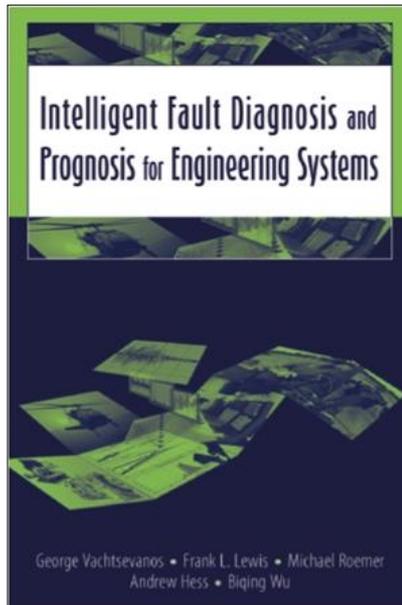


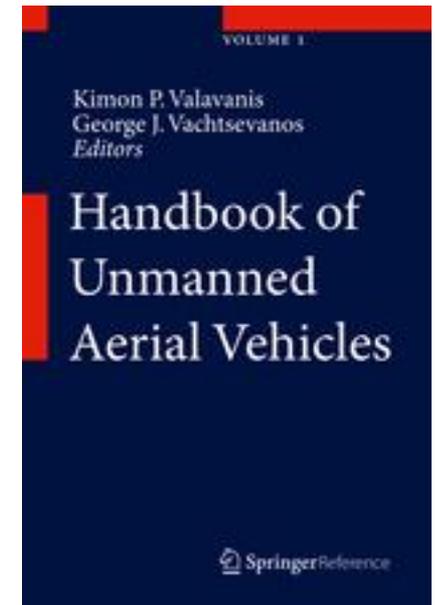
# A NOVEL APPROACH TO INTEGRATED VEHICLE HEALTH MANAGEMENT



**George J. Vachtsevanos**  
*Georgia Institute of Technology*

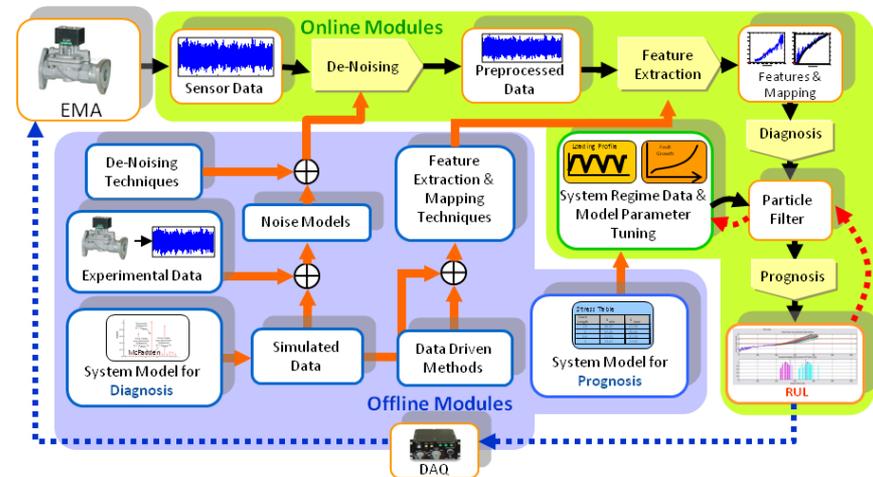
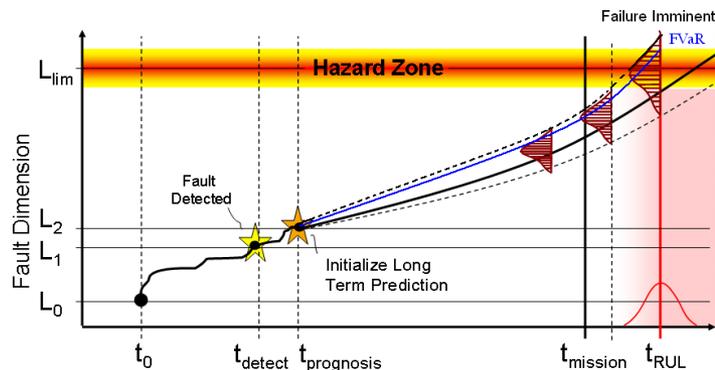
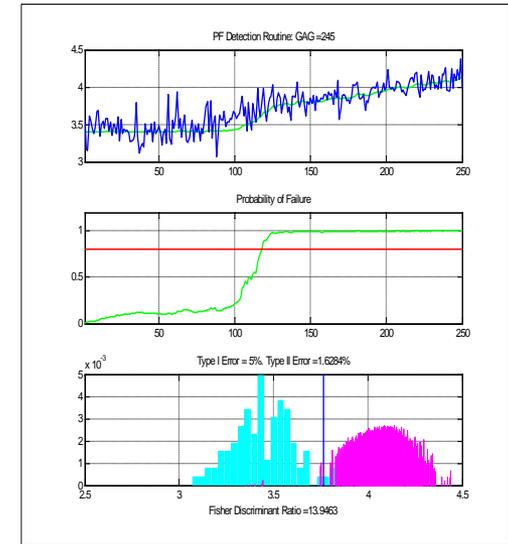
and

**Kimon P. Valavanis**  
*University of Denver*



# The Technology Base

- *Prognostics & Health Management Technologies*
- *Integrated Vehicle Health Management*
- *Autonomy and Autonomous Systems*
- *Resilient Design & Operation of Aerospace Systems*
- *Safety Assessment and Risk Management*
- *Swarms of Autonomous Systems*
- *TRL 4-6*



# Current Infrastructure Needs

**Ability to Predict Future Health Status**

**Max Life Usage**

**Ability to Anticipate Problems & Req'd Maint Actions**

**MAX SGR**

**Performance Based Maint**

**Better FD/FI Efficiency**

**Quick Turn Around Time**

**Small Logistics Footprint**

**No RTOK**



**Accurate Parts & Life Usage Tracking**

**Low # of Spares**

**No False Alarms**



**No Surprises**



**Maintenance Mgt**

**Opportunistic Maintenance**

**Mission Planning**

**Short & Responsive Supply Pipeline**

**No/Limited Secondary Damage**

**No/Min Inspections**

**Too Large & Costly**

**Limit Impact of Quality Control Problems**

**Immediate Access to all Available Information**

**System Performance Feedback**

- Health-based vs Usage-based Prognosis
- Prognostics vs Trending
- Uncertainty Representation, Propagation and Measurement
- Performance Metrics – Accuracy, Precision and Convergence

