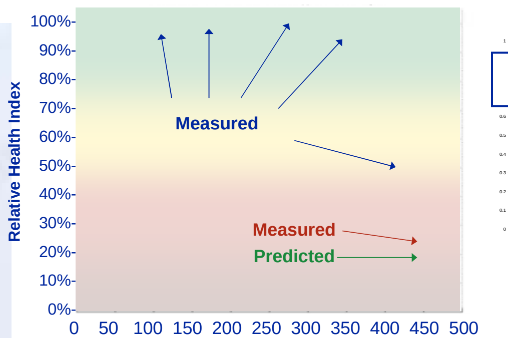
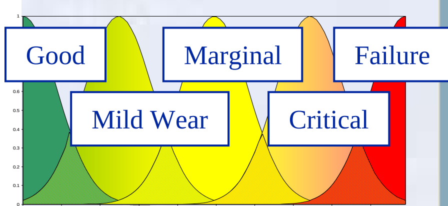
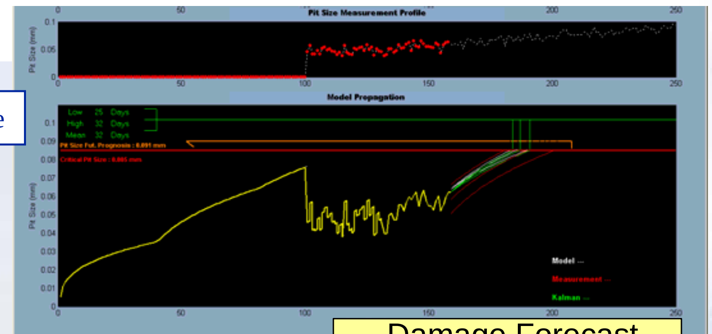
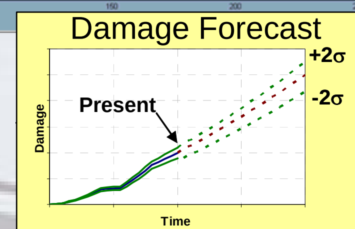
Impact Technologies PHM and Structural Health Management









Carl Byington, P.E.

Director, Impact Technologies, LLC

carl.byington@impact-tek.com

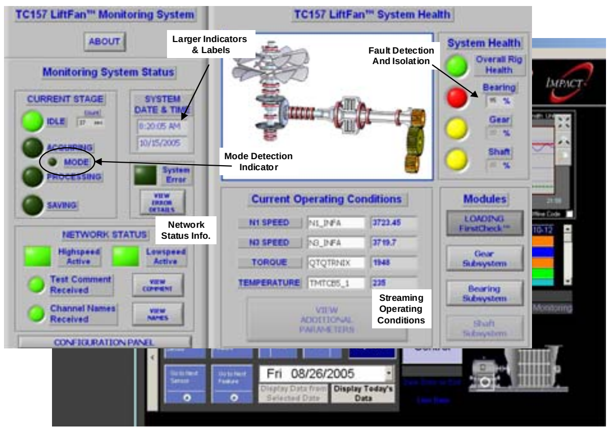
IMPACT

Who is Impact?

- **Founded in 1999, currently ~90 employees, experienced Mechanical, Electrical and Software Engineers and Scientists dedicated to** Predictive Equipment Health Management Technologies
- Customers include: **U.S. Navy, Air Force, Army, DARPA, DOE, EPRI, Boeing, Honeywell Engines, General Dynamics, Northrop Grumman, GE, Rolls Royce, P&W, UTC, NASA, Lockheed Martin, Dresser-Rand, etc.**
- Top DOD Small Business contractor in the U.S. for Automated Health Management technologies
- Typical Roles: Technology Research and Development, Software Development and Licensing, System Design and Integration, Engineering Support
- 3 offices:
  Rochester, NY;
  State College, PA
  & Atlanta, GA

Impact Portfolio

Automated Equipment Health Monitoring SW

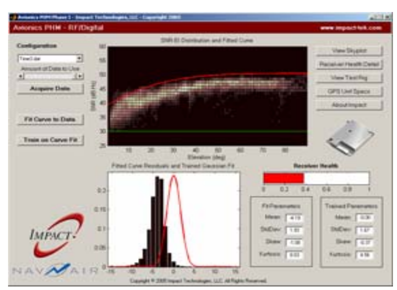


Integrated Vehicle Health Management

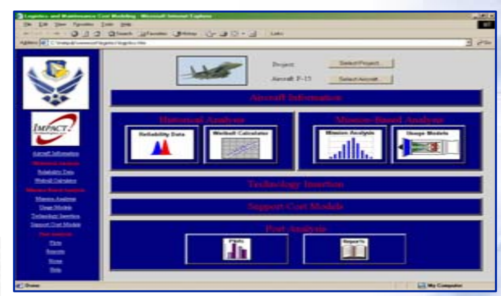
System Specific Diagnostics/Prognostics

Advanced Sensor & Embedded Monitoring

Electronics/Avionics PHM



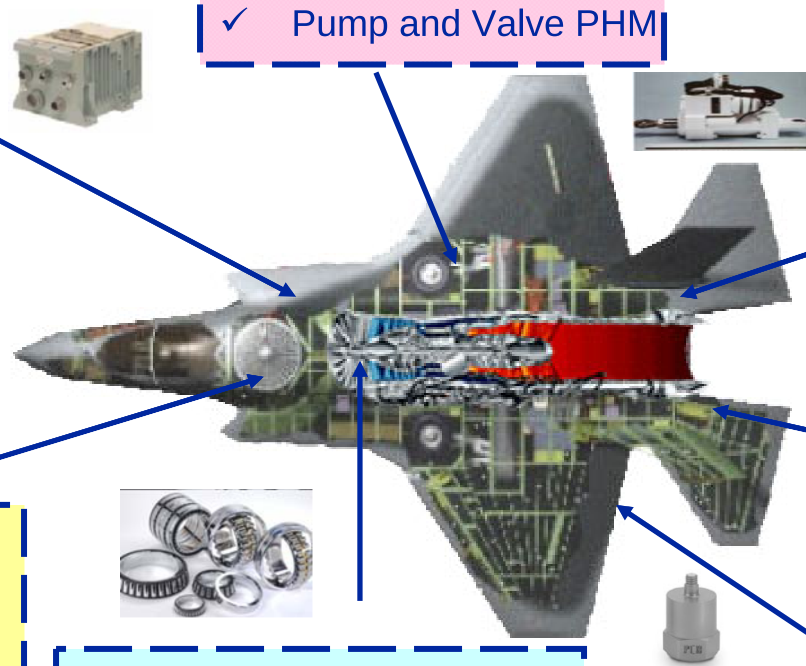
Decision Aids, Maintenance & Logistics Tools



Array of PHM Technologies

Fuel/Hydraulics
- ✓ Fuel System Models
- ✓ Pump and Valve PHM

Avionics
- ✓ Evidence-Based BIT Reasoner
- ✓ System-Level Bayesian Network
- ✓ Power Supply Monitoring
- ✓ Radar System Monitoring



Actuator & Controls
- ✓ Real-time Control/ Response Modeling
- ✓ EMA/EHS Actuators
- ✓ Model and Feature-Based

Sensors/Data
- ✓ Steady State/ Transient Mode Detect
- ✓ Sensor Validation Module
- ✓ Virtual Sensors

Propulsion
- ✓ Performance Diagnostics & Prognostics
- ✓ Blade/Disk Usage & Useful Life Remaining
- ✓ Engine Fuel System Monitoring
- ✓ Lube Oil Monitoring

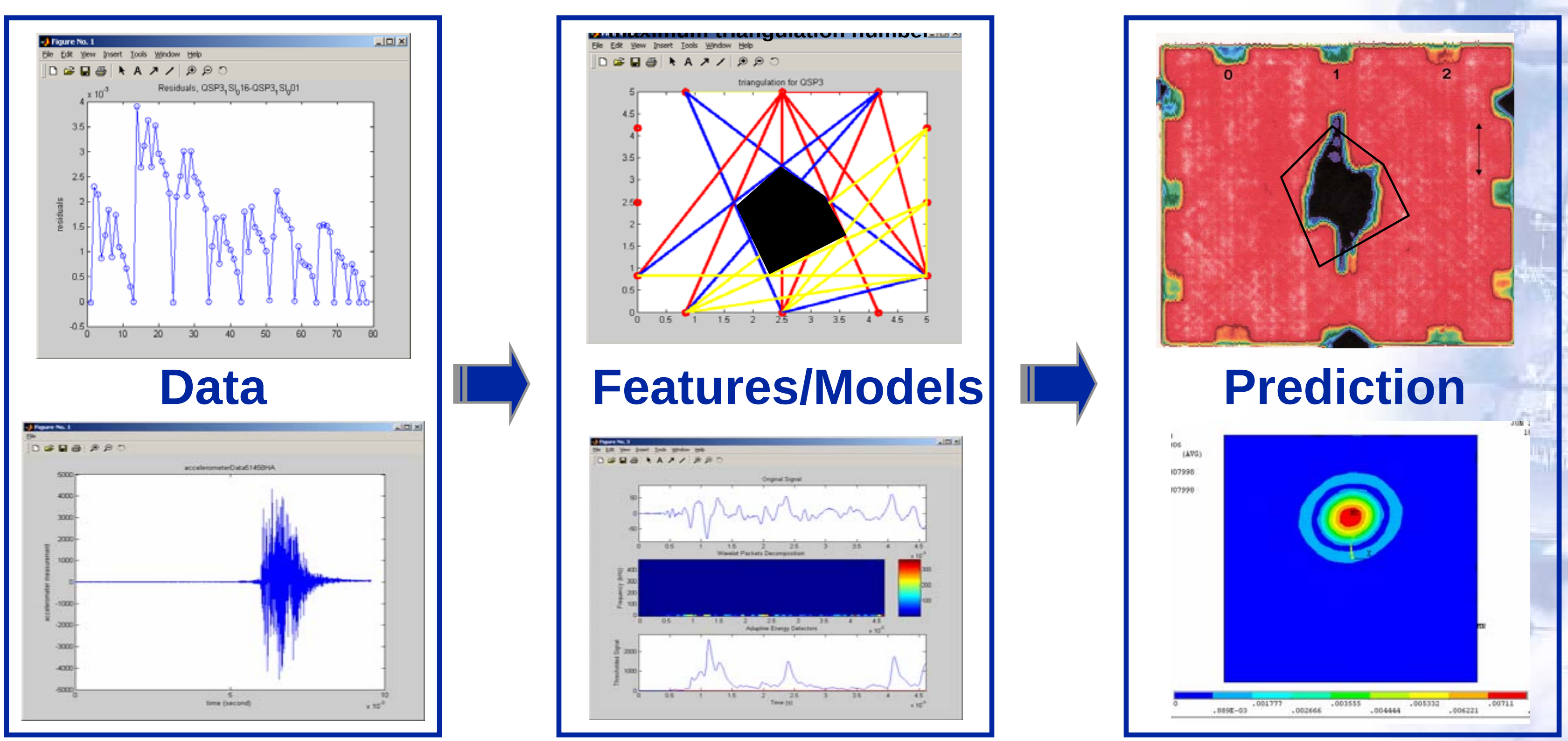
Drive Train
- ✓ Vibration Monitoring
- ✓ Bearing/Gear Prognostics
- ✓ Shaft Monitoring
- ✓ Clutch Diagnostics
- ✓ Lube System Monitoring

