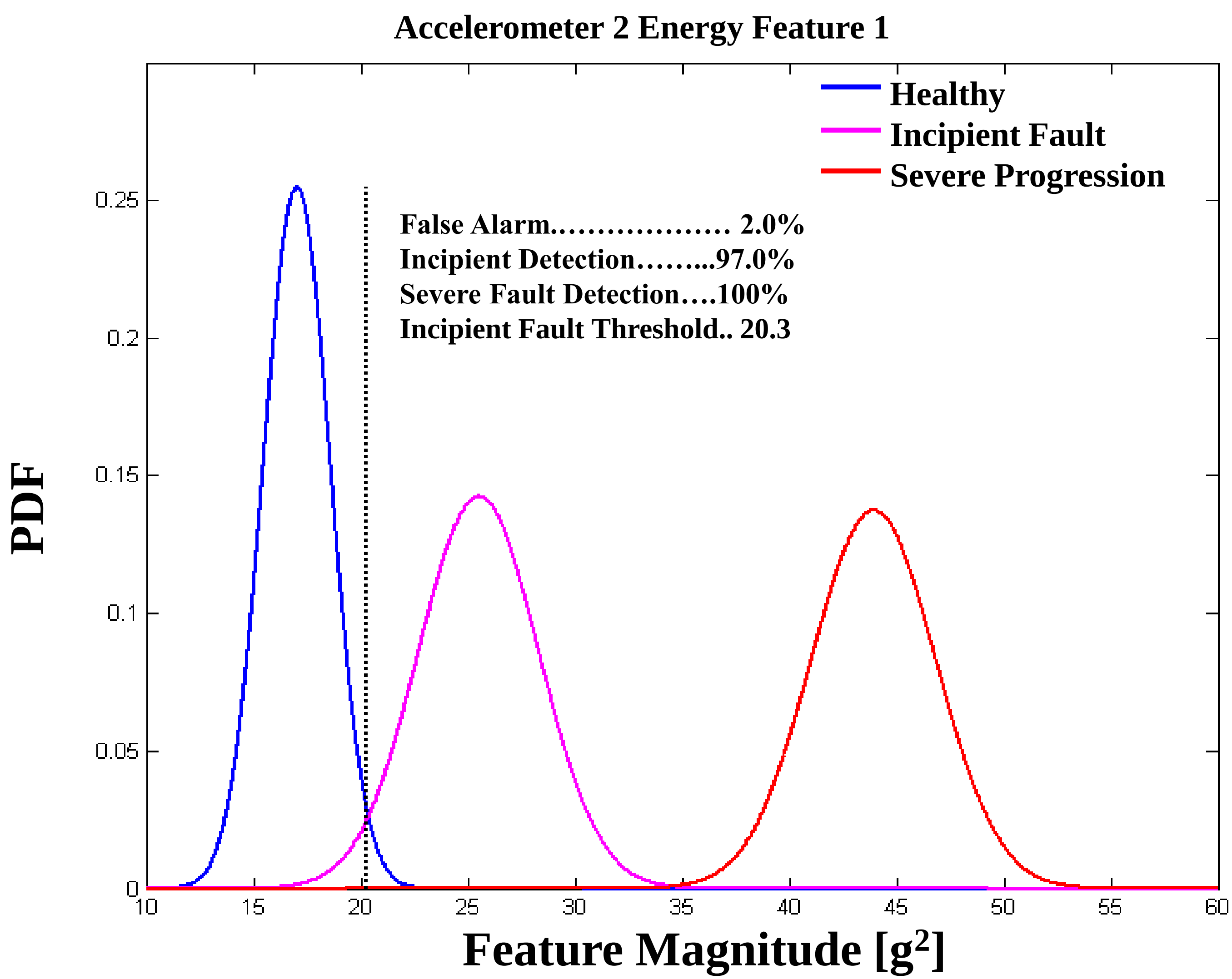
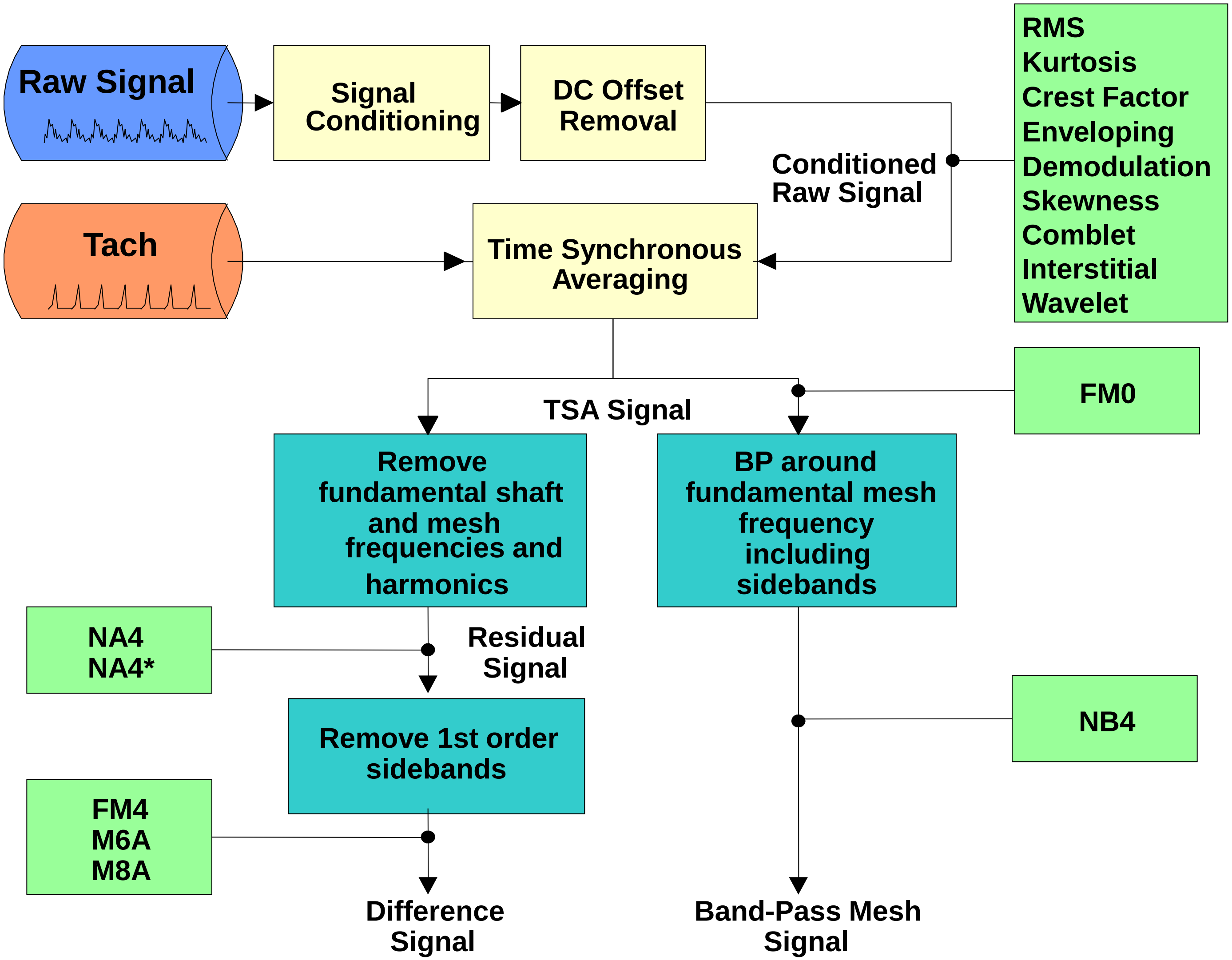
Statistical Detection Analysis

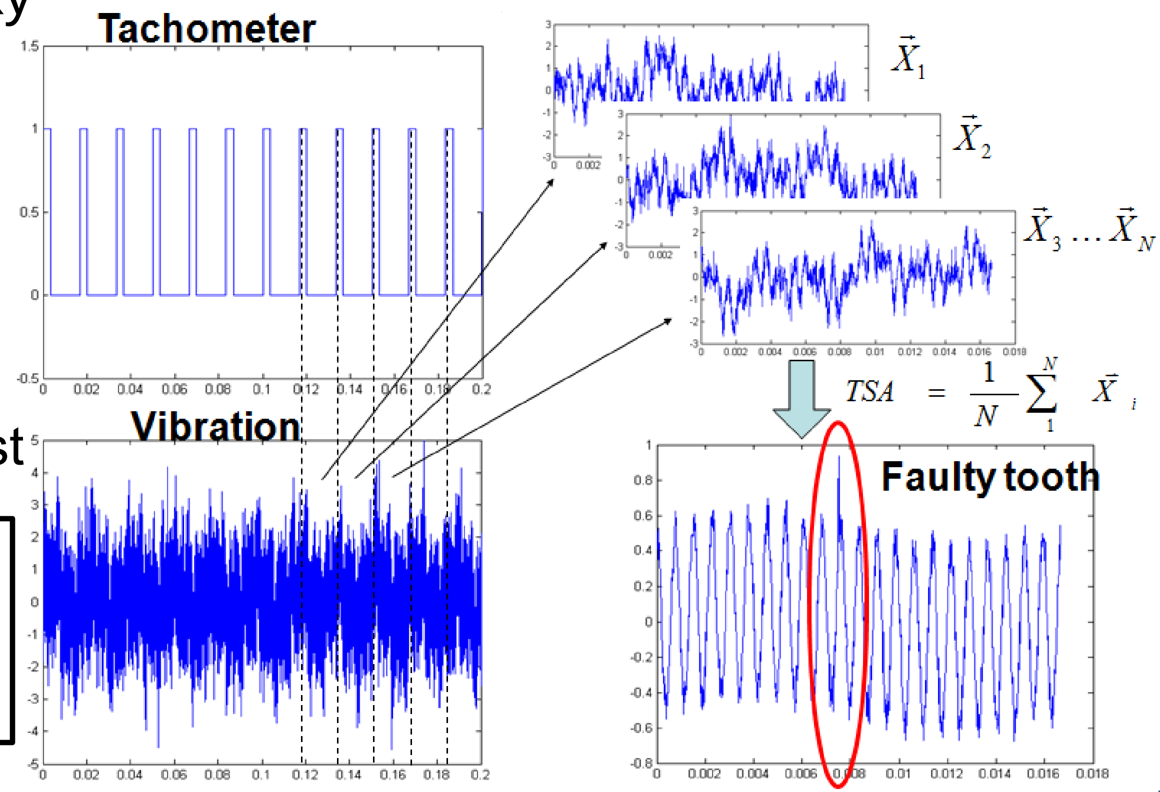


GearMod Vibration Feature Extraction



Gear Fault Detection and Isolation

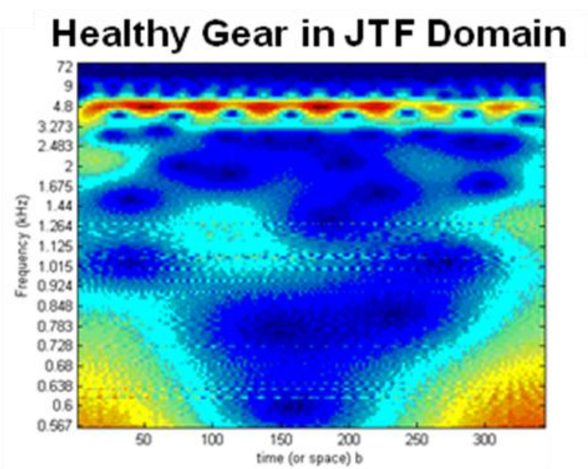
- Gear PHM performed using common gear processing techniques plus additional signal processing methods
  - ❑ Time Synchronous Averaging (TSA) at core of algorithm
  - ❑ Time and frequency domain features calculated
- Planetary gears are tricky
  - ❑ Moving frame of refer. leads to modulation
- Often lack tachometer on target gear shaft
  - ❑ Needed for many TSA
  - ❑ 'No Tach' methods exist