## **Uncertainty – The Achilles’ Heel of PHM**

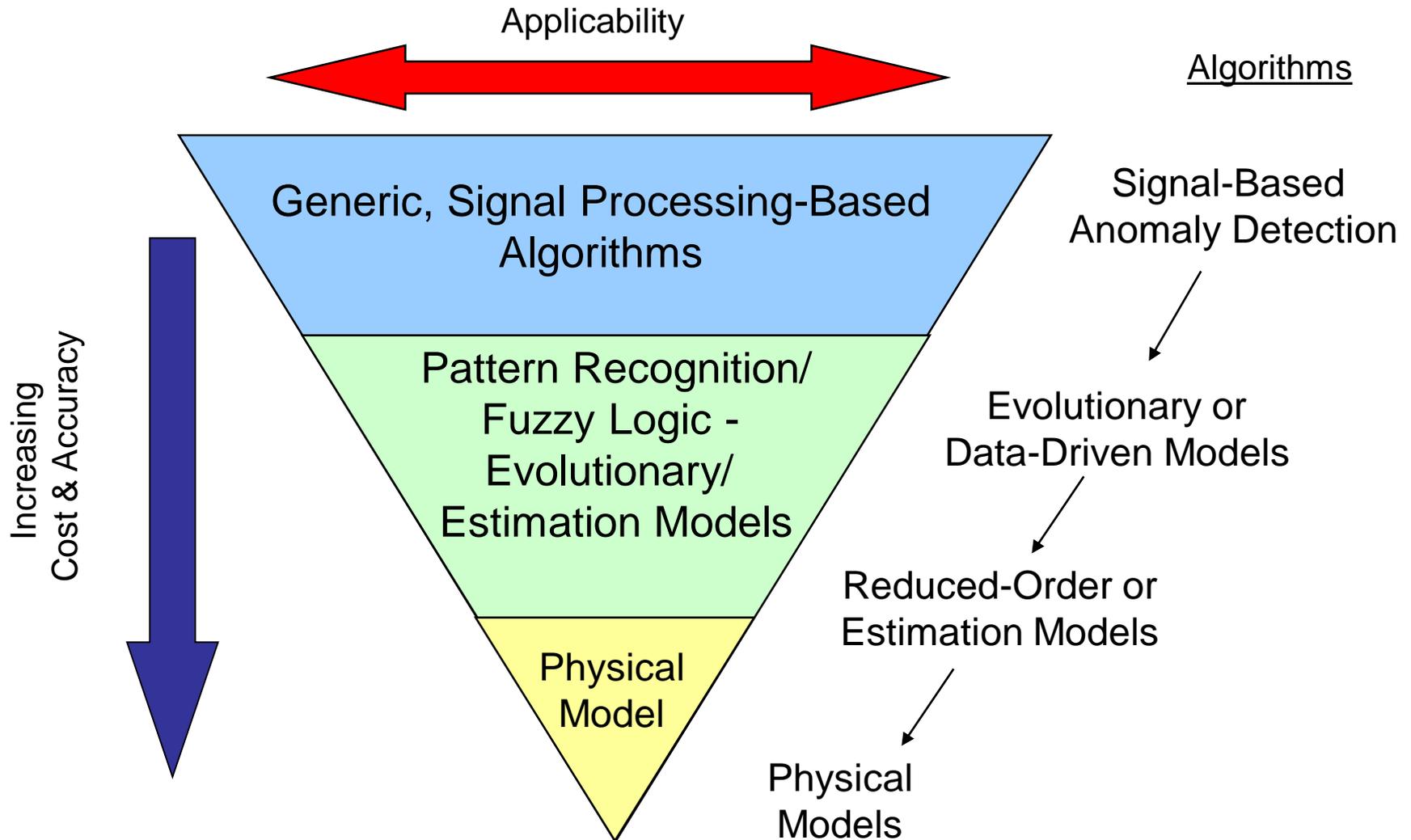
- **Uncertainty representation – the uncertainty tree**
- **Uncertainty propagation – inherent property of prognosis**
- **Uncertainty management: Kernel functions (tails of distributions); Feedback loops for model parameter updating as data is streaming in**

- **Why Choose This Technology?**

- Enable Condition Based Maintenance (CBM) and Asset Management Concepts
- Enhance Safety
- Increase Availability and Readiness
- Eliminate False Alarms
- Eliminate Cannot Duplicate (CND) and Retest OK (RTOK)
- Reduce Life Cycle Costs
- Maximize PHM Benefit from Limited Specialized Sensors
- Take Max Advantage of the “Smart” Digital Systems

**Natural Evolution of Legacy Diagnostic Capabilities Coupled with the Added Functions, Capabilities, and Benefits offered by New Technologies**

# Select and Develop PHM Algorithms



# PHM Technology Needs



**What do I need in order to apply PHM technologies to an aircraft?**

- 1. Data! Data! Data!**
- 2. Sensors and Sensing Strategies**
- 3. Computing and Communications**
- 4. HUMS Equipment – H/S**
- 5. Algorithms**
- 6. Expert Personnel**
- 7. Acceptance by Management**

# CBM+/PHM – The Cost

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- “There is no free lunch”
- Sensors and sensing requirements
- Health and usage monitoring hardware/software
- Communications and computing requirements
- Land-based data warehouses
- Expert personnel for all phases of CBM+/PHM technologies
- Acceptance by management/decision makers/bean counters

# Success Criteria for PHM/CBM+

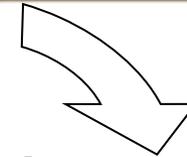
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- *Goal: Reduce maintenance cost by 30%*
- *Goal: Improve Reliability, Availability, Maintainability and Safety of ground facilities and air platforms*
- *Goal: Reduce time for repair of aircraft by several days.*
- *Goal: Increase uptime of critical maintenance facilities to 98%*
- *Goal: Achieve JIT practice in inventoried equipment / supplies / spares*
- *Goal: Optimum utilization of maintenance personnel / resources – improve productivity by 10%*
- *Goal: Migrate to CBM+ practices throughout all enterprise operations*