Structures
- ✓ Damage Localization
- ✓ Severity Determination
- ✓ Continuous Monitoring and Prediction of Structural Health

Some SHM Developments

- AFRL Composite Damage Localization
- JSF Gearbox Corrosion Modeling
- NAVAIR Gear Prognosis
- DARPA Structural Integrity Prognosis Systems

AFRL Damage Detection, Isolation and Prediction



Michael J. Roemer, Jianhua Ge, Alex Liberson

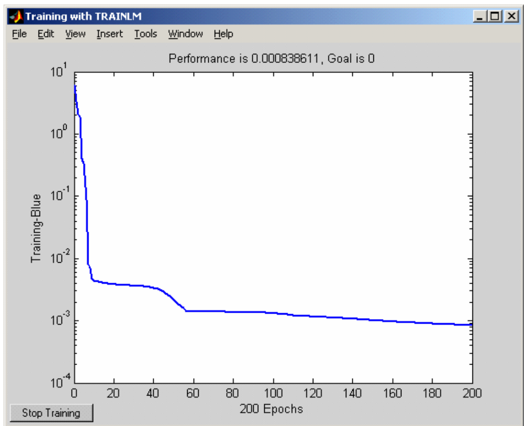
Impact Technologies, LLC

Dr. G. P. Tandon, Dr. R. Y. Kim

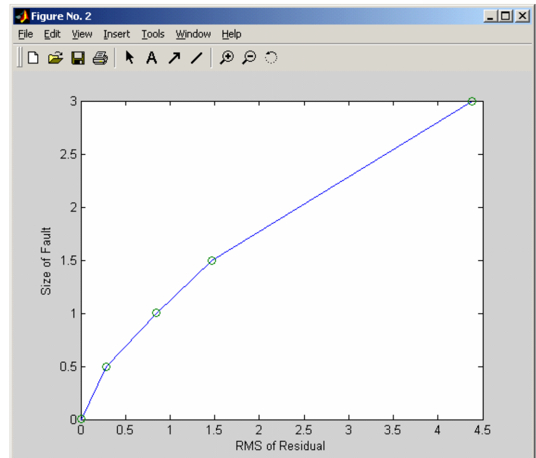
University of Dayton Research Institute

IMPACT

Neural Network Training Results (Total 24 (4*6) sensors)



Training Processing of the Neural Network for Uni-Directional Composite



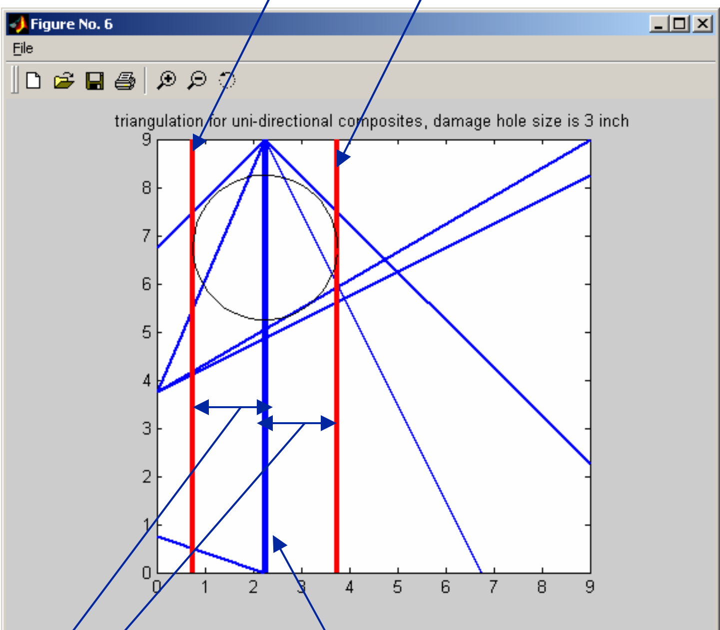
Relationship Between Damage Size and RMS of Residuals for Uni-Directional Composite

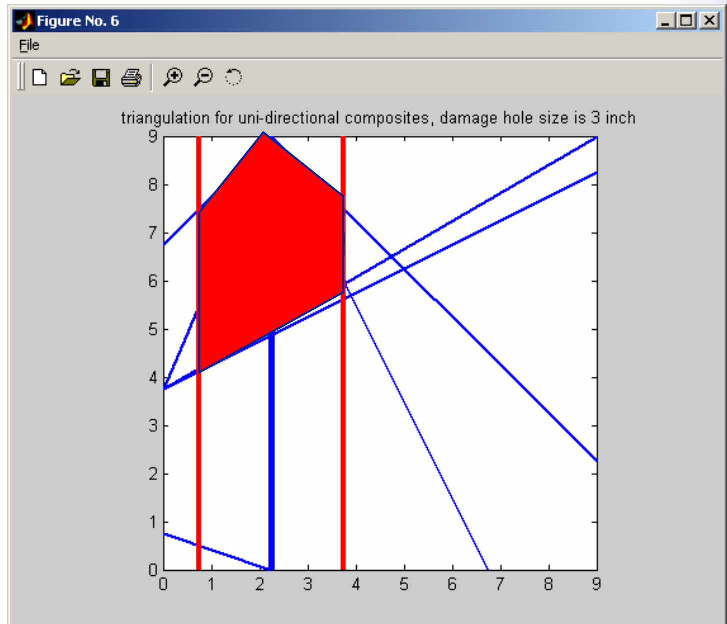
RMS of Residuals (Input of The Neural Network)	0	0.2839	0.8411	1.4679	2.2659	4.3759
Size of Damage (Output of the Neural Network)	0.0142	0.4634	1.0454	1.4758	1.9142	3.0019
Truth Size of Damage	0	0.5	1	1.5	2	3

Results for Determination of Damage Size via Neural Network for Uni-Directional Composite Damage

Determination of the Damage Geometry

Two red lines that are parallel with the line of maximum residual
And the distance is decided by the output of the neural network (size of damage).
The damage should be in the area between two red lines.





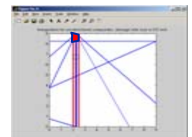
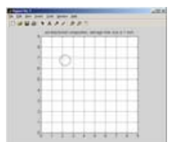
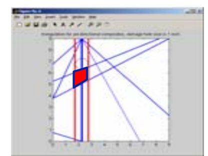
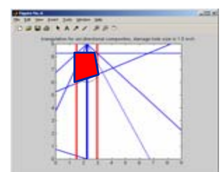
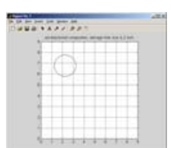
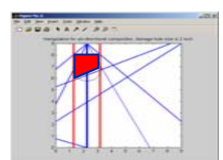
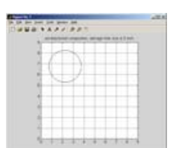
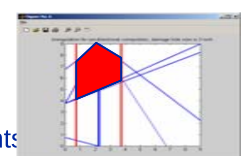
Half of the output of the NN

The line with maximum Residual

The circle is the truth damage.
Other blue lines denote the largest residuals in direction of 0, 30, 45, 60, 90, 120, 135, and 150 degrees.
The right line shows the estimated damage geometry by the operator using the information from the left figure.