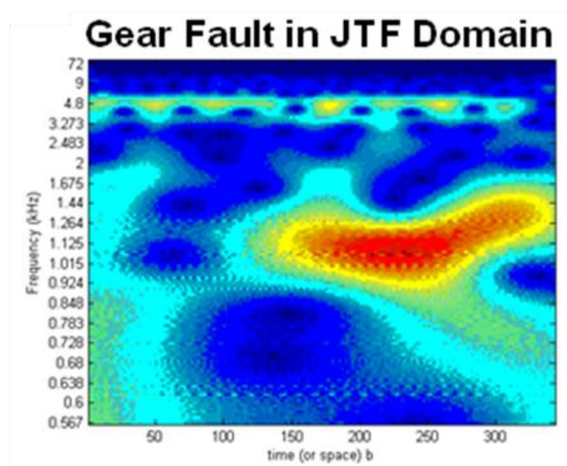


Lesson:
Component specific processing crucial

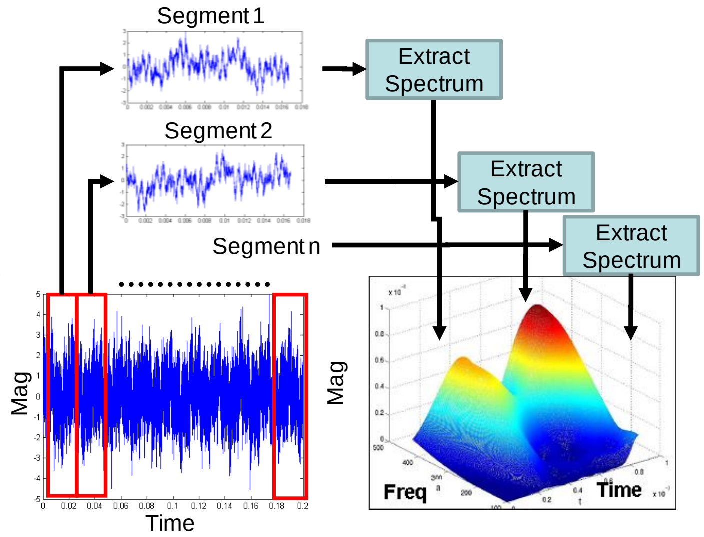
Joint Time-Frequency Analysis (JTFA)

- Typical frequency domain analysis assumes signal is “stationary”, but signal is often non-stationary and evolving
  - *Smearing increases missed detections & false alarms*
- Two main causes of spectral smearing:
  - Changing operating conditions (speed and torque changes)
  - Certain component faults and their progression lead to non-stationary vibration signals (such as corrosion)
- JTFA transform time/freq domain signal into time-frequency domain
  - Allows analysis during transients and coverage of ‘non-periodic’ faults
  - Already used within many disciplines (reduces risk)





Popular JFTA Techniques



Short Time Fourier Transform

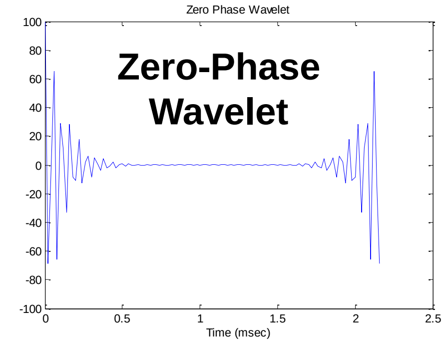
- Discrete time FFT over many small time segments
- Assumes stationary over each window
- Low computational intensity
- Must trade time vs. frequency resolution

Choi-Williams Distribution (CWD)

- Derivative of CCDF, uses exponential kernel to suppress cross terms
  - Cohen's Class Distribution: utilizes bilinear transformations through use of a kernel function
  - Cross terms: interferences caused by linear combination of auto and cross terms that result in signal redundancy
- Good frequency and time resolution

Continuous Wavelet Transform

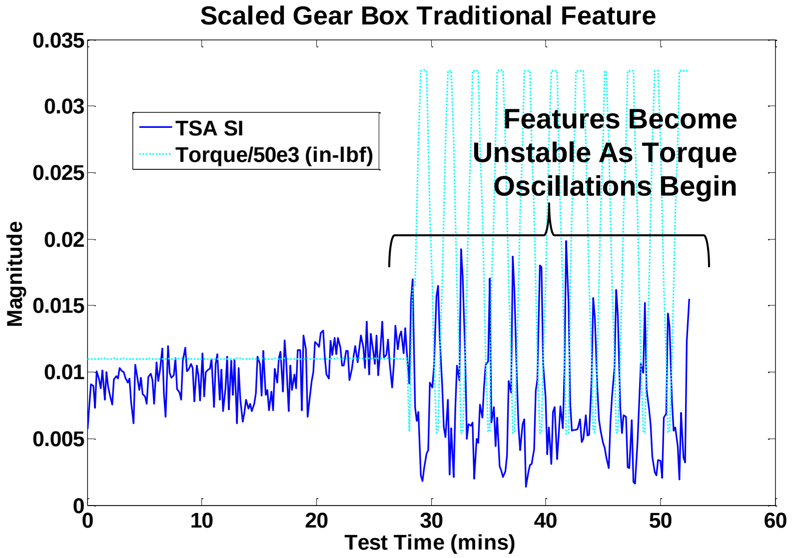
- Zero-phase: phase depends solely on signal's phase within passing band (better for event localization)
- CWT phase = phase modulation
- CWT magnitude = amplitude modulation
- Can detect events & exact time of those events

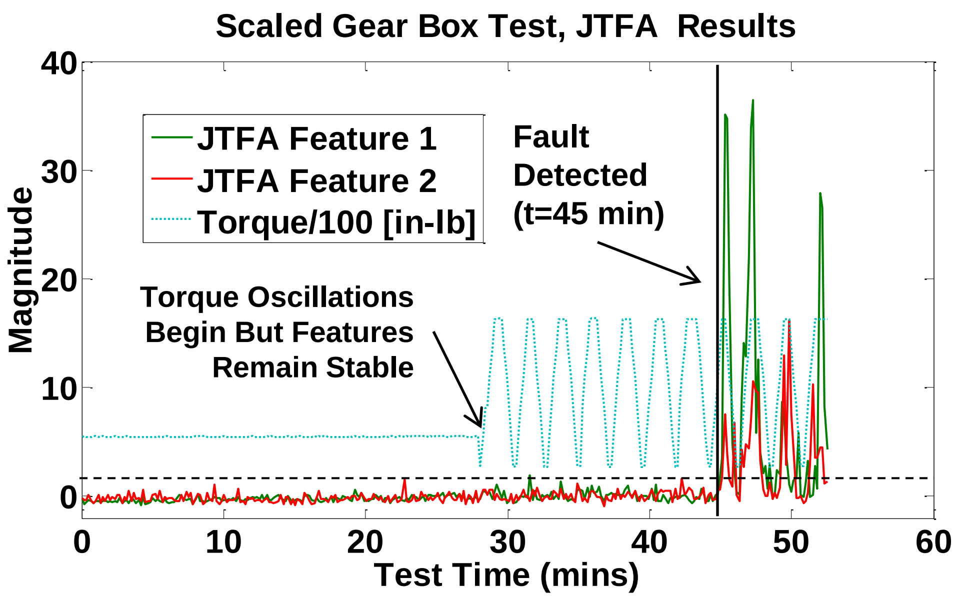


Gearbox Fault Detection with JTFA

- Evaluated benchmark dataset from scaled gearbox test conducted at large University
  - Resulted in gear tooth fracture at ~45 minutes
- JTFA features are sensitive to fault but insensitive to changing torque
  - Most traditional gear features are either sensitive to changing torque, increasing P(FA), or insensitive to fault, decreasing P(D)

Resulting failed gear

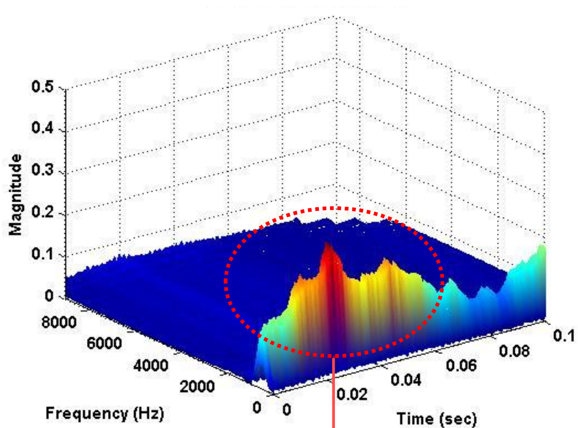




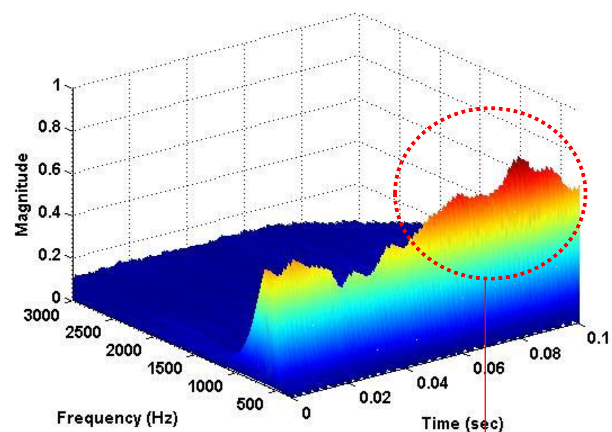
Gearbox Fault Detection with JTFA

- Same results shown in 3-D Space for 2 different JTFA Methods

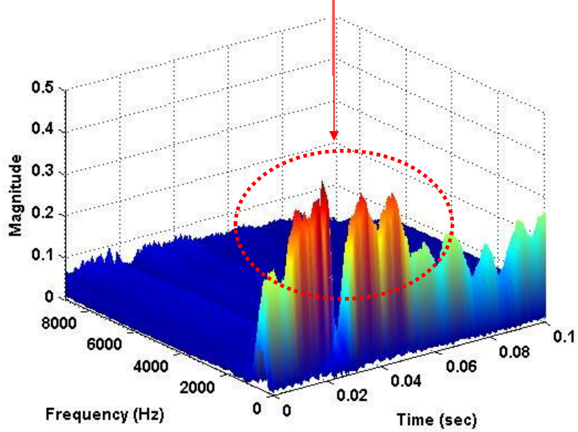
Healthy Gear Response (t=1.5 minutes)



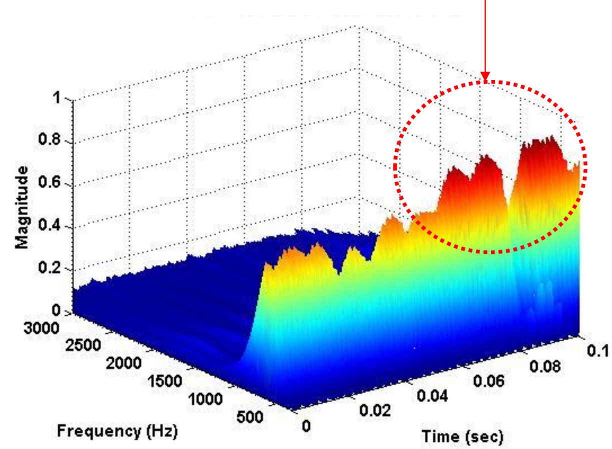
Healthy Gear Response (t=1.5 minutes)



Faulted Gear Response (t=50.2 minutes)