- Data Pre-processing for improved fault signal to noise ratio – filtering, blind deconvolution, PCA, etc.
- Feature or Condition Indicator (CI) extraction and selection – performance metrics
- Novel Deep Learning (DL) methods for feature extraction/selection and classification/control
- Health Indices

# Electronics/Avionics PHM

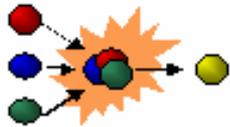


## Validation

Confirm prognostic approach

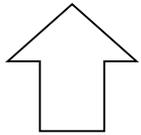
## Failure Mode Analysis

Identify Known Failure Modes



## Data Fusion

Combine Evidence Sources



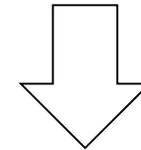
$$\bullet f_2 = \frac{V_{o,\max} - V_o(t)}{V_{o,\max} - V_{o,\min}}$$



# Electronic Prognostics

## HALT Test

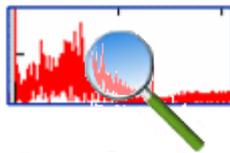
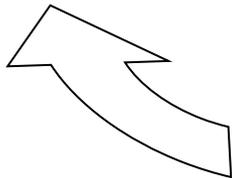
Highly Accelerated Life Testing



$$\bullet f_1 = t_0 \sum_{i=1}^M \left[ \Delta t_i \cdot e^{-\frac{E_a}{kT_j}} \right]$$

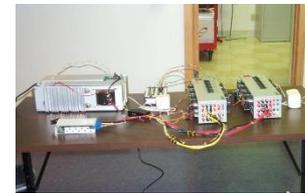
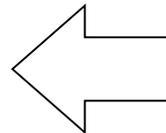
## Feature Model

Quantify Failure Precursors



## Analyze

Identify Prognostic Features



## Experiment

Seeded Fault Testing

## Usage Models

Quantify Acceleration Factors

# Wiring Faults

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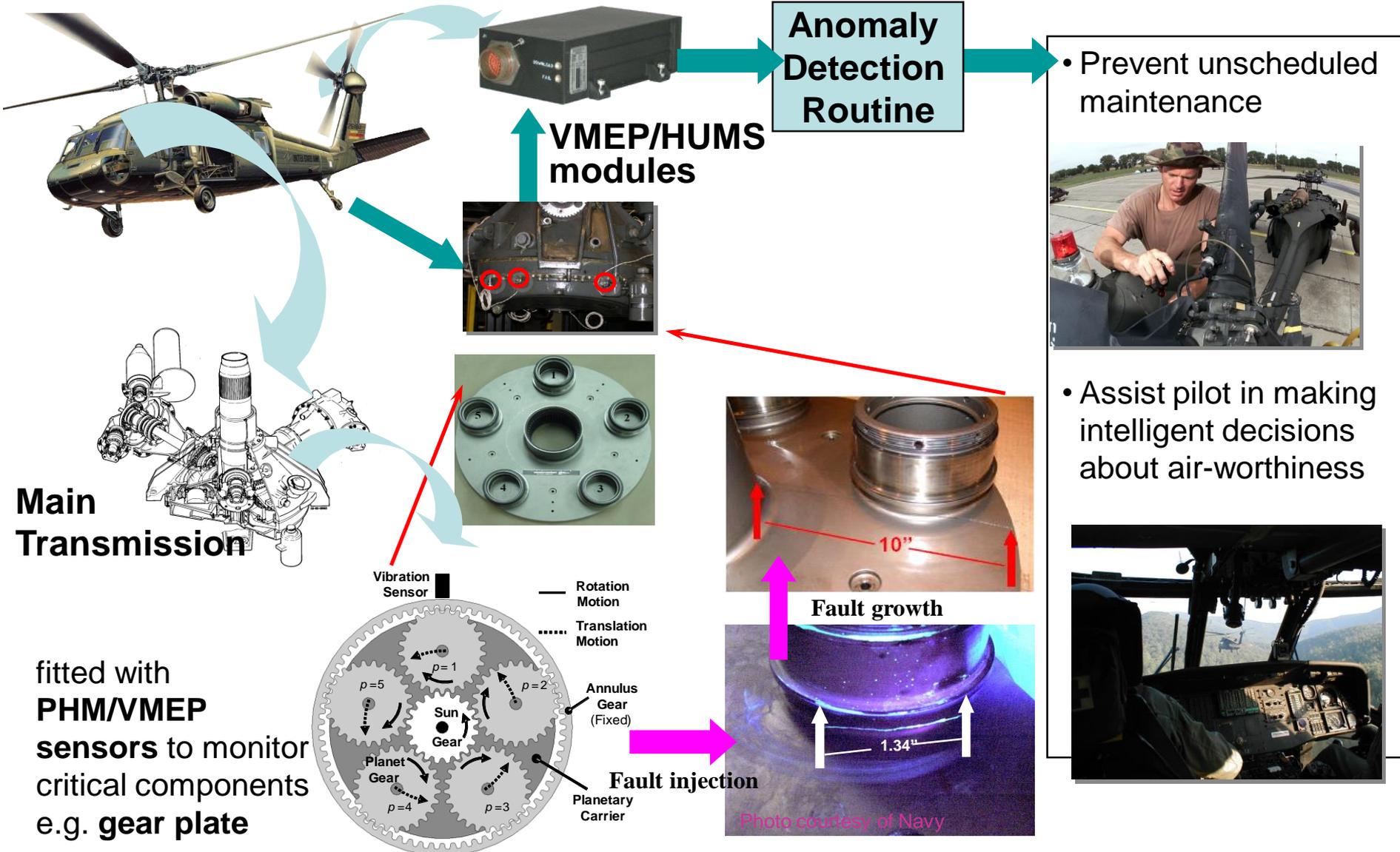
It is the Wiring Stupid!!