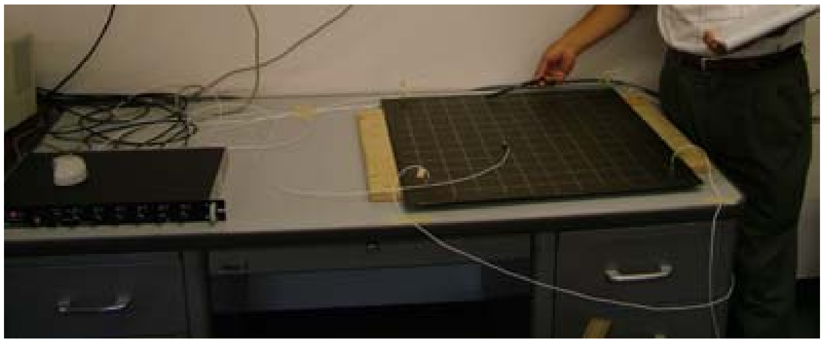
Uni-directional Composite Results

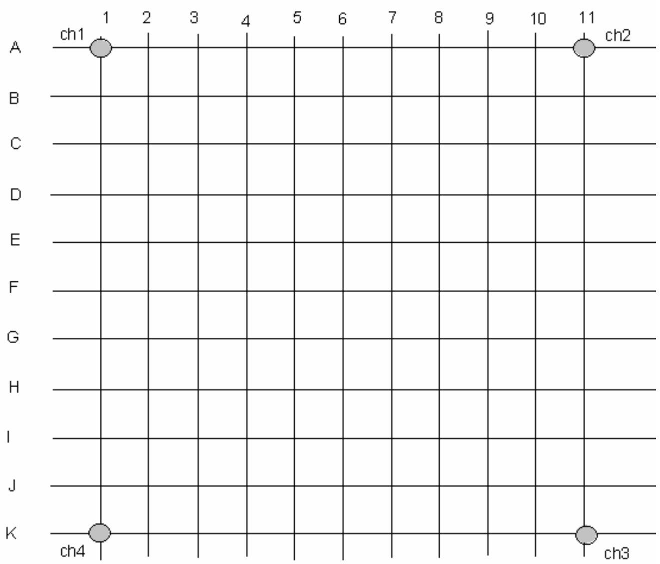
Truth Data | **Diagnosis Results**

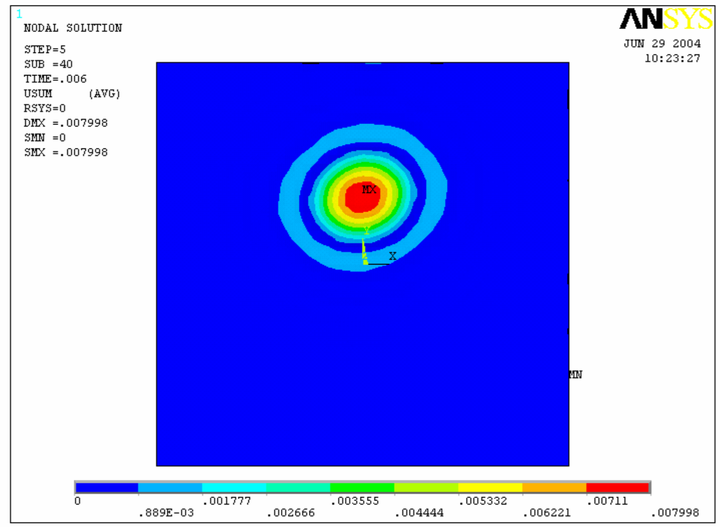
Size of truth damage	Location Of Damage	Geometry Of Damage	Size of Damage From Neural Network	Location and Geometry (red area) Using Triangulation + Knowledge about size Of damage
0.5 inch		circle	0.4634 inch	
1 inch		circle	1.0454 inch	
1.5 inch		circle	1.4758 inch	
2 inch		*circle*	*1.9142 inch*	
3 inch		circle	3.0019 inch	

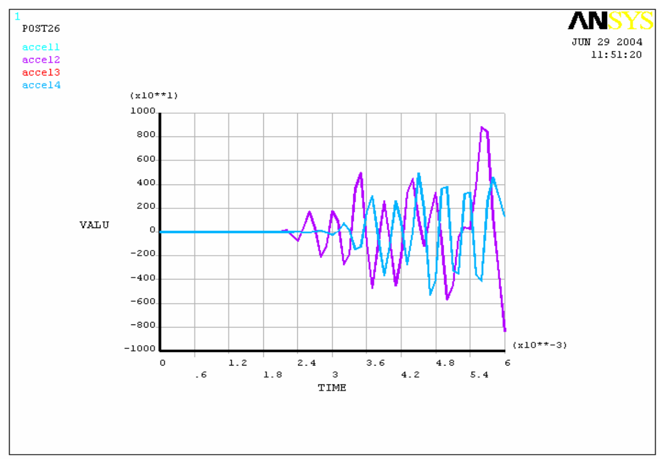
Accelerometer-Based Feature Extraction and Analysis

Flexural Wave Propagation in a Laminate Composite Plate





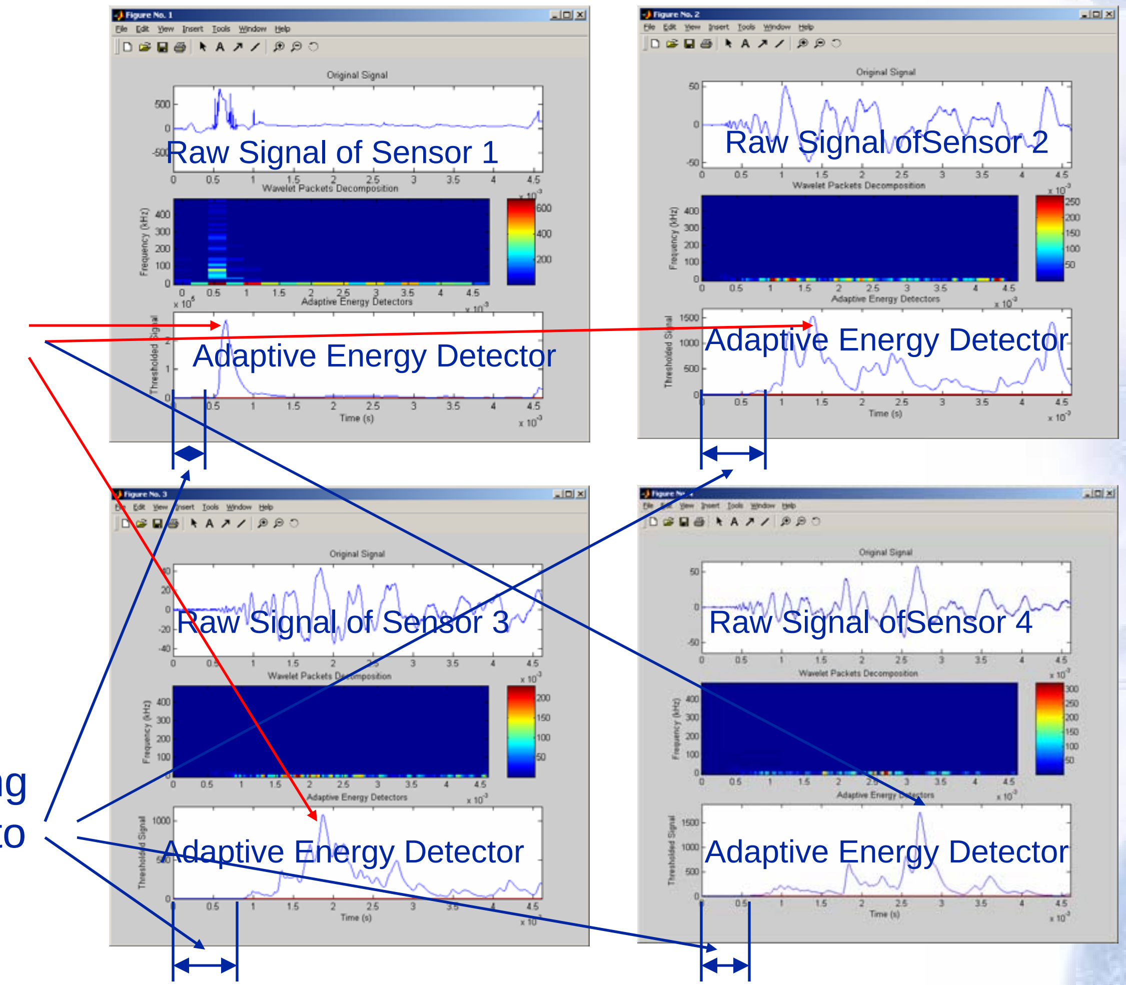




Feature Extraction Using Wavelet Packets and Higher-Order-Statistics

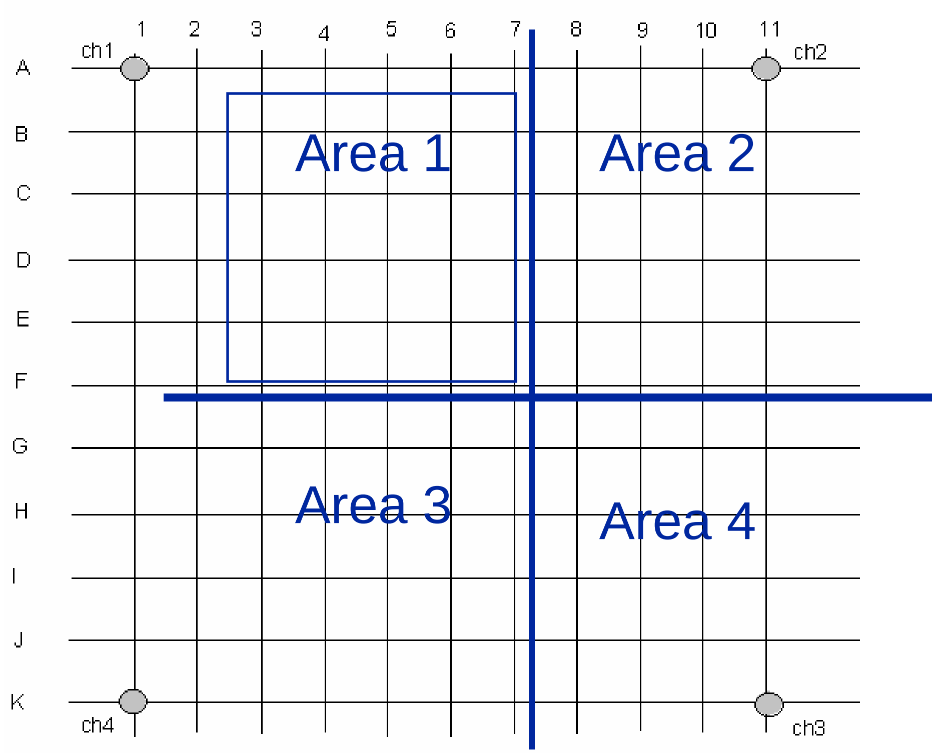
Energy Feature:
The maximum energy amplitude

Time Feature:
Time at which wave arriving time from impact location to each sensor