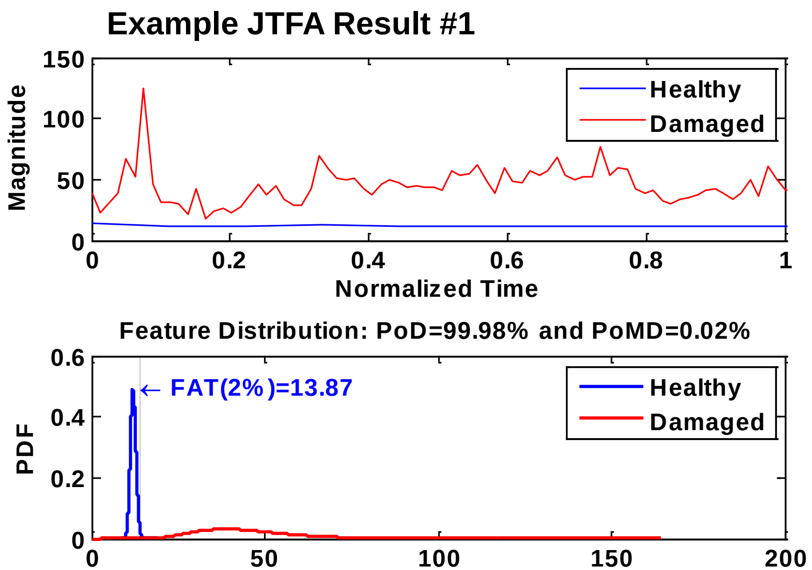


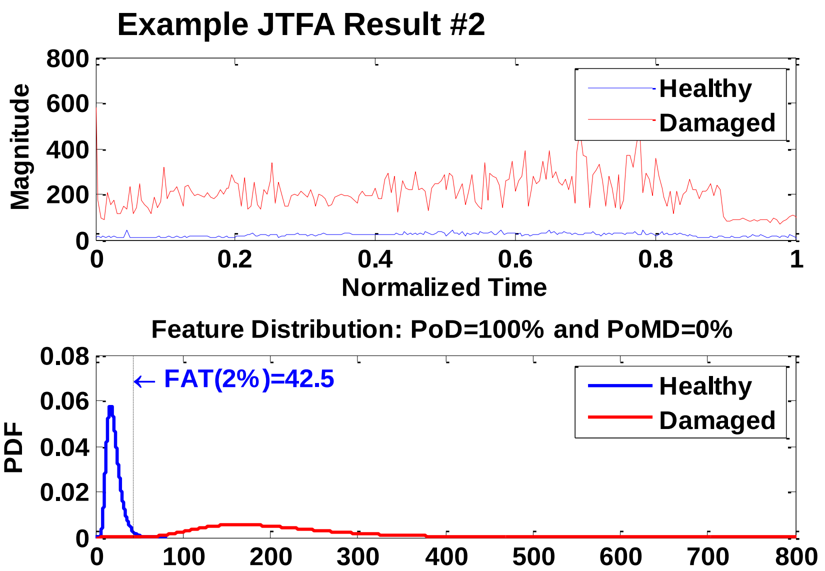
Faulted Gear Response (t=50.2 minutes)



Fault Detection Capability

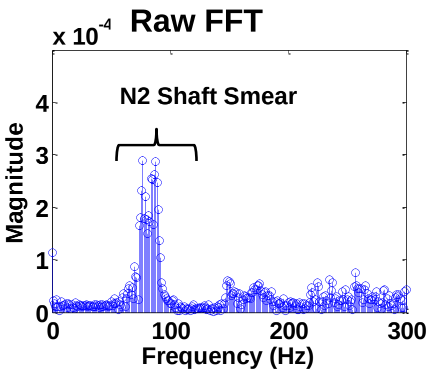
- Developed JTFA features also demonstrated on data from USAF Gas Turbine Engine Gearbox
  - Data collected with engine operational (i.e., typical 'noisy' environment)
- Compared results from a healthy gearbox to results from a gearbox with a faulted planetary gear (fretting and corrosion)
- Fault not detected with traditional TSA-based Kurtosis, NA4, or FM4 features
  - P(D) < 6 % for each of these features
- Fault detected using JTFA approach with P(D) > 99%

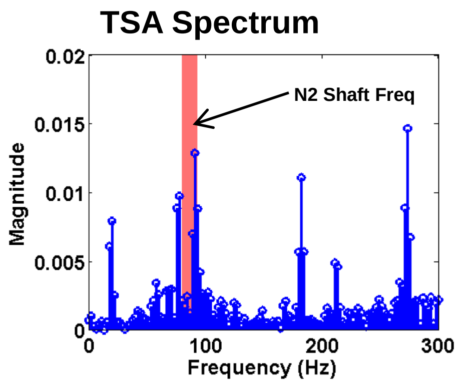


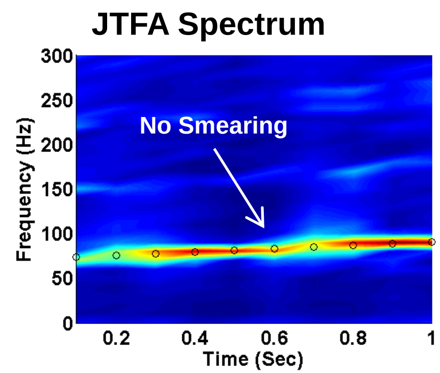


JTFA Enables Transient Analysis

- Evaluated data from USAF engine undergoing speed changes in OEM test cell
  - Changing speed causes transient frequency content and smearing
  - Smearing not an issue for JTFA Approaches since time is considered

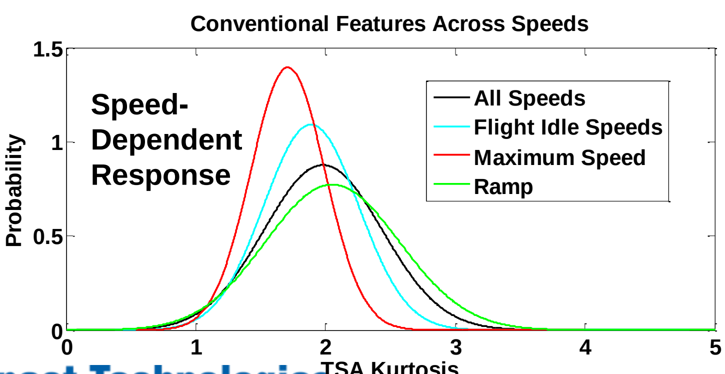


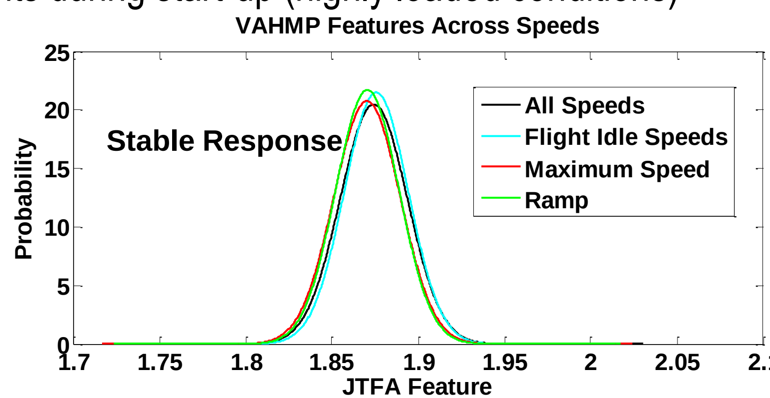




*Results show N2 ramps from 4420 to 5455 RPM over 1 second

- JTFA features are less sensitive to changes in steady speed + transients
  - Allows wider implementation and a single threshold approach
  - Allows analysis of accessory components during start-up (highly loaded conditions)





*PDFs represent results of statistical feature analysis under different conditions

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Real-time Oil Monitoring

- Often cited that 50-80% of mechanical equipment failures are lubricant effectiveness related (more so than bending fatigue or load driven)
- Effective lubrication maintains safe, high performance operation and enables gearbox service life extension
- Major drawbacks in traditional lab analysis
  - Lag time between sampling and analysis results
  - Man-in-the-loop and sampling/transmission/testing errors
  - Repeatability / accuracy of lab analysis
  - Variability between labs and between analysis methods
  - Cost of labor and downtime associated
- Schedule-based maintenance can miss sudden changes in oil quality that can lead higher risk of failure
- Real-time quantitative debris detection is complimentary and can be fused with other mechanical component condition indicators (i.e., vibration, temp.)

Oil Analysis Description

Most oil analysis techniques fall under one of three main categories:

Condition/Quality: A direct or indirect measurement of the oil condition can be based on additive depletion, oxidation, thermal breakdown, or other physical/chemical properties (viscosity, density, TAN/TBN, dielectric, etc.). Fluid or dissolvable contaminants can also affect condition and ability of oil to meet its function.

Debris: Determining the presence and possibly size, shape, morphology to indicate the possible origin of both metallic and in some cases nonmetallic debris or larger particulate.

Elemental/Alloy: More precision (usually spectroscopic based) equipment is used to determine the presence of certain elements in the fluid system. It can also be used to measure the amount of desirable elements present (i.e. additives) as well as undesirable (iron, aluminum, etc.).

What do we care about in Oil?

Key Oil Parameters & Measurements

- Debris
- Color
- Temperature
- Viscosity
- Density
- Water Content
- Total Base Number (TBN)
- Total Acid Number (TAN)
- Elemental Presence
- Conductivity
- Dielectric Constant

A Few Motivations

"In a large diesel engine test, 10% fuel contamination removed as much as 27% of piston ring metal in 100 hours of operation."[1]

"Contamination is believed to cause over 70% of all fluid (hydraulic) power failures."[2]

"Water contamination in lubricants can cut bearing life by as much as 80%!"[3]

1. Toms, Larry A., Machinery Oil Analysis: Methods Automation and Benefits, 1995.
2. Hunt, Trevor M., Condition Monitoring of Mechanical and Hydraulic Plant, Chapman & Hall, New York, 1996.
3. Eliot, Stephen W., *Fighting Bearing Failures with Additive Chemistry*, Practicing Oil Analysis, January 1999.

Wind Turbine Oil Degradation and Contamination – The 3 Enemies [3]

- **Particles** – metallic particles can be both an indication of wear and initiators of collateral damage through debris "dents" acting as stress risers or blocking fine clearances causing oil starvation [3]
- **Water** – water contamination can lead to corrosion as well as accelerated breakdown of the lubricant's additive package, ultimately leading to micro-pitting and consequently lowered fatigue life [3]
- **Varnish** – generally caused by thermal stress and oxidation, varnish is a thin insoluble contaminant comprised of oil degradation by-products and depleted additive molecules; can lead to loss of operating clearances or loss of heat transfer capability [4]

[3] NREL Wind Turbine Condition Monitoring Workshop, October 8 2009, Lubrizol corporation, Wind Turbine Gearbox Lubrication: Performance Selection and Cleanliness, Michelle Graf