It is estimated that about 46% of aircraft faults are attributed to wiring faults/failures

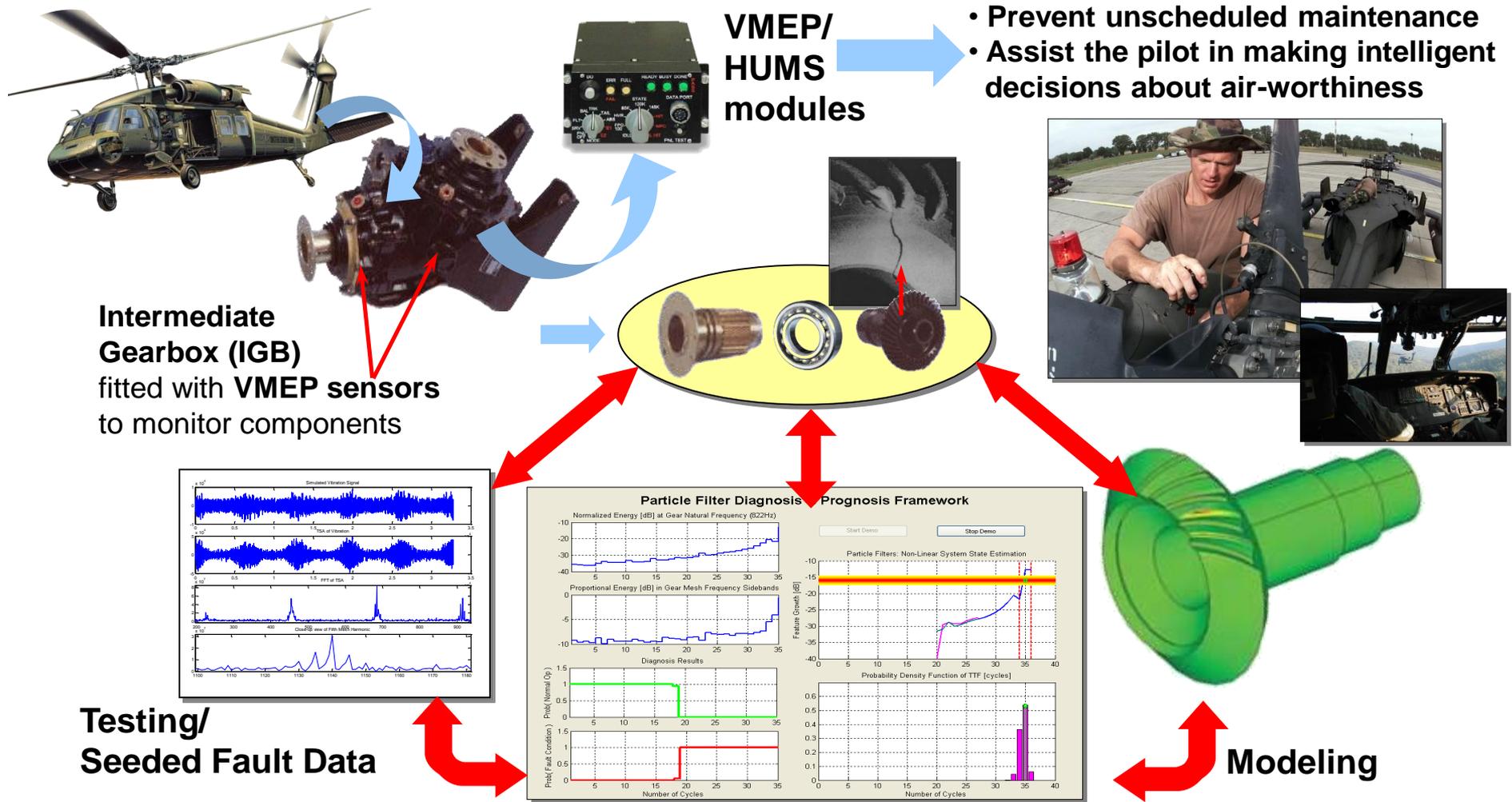


- Main transmission gearbox (DARPA Prognosis Program)
- Oil cooler bearing (ARL)
- Intermediate gearbox (ARL)
- Integrated Vehicle Health Management
- Avionics/Electronics (Army advanced diagnostics)
- Corrosion detection and prediction (AF)
- Blades of an HPC Disk-diagnostics/prognostics (P&W)
- Autonomy and Autonomous Systems