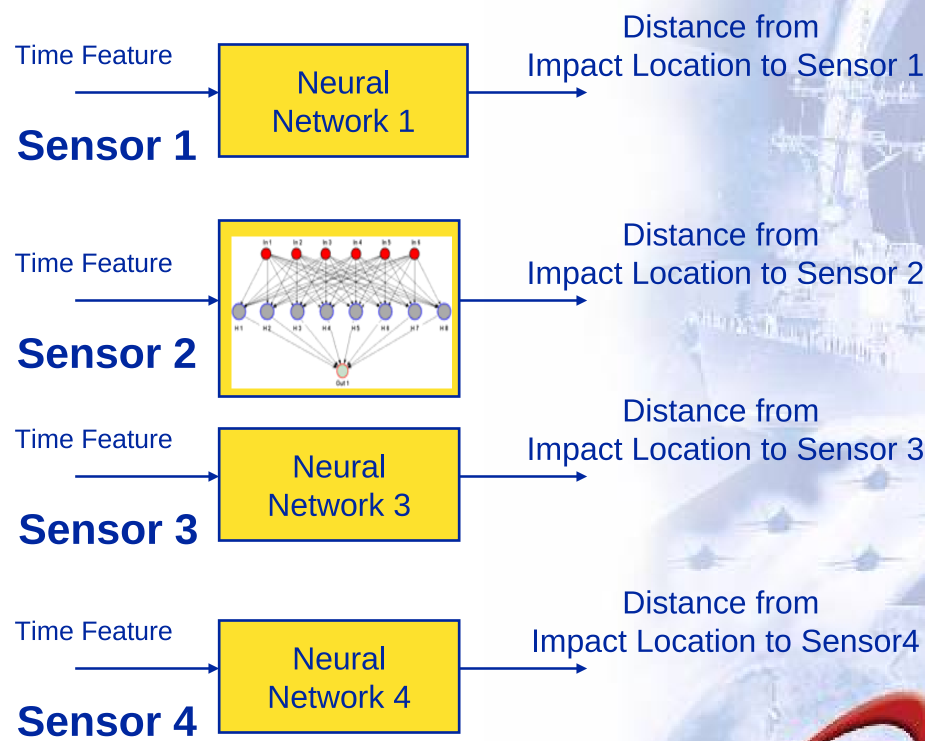


Energy & Arrival Time Feature Analysis

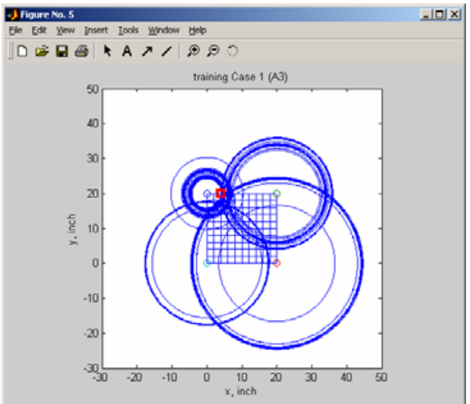
Energy Analysis

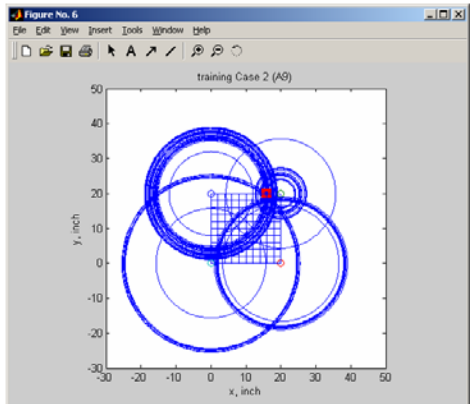


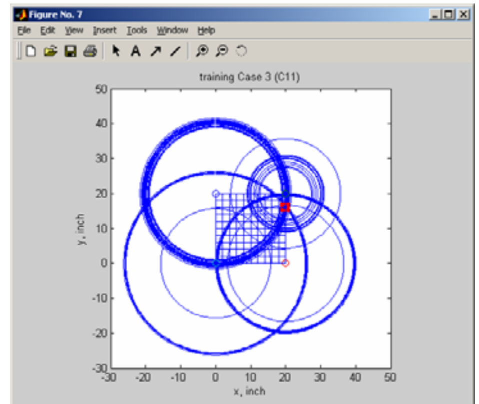
Arrival Time Analysis

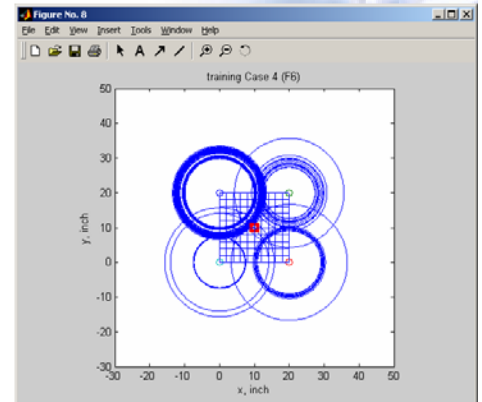


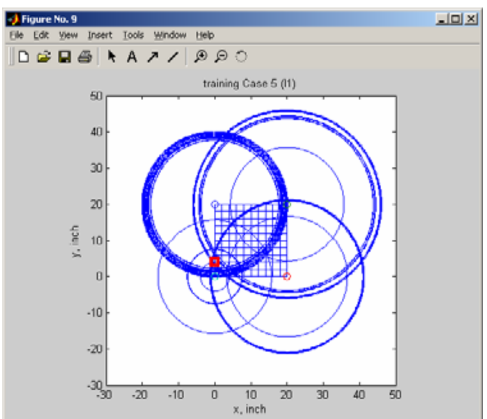
NN Outputs and Triangulation for Seven Training Cases