[4] http://www.oilanalysis.com/article_printer_friendly.asp?articleid=1027

Wind Turbine Gearbox Oil: Condemning Limits

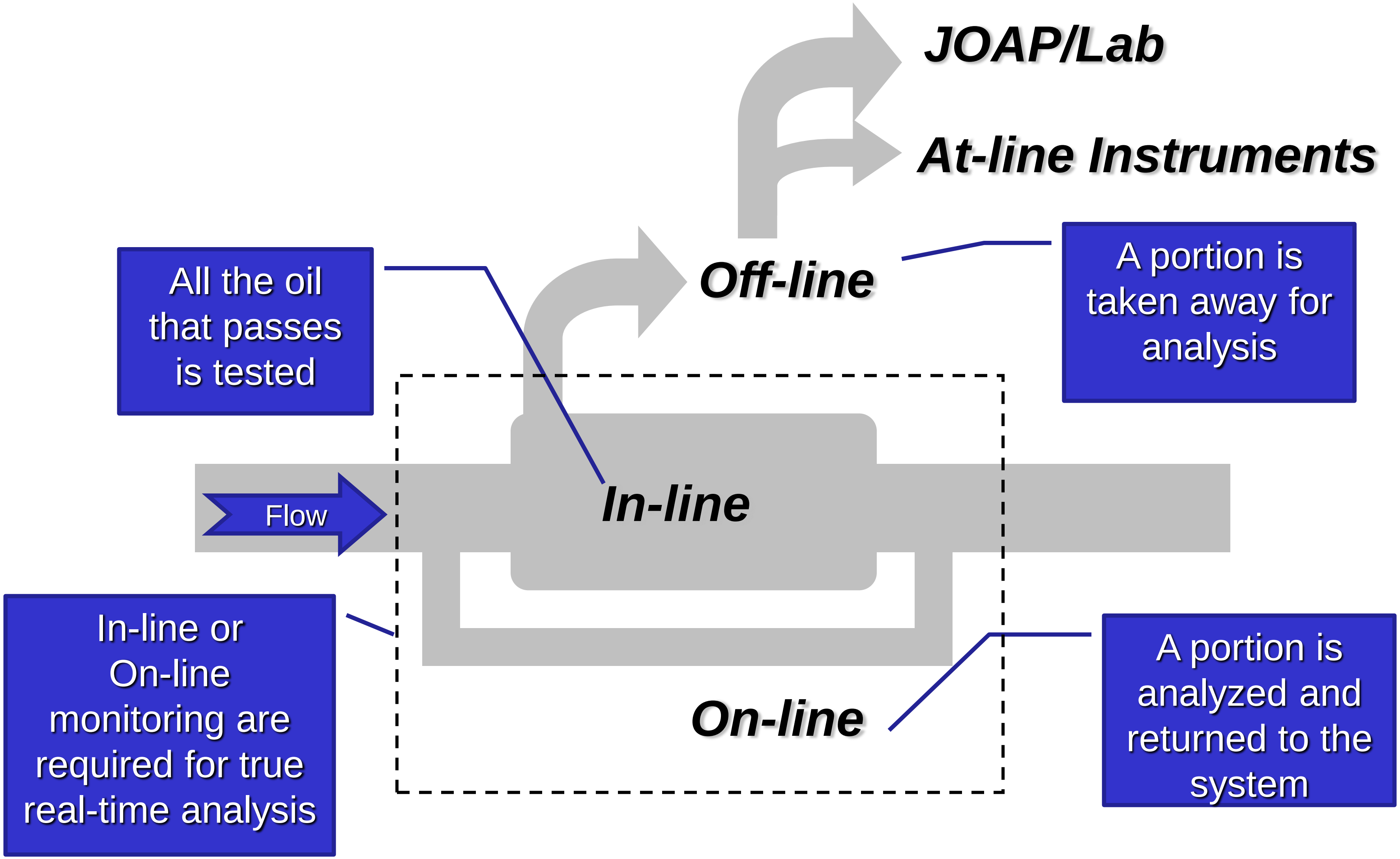
Analysis parameter	Borderline	Unsatisfactory
Water (Karl Fischer)[1)]	0.05%	>0.10%
Sediment (see F.5.2.3)	–	visible
AN increase over fresh oil	40%[2)]	>75%[2)]
Viscosity change from ISO VG limits	10%	>20%
Iron (Fe), ppm	75–100	>200
Copper (Cu), ppm	50–75	>75
Silicon (Si) increase over fresh oil, ppm	15–20	>20
ISO 4406:1999 cleanliness (Acceptable is –/16/13)	–/17/14	–/18/15

NOTES:
1) For limits of water miscible PAG oils, consult lubricant manufacturer.
2) Values to be advised by the lubricant manufacturer.

[5] ANSI/AMGA/AWEA 6006-A03, Annex F: Lubrication selection and condition monitoring, Pg 12

Water Contamination: Borderline = 500 PPM, Unsatisfactory > 1000 ppm

How are we going to get this data?



Oil Sensors and Features

- **Oil Condition/Contamination** - often large lab instruments
  - **FTIR (bench and handheld)** – lubricant condition and contamination
  - **Viscometer –** lube viscosity
  - **Crackle test/Karl Fisher** – water contamination
  - **Flashpoint/Fuel meter** – fuel contamination
  - **Electrochemical impedance spectroscopy (EIS)** –
    - Fuel/water contamination, degrading oil, temp, &RH
- **Online/inline debris detection**
  - **Atomic emission spectroscopy** - wear debris and dirt
  - **LaserNetFines** - silhouette of particle, plus size and shape
  - **Ferrography** - particle size, shape, ferrous/non-ferrous
  - **Magnetic chip collector** - particle size and count (ferrous)
  - **Inductive sensor** - particle size, count, and type (ferrous/nonferrous)

Impact's Oil Condition Monitor

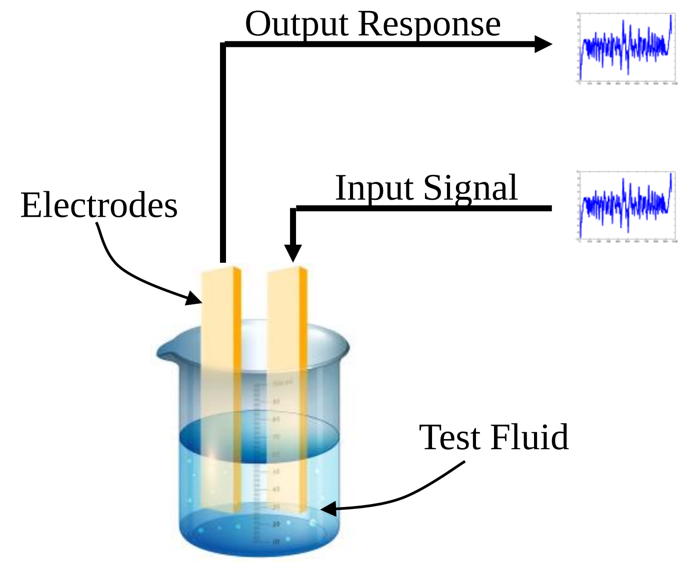
Both types required to fully cover failure modes
Need to be in line/on line sensors integrated into lubrication system, configured to system requirements

SmartMon-Oil
Aerospace Gearbox Monitor

- Multi-sensor fluid quality monitor
  - Broadband Impedance Spectroscopy, RH, Temperature measurements
- Uses patented broadband measurement technique
  - Measure more fluid parameters => trend more fluid degradation modes
  - Much faster than traditional EIS measurements
- Onboard processing
  - Smart sensor converts measurements to meaningful information
  - Impedance and feature calculations
  - Diagnostic and prognostic algorithms
- Small form factor / lightweight design
- Digital communications interfaces
  - CAN – J1939
  - RS-485/422 - Modbus

OCM Operating Principle

- The underlying technology is electrochemical impedance spectroscopy (EIS)
- Fluid under test is subjected to a dynamic electrical signal and the fluid's chemical and physical effects on the signal are measured
- Instead of parallel plates, concentric, cylindrical tubes are implemented
- Broadband measurement technique allows:
  - Identification of information "rich" frequencies
  - Faster processing over traditional EIS
  - Insight to oil condition at much reduced cost compared to optical or reagent based methods
- Additional sensing is usually integrated (Temp and RH)



Evolution of Real-time OCM

Development History

Generation 3

2002-2005 – Navy Phase III: Debris Extraction and Quality Evaluation System

Generation 4

2004-2007 – NYSERDA Funding: Oil Quality Sensor for Vehicle Applications

Generation 5

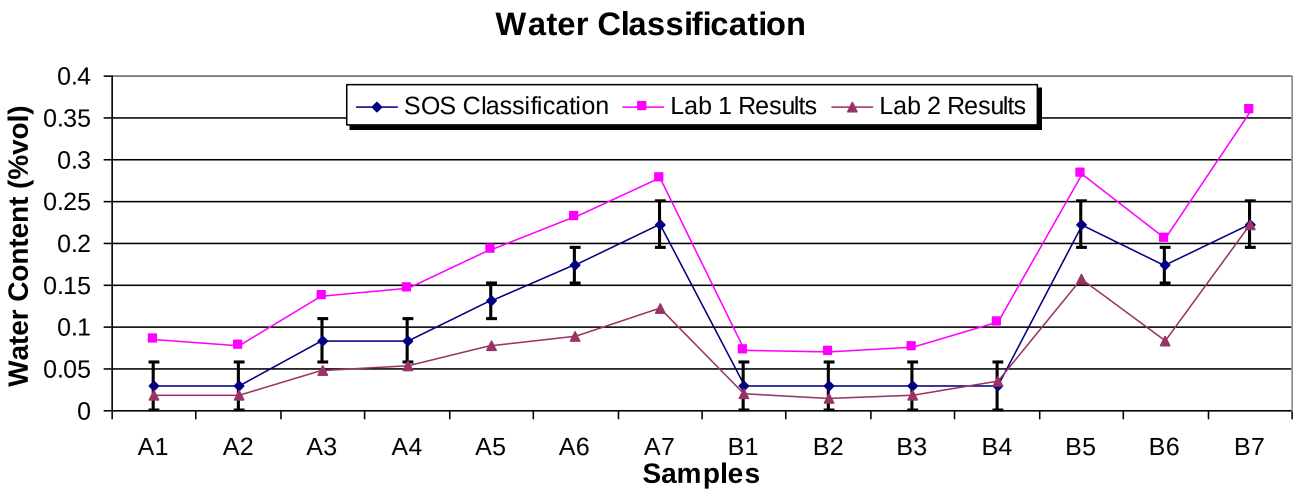
2006-2009 – NAVAIR Phase II SBIR: Monitoring for Corrosion Conditions in Aircraft

Generation 6

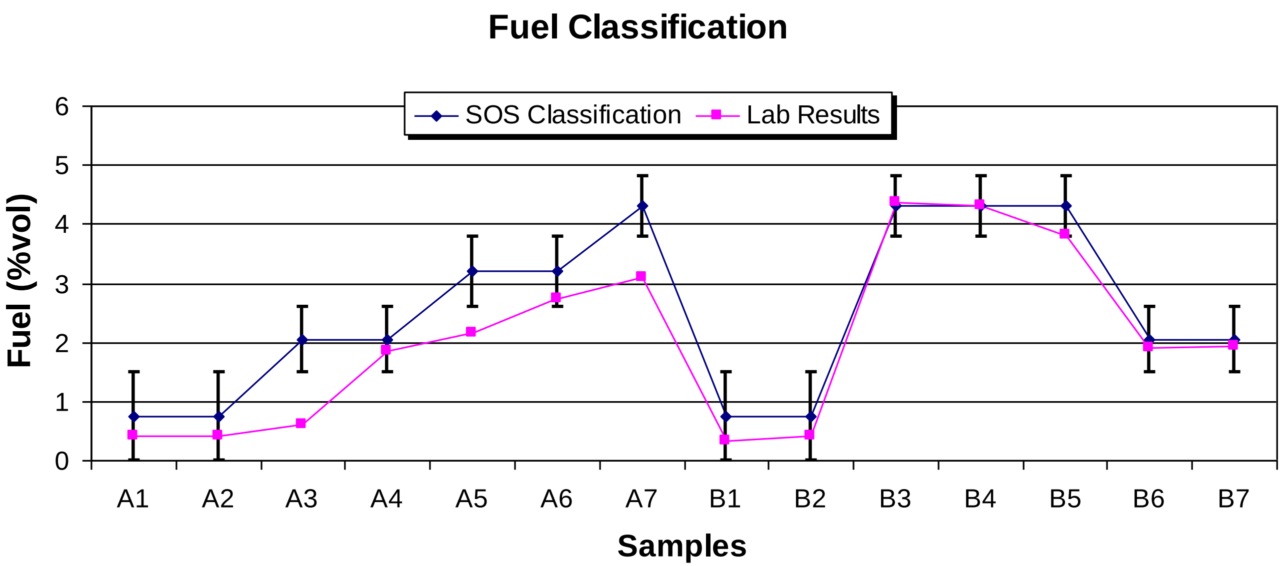
2010-2012 – US Army TARDEC: Oil Condition Monitor for Army Ground Vehicles

Maturing and exercising the technology across a number of applications and industries.