# The System

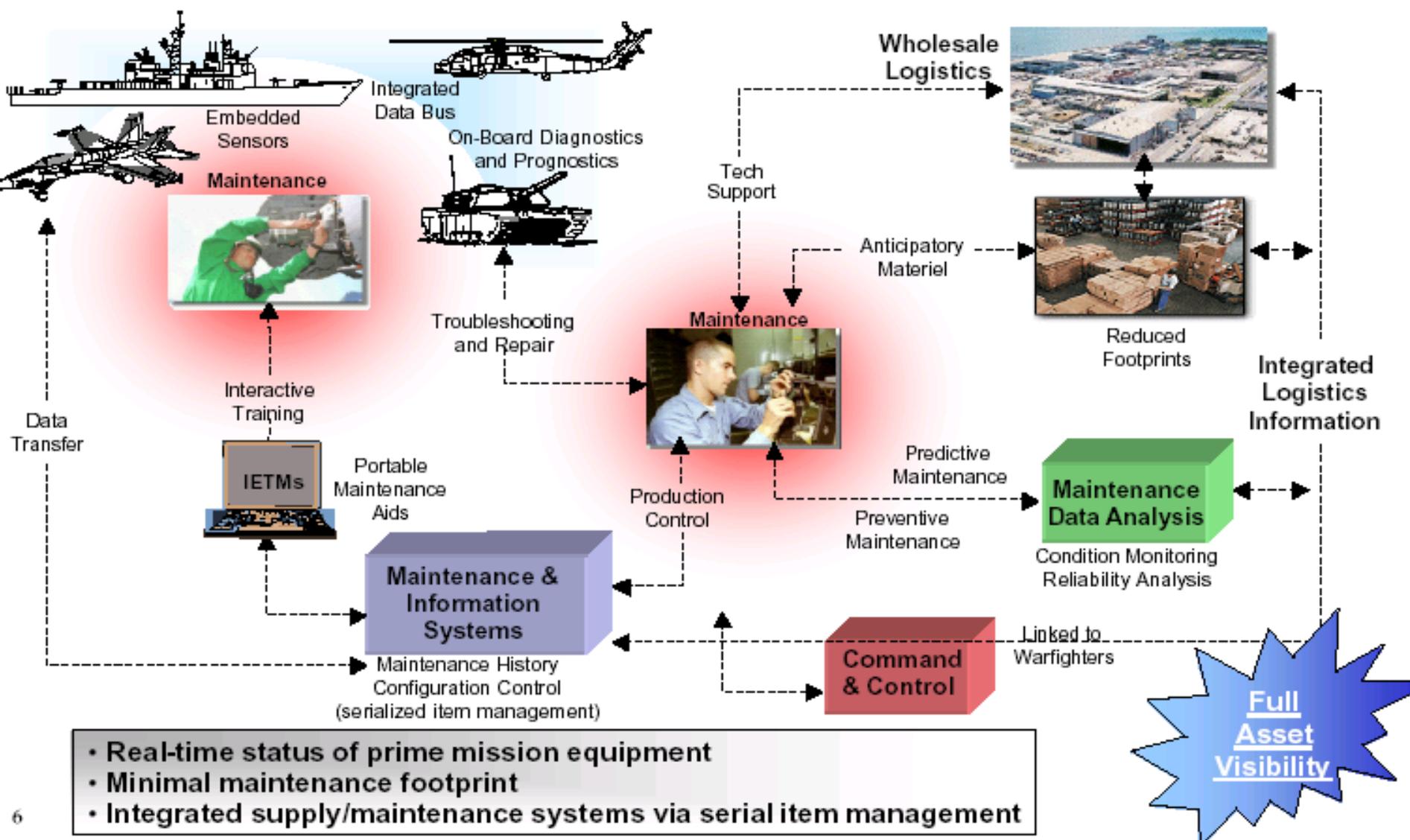


# Testing, Modeling, & Reasoning Architecture



**Reasoning Architecture for Diagnosis-Prognosis**

# CBM+: Maintenance-Centric Logistics Support for the Future



- Real-time status of prime mission equipment
- Minimal maintenance footprint
- Integrated supply/maintenance systems via serial item management

# Integrity Management: IVHM

## Putting the "P" in "PHM"

- Maintenance planning
- Mission planning
- etc.

- De-noising
- Filtering
- etc.



- Future capabilities
- Component RUL
- etc.

- Signal statistics
- Estimated parameters
- etc.