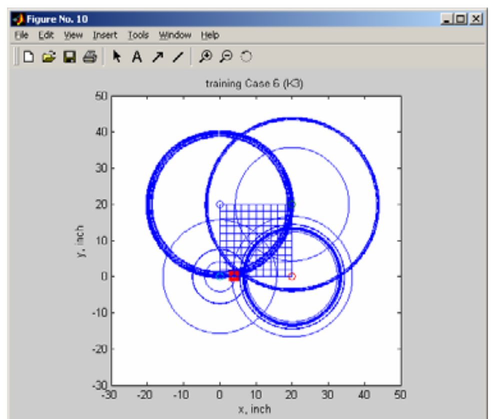


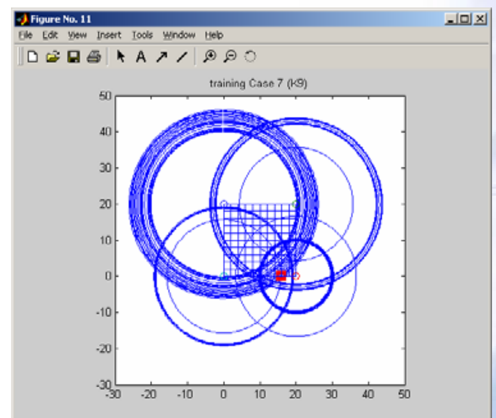




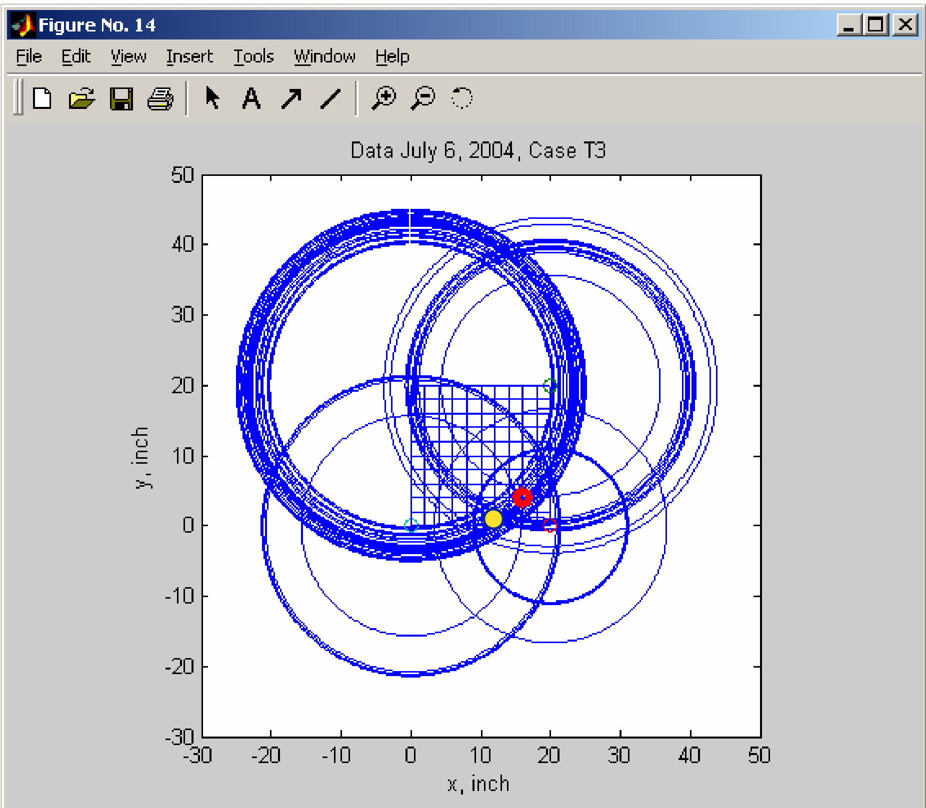


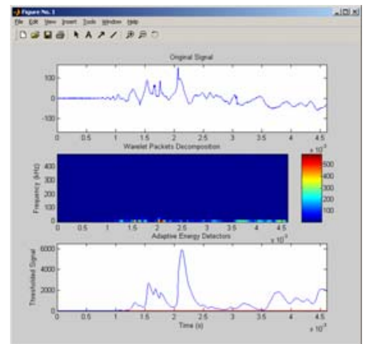




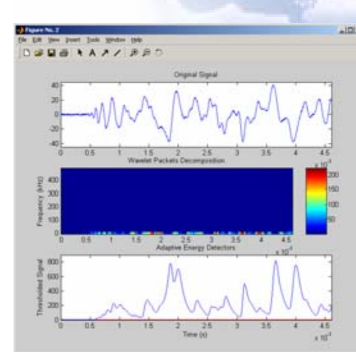


Test Case 1

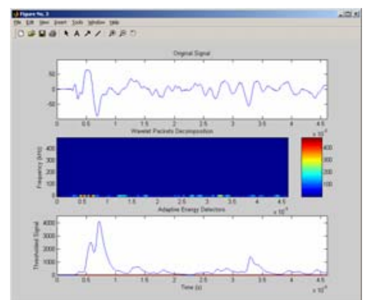




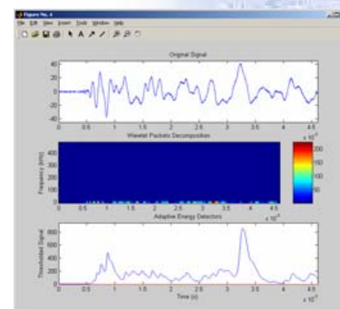
Sensor 1



Sensor 2



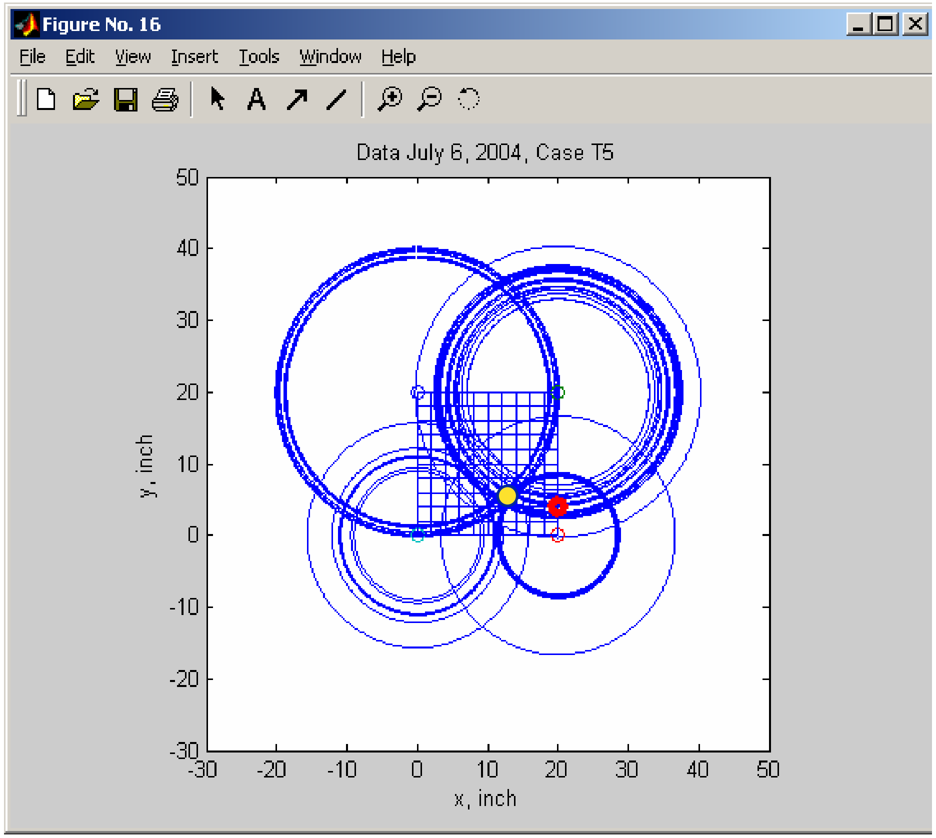
Sensor 3

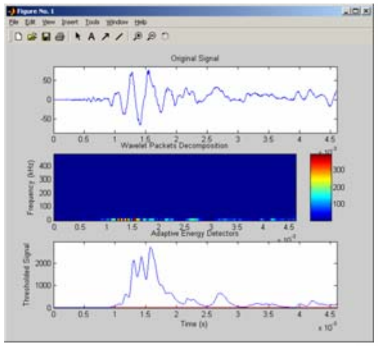


Sensor 4

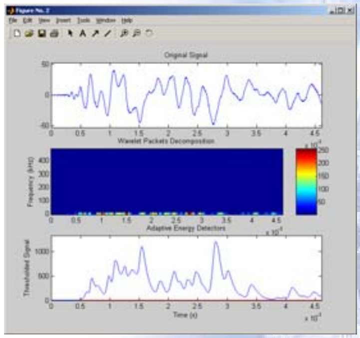
- Estimated impact location
- Truth impact location

Test Case 2

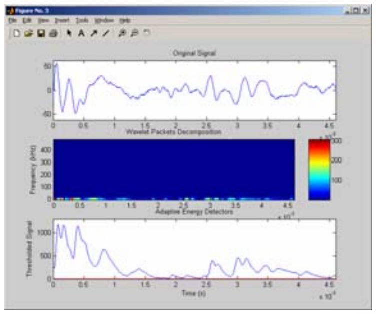




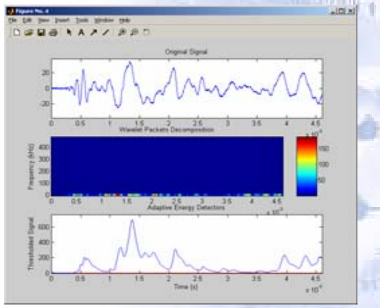
Sensor 1



Sensor 2



Sensor 3

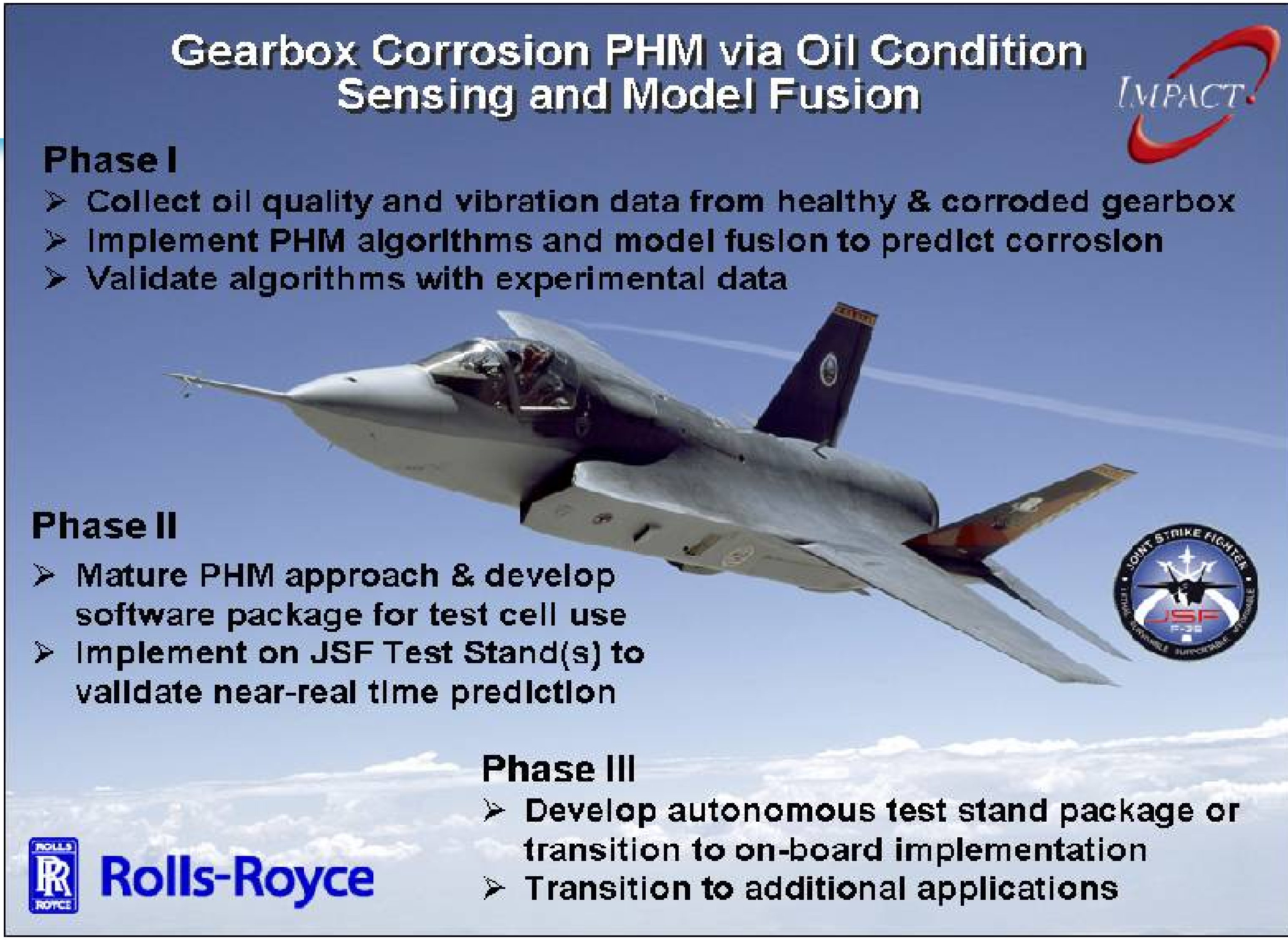


Sensor4

- Estimated impact location
- Truth impact location

Composite Effort Summary

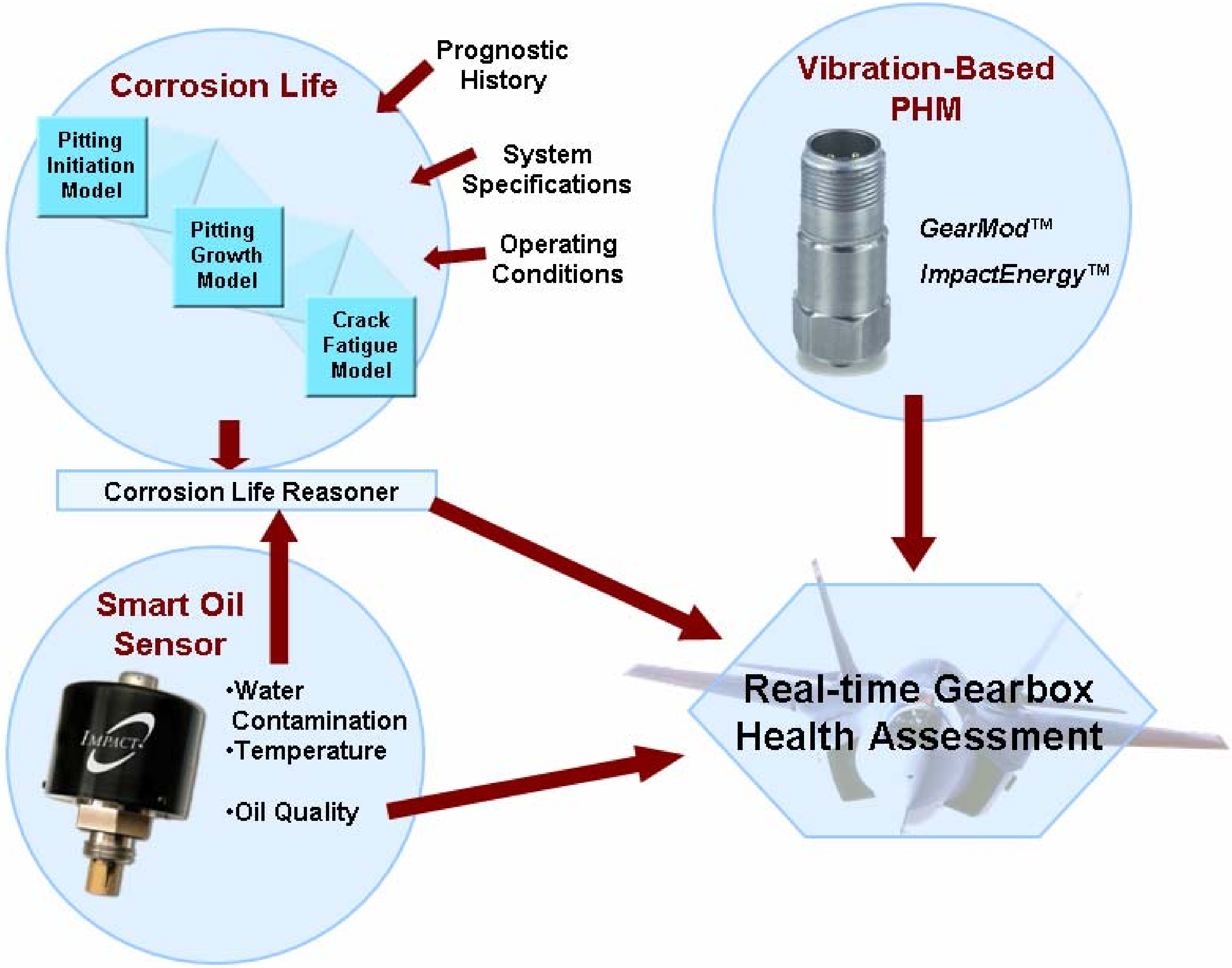
- Integrated Approach for Determining Damage Location and Severity for Composite Structures
- Structural Features – Resistivity, Acceleration
- Models - Finite Element Approach for Determining the Impact Location
- Evaluation of Independent Approaches to Structural Health Monitoring
- Continuing Work - GEAE Engine Half-Case