Correlation and Validation with Lab

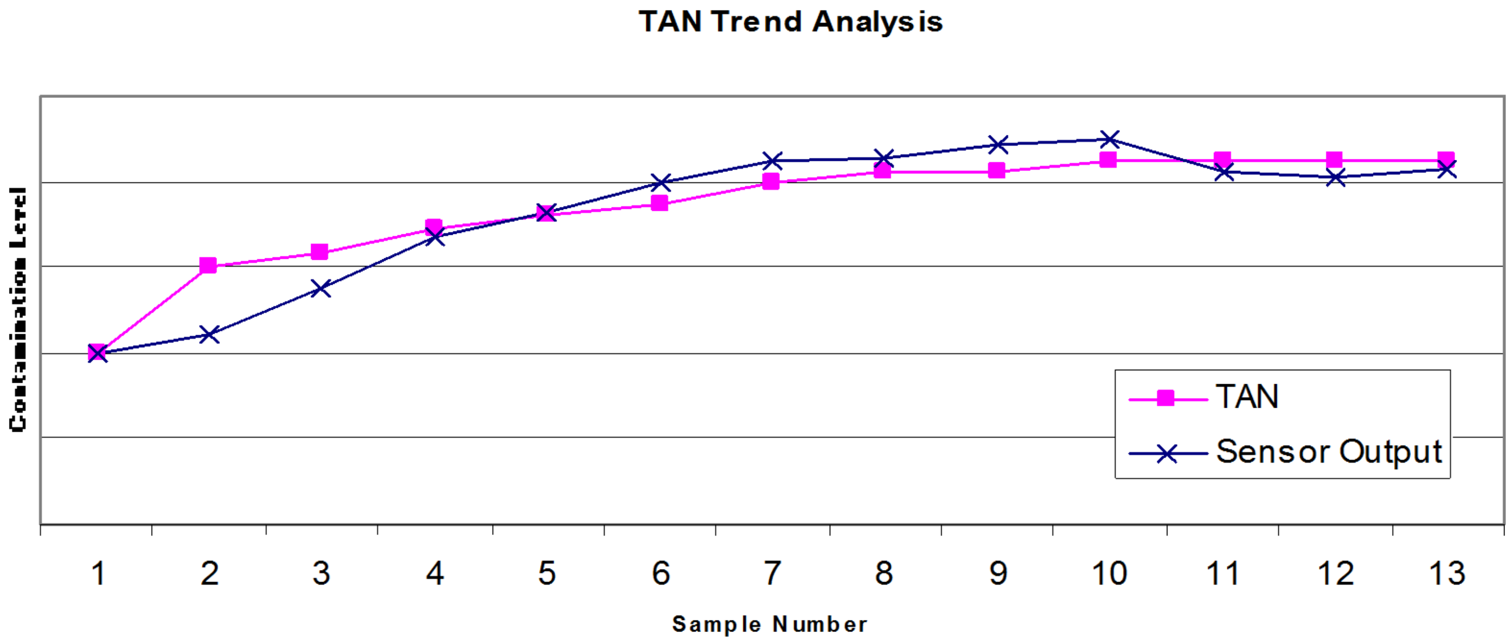


Lab results for water are inconsistent. Sensor accurately tracks variation in water content and less than 500ppm.



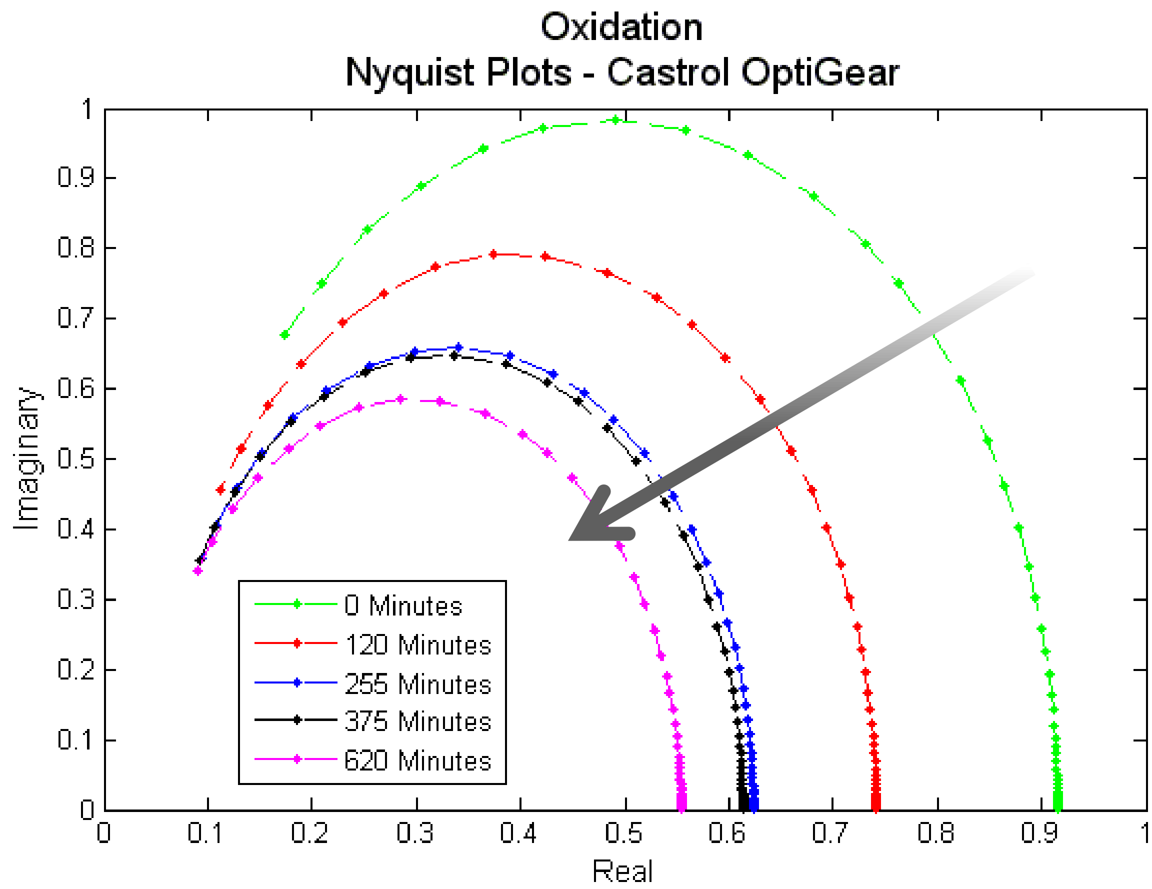
Sensor estimates fuel content in oil with a high level of accuracy. Misclassifications are never severe.

Correlation and Validation in the Lab



Sensor output trends well with Total Acid Number as reported by traditional laboratory titration methods

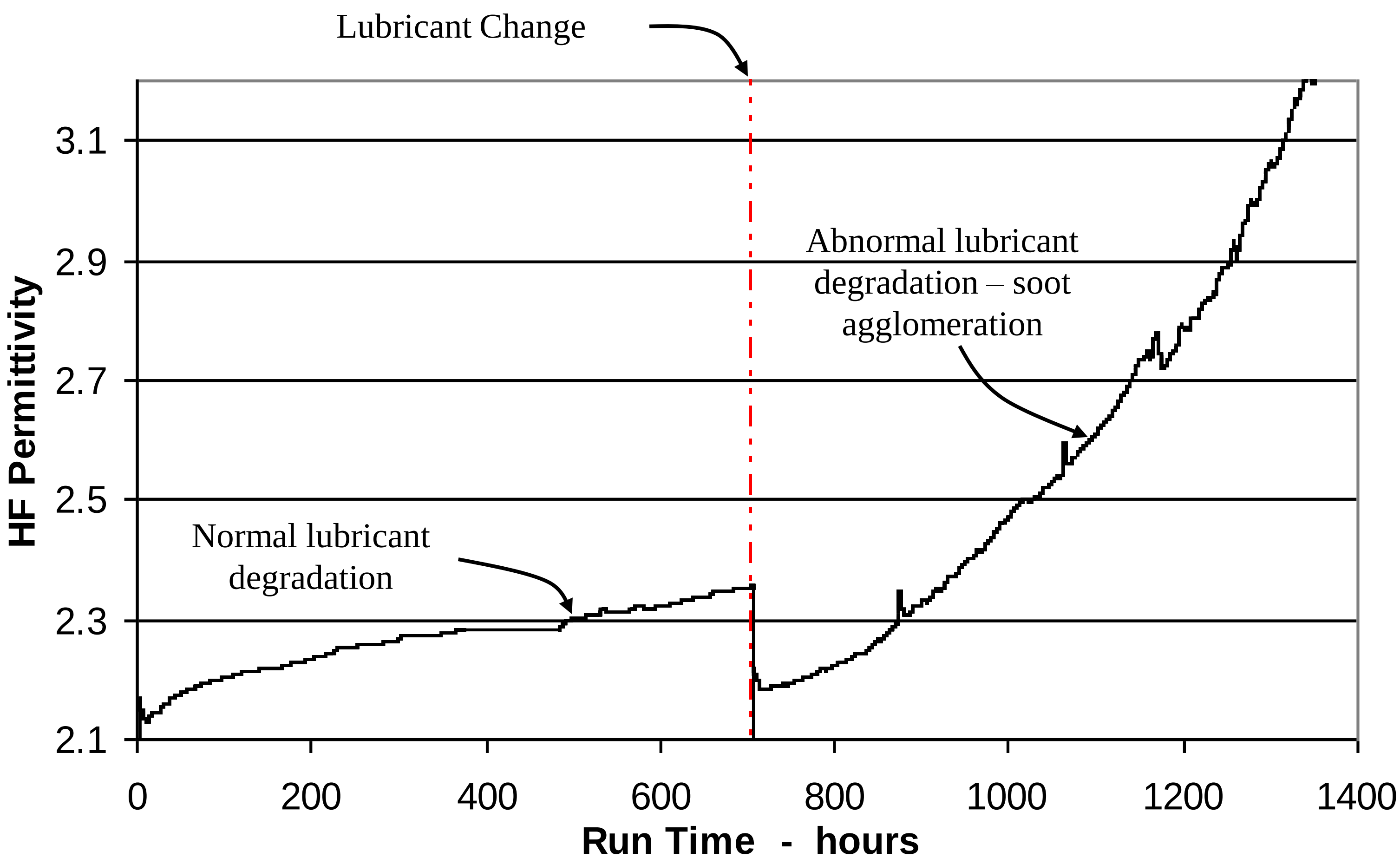
Oil Quality Sensor Results - Oxidation Test



Effect of oxidation is clearly visible and trendable through EIS measurements

Test conducted using Tannas Quantum Rotating Pressure Vessel Oxidation Tester with copper catalyst only. Readings taken at 64 degrees Celsius

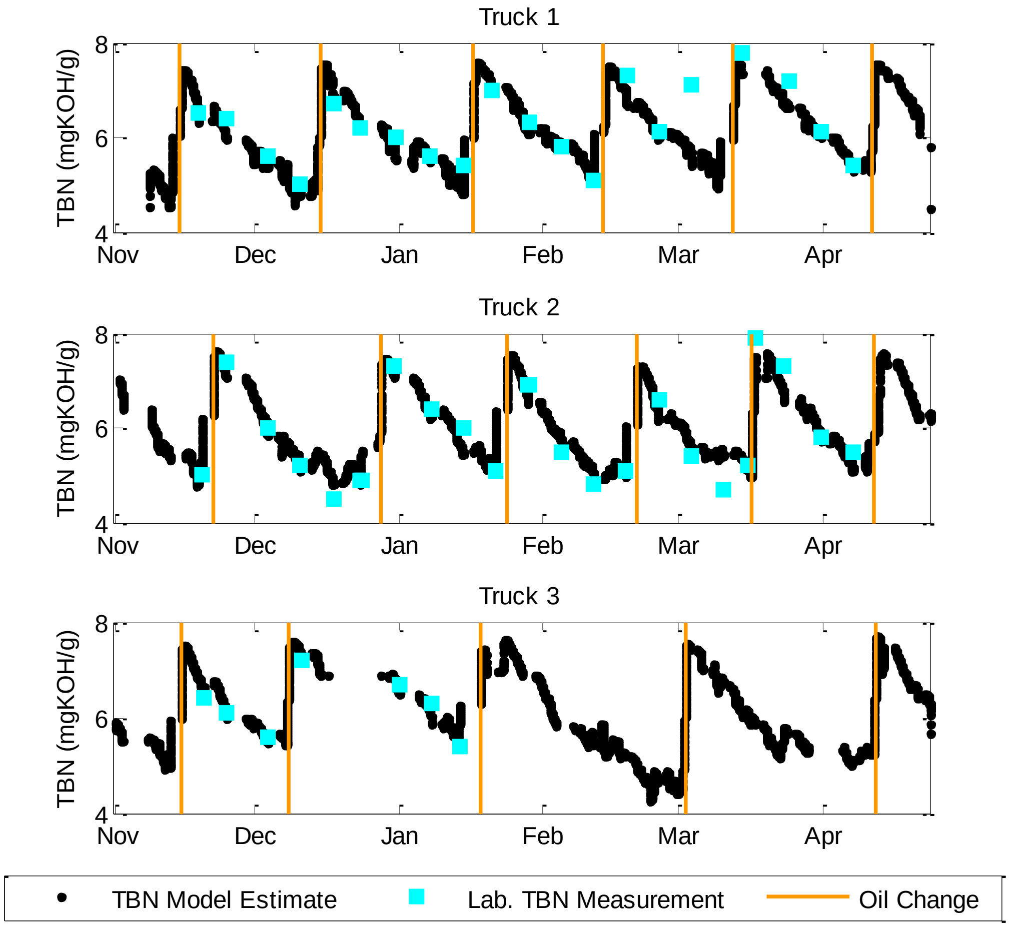
Incident Detection – Wrong Lubricant



GV Oil Condition Monitor

- Example TBN Comparison

TBN values observed in the laboratory data ranged from 2.8 to 7.9 (mgKOH/g), the standard deviation of the modeling error is 6.3% of the range of the laboratory measurements.