Remaining Useful Life

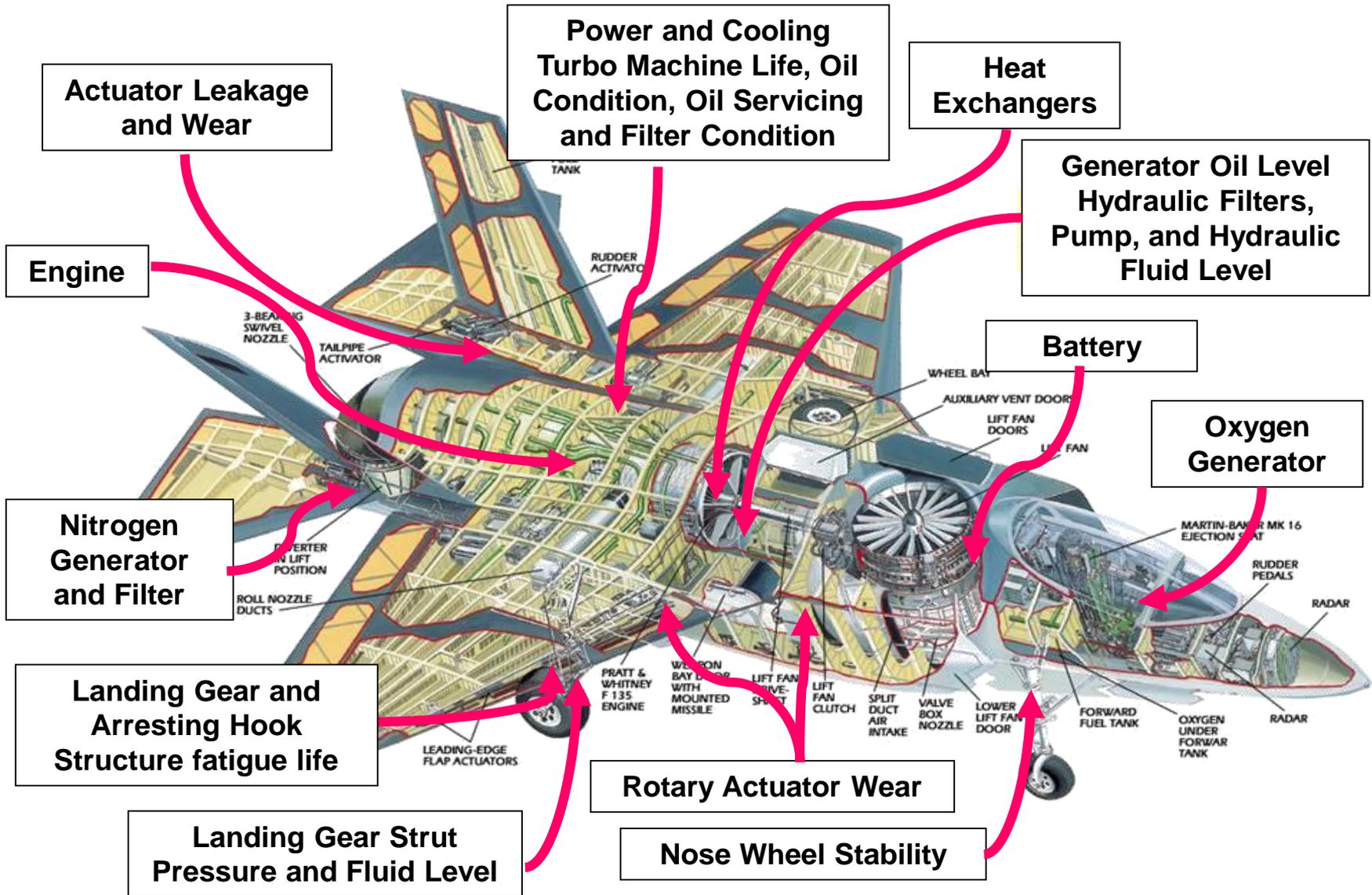
Preprocessed Data



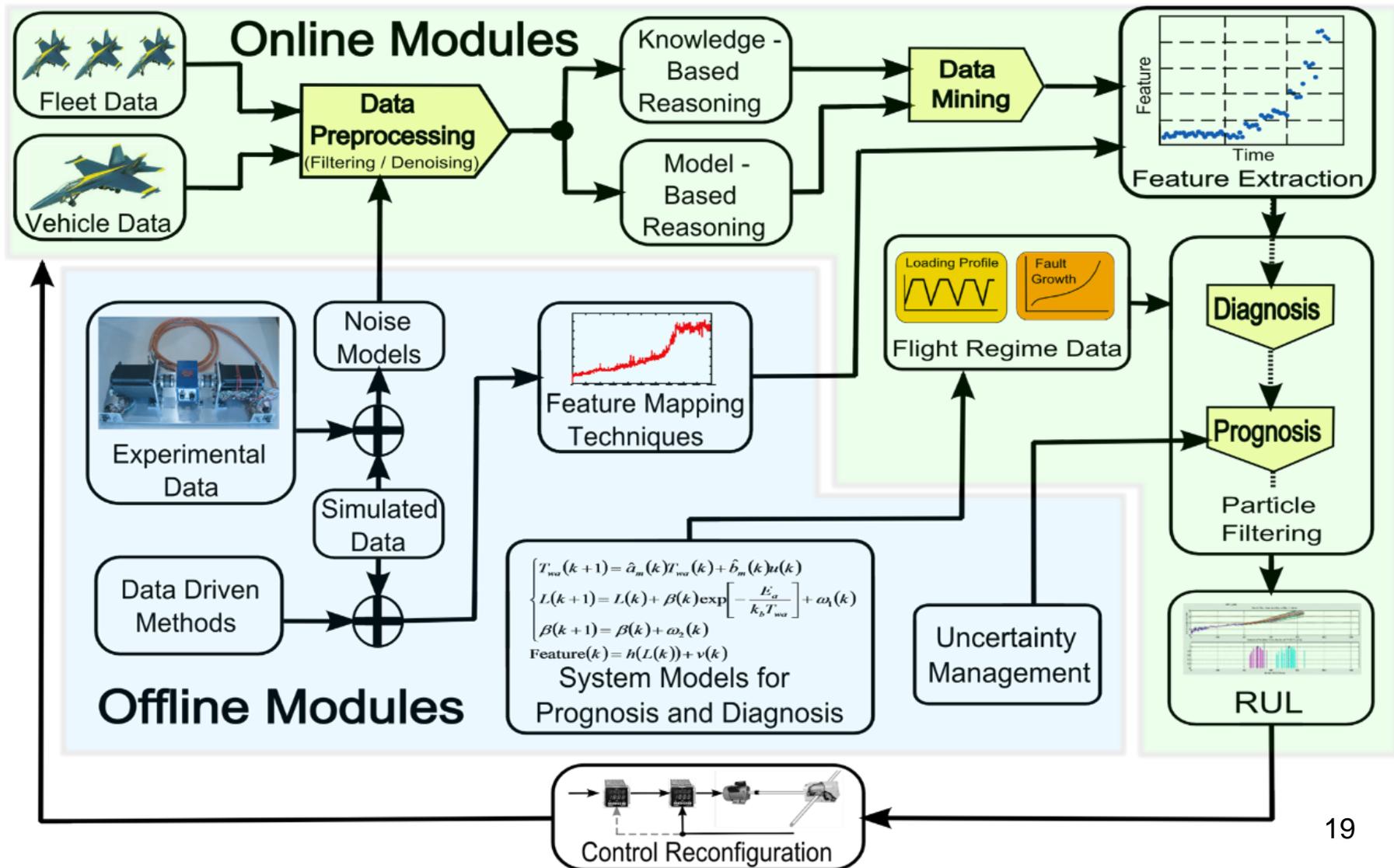
- Fault status
- System capabilities
- etc.



# F-35 Prognostic Candidates



# The On-Board PHM Architecture



# The Particle Filter Framework – A Bayesian Estimation Approach to Prognosis



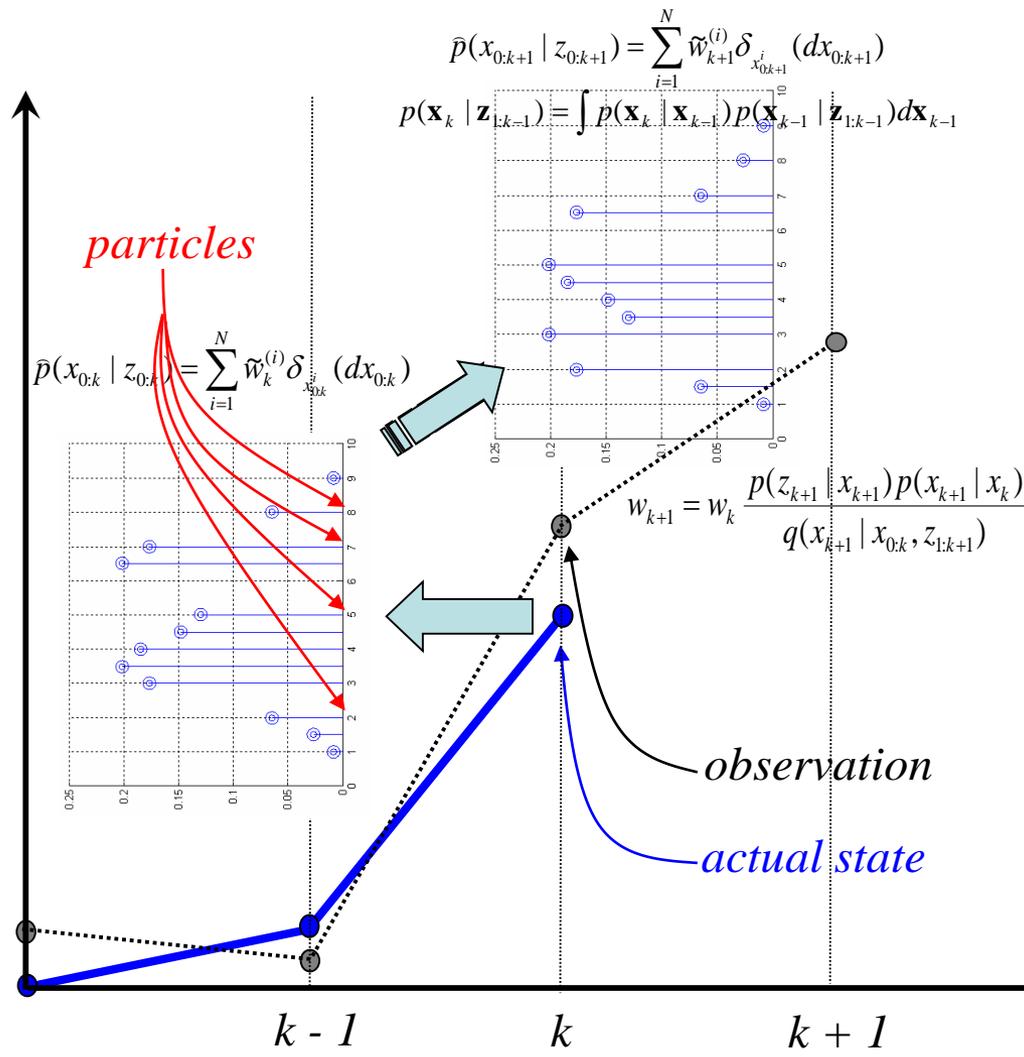
- **What are Particle Filters?** An application of Bayesian state estimation:
  - Estimation of the *posterior pdf* of a state,  $x_k$ , based on all previous measurements,  $z_{1:k}$
- The estimation involves two main steps: **Prediction step / Update step**
- ❖ **Prognosis: Uncertainty Management**

