Intro to Diagnostics Short Course

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Let's get our nomenclature and objectives straight

- Are we saying Diagnostics is:
  - Anomaly detection?
  - Fault Detection?
  - Fault Classification?
  - Fault Isolation?
- What are the reasons we develop diagnostics?
  - Safety?
  - Testability?
  - Control?
  - Health Management?
- What are the Diagnostic requirements?

Detection through Prognosis

- Detection

  Monitored parameter(s) has departed its normal operating envelope

- Diagnosis

  Identify, localize, and determine severity of an evolving (incipient fault through functional failure) condition

- Prognosis

  Reliably and accurately forecast remaining operational time to end of useful life, future condition, or risk to complete mission

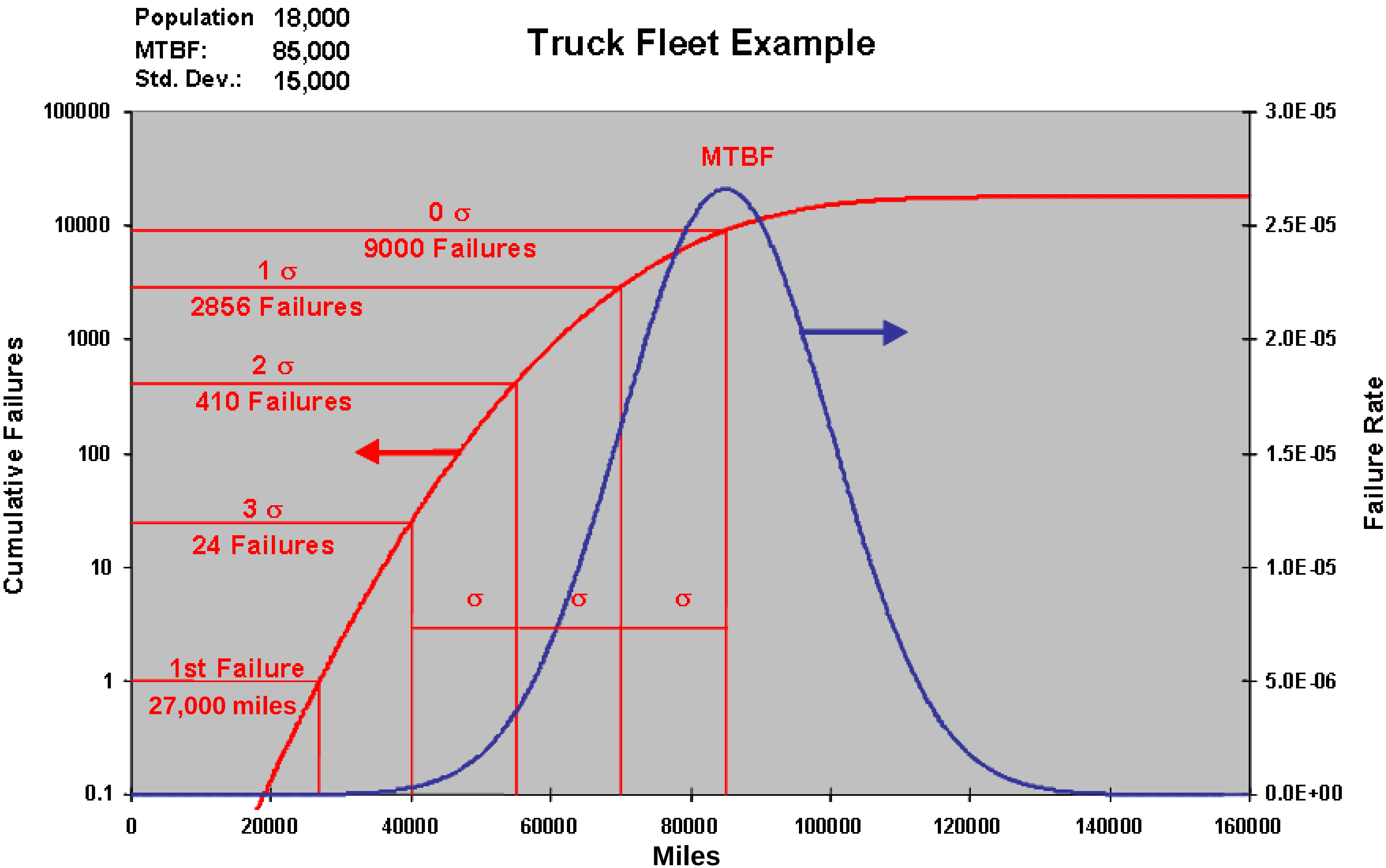
Simple example of the impact of Diagnostics on Maintenance and Operations

Credit: Adapted from original concept developed by Ken Maynard at the Penn State Applied Research Lab

PHM Trucking Company

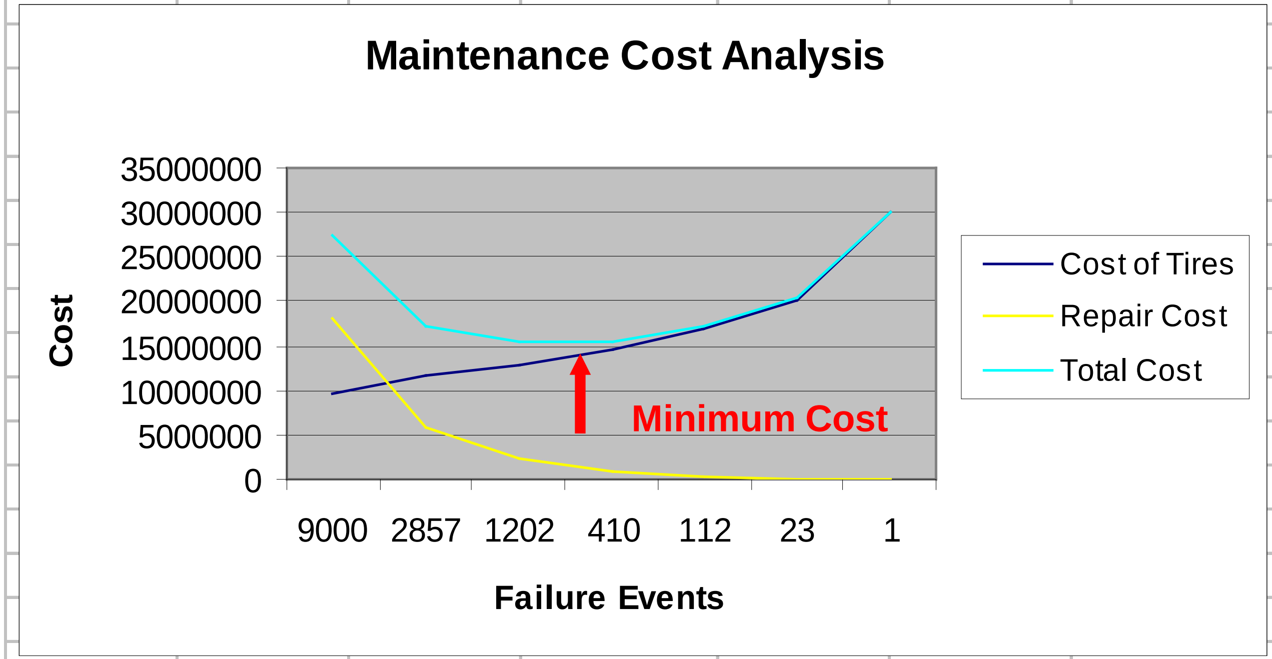
- Fleet of 1000 18-wheeled tractor-trailer trucks
- Tires:
  - Total tires in use: 18,000
  - Mean life: 85,000 miles
  - Standard deviation: 15,000 miles
  - Cost: $500 per tire
  - Roadside repair cost: $2000
  - Average tire usage: 90,000 miles/year
- When should tires be changed?

Effect of Time-Based Maintenance



Maintenance Cost Analysis

Sigma σ	Miles	# of Tire Changes per year	Cost of Tires	# of Road Failures	Repair Cost	Total Cost
0	85000	19059	9529412	9000	18000000	27529412
1	70000	23143	11571429	2857	5713200	17284629
1.5	62500	25920	12960000	1202	2404800	15364800
2	55000	29455	14727273	410	820800	15548073
2.5	47500	34105	17052632	112	223200	17275832
3	40000	40500	20250000	23	46800	20296800
3.8667	27000	60000	30000000	1	1998	30001998



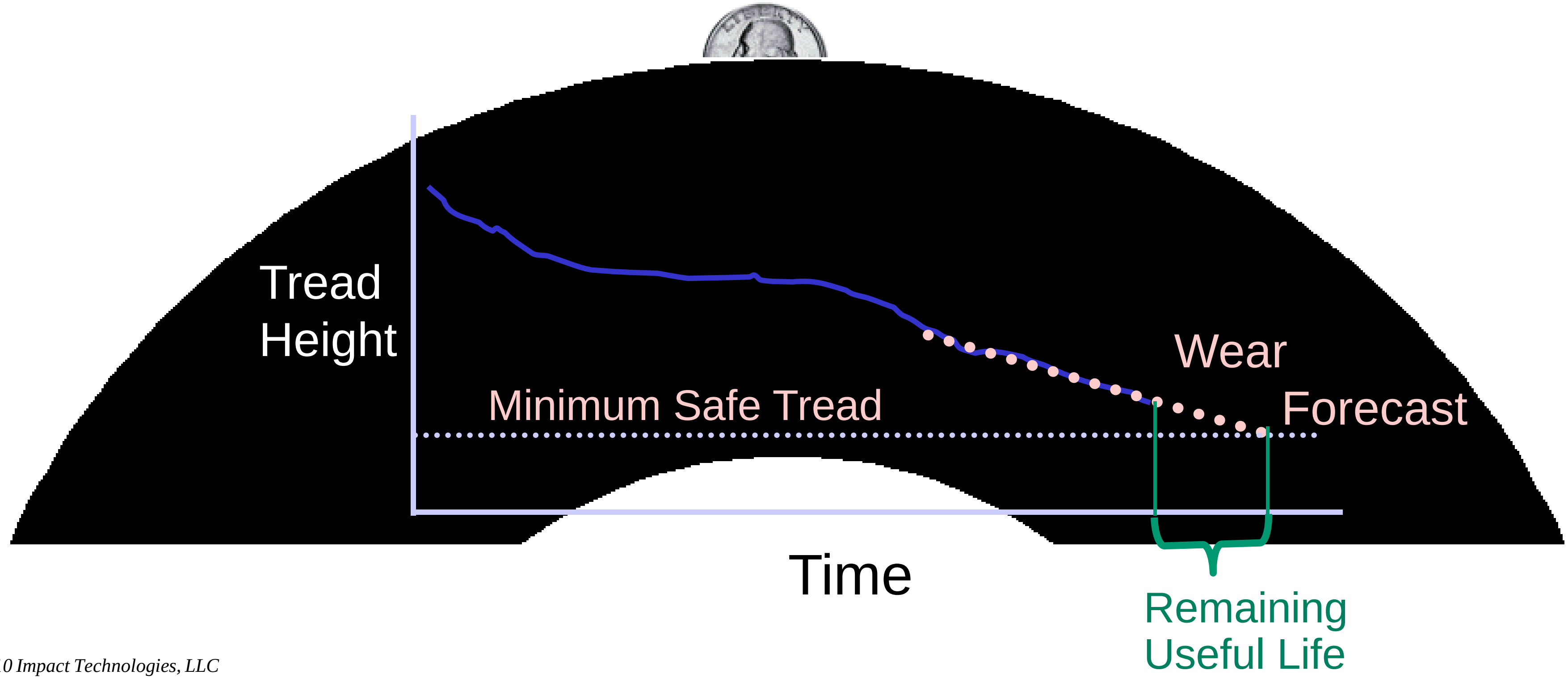
How to save over $120,000 per year:

Fire the person who made the chart!

And Apply Sophisticated CBM/PHM

Diagnostics (Condition Monitoring): If you can see George's chin, replace the tire!

PHM: Measure the Tread Height over time and forecast time to minimum tread.



Revisit Maintenance Cost Analysis

By using CBM,
we can approach
this tire cost

Sigma σ	Miles	# of Tire Changes per year	Cost of Tires	# of Road Failures	Repair Cost	Total Cost
0	85000	19059	9529412	9000	18000000	27529412
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3.8667	27000	60000	30000000	1	1998	30001998

By using CBM, we
can approach this
road failure cost

Result:

With CBM/PHM, we can target maintenance costs of approximately 40% of the best that statistically (traditional reliability) based maintenance can offer

Watch out for the fine print!