Some Available Particle Detection Technologies

- Ferromagnetic debris collection

  - Magnetic sensor head

  - Collection grid

- Magnetic inductive coil

Magnetic Sensor Head

Technology Overview

- Magnetized sensor head attracts suspended ferrous particles until an end condition is reached:
  - Saturation of sensor head
  - User-defined weight (mg) has be collected
- Once end condition is achieved the sensor head “flushes” itself of accumulated particulate and repeats the cycle
- Rate of debris generation is developed from time between “flushes”

Magnetic Sensor Head
Examples of Commercially Available Sensors

DEMON-6 - Caledonia Instrumentation Systems Ltd.

(**De**bris **Moni**toring version 6)

Now Marketed through Impact Systems UK

TechAlert™ 20 - MACOM Technologies Ltd.

Now Marketed through Impact Systems UK

Magnetic Sensor Head
Examples of Commercially Available Sensors

Tedeco® Chip Detector * - Eaton Corporation
http://www.eaton.com/EatonCom/index.htm

* Note: Tedeco® Chip Detector does not contain "flush" feature

Total Ferrous Debris Sensor -
Kittiwake Developments Ltd.
http://www.kittiwake.com/

Collection Grid
Technology Overview

- A grid is placed in the path of oil flow
- Suspended metal particles become trapped in the grid and bridge gaps between electrically conductive elements
- Sufficient density of trapped particles completes a circuit which indicates that a threshold level of debris is present in the oil

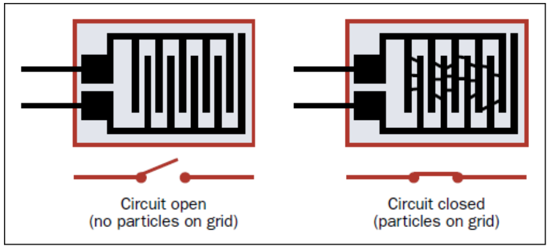
Collection Grid

Examples of Commercially Available Sensors

Spinner II® Grid Switch™ -

T.F. Hudgins, Inc.

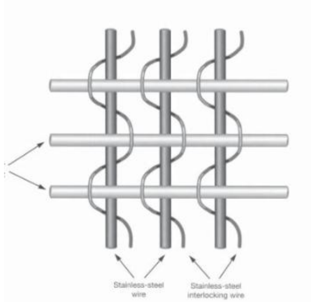
http://www.spinnerii.com



•Grid attracts ferrous particles only

Electromesh® - Eaton Corporation

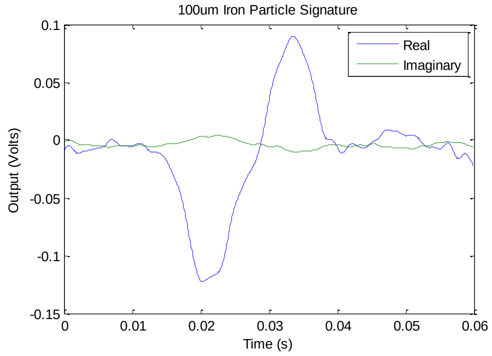
http://www.eaton.com/EatonCom/index.htm

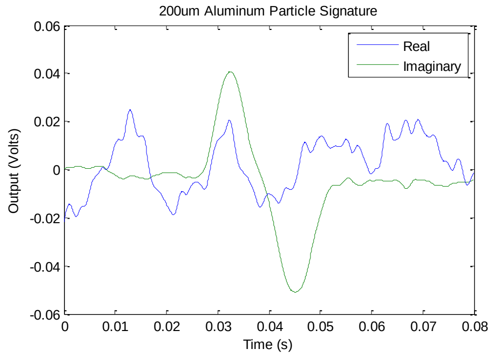


•Flow through design captures both ferrous and non-ferrous particles

Inductive Coil
Technology Overview

- Lubricant flows through a transducer coil
- Suspended metallic particles (ferrous and non-ferrous) are detected by monitoring:
    - Change in the inductance of the coil (TechAlert™ 10)
    - Change in an alternating magnetic field (MetalSCAN™)
    - Change in reluctance and inductance (Patrol™)
- Ferrous and non-ferrous particles affect the sensors differently and can thus be monitored independently
- Inductive coil sensors can detect the size and quantity of suspended particles





Inductive Coil
Examples of Commercially Available Sensors

Metallic Particle Sensor - Kittiwake Developments Ltd.

http://www.kittiwake.com/

MetalSCAN - GasTOPS Ltd.

http://www.gastops.com/

Inductive Coil

Examples of Commercially Available Sensors

Tedeco® IQ® Debris Monitoring System -
Eaton Corporation

http://www.eaton.com/EatonCom/index.htm

Patrol DM - Impact Sensors, LLC

http://www.flowtonics.com/Patrol-DM/Index.html

Impact Patrol-DM™ Debris Monitor

- Proven technology
  - Successful field applications through licensing
  - Best-in-class sensing capability (40μm ferrous detection ability with half inch bore)

- Inductive coil design

	Particle Types Detected			Debris Quantity	
	Ferrous	Non-Ferrous Metal	Non-Metal	Direct Count	Mass per Time
Magnetic Sensor Head	✓				✓
Magnetic Collection Grid	✓	✓‡			✓‡
Inductive Coil	✓	✓	*	✓	**

‡ *Not all commercial brands*

*** Under development at Impact***

***** Can be estimated with good accuracy***

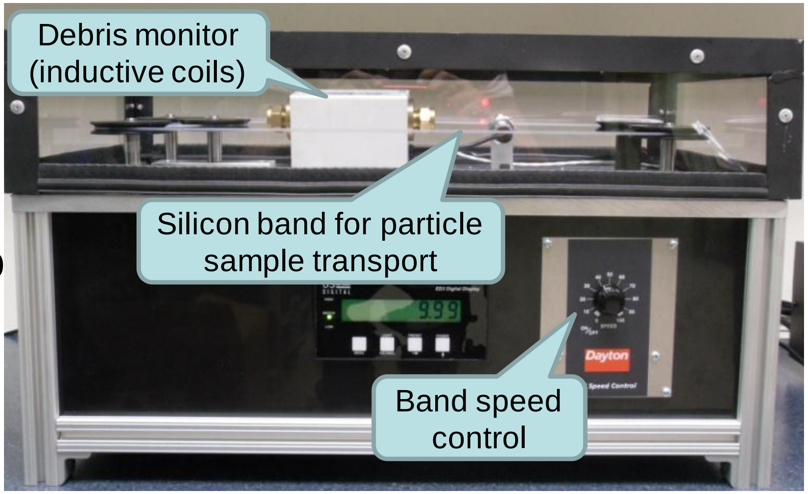
Calibrating for debris you can barely see

Debris Monitor Validation System

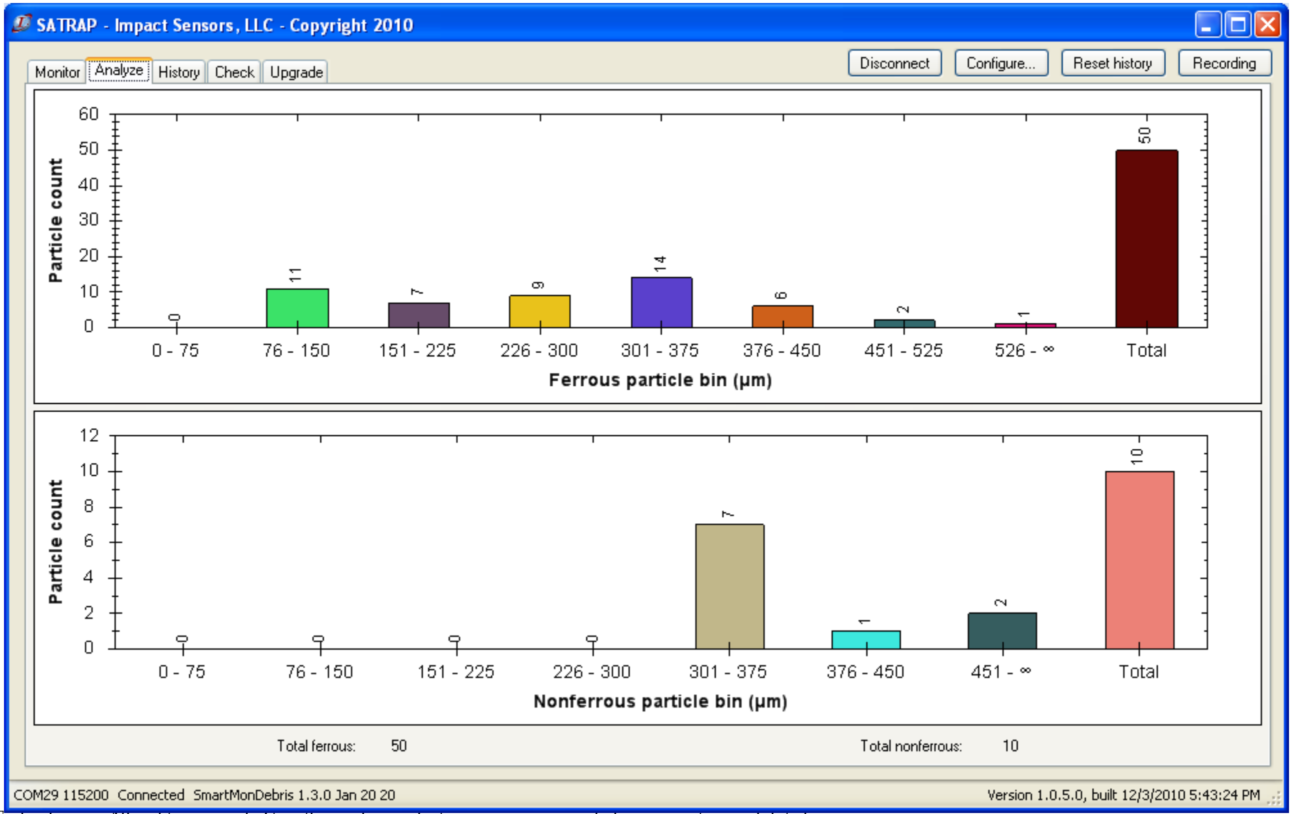
Lube System Test Stand

Validation of Debris Monitoring

- Monitor calibration with particle samples of controlled sizes and shapes

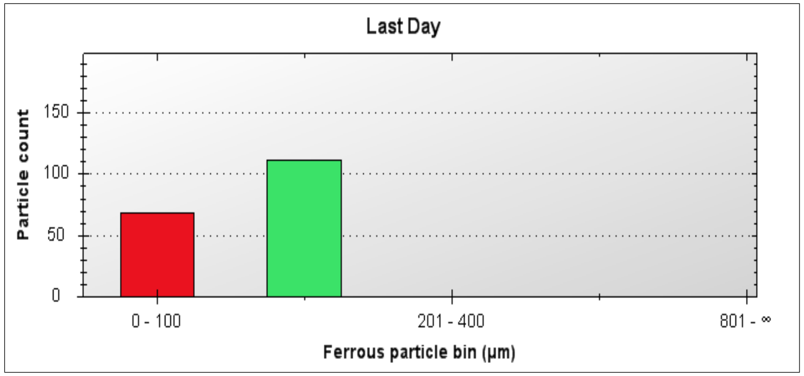


- Silicon band tests
  - Particle samples of varying sizes and shapes on silicon band circle through debris monitor at different speeds
  - Sensor response characterized for particle sizes, shapes, orientations and metal type; statistically significant sensitivity, accuracy and repeatability
- Gearbox test stand with flowing oil

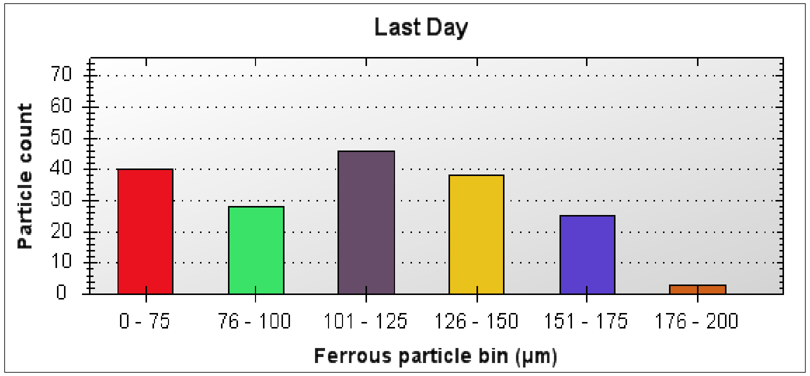


Reconfigurable Binning

Conventional Binning



Customized Binning



Capturing particle size estimates also allows for more detailed histogram analysis via reconfigurable bins

Would you ignore an 800% change in output from any other sensor? That is the difference between a 100µm and 200µm particle in terms of mass.