## **Corrections on TTF estimates**

- ❖ At every time instant  $t_{o+j}$ ,  $j = 0 \dots k$ , the particle filter estimate is updated considering the new observation  $z_{o+j}$  and a long term prediction is generated.
- ❖ The predicted TTF pdf and its expected value  $T_k$  are computed.
- ❖ Define  $C_j$  as the set of corrections that were applied to the TTF estimation, given the observations until  $z_{o+j}$ .

# The Particle Filter Framework

❖ Particle: Possible realization of the states of a process.



❖ Every particle is associated with a **weight**

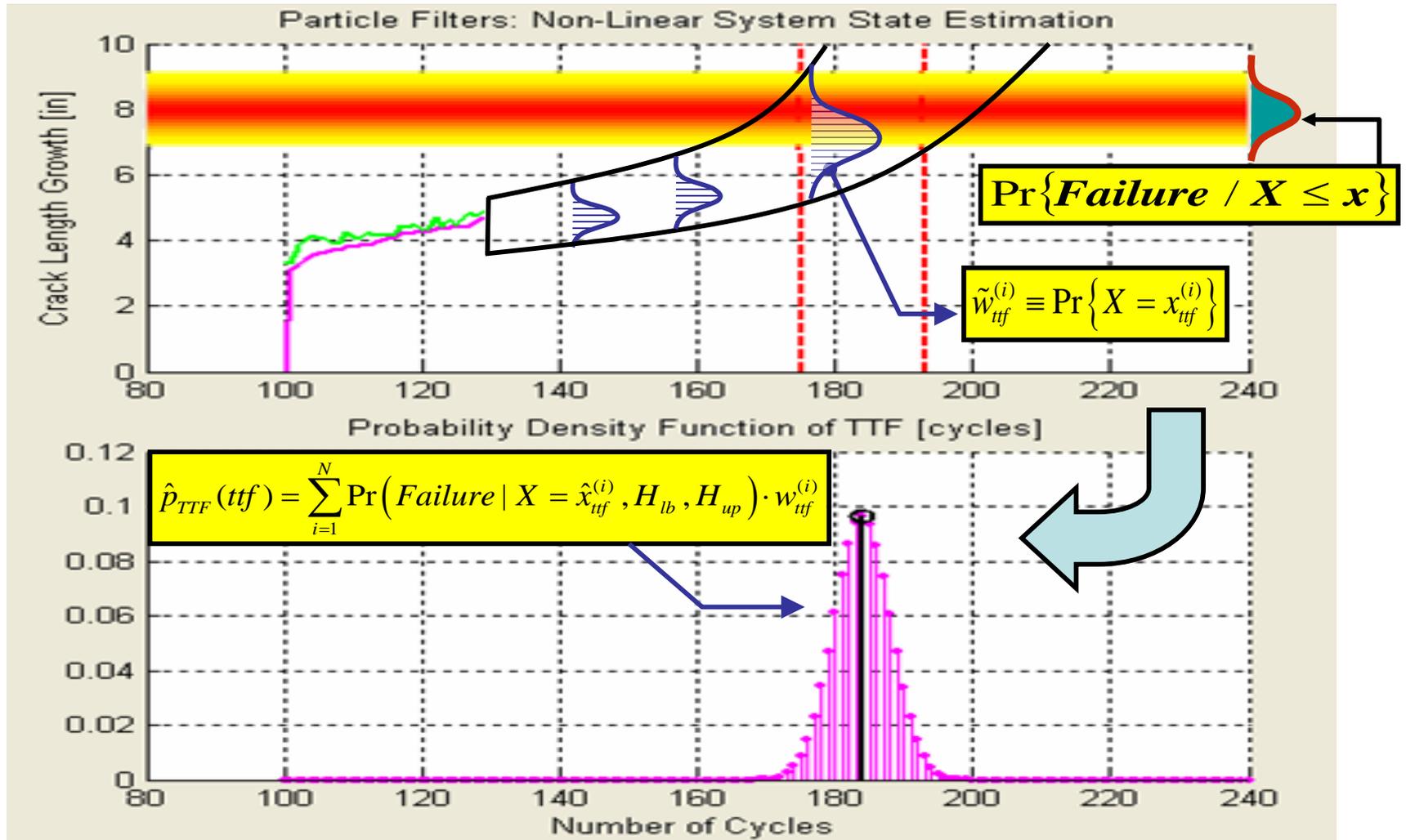
- Particles, together with their weights, represent a sampled version of the PDF.

❖ We only need to study the propagation of weights in time!