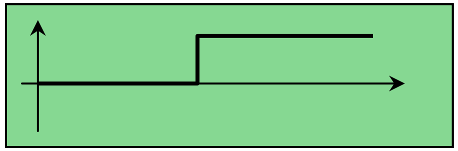
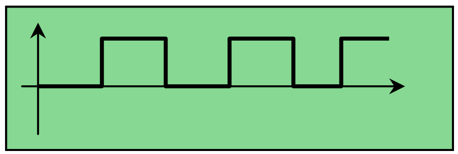
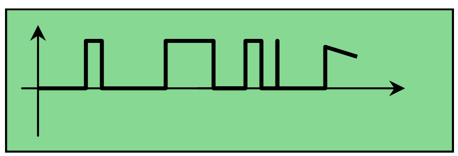
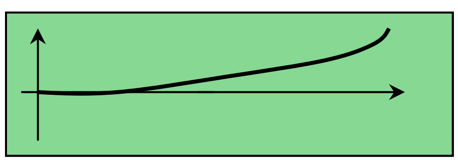
Note: actual savings would vary depending on the details of the maintenance situation

BIT and BITE
(logic-based diagnostics)

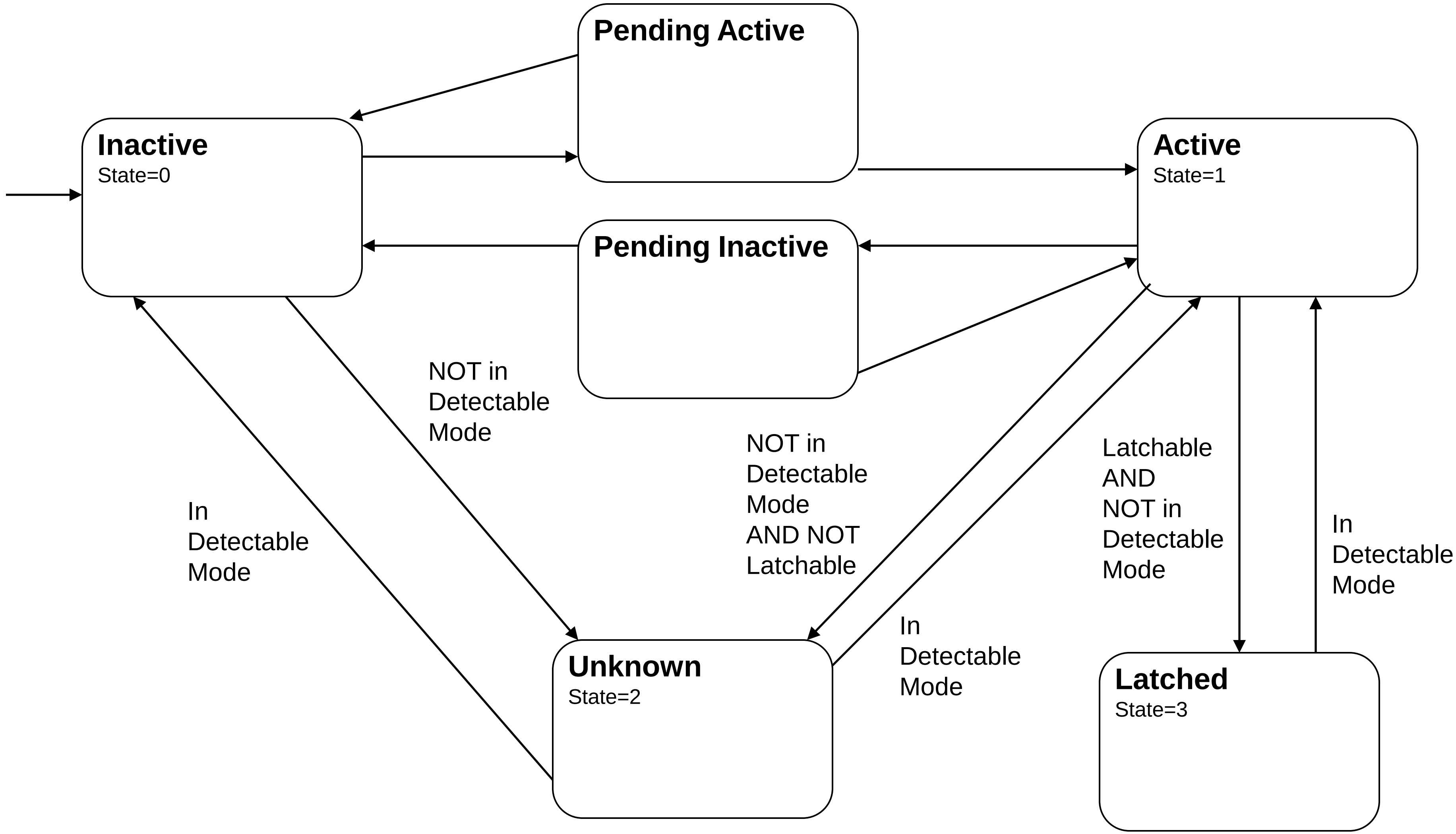
- BIT – Built In Test
- BITE – Built In Test Equipment

- CBIT – Continuous BIT
- PBIT – Power-up BIT
- IBIT – Initiated BIT

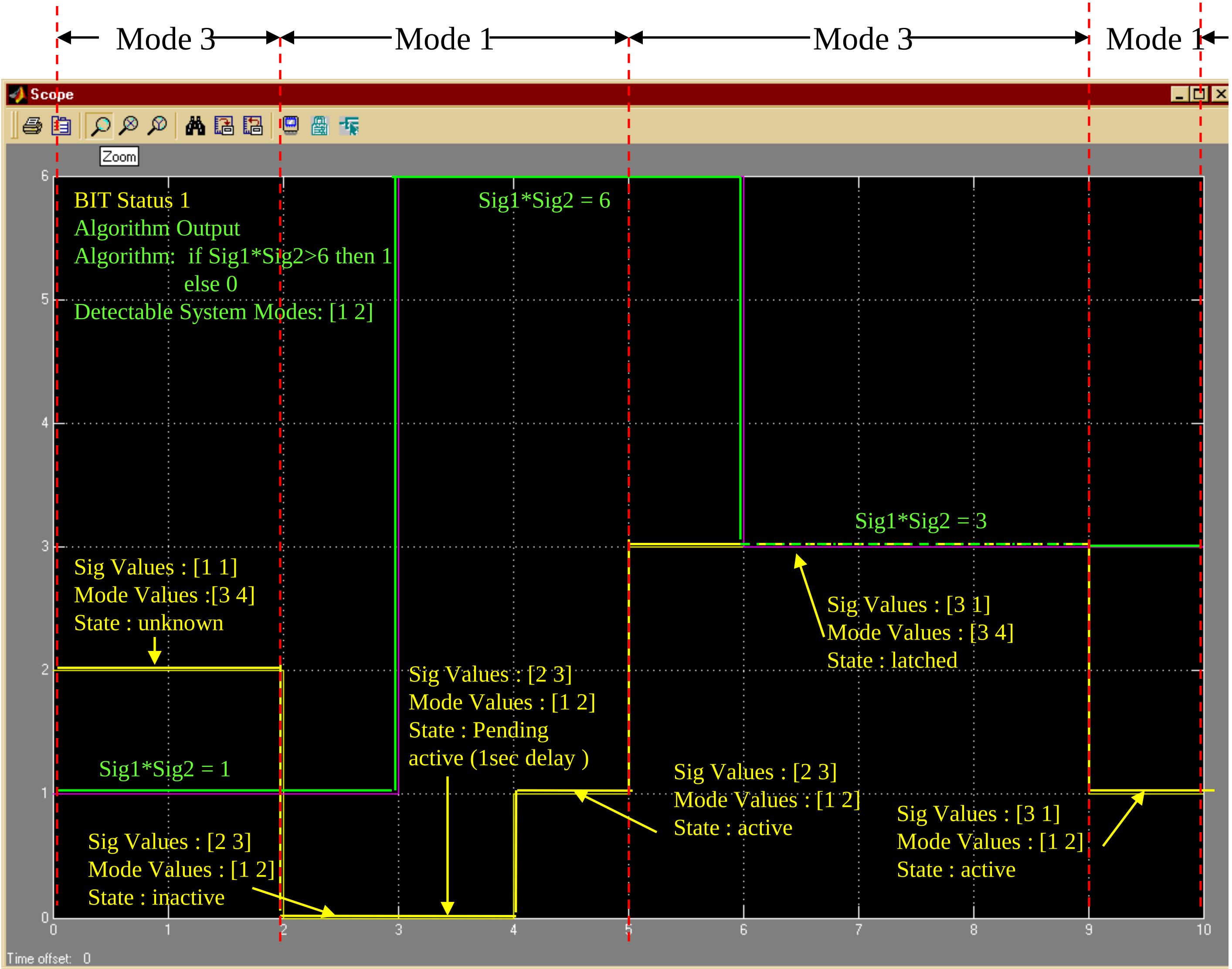
Problem Types

Binary Fault		Simple fault/no fault.
Intermittent but Repeatable		Intermittent fault occurs with high correlation to input parameter set (can be repeated).
Intermittent but Pseudo-Random		Pseudo-Random intermittent faults are the most difficult to isolate.
Graceful Degradation		Graceful component degradation can be detected and predicted using system models and time correlated tracking parameters.

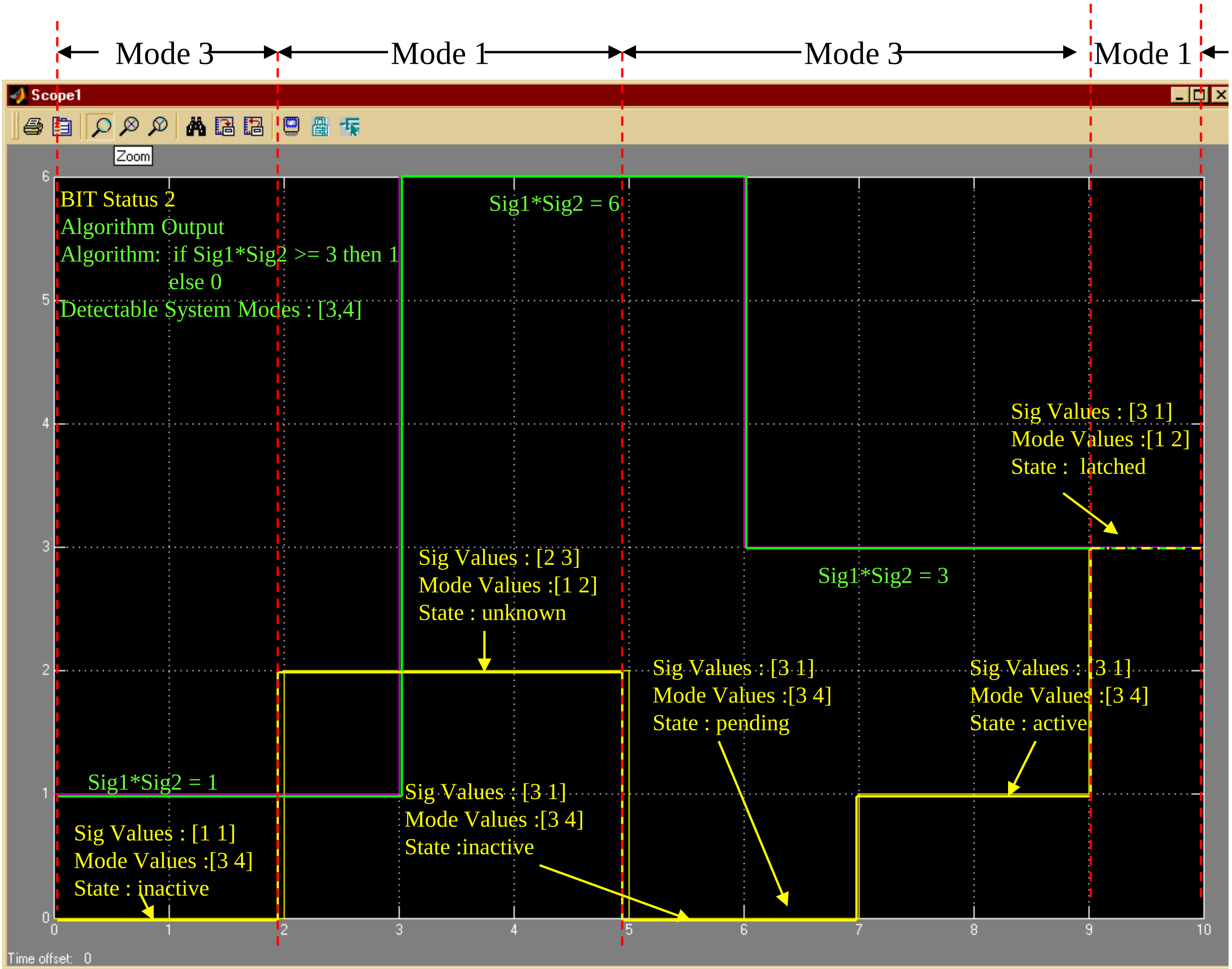
BIT Logic


Pending Active
Inactive
State=0
Active
State=1
Pending Inactive
NOT in
Detectable
Mode
NOT in
Detectable
Mode
AND NOT
Latchable
Latchable
AND
NOT in
Detectable
Mode
In
Detectable
Mode
In
Detectable
Mode
In
Detectable
Mode
Unknown
State=2
Latched
State=3

IMPACT



Mode 3
Mode 1
Mode 3
Mode 1
Scope
Zoom
BIT Status 1
Algorithm Output
Algorithm: if Sig1*Sig2>6 then 1
else 0
Detectable System Modes: [1 2]
Sig1*Sig2 = 6
Sig1*Sig2 = 3
Sig Values : [1 1]
Mode Values :[3 4]
State : unknown
Sig1*Sig2 = 1
Sig Values : [2 3]
Mode Values : [1 2]
State : inactive
Sig Values : [2 3]
Mode Values : [1 2]
State : Pending
active (1sec delay)
Sig Values : [2 3]
Mode Values : [1 2]
State : active
Sig Values : [3 1]
Mode Values : [3 4]
State : latched
Sig Values : [3 1]
Mode Values : [1 2]
State : active
0 1 2 3 4 5 6
0 1 2 3 4 5 6 7 8 9 10
Time offset: 0



Mode 3
Mode 1
Mode 3
Mode 1
Scope1
Zoom
BIT Status 2
Algorithm Output
Algorithm: if Sig1*Sig2 >= 3 then 1
else 0
Detectable System Modes : [3,4]
Sig1*Sig2 = 6
Sig Values : [3 1]
Mode Values :[1 2]
State : latched
Sig Values : [2 3]
Mode Values :[1 2]
State : unknown
Sig1*Sig2 = 3
Sig Values : [3 1]
Mode Values :[3 4]
State : pending
Sig Values : [3 1]
Mode Values :[3 4]
State : active
Sig1*Sig2 = 1
Sig Values : [3 1]
Mode Values :[3 4]
State :inactive
Sig Values : [1 1]
Mode Values :[3 4]
State : inactive
Time offset: 0

Diagnostic Metrics

Detection Statistics

		Indication?	
		Positive	Negative
Fault Present?	True	True-Positive (DP)	True-Negative (1-DP)
	False	False-Positive (FA)	False-Negative (1-FA)

Detection Performance Assessment

DECISION MATRIX			
	Cases with a Fault (F1)	Cases with No Fault (F0)	Total
Fault Indicated (D1)	A: Number of Detected Faults	B: Number of False Alarms	A+B: Total Number of Alarms
Fault Not Indicated (D0)	C: Number of Missed Faults	D: Number of Correct Rejection	C+D: Total Number of Non Alarm
	A+C: Total Number of Faults	B+D: Number of Fault Free Cases	A+B+C+D: Total Number of Cases
	Detection Rate: A/(A+C)	False Alarm Rate: B/(B+D)	Accuracy: (A+D)/(A+B+C+D)

Detection Performance Example

DECISION MATRIX			
	Cases with a Fault (F1)	Cases with No Fault (F0)	Total
Fault Indicated (D1)	A: Number of Detected Faults	B: Number of False Alarms	A+B: Total Number of Alarms
Fault Not Indicated (D0)	C: Number of Missed Faults	D: Number of Correct Rejection	C+D: Total Number of Non Alarm
	A+C: Total Number of Faults	B+D: Number of Fault Free Cases	A+B+C+D: Total Number of Cases
	Detection Rate: A/(A+C)	False Alarm Rate: B/(B+D)	Accuracy: (A+D)/(A+B+C+D)

Collected Experience on an existing condition monitoring system or through test experience

25 faults were correctly detected (a = 25)
32 flagged faults were no fault found (b = 32)
7 faults occurred and were not detected (c = 7)
10,000 correctly identified as no fault (d = 10,000)

$$CorrectDetectionRate = (D1/F1) = \frac{a}{a+c} = \frac{25}{25+7} = 0.781 = 78.1\%$$