Sensing Technology Comparison

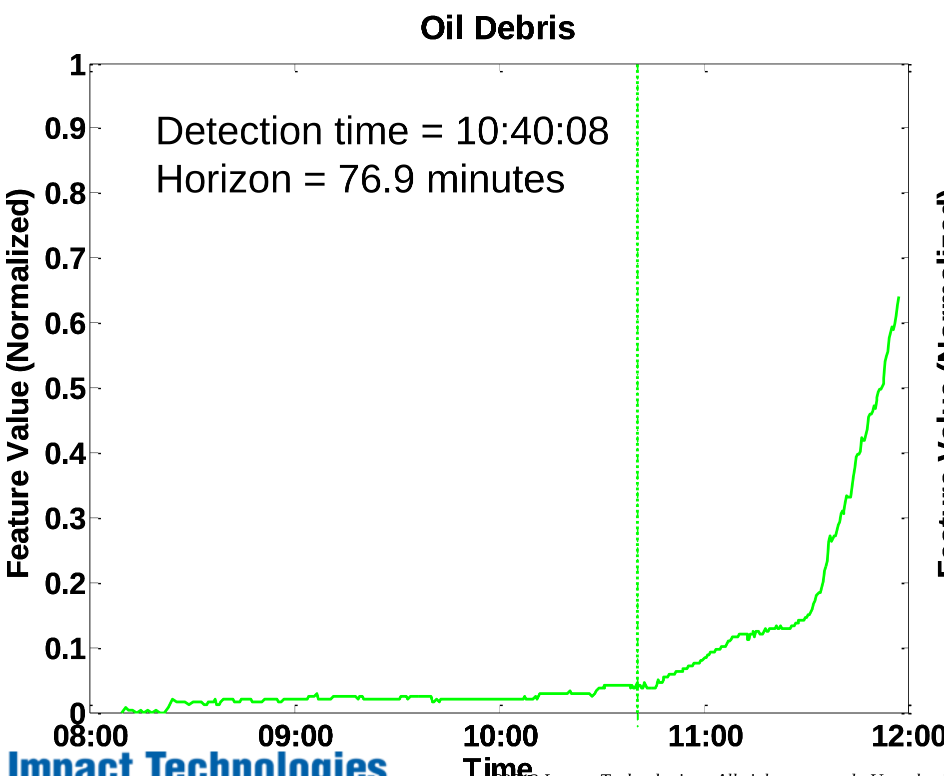
Technology Abilities	ODM	Legacy Vibration	ImpactEnergy™ PHM
***Incipient* fault detection** Steel bearings	*Maybe*	*Usually No*	**Yes – Field and OEM Tests**
***Incipient* fault detection** Hybrid Ceramic bearings	*Maybe*	*Unknown-No*	**Yes – OEM tests**
***Severe* fault detection** Steel bearings	**Yes**	**Yes**	**Yes – Field and OEM Tests**
***Severe* fault detection** Hybrid Ceramic bearings	**Yes**	**Yes**	**Yes – OEM tests**
Element Fault isolation	**No**	*Maybe*	**Yes**
Prognostics	**Enables**	**End of Life**	**Enables**
System Coverage	**Limited**	**Limited**	**High**

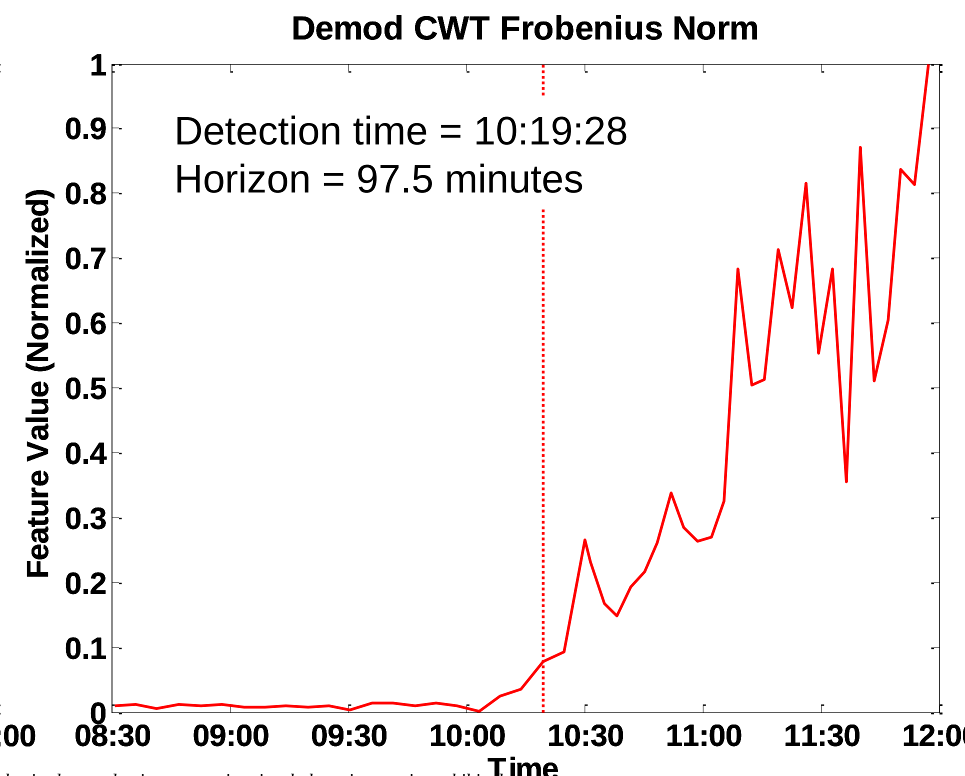
Bearing Seeded Fault Test

- Small, high speed, high load bearing test rig
  - **Load**: >3000 lbf radial (>150% static rating); >10,000 RPM
  - **Initial condition:** small indent (<<5% circum.) in inner race wear path
  - **Final condition**: large spall 20-30% of inner race circum (~3.5 hours)
- **Vibe + Oil** accurately characterizes defect size levels and risk of failure
  - Alone vibe provided +20.6 minutes of detection horizon vs. oil sensor, but not severity level (directly)
  - **But together confident fault level indication (oil) + early warning (vibration)**

Comparing Detection Times

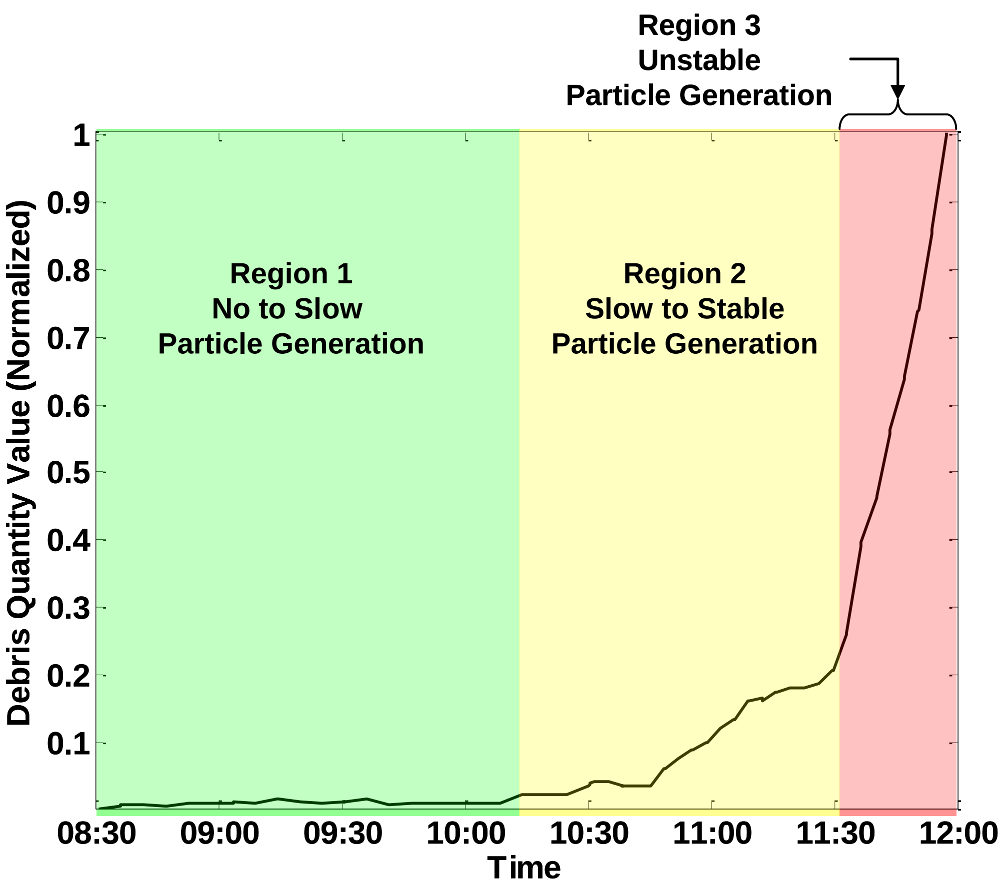
- Set threshold for P(FA) = 2%, above which feature indicates fault
- Oil debris sensor detects anomaly at ~10:40 w/ P(D) = ~81%
- CWT Frob. Norm detects bearing fault at ~10:19 w/ P(D) of ~100%, other JTFA features similar
- Vibe provides +20.6 minutes of detection horizon and +19% P(D) versus oil sensor, but vibe not severity level (directly)





Oil Debris Results

- Normalized oil quantity trend clearly shows increasing particle generation rate
- Identified 3 distinct regions of particle generation, similar to typical phases of fatigue crack growth per Paris Law ($da/dN = c\Delta K^m$)



•Region 1 (0-2 particles per minute) = Slow Growth incipient fault state [low risk of immediate failure]