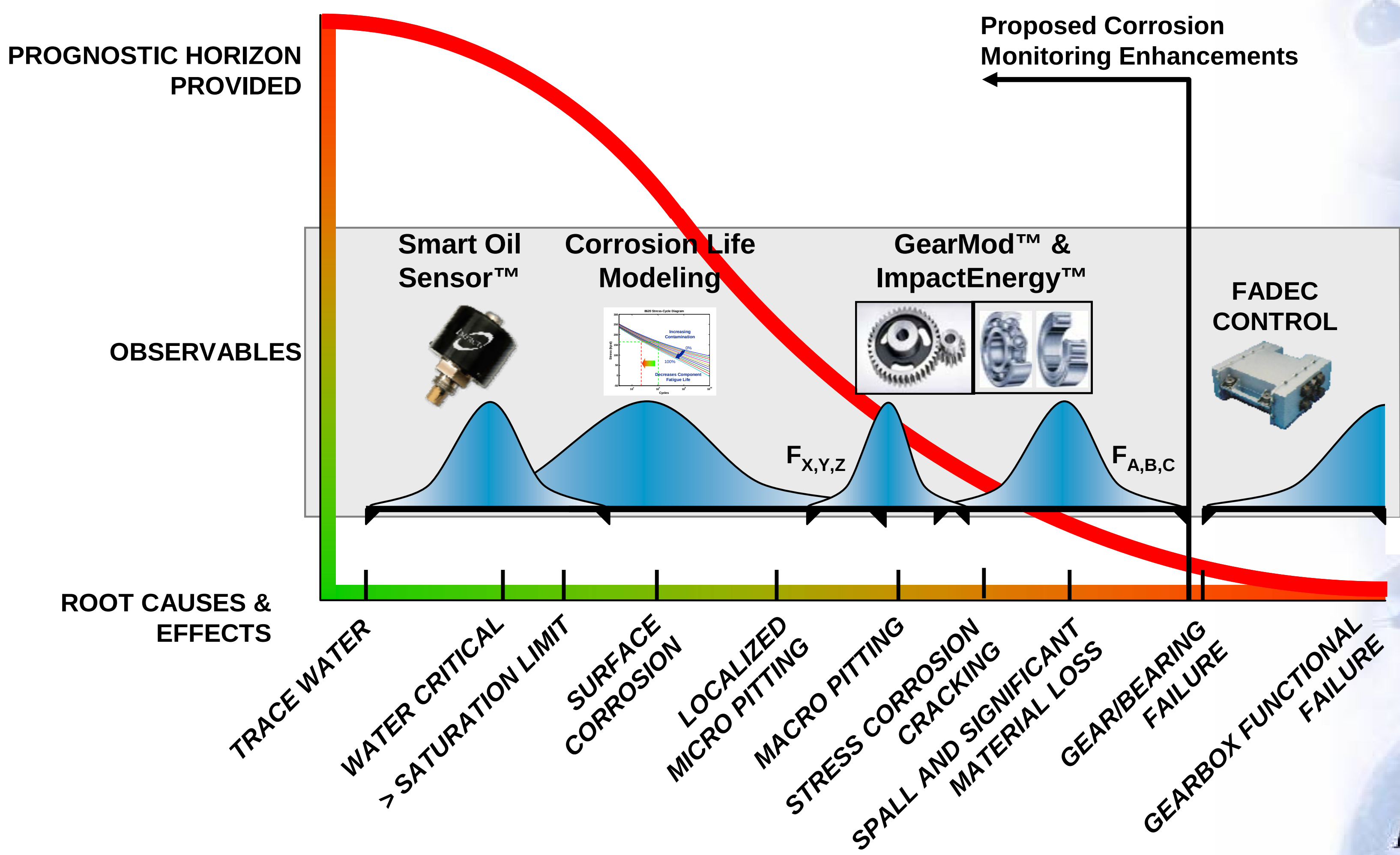
Carl Byington, Ryan Brewer, Sanket Amin, Vijit Nair, Adam Mott

Impact Technologies, LLC

Corrosion PHM Framework and Elements



Corrosion-based Fault-to-Failure Prognostic Horizon



Corrosion Reduces Fatigue Life

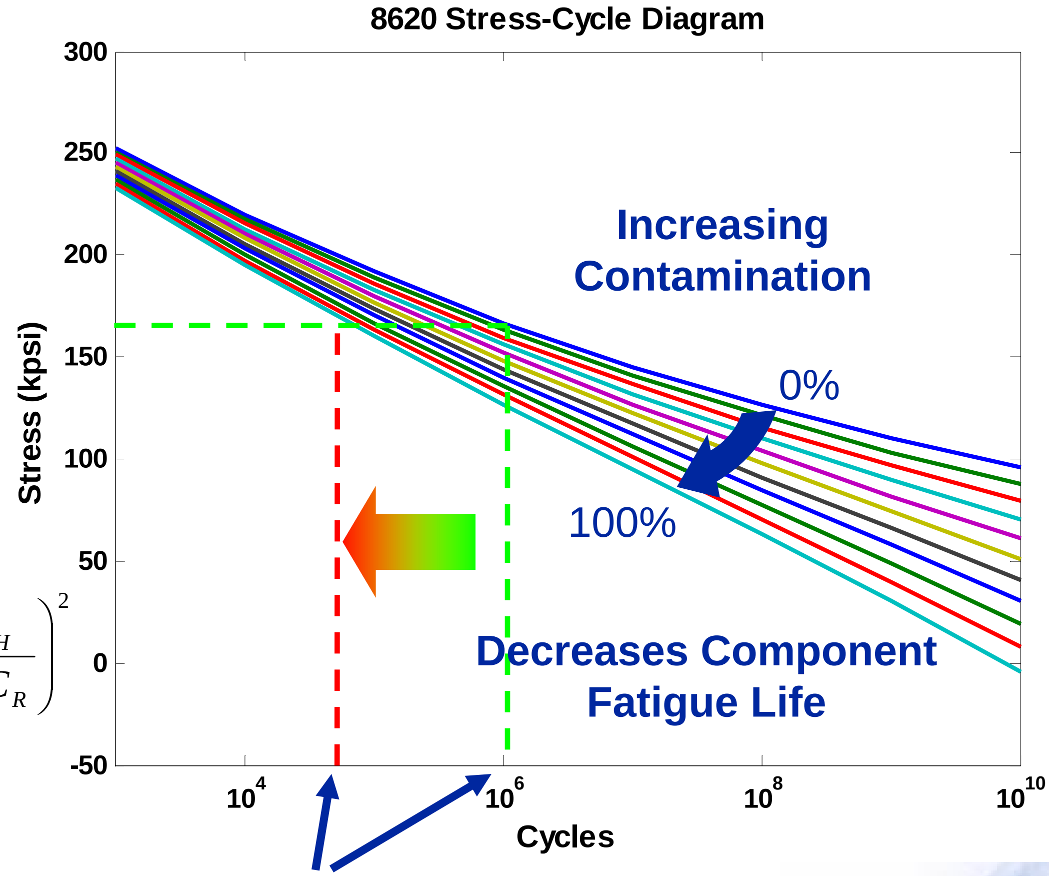
Phase I Focus
Gear Pitting Initiation

AGMA Surface Durability Formulas

$$s_{wc} = \frac{s_{ac} C_L C_H}{S_H K_T C_R}$$

$$s_c = C_p \sqrt{\frac{2T_P}{F d^2 I} K_o K_v K_M C_s C_{xc}}$$

$$P_{ac} = \frac{n_P F}{126{,}000} \frac{I}{K_o K_v K_m C_s C_{xc}} \left(\frac{s_{ac} d C_L C_H}{S_H C_p K_T C_R} \right)^2$$



Formulas Updated To Incorporate SOS Measurements

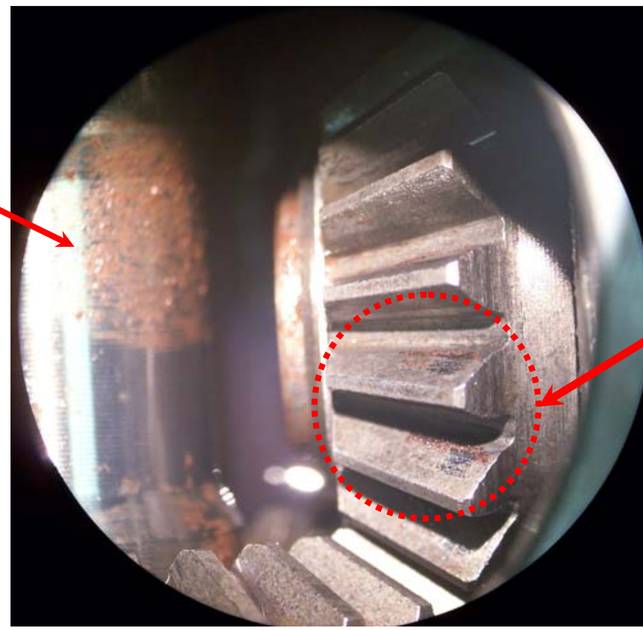
Potential Fatigue Life Reduction Can Be Orders of Magnitude