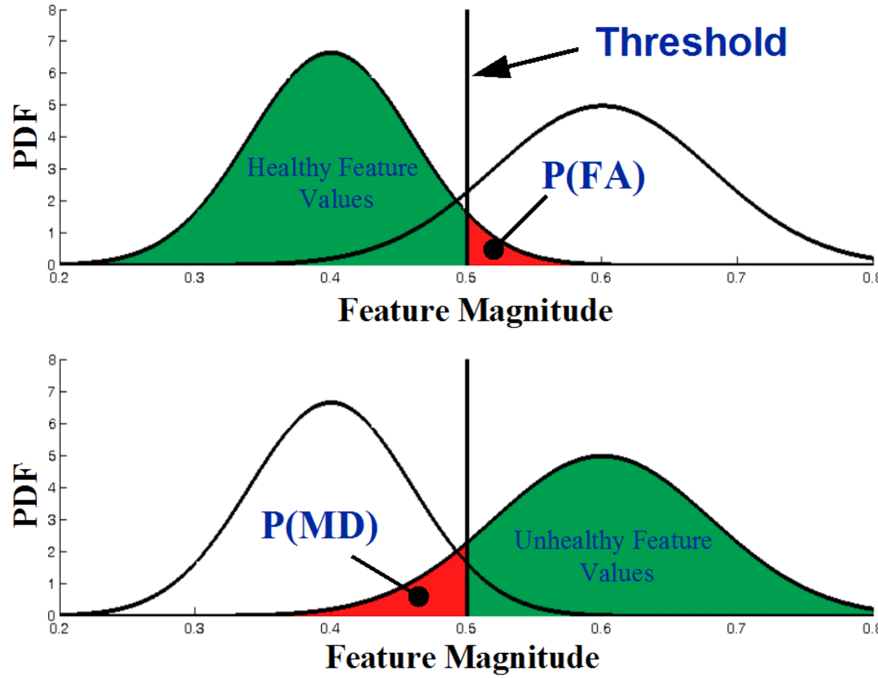
$$FalseAlarmRate = (D1/F0) = \frac{b}{b+d} = \frac{32}{32+10{,}000} = 3.19e-3 = 0.319\%$$

$$Accuracy = (D1/F1 \& D0/F0) = \frac{a+d}{a+b+c+d} = \frac{25+10{,}000}{25+32+7+10{,}000} = 0.9961 = 99.61\%$$

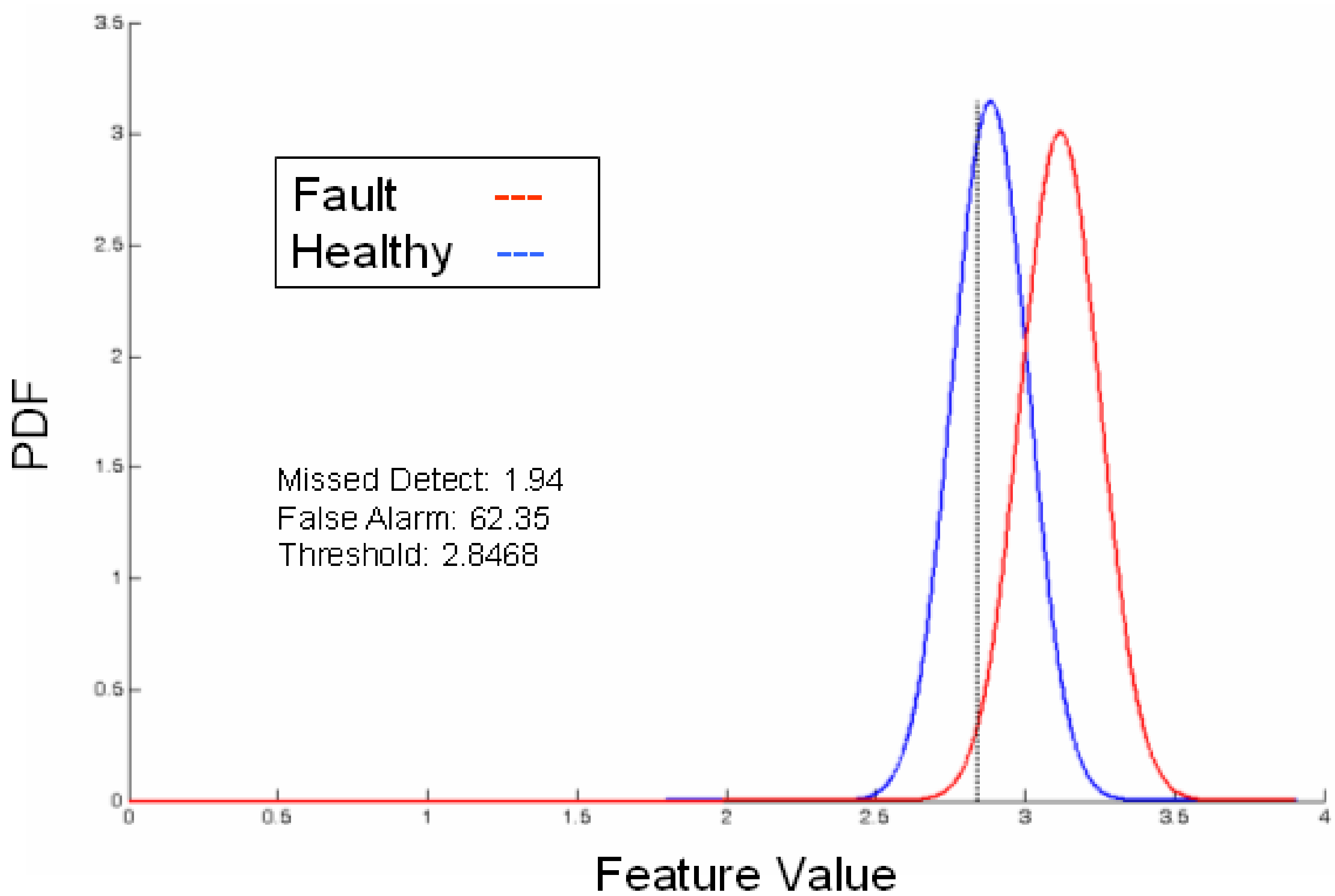
Statistical Detection Theory

Threshold Classification

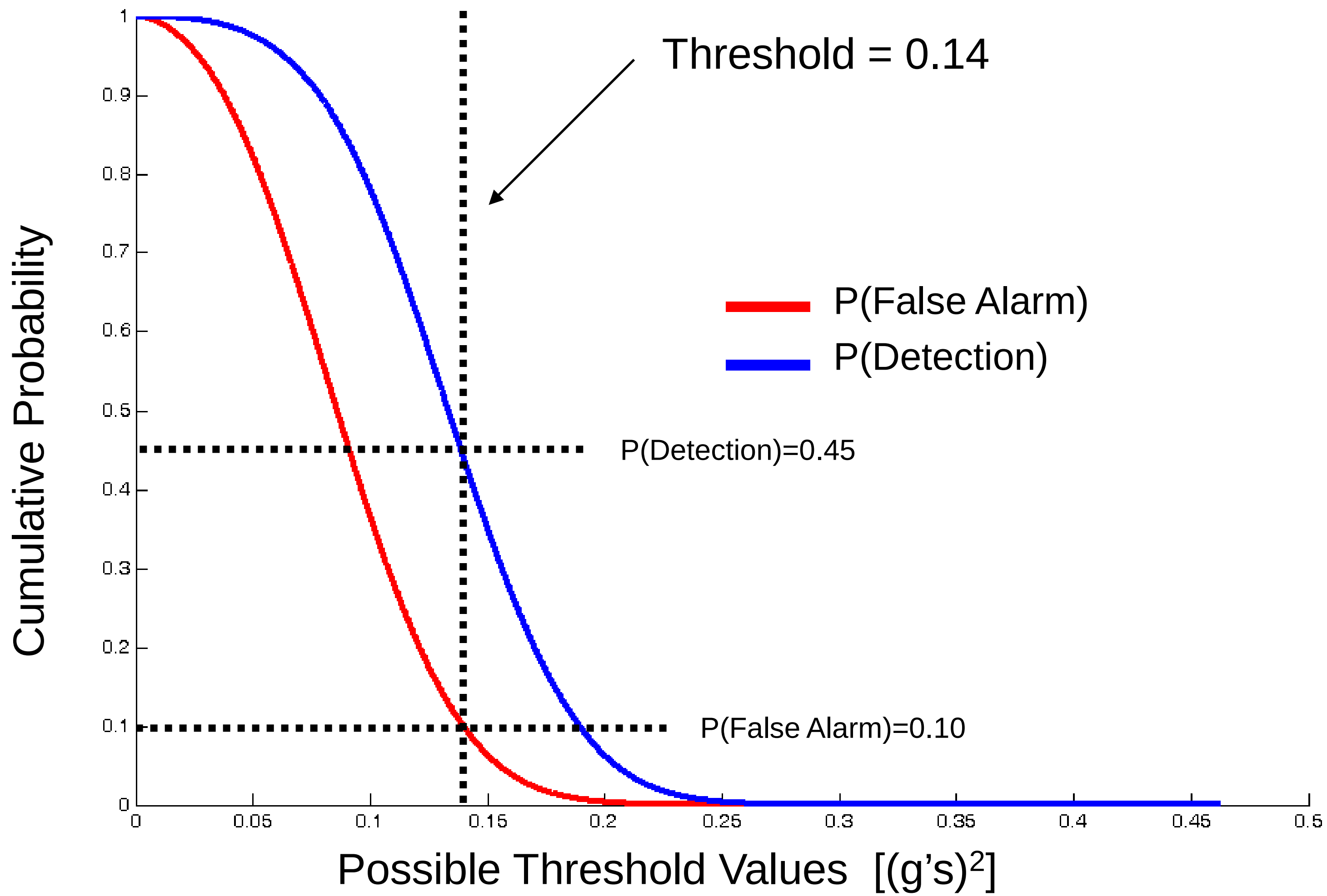
- Feature distributions representing healthy and faulted cases
- Fault threshold value determines the P(MD) & P(FA)
- Feature performance is dependent on area of overlap (separation) of statistical distributions
- Small samples require estimate of variance to create distribution



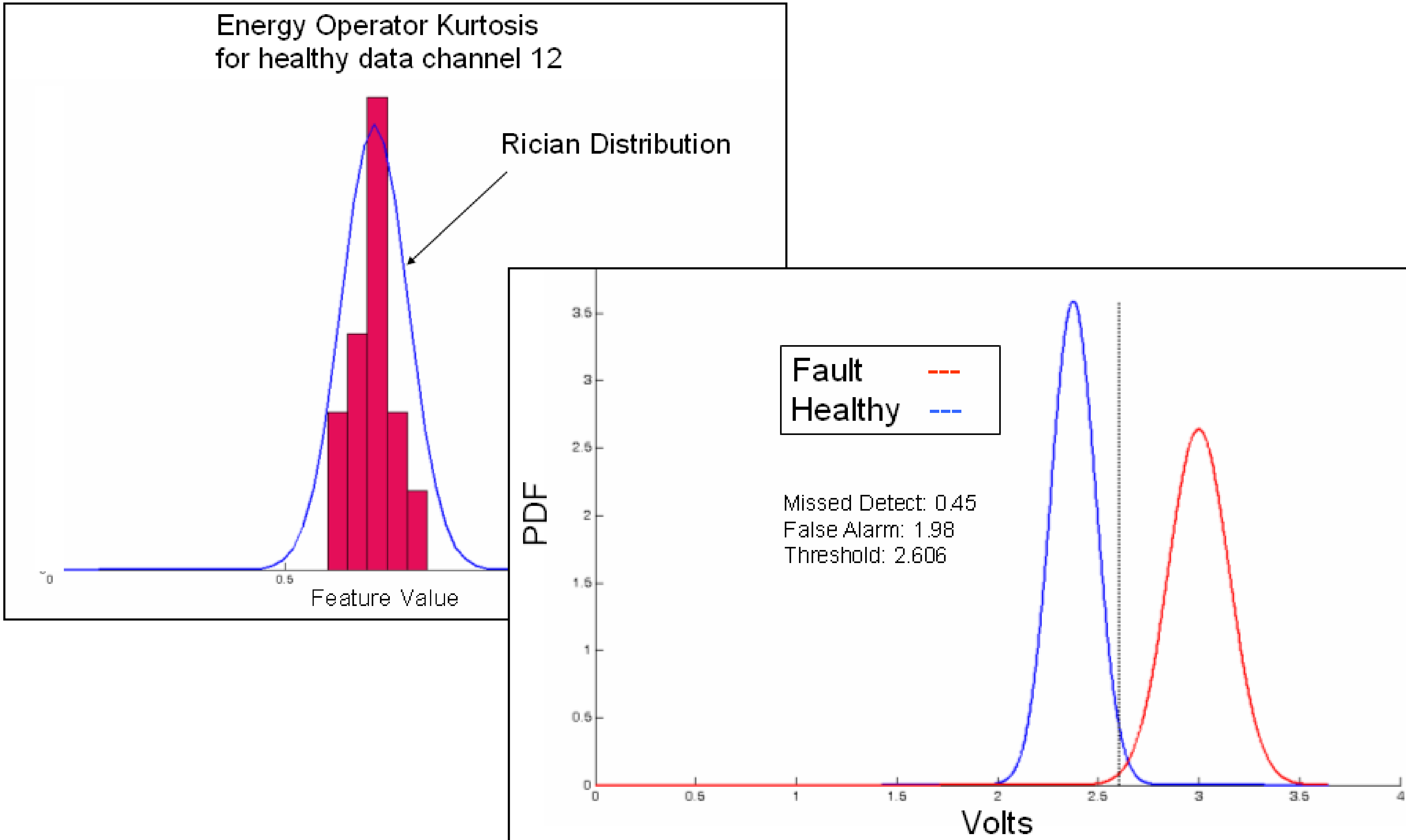
Threshold Setting for Minimizing Missed Detection (usually not acceptable)