❖ Steps:

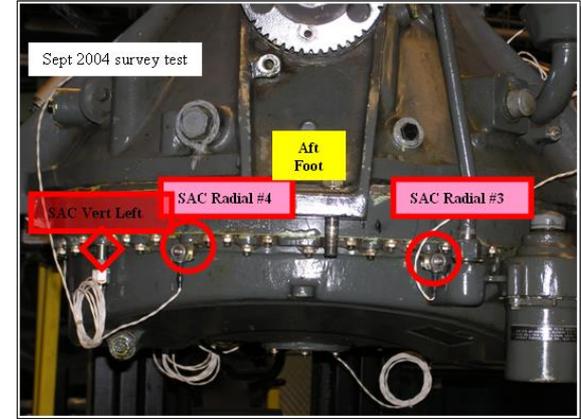
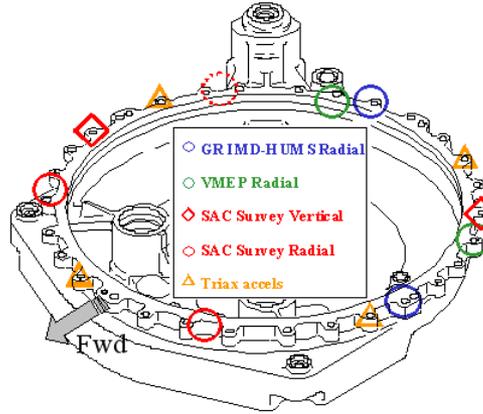
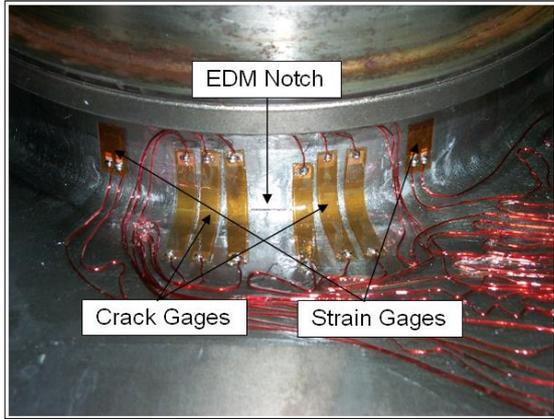
- Predict the “*a priori*” PDF parameters, using the model
- Update **parameters**, given the new observation

# The Particle Filter Framework

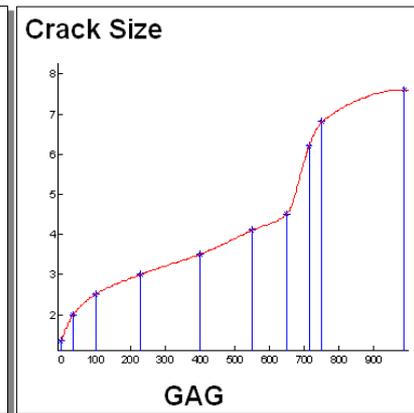
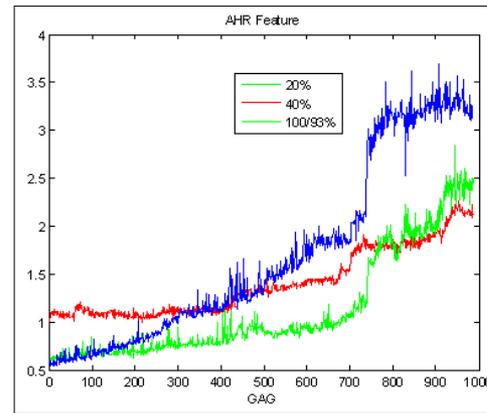
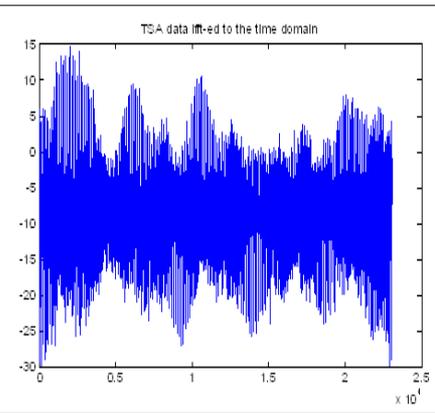
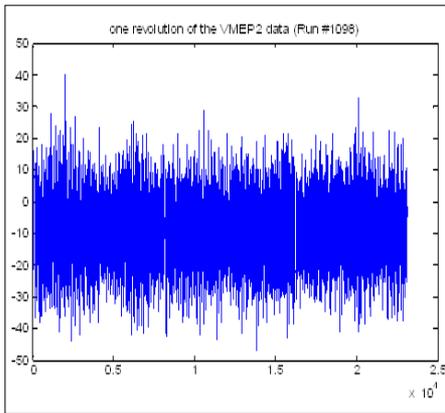


# Particle Filtering Fault Detection and Identification Framework

## Seeded Fault Test

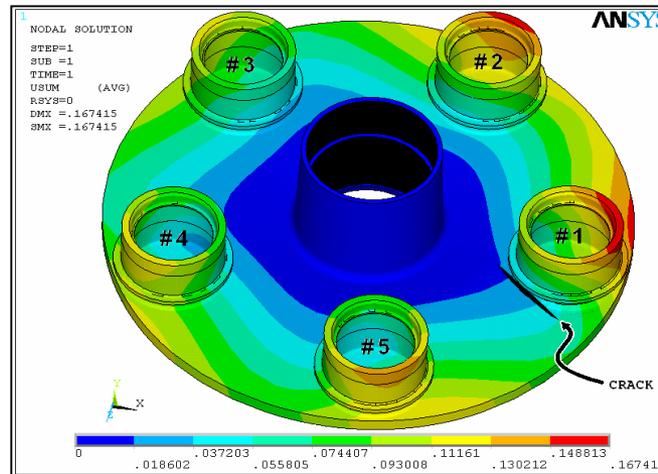


## Test Results



# FDI Case Study: Cracks in Planetary Carrier Plate

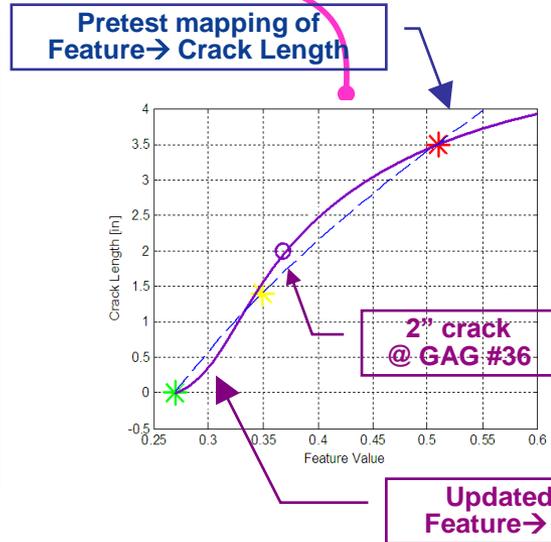