IMPACT

Phase I Corrosion Failure Progression

- Corrosion was induced by incrementally adding water contamination to the oil
- The test rig was operated under accelerated loading conditions to produce initiation and some progression

Shaft Corrosion



Tooth Flank Corrosion

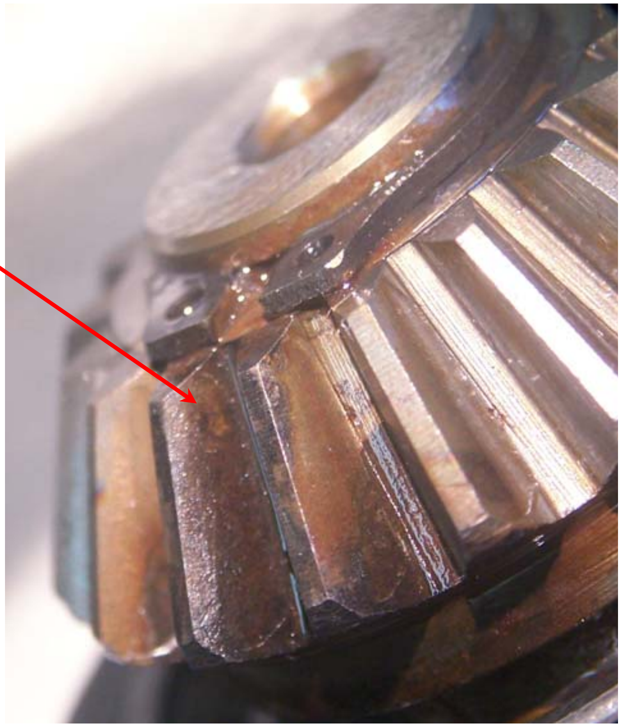
- Corrosion life demonstrated was consistent with model predictions but accelerated testing extrapolation needs to be addressed

IMPACT

Seeded Corrosion Fault

- A more severe level of damage was created by subjecting gear teeth on a separate gearbox to $FeCl_3$ acid

Corroded Tooth



- Damage clearly detectable with vibration and verified with visible determination

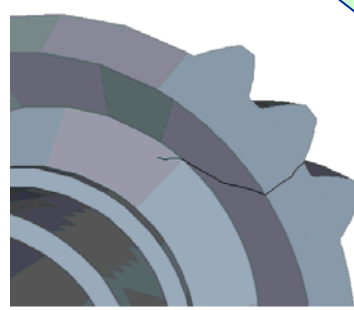
Corrosion Effort Summary

- Identified gearbox contamination sources, root causes of critical corrosion failure modes, and prognostics framework
- Demonstrated SOS ability to detect water in Aeroshell gearbox oil
- Implemented vibro-acoustic algorithms for gearbox failure testing
- Evaluate and selected corrosion model for Phase I feasibility demonstration
- Implemented PHM addresses ***on-demand prognostics*** for gearbox mechanical components

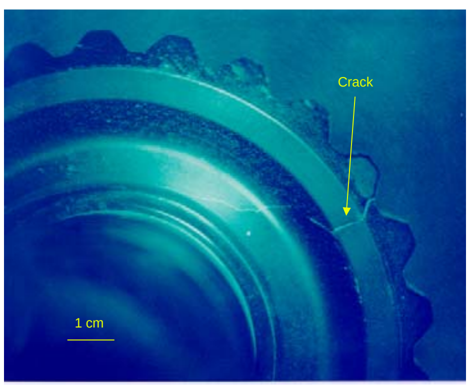
Gear Prognostics Module Example

Solid Model Development

FEA and Fracture Mechanics

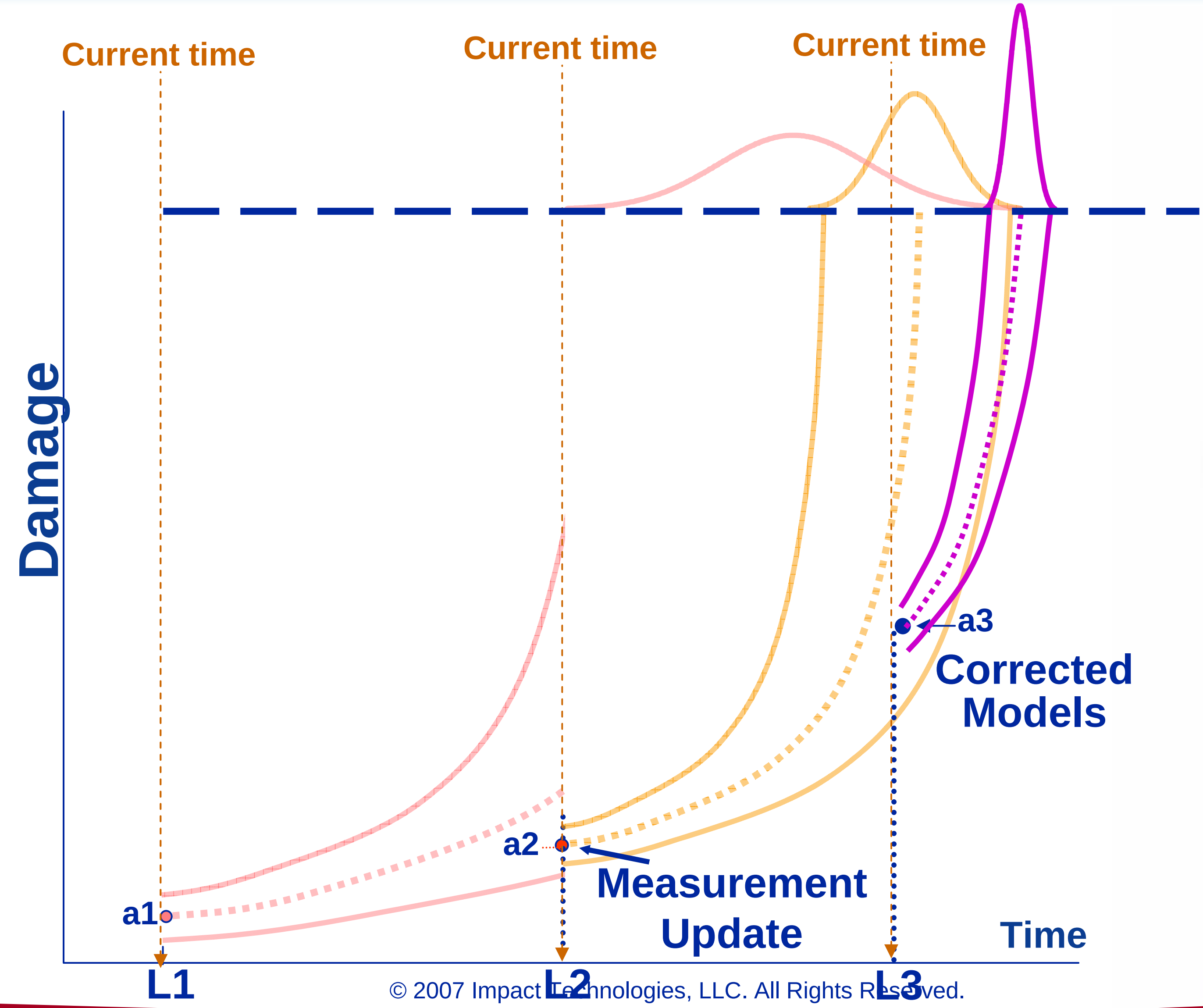


Correlation

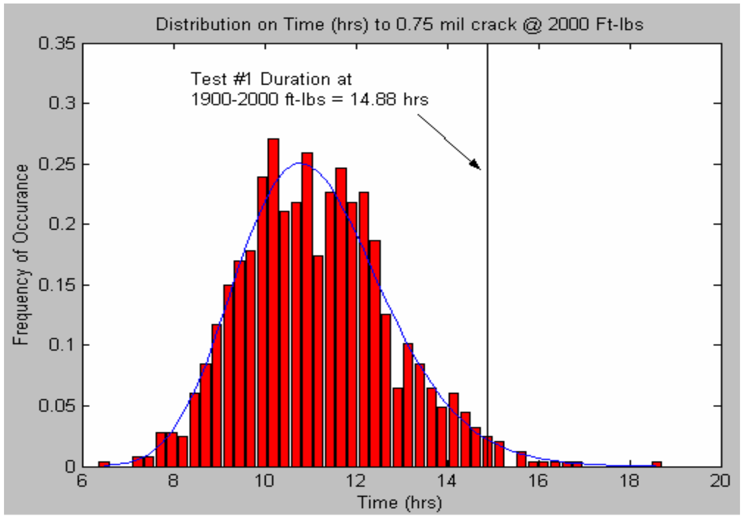


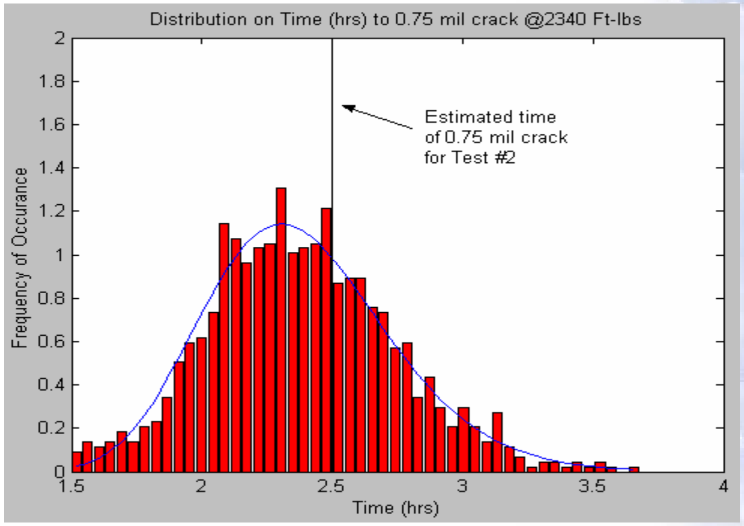
Avinash Sarlashkar, Joel Berg, Eric Schenk - Impact