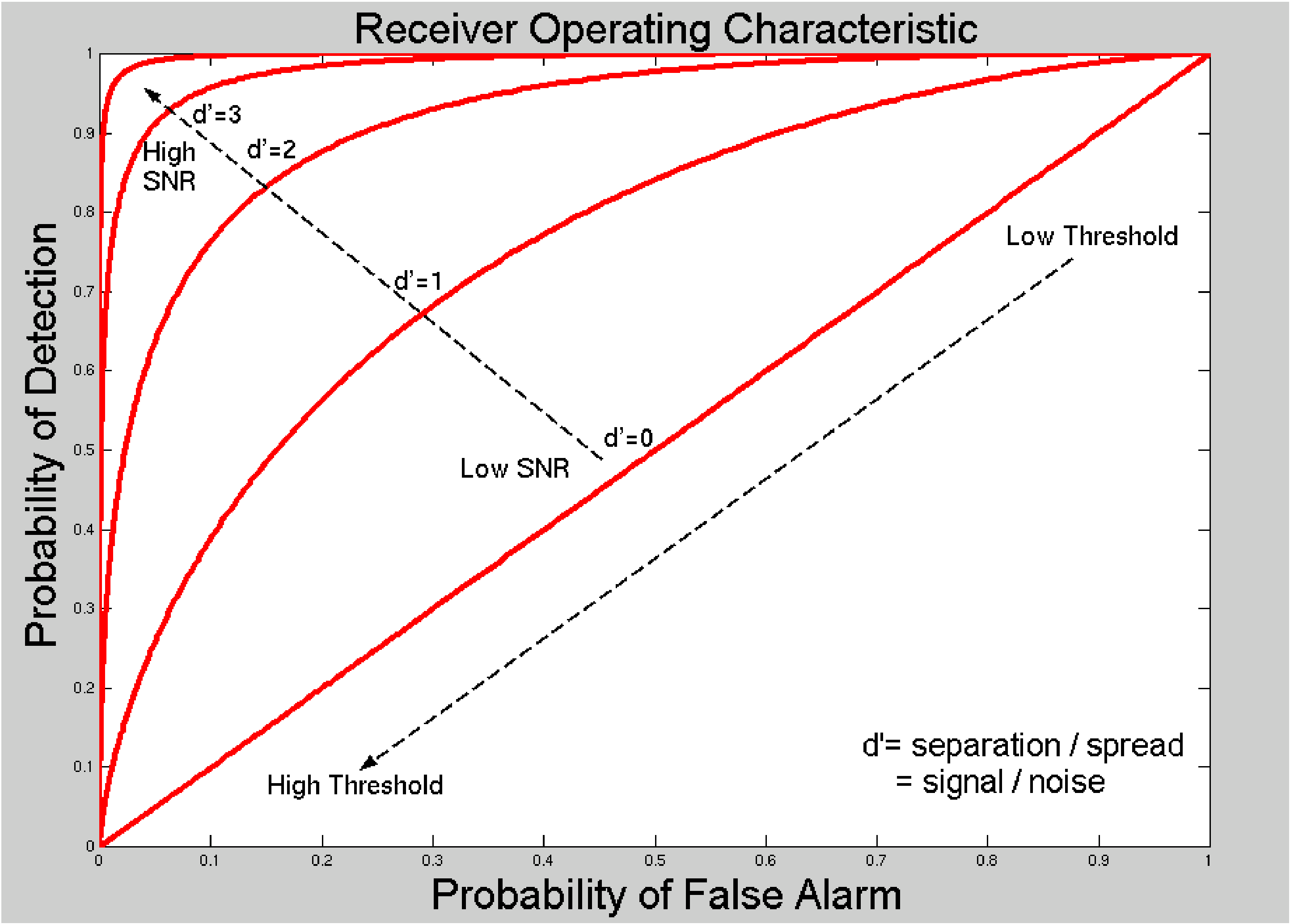
Verify Trade-Off Between False Alarm and Detection (optimal if we have the data)



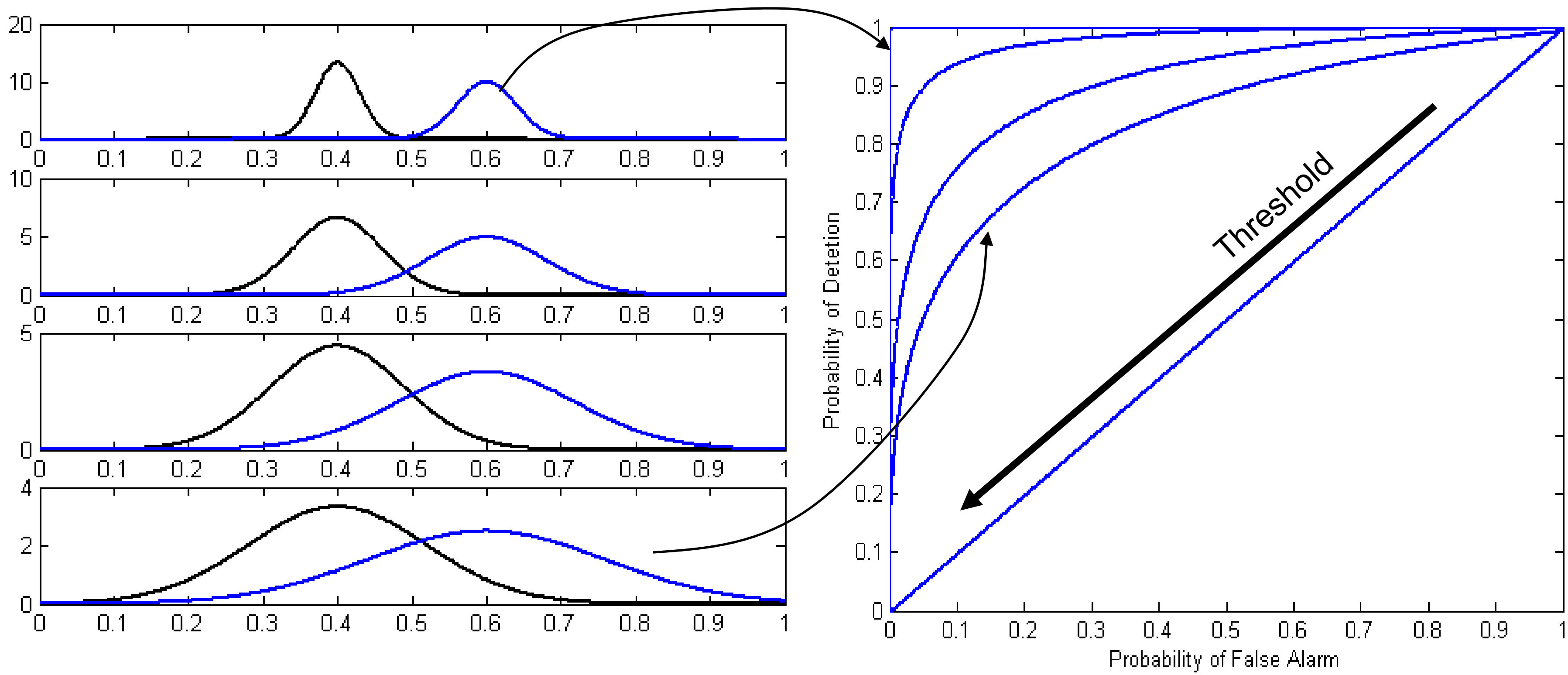
Setting Threshold with FA Verification



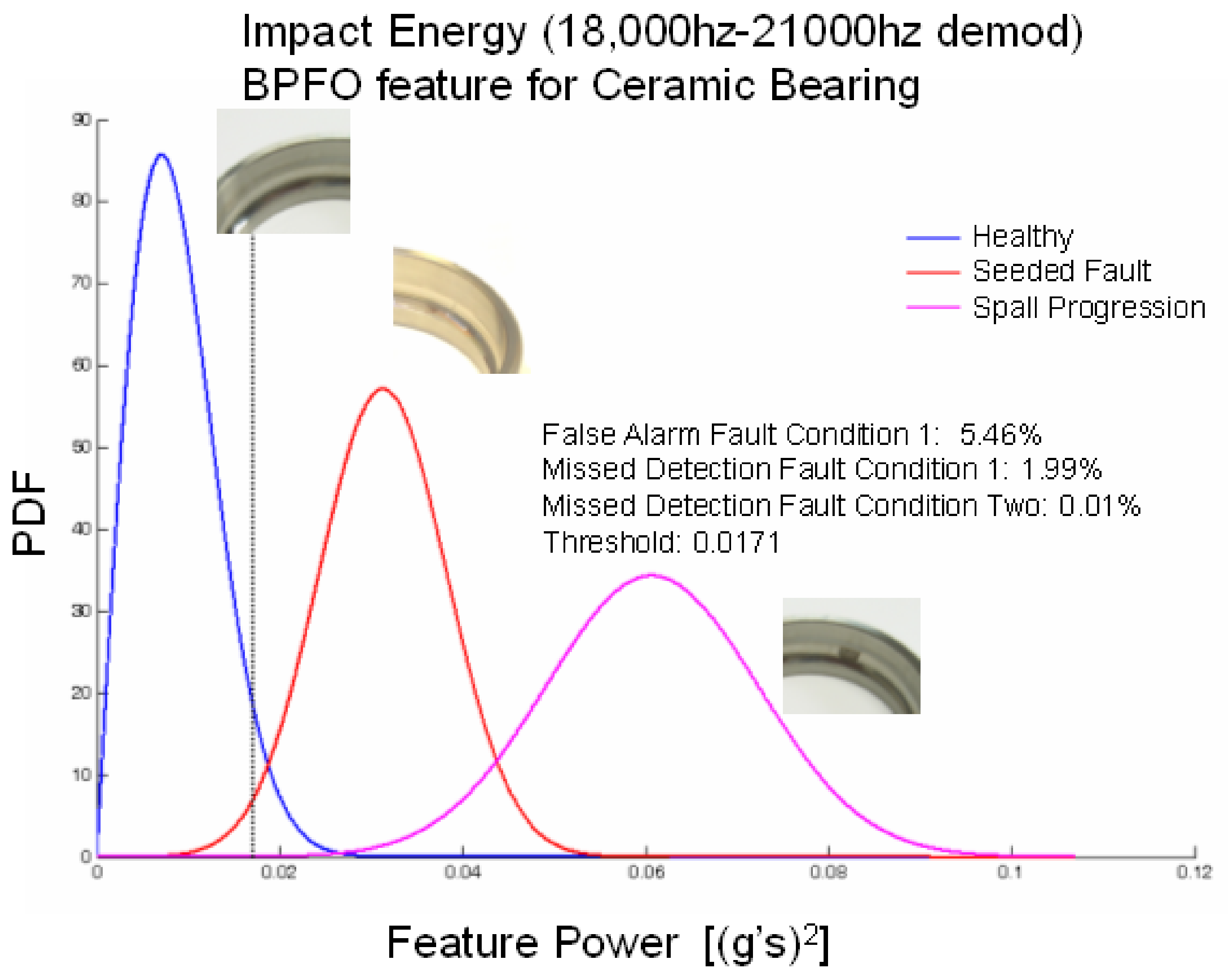
Receiver/Operator Curves (ROC)



Receiver Operating Characteristics



More complication….Detection at Multiple Damage Levels



Isolation

Expert Systems – Simple Diagnosis

IF engine_getting_gas
AND engine_turns_over
THEN problem_with_spark_plugs

IF NOT engine_turns_over
AND NOT lights_come_on
THEN problem_with_battery

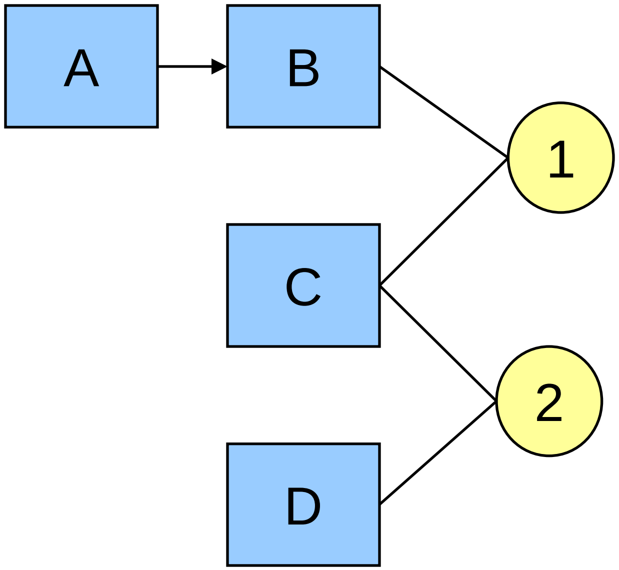
IF NOT engine_turns_over
AND lights_come_on
THEN problem_with_starter

IF gas_in_fuel_tank
AND fuel_pump_on
THEN engine_getting_gas

Reasoner: Is it true that there's gas in the fuel tank?
Input: Yes.
Reasoner: Is it true that the engine turns over?
Input: No.
Reasoner: Is it true that the lights come on?
Input: No.
Reasoner: I conclude that there is a problem with battery.

http://www.uonbi.ac.ke/acad_depts/ics/course_material/ICS625/

Model-based Diagnostics

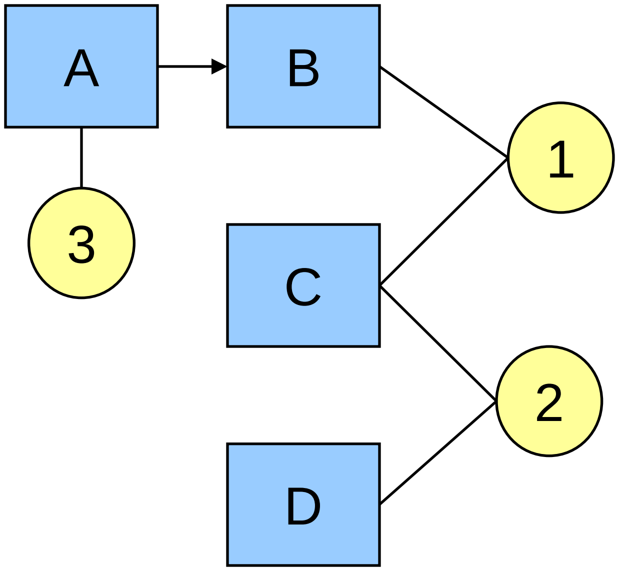


1	2	Root Cause	Number Isolated to
0	0	ABCD	4
0	1	CD	2
1	0	ABC	3
1	1	C	1

Component	Minimum Ambiguity Group Size
A	3
B	3
C	1
D	2

% of Combinations that Isolate to:	% of Components that Isolate to:
1: 25% 2 or less: 50% 3 or less: 75% 4 or less: 100%	1: 25% 2 or less: 50% 3 or less: 100%

MBD con't



% of Combinations that Isolate to:

1: 50%

2 or less: 66%

3 or less: 83%

4 or less: 100%

1	2	3	Root Cause	Number Isolated to
0	0	0	ABCD	4
0	0	1	A	1
0	1	0	CD	2
0	1	1	Conflicting	-
1	0	0	ABC	3
1	0	1	A	1
1	1	0	C	1
1	1	1	Conflicting	-

MBD Con't

1	2	3	Root Cause	Number Isolated to
0	0	0	ABCD	4
0	0	1	A	1
0	1	0	CD	2
0	1	1	Conflicting	-
1	0	0	ABC	3
1	0	1	A	1
1	1	0	C	1
1	1	1	Conflicting	-

Component	Minimum Ambiguity Group Size
A	1
B	3
C	1
D	2

% of Components that Isolate to:
- 1: 50%
- 2 or less: 75%
- 3 or less: 100%

Isolation to 1 component = 2X improvement
Isolation to 2 or less = 1.5X improvement

<u>Without Reasoning</u>!

Bayesian Approach

- Describe Entities and Relationships
- Encapsulates *a priori* knowledge and updates with more experience
- Permits robust diagnostics with incomplete knowledge or modeling capability

Accuracy or Causality of Evidence

Failure Mode Probability Given Evidence

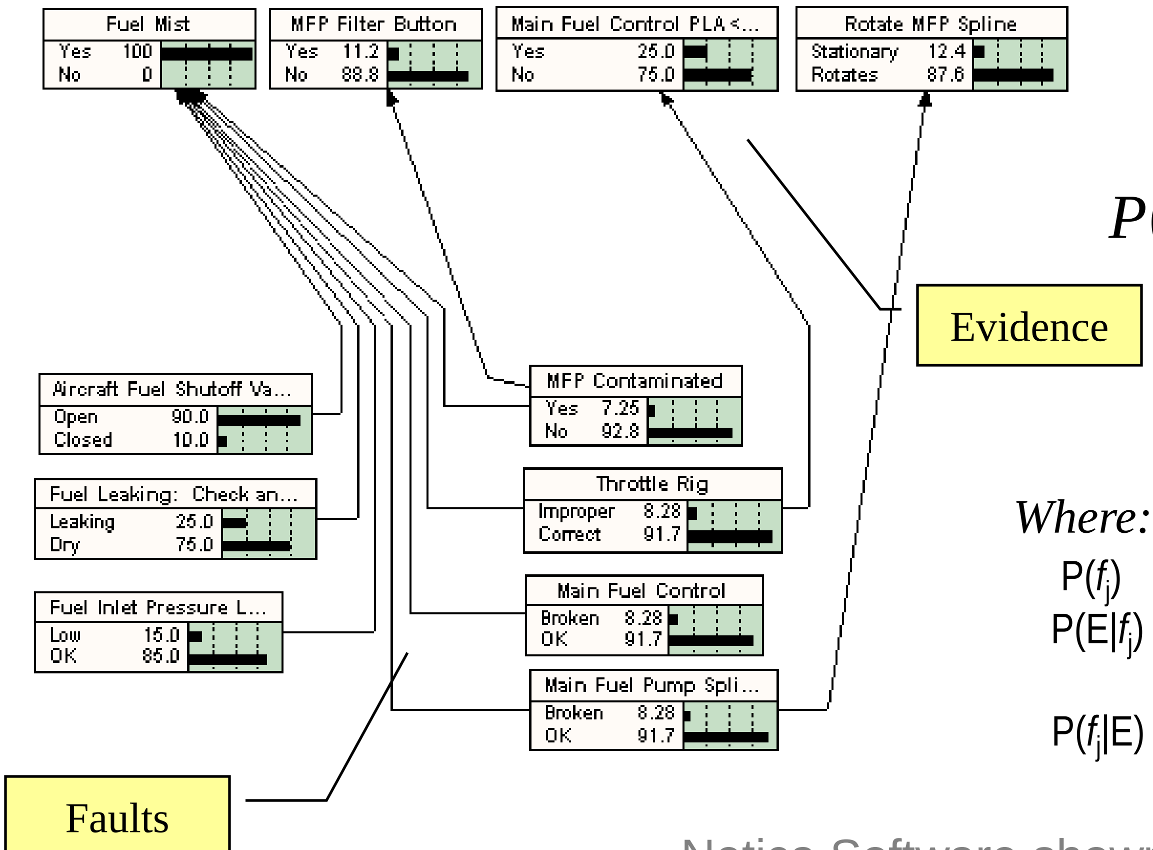
A priori Failure Rate

$$P(FM/E) = \frac{P(E/FM)\cdot P(FM)}{\sum P(E)}$$

Summation of other Fault Evidence

Bayesian Belief Network Implementation

Malfunction = No Start



$$P(f_1|E) = \frac{P(E|f_1)\cdot P(f_1)}{\sum_{j=1}^{n} P(E|f_j)\cdot P(f_j)}$$

Where:

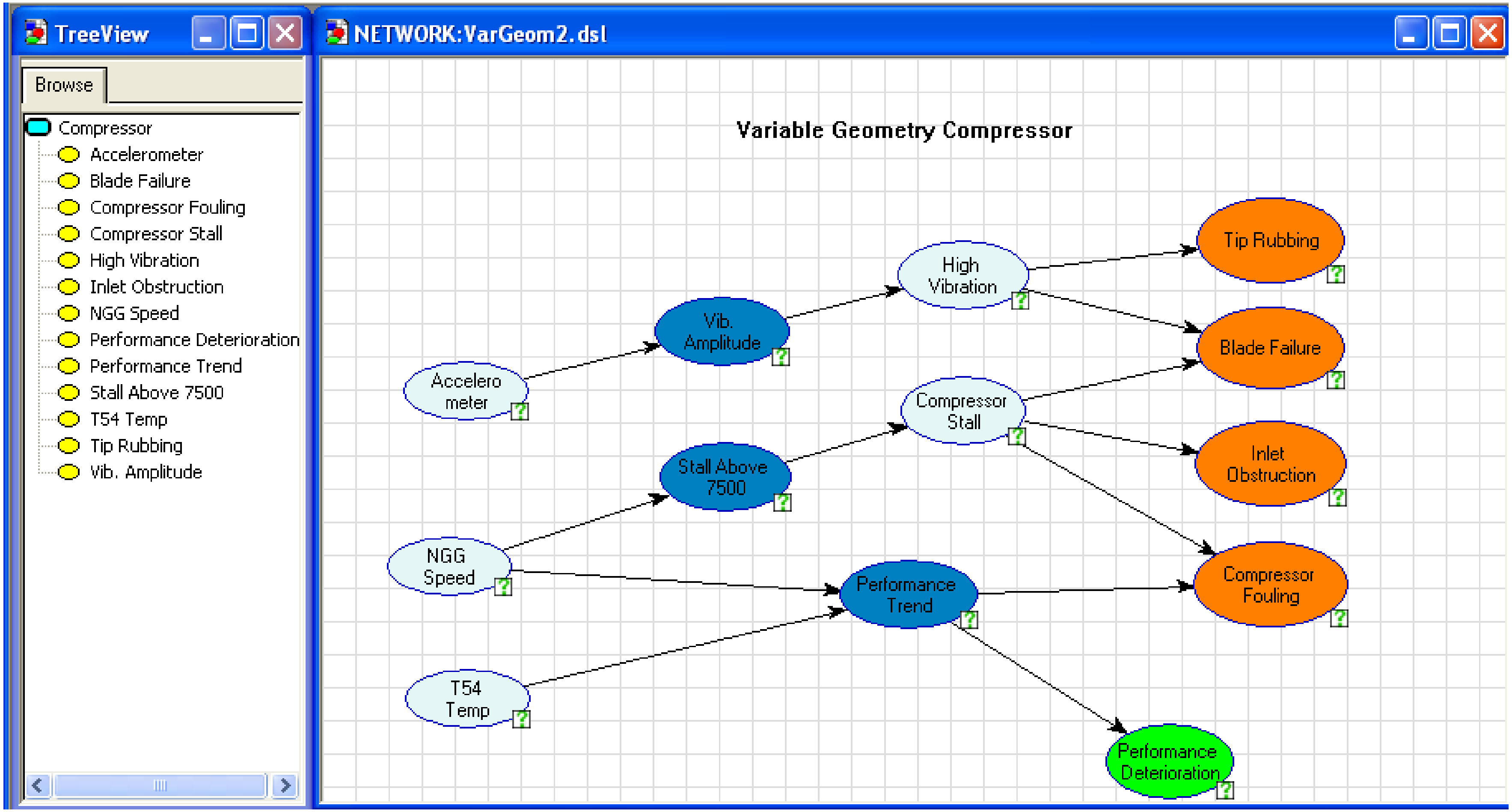
$P(f_j)$ = A-priori probability of fault f_j

$P(E|f_j)$ = Probability of evidence E occurring when f_j exists

$P(f_j|E)$ = Posterior probability of f_j

Netica Software shown
http://www.norsys.com/netica.html

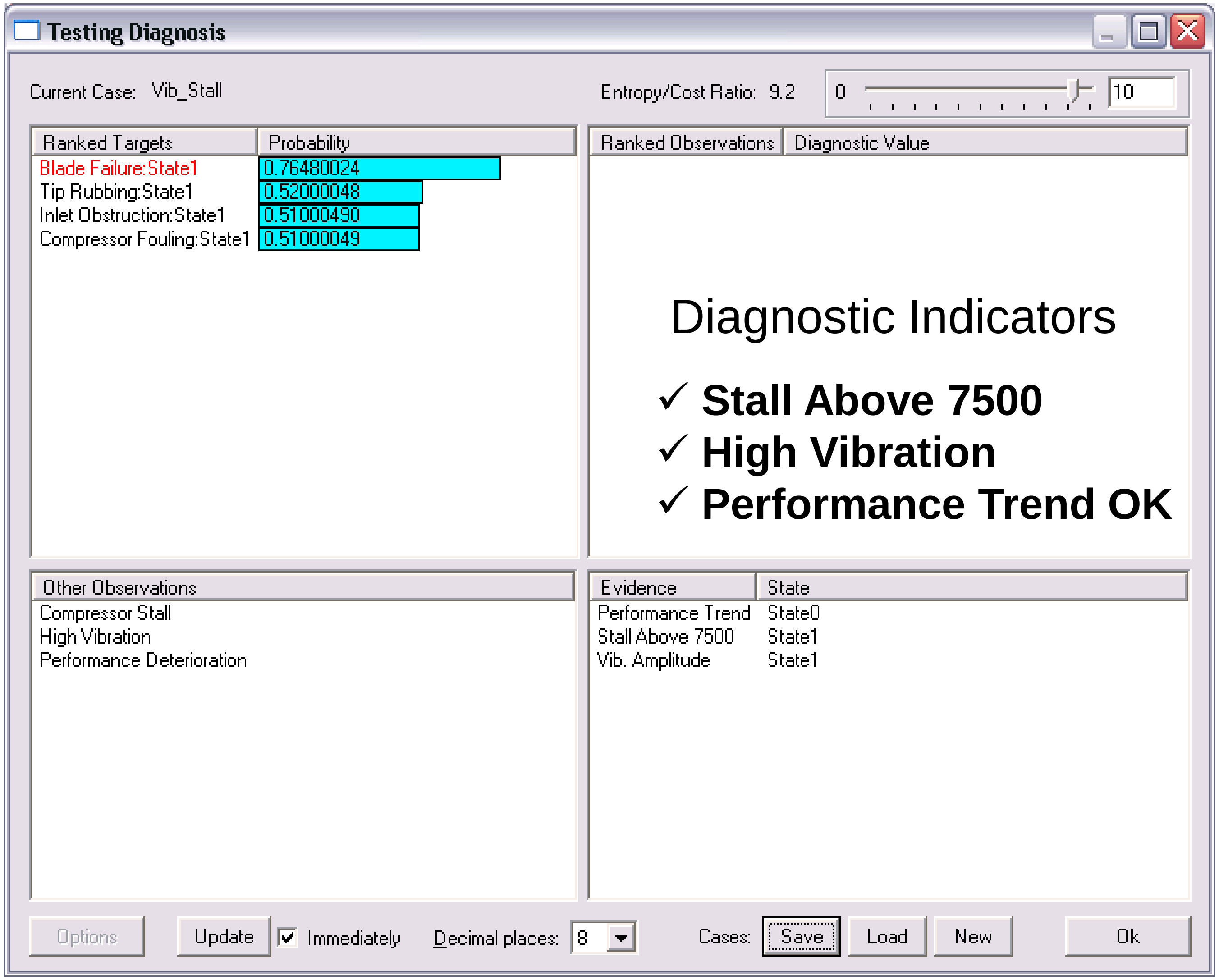
Example: Gas Turbine Compressor Fault Diag.



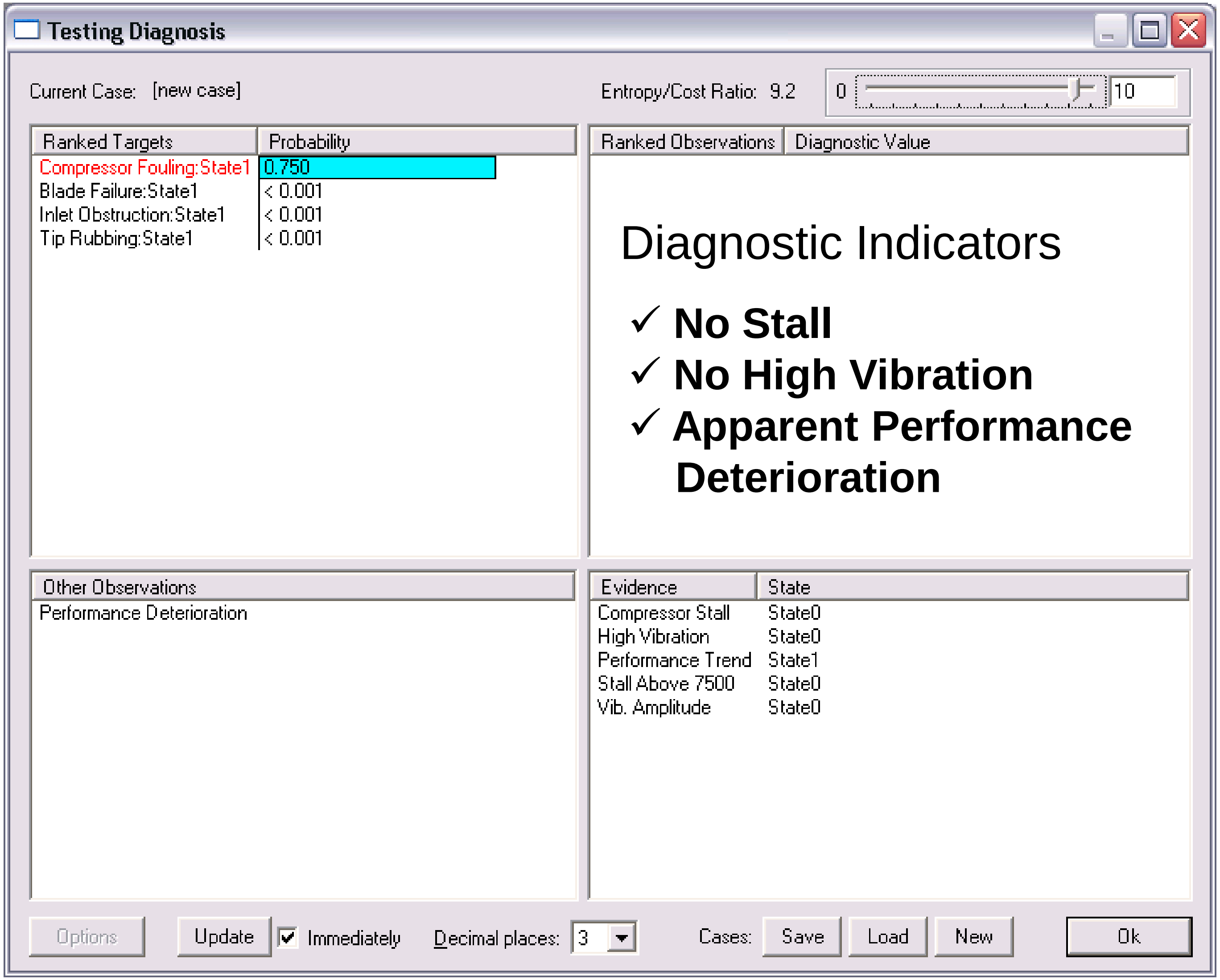
Sensor/Observation | Diagnostic | Prognostic | Failure Mode

GeNie Software shown - http://www2.sis.pitt.edu/~genie/

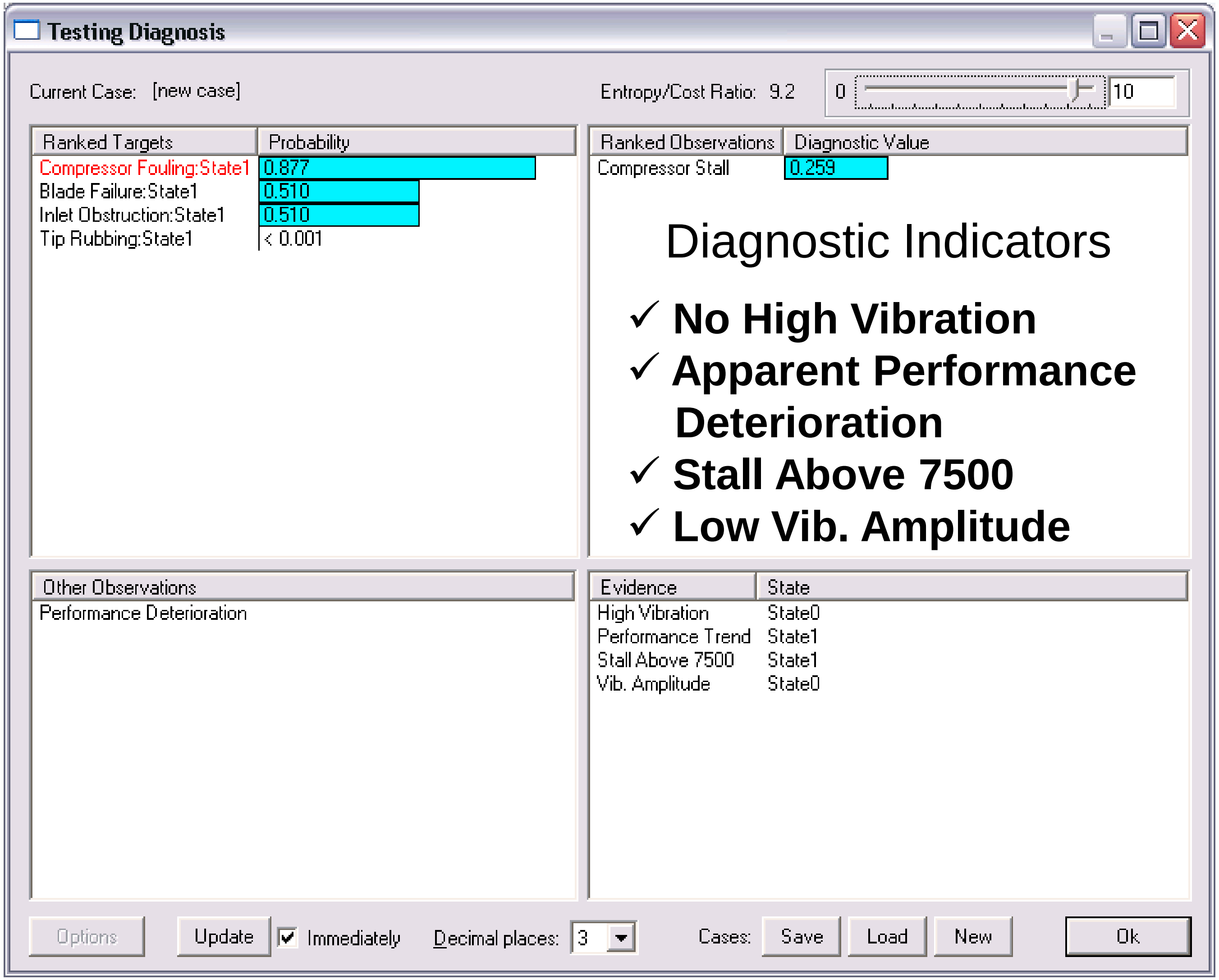
Evidence Case 1



Evidence Case 2



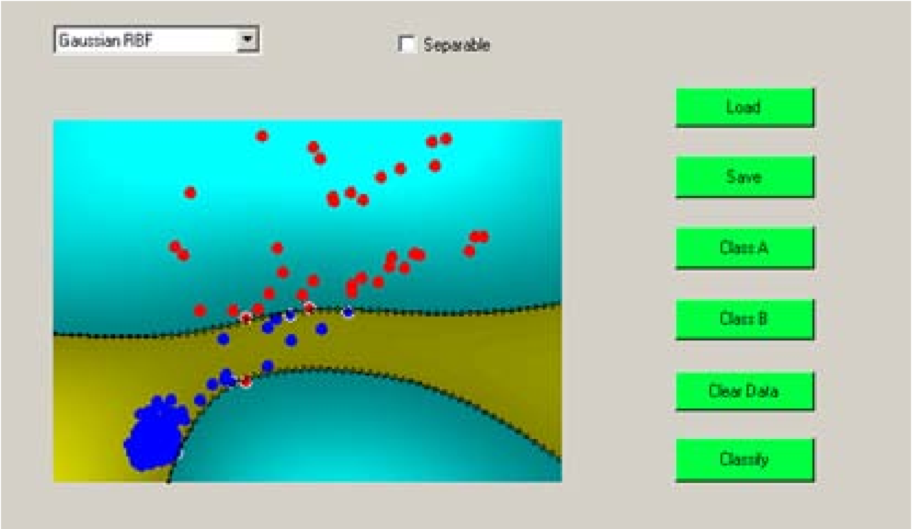
Evidence Case 3



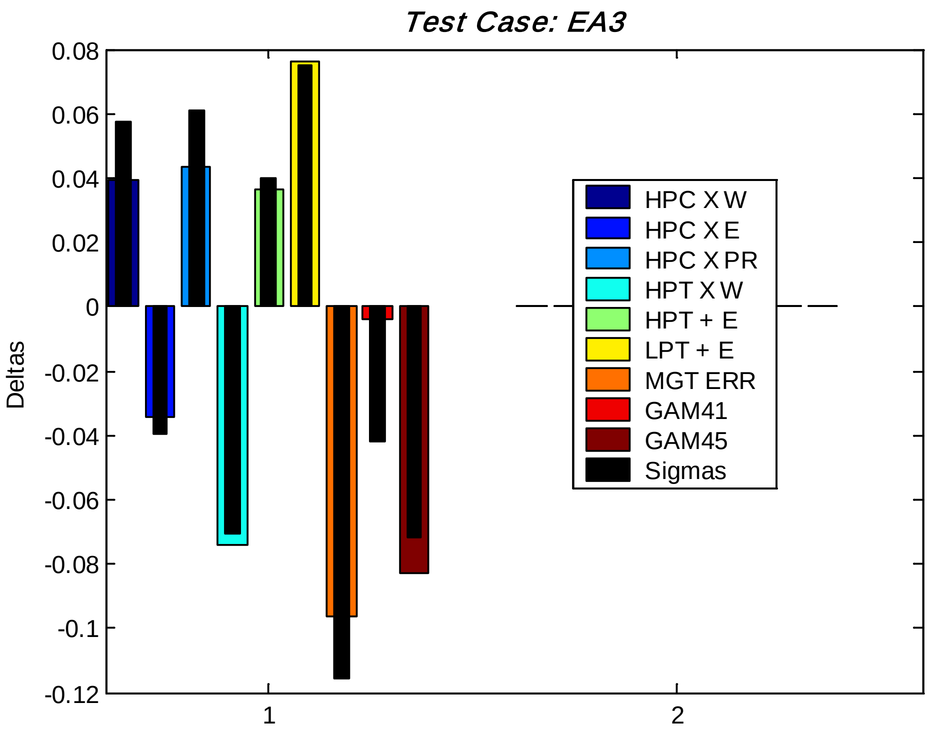
Classifiers

Some Types of Classifiers

- Neural Network (non-linear estimators)
- Kohonen maps
- Principal Component Analysis (PCA)
- Support Vector Machines (SVN)



Rule based Pattern classification



1) Fault Identification

Normalize patterns
Calculate residuals
Apply rules
Search for min RMS

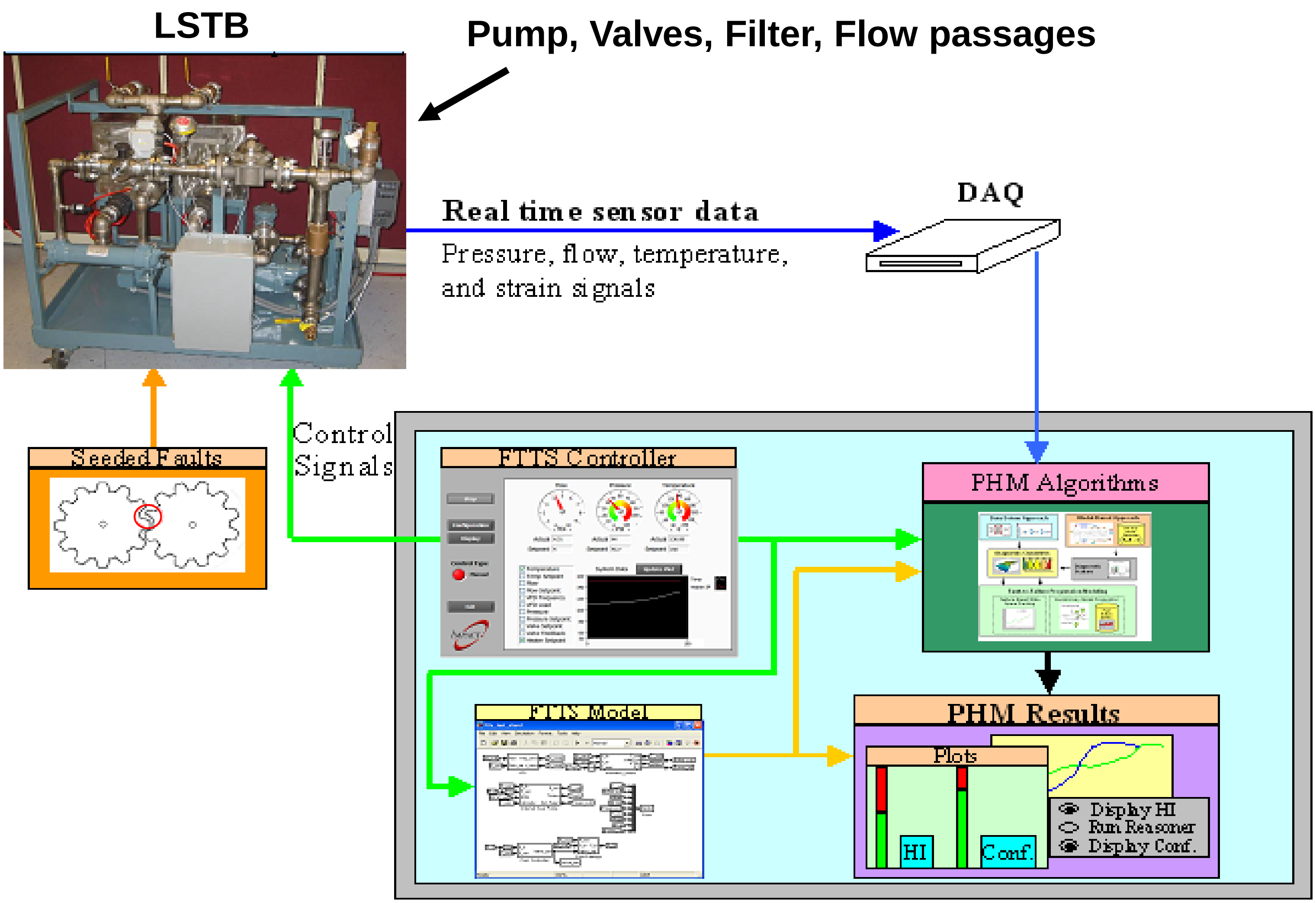
2) Severity classification

Use un-normalized candidate pattern

Scale to best fit

Case Study

Accessory - Lube System Test Bed



Lube System Test Bench (LSTB)

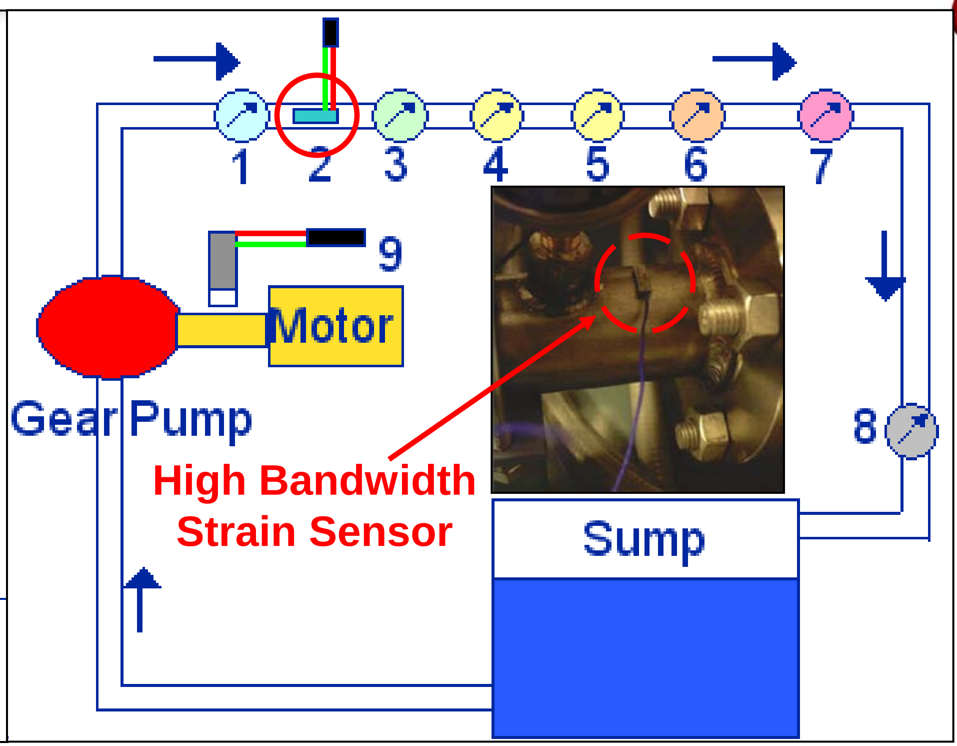
- Testing performed using in-house Lube System Test Bench (LSTB)
  - Incorporates sensors representative of current aircraft systems + new sensors
  - Allows real time data acquisition, analysis, FDI and RUL prediction
- Collected data from healthy and seeded fault tests
  - Pump cavitation, valve malfunction, filter clogging, leakage, damaged pump, etc.

Lube System Test Bench Should Be

- Rated to 150 psi, >250°F, and 30 GPM of flow
- Internal gear pump, driven by induction motor
- Temperature, pressure, flow sensors
- Valve controls oil pressure, heating tape controls temperature
- VFD controls pump

LSTB Sensors

1. Omega high bandwidth pressure transducer (model DPX101-250)
2. PCB strain transducer (model 740B02)
3. Trend thermometer (model 50025A0094A, 50-500 F)
4. Trend thermowell (model 2110103)
5. Kobold flow meter (model OMP-1240A5F4S, 2.6-66 USGM)
6. Weksler pressure gauge (model 251L4PE, 0-160 psi)
7. NBS thermowell
8. Ashcroft low bandwidth pressure transducer (model A2-7-MO2-42-AA-100)
9. Monarch Instruments optical tachometer (model ROS-P)



Sensor #	Sensor Type	Output	Bandwidth	Status
Ashcroft A2-7-MO2-42-AA-100#	Pressure transducer	4-20 mA	Low bandwidth	Existing
NBS 10C-86-100-S-1-A-8-T-2.5”-W-SL27-1/2”-S.260-U=1”-316-2.75”	RTD	4-20 mA	Low bandwidth	Existing
Kobold OMP-1240A5F4S	Flowmeter	4-20 mA	Low bandwidth	Existing
PCB 740B02	Strain sensor	0-10 V	High bandwidth	New
Omega DPX101-250	Pressure transducer	0-5 V	High bandwidth	New
Monarch Instruments ROS-P	Optical tachometer	0-10 V	High bandwidth	New

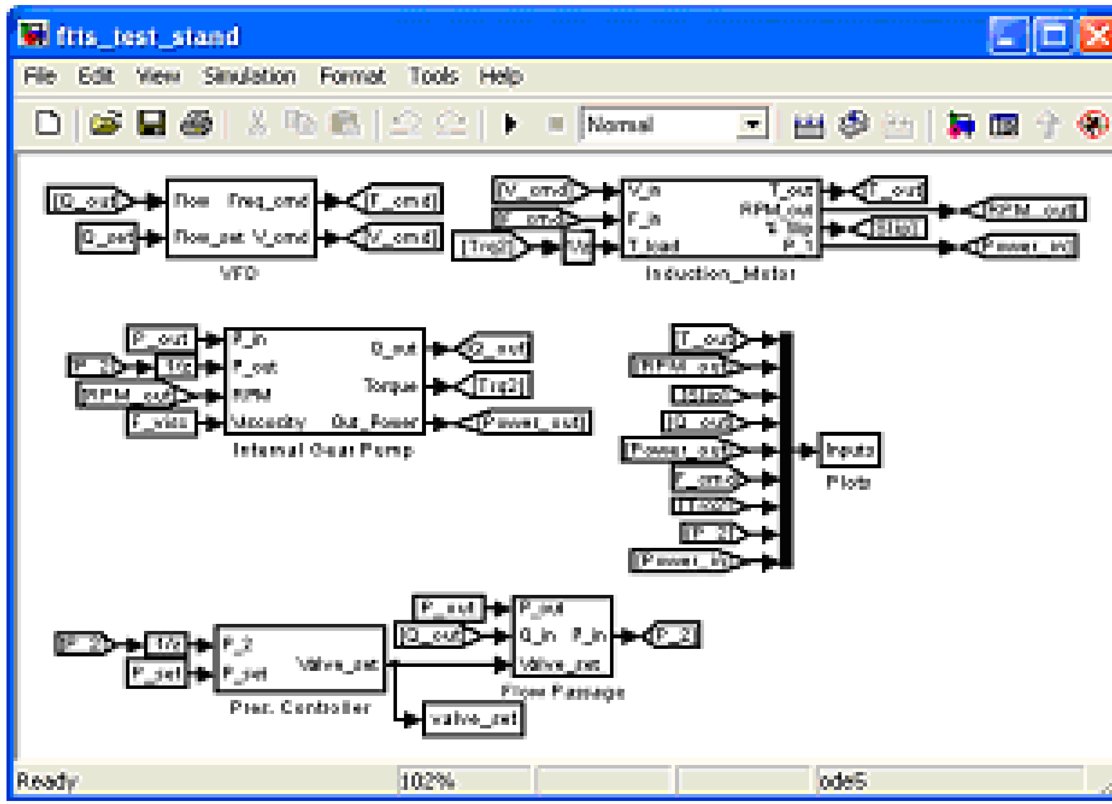
Test Matrix for Data Collection

Case	Description	Leakage Valve	Temperature Setpoint (F)	Pressure Setpoint (psi)	Flow Setpoint (GPM)
Baseline	Unfaulted case	Shut	100, 120 and 140	10, 25 and 40	6, 12 and 15
Leakage	Flow leakage back to sump	~10% open			
Clogged filter	Replace filter with a clogged filter	Shut			
		~10% open			
Valve malfunction	Modify valve command signal	Shut			
		~10% open			
Damaged gear teeth	Modify flow command signal	Shut			
		~10% open			
Cavitation	Drain the sump	Shut			

Dynamic Model of LSTB

- Developed SIMULINK model of Lube System Test Bench components to demonstrate developed model-based approach

- Separate block for each component
  - VFD
  - Induction motor
  - Gear pump
  - Pressure controller
  - Flow passages
- Fault blocks may also be added



Critical Baseline Model Parameters

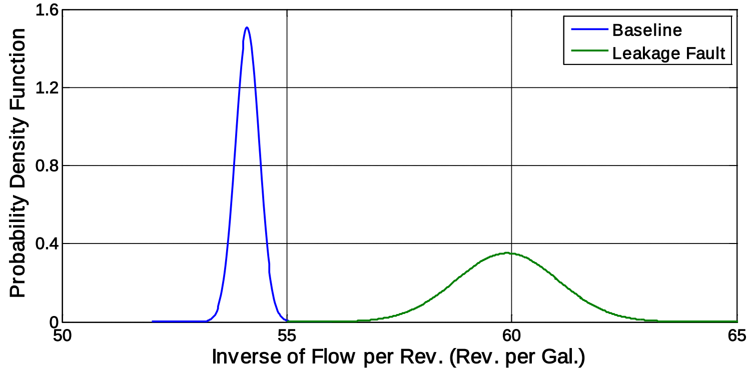
Parameter	Flow per Revolution	Temperature Coefficient of Viscosity	Inlet Pressure	Leakage Flow
Symbol (Unit)	*q* (Gal./rev.)	*b* (K)	*P* (PSI)	Q_{L0} (GPM)
Value	0.018622*	4838	0.011948	0.026424

* Pump Manufacturer's (Viking's) Specifications:

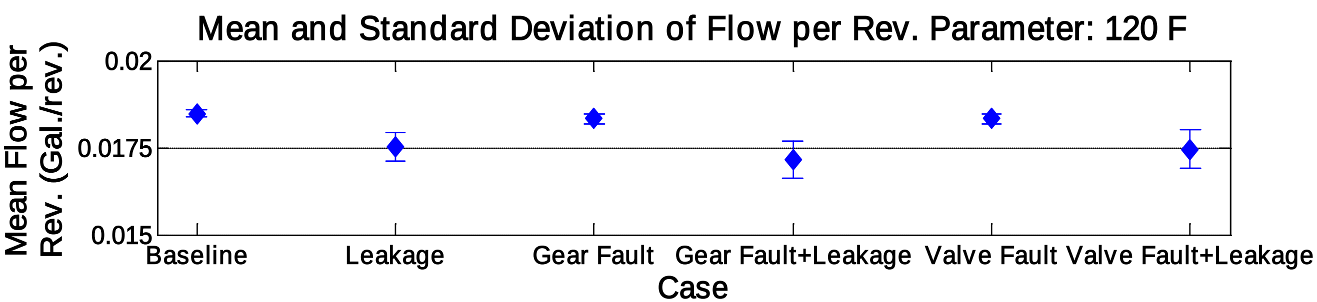
Max. Displacement: **0.01898** Gal./Rev.

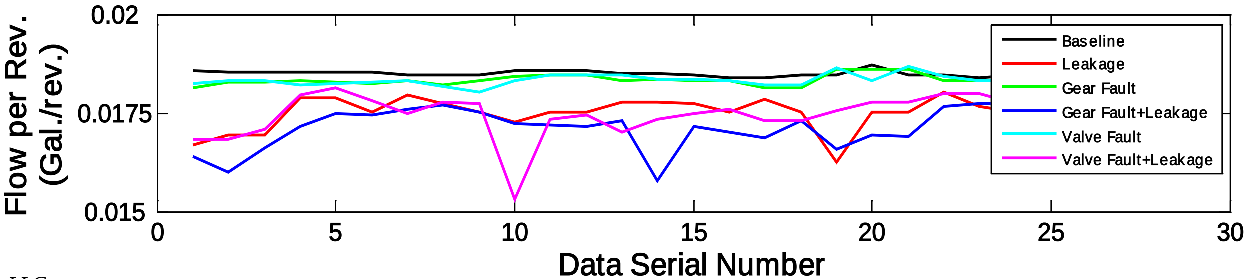
Model-Based Results – Leakage Faults

- Leakage faults successfully detected using Flow per Rev. parameter
  - Represents fluid volume transported per shaft revolution
  - Decreased for leakage cases
  - Unaffected by other faults
  - Invariant with operating pressure



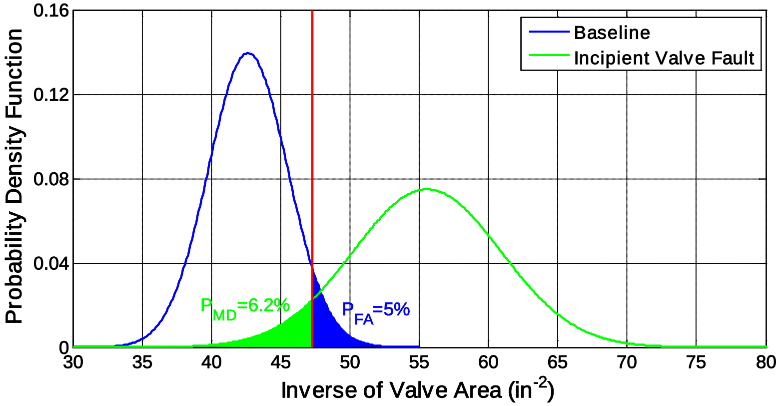
- Good separability between baseline/faulted cases

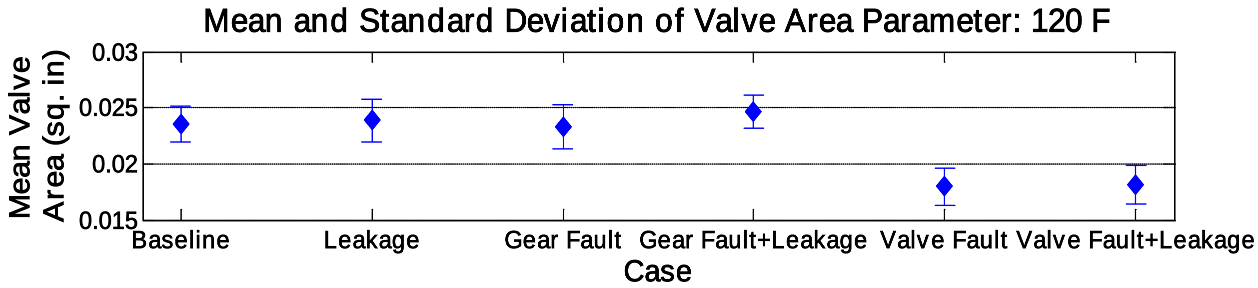


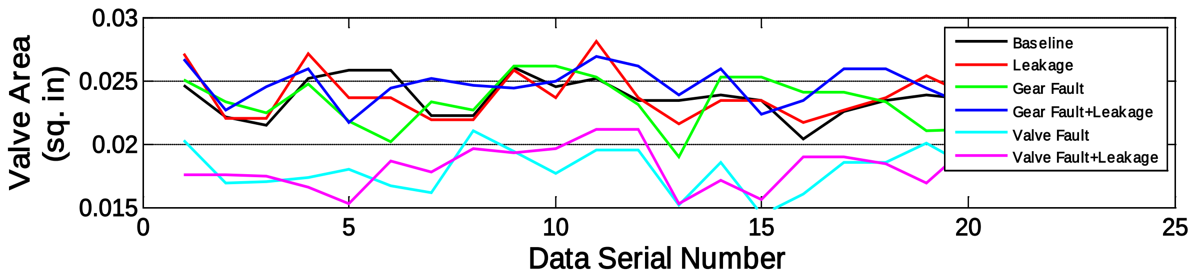


Model-Based Results – Valve Malfunction

- Valve fault successfully detected using *Valve Area* parameter
  - Represents effective area of fully open valve
  - Decreased for valve fault cases
  - Relatively constant for other cases
- Demonstrated good incipient fault detection capability
  - 6.2% MD for 5% FA

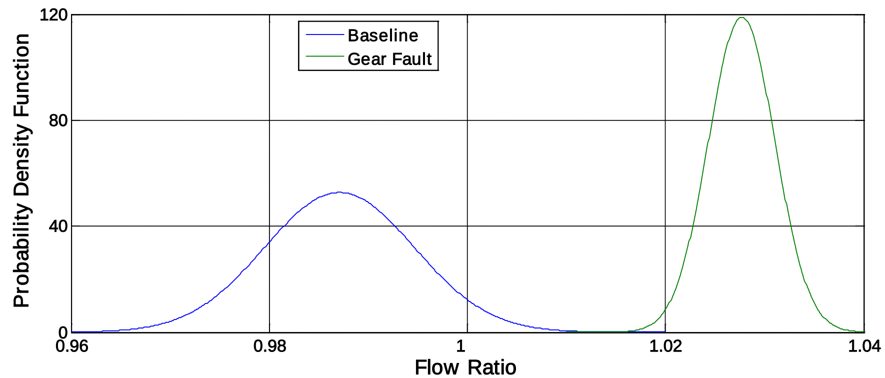




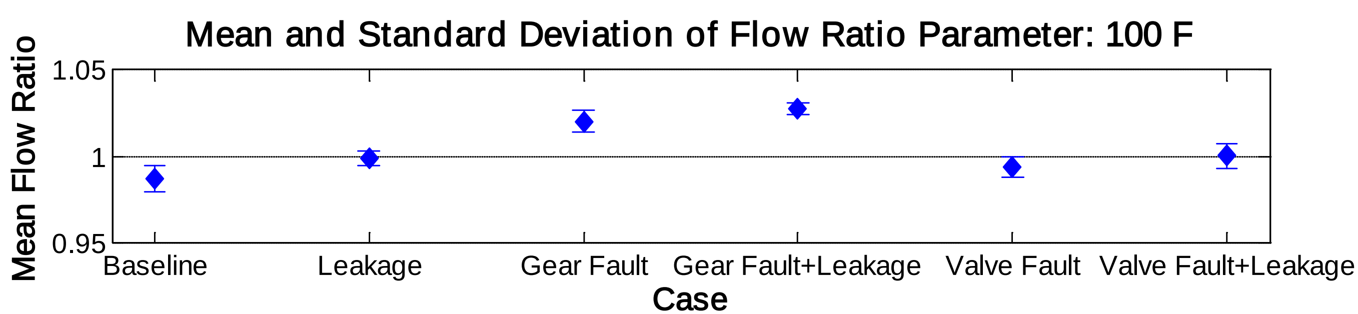


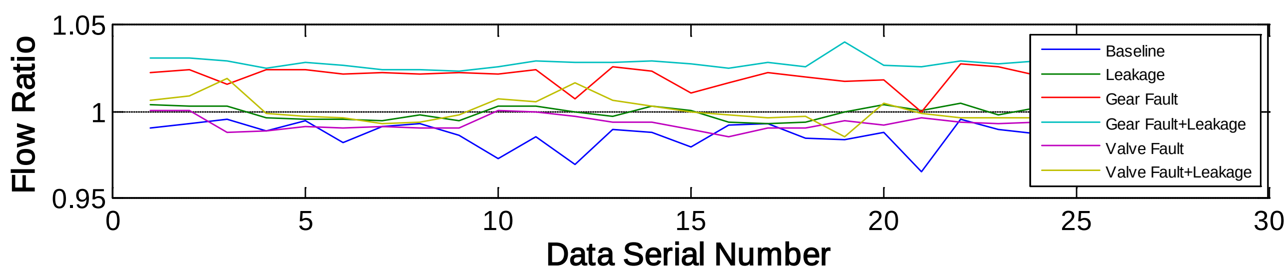
Model-Based Results – Gear Faults

- Gear fault detected using Flow Ratio parameter
  - Ratio between flow setpoint and measured (average) flow
  - Increased for gear fault runs, regardless of leakage
  - Unaffected by other faults

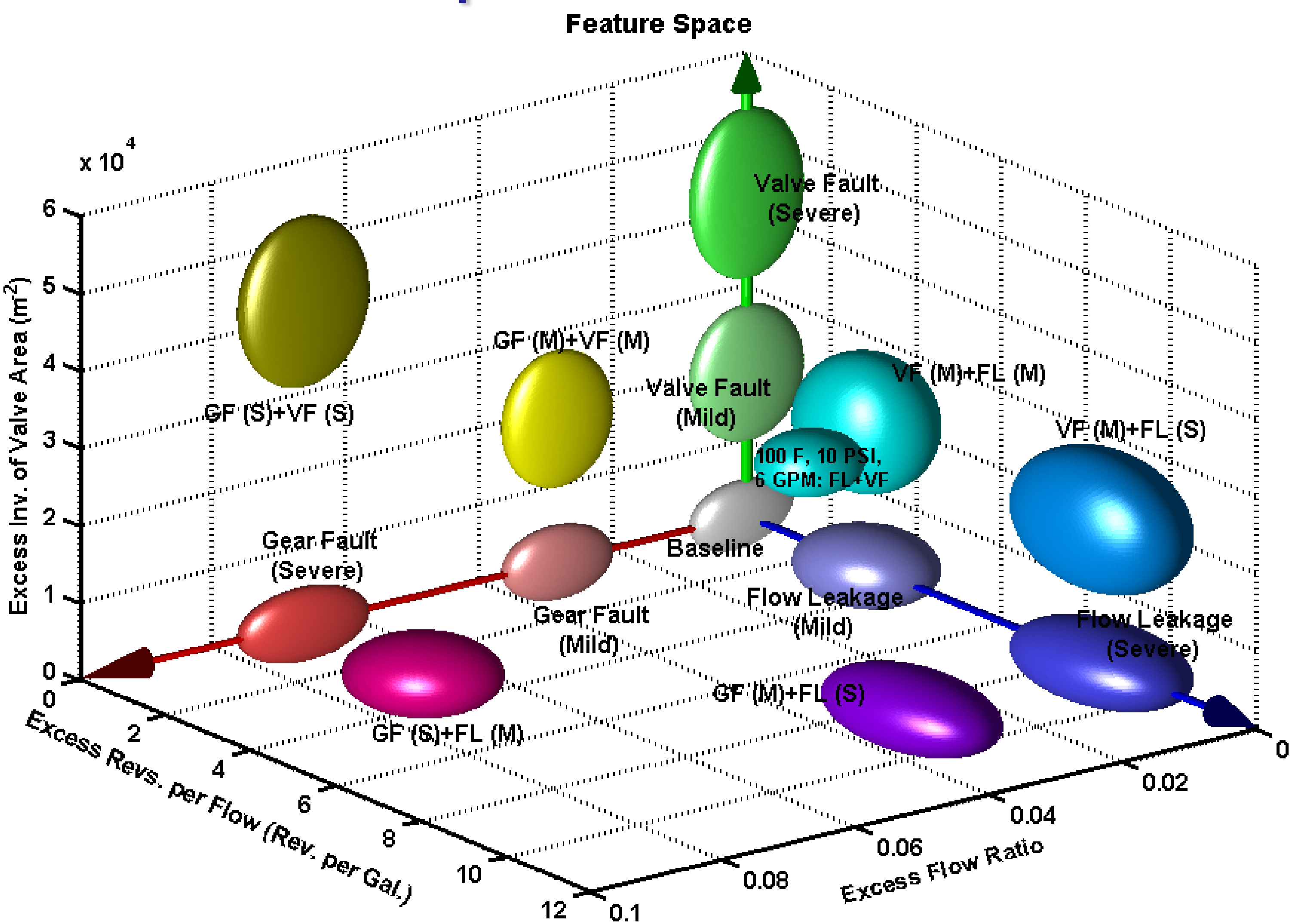


- Good separation between baseline/faulted cases



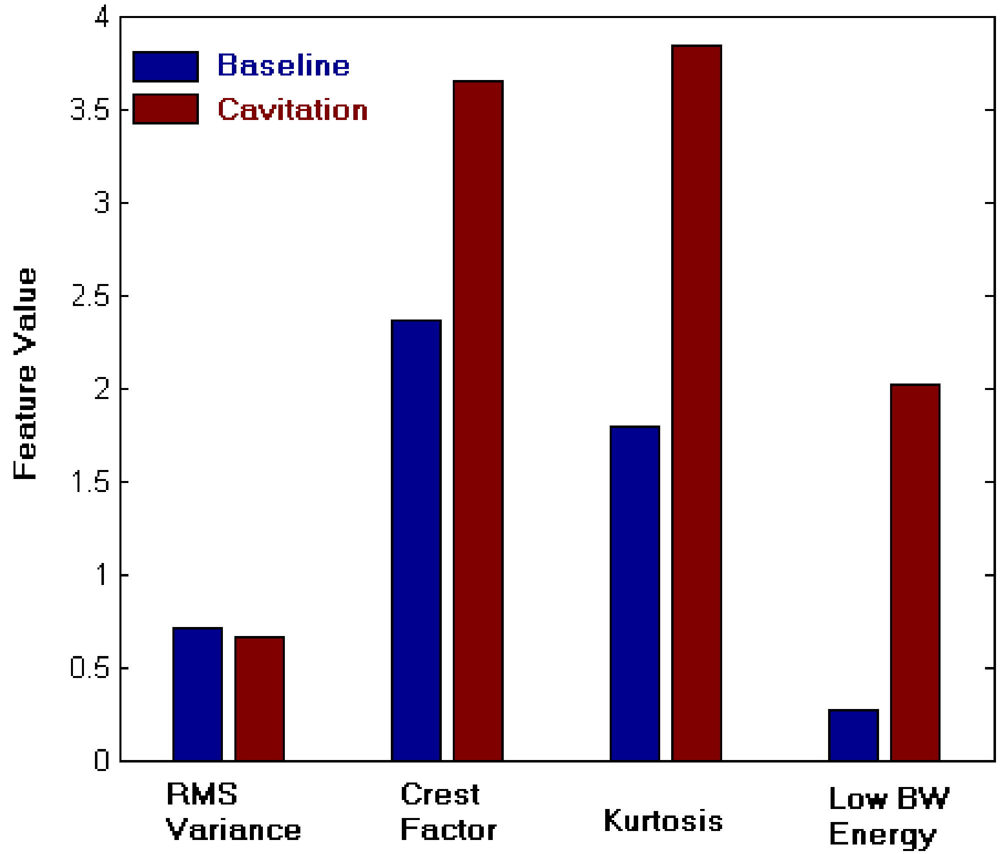


Fault Feature Space



Data Driven Results – Cavitation

- Successfully detected cavitation using data-driven techniques
  - Cavitation hard to model explicitly
  - Variations in delivered pressure expected with cavitation
  - Evaluated various statistical features for pressure signal
  - Cavitation successfully detected using Crest Factor, Kurtosis, and Low Bandwidth Energy features

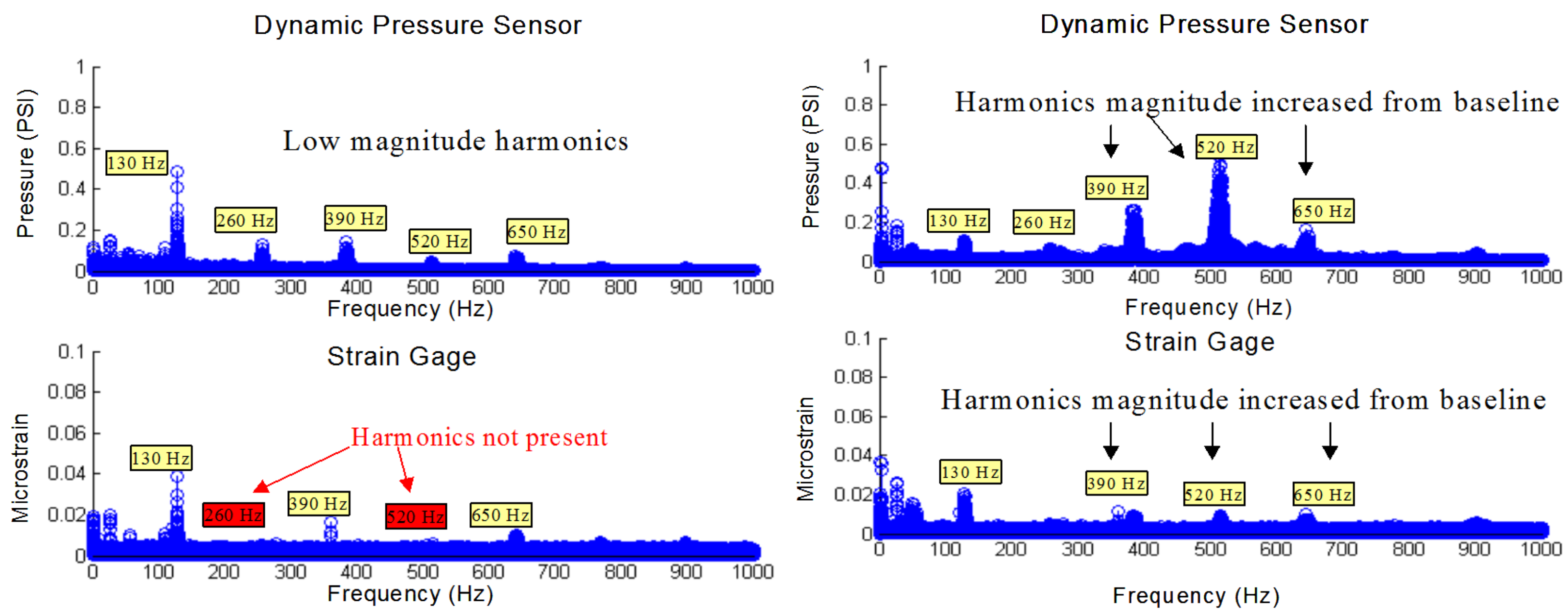


Distributed Sensor Results – Cavitation

- Successfully detected cavitation without breaking fluid line
  - Pressure data may not be available in actual aircraft system
  - Non-invasive high BW strain data also responded to cavitation
- Further tests will be performed
  - Additional features from strain data

Baseline

Cavitation



Frequency (Hz)

Frequency (Hz)

Fault and Effects Summary

Fault	Model-Based Algorithm			Data-Driven Algorithm	
	Critical Parameter	Symbol	Effect	Signals	Effect
Leakage	Flow per rev.	q	Decreases	Pressure Non-intrusive strain	Sharp peaks in spectrum
Gear Fault	Flow ratio	Q_s/Q	Increases	NA	NA
Valve Fault	Valve area	A_v	Decreases	NA	NA
Filter Clogging	Suction side pressure	P_s	Decreases	Non-intrusive strain	Analysis in progress
Cavitation	Not detectable	NA	NA	Pressure Non-intrusive strain	Harmonics in spectrum