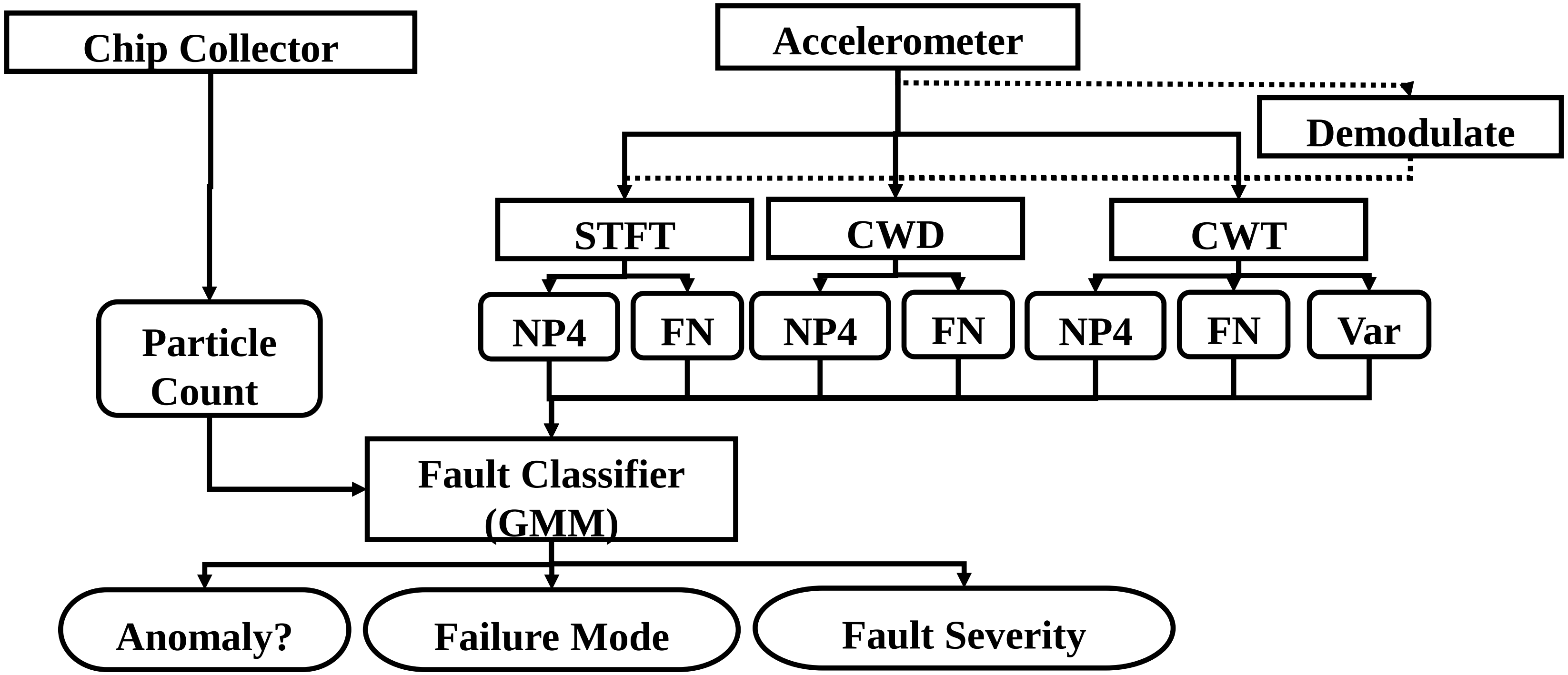
•Region 2 (2-5 particles per minute) = Stable Growth moderate fault state [medium risk of immediate failure]

•Region 3 (>5 particles per minute) = Unstable Rapid Growth severe fault state [high risk of immediate failure]

Impact Technologies
A Sikorsky Innovations Company

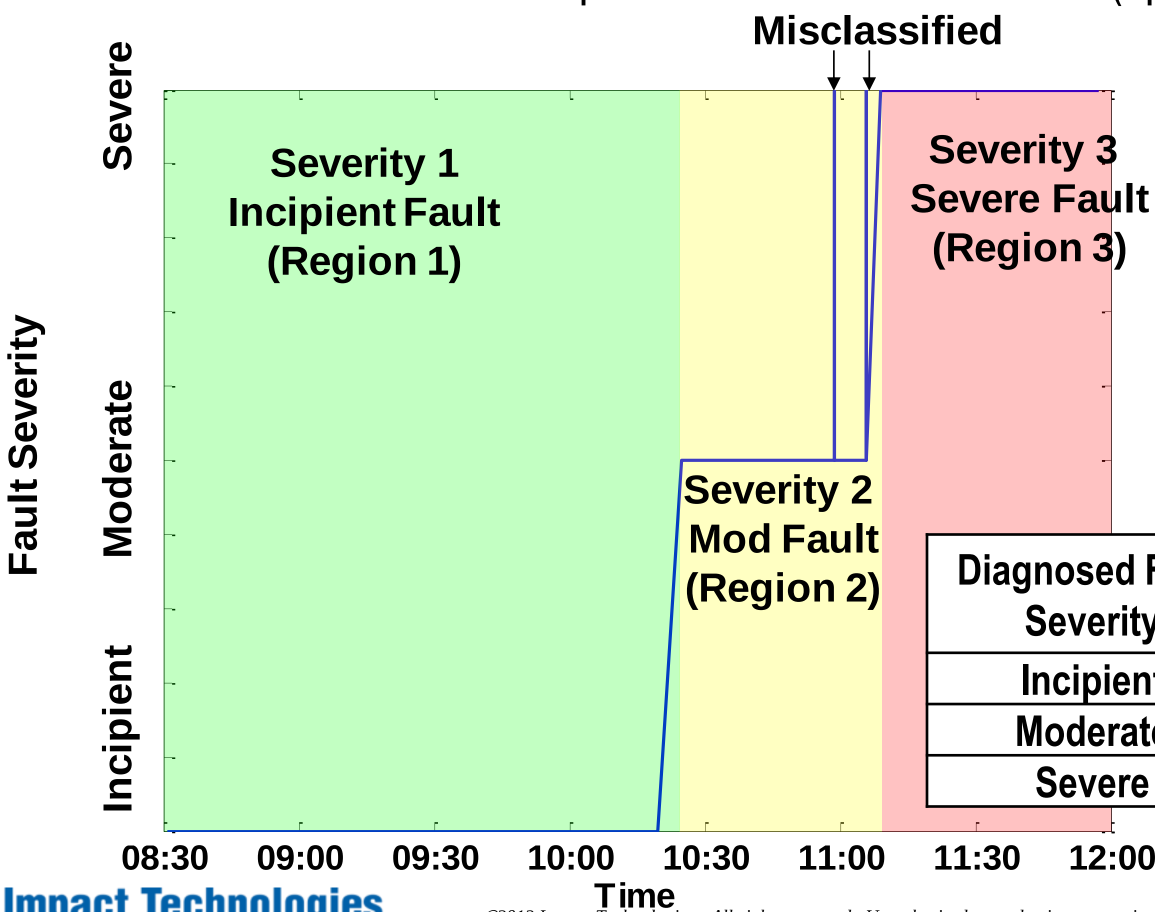
Fault Classifier

- Using multiple sensor features increases diagnostic performance/usefulness
- Unsupervised learning modeling Gaussian Mixture Model (GMM) used
  - Clustering type with convex combination of probability distributions
  - Constructed to classify bearing damage severity



Combined Damage Assessment

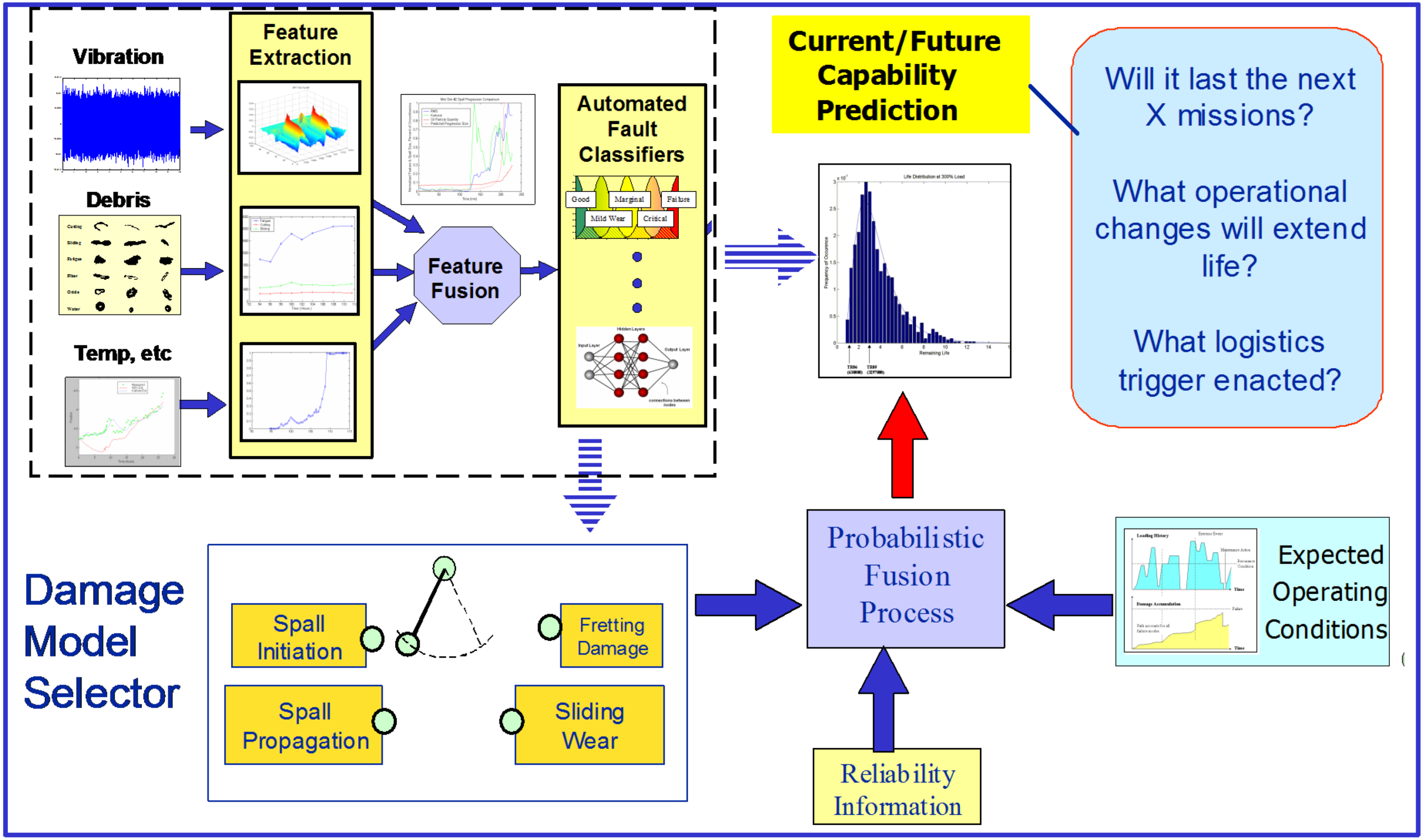
- Fused diagnostic accurately characterizes defect size levels
- Inherently indicates risk of failure
- Combines confident fault level indication (oil) w/early warning (vibration)
- Results can be used to predict discrete defect size (spall size)



- Blue line: GMM severity level classification
- Table summarizes results
- Misclassified pts to higher level, more desirable than too lower level

Diagnosed Fault Severity	Real Fault Severity		
	Incipient	Moderate	Severe
Incipient	100%	0	0
Moderate	0	96.9%	0
Severe	0	3.1%	100%

Prognostic Integration



Some Closing Thoughts

- To realize true O&M cost benefits a robust, integrated, automated CBM system that has:
  - Multiple sensors to allow visibility of all relevant failure modes
  - Accurate, reliable, and early fault detection capabilities
  - Careful selection of algorithms and necessary analysis components
  - Methods to distill sensed data to actionable information
- Sensor health equally important to assess
  - Unhealthy sensors/signals can cause erroneous results
- Gear Analysis
  - Many per rev encoder (raw) would be ideal for TSA
  - Appropriate TSA processing required (time domain vs order domain)
  - Long sample duration needed for low speed/planetary gears
- Bearing Analysis
  - Ensure sensor orientation is appropriate for targeted bearing
  - Increased bandwidth would allow demodulation at higher frequencies
  - For lower frequency bearings, seismic accels or velocimeters would be better suited for diagnostics
- Need truly integrated CBM, fusing multiple accelerometers and other sensors (debris, temperature, etc)
  - Fuse commensurate raw signals (accelerometers) to reduce noise and improve signal-to-noise ratio
  - Fuse non-commensurate sensor information (accelerometers and oil sensor) to improve fault detection capability
- Diagnostic performance enables prognostics – which produces more benefits
- Good idea to verify and validate components of CBM system on a variety of full-scale and component tests