Adaptation Iteratively Improves Prognosis



Test 1 & 2 - Failure Progression Results





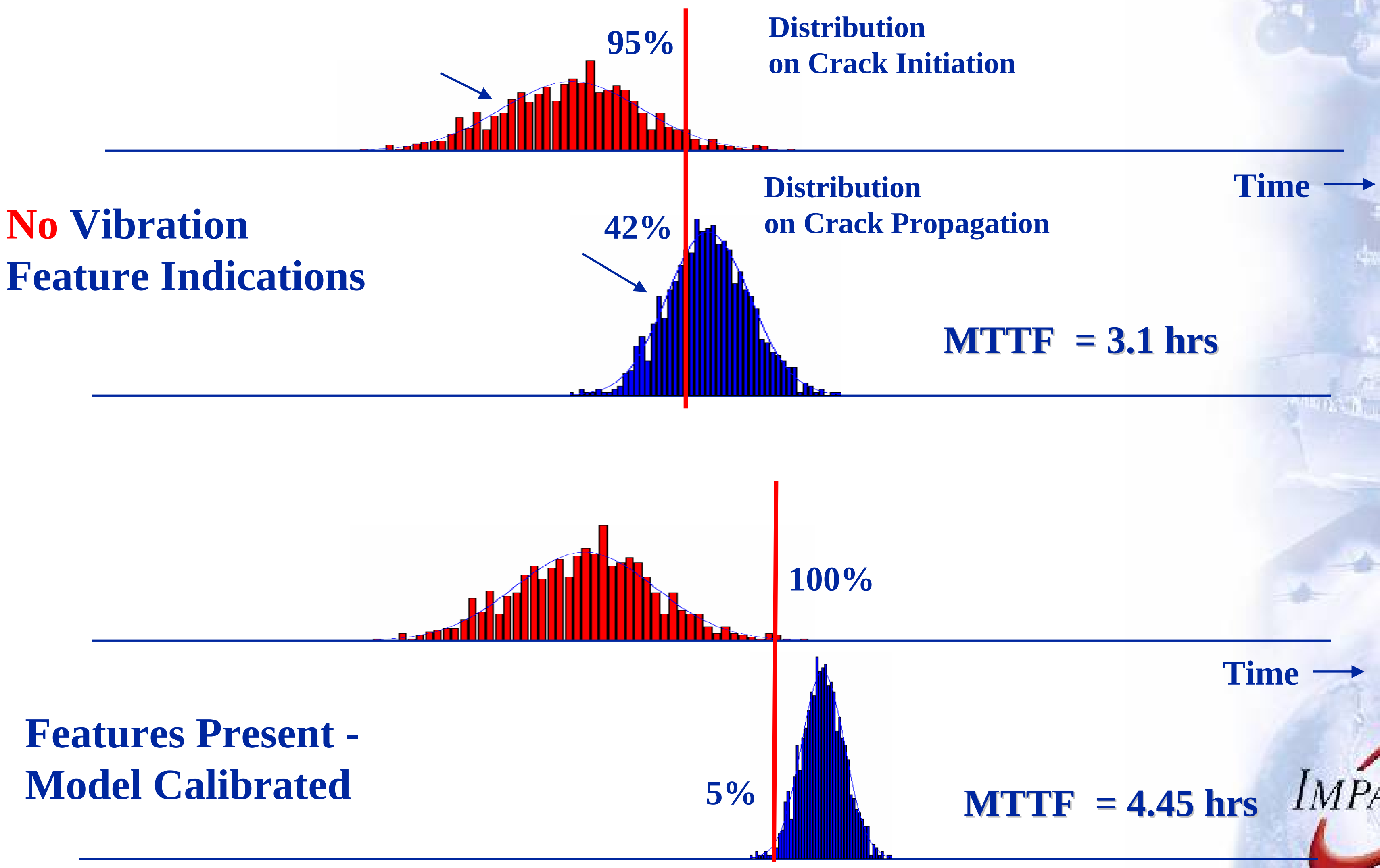
Crack Initiation and and Propagation to 0.75 mils

Test #	Torque	Predicted Initiation Time (hrs)	Standard Deviation	Predicted Initiation Time (Cycles)	Estimated Time to Initiation (hrs)	Estimated Time to Initiation (Cycles)	Difference (# Stdevs)	Percentile
1	2000	11.09	1.64	2738786.40	15.00	3704400	2.38	98.00
2	2340	2.38	0.36	587764.80	2.50	617400	0.33	63.00

Crack propagation to Critical Crack Length (0.825" or approx. 2 cm)

Test #	Torque	Predicted Propagation Time (hrs)	Standard Deviation	Predicted Initiation Time (Cycles)	Observed Time to Failure (hrs)	Observed Time to Failure (hrs)	Difference (# Stdevs)	Percentile
1	2340	4.85	1.13	1197190.00	6.00	1481760	1.02	82.00
2	2340	4.85	1.13	1197190.00	3.00	740880	-1.64	4.20

Benefits of Predictive Model Updating



DARPA Structural Prognosis Approach

- Characterize component material
  - microstructure, residual stresses, manufacturing defects, etc.

- Use physics of failure models with anticipated usage to predict component damage and damage accumulation

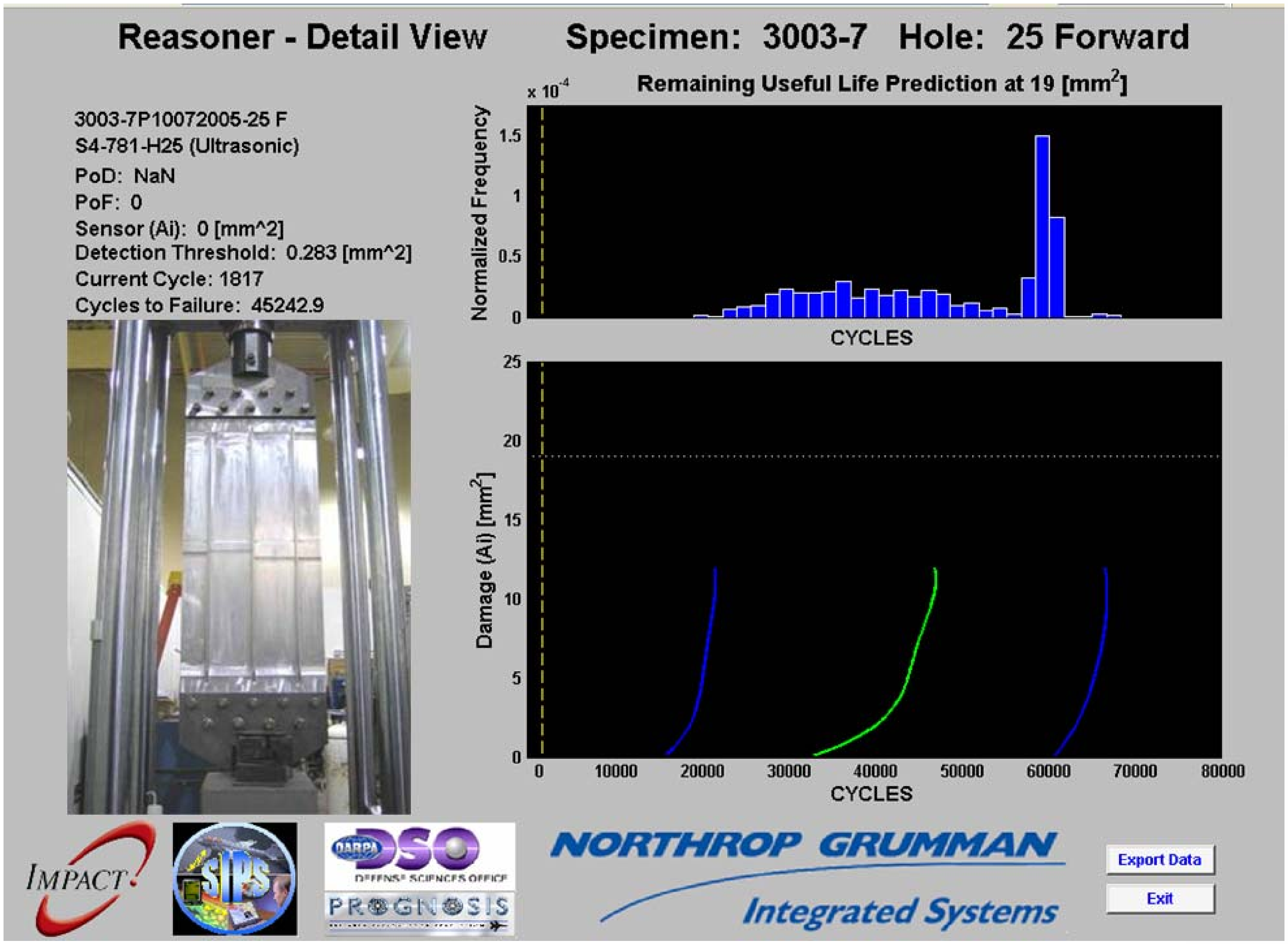
- Employ state awareness tools (system operating sensors, specialized, and virtual sensors) in real or near real time to monitor operating environment and detect extent of damage
  - temperature, stress, vibratory modes, etc.

- Integrate model predictions and sensor data through reasoners to make a *probabilistic assessment* of *future capability* given intended mission Parameters

David Muench, Liang Tang, Brian Walsh, Avinash Sarlashkar, Joel Berg, Mike Koelemay, Greg Kacprzynski - Impact Technologies

Steve Engel, et al. – Northrop Grumman

Applied to Aircraft Panel



Summary

- Impact is involved in a range of PHM and SHM programs dealing with understanding of failure modes, symptom/effects, sensing capability, failure physics modeling, and predictive tools
- PHM/SHM needs span across services and DARPA has recognized need for structural prognosis capability
- Good collaborative interests with Penn State Center
  - Projects and Research Faculty
  - Engineering Co-op and Graduate Students

- Thank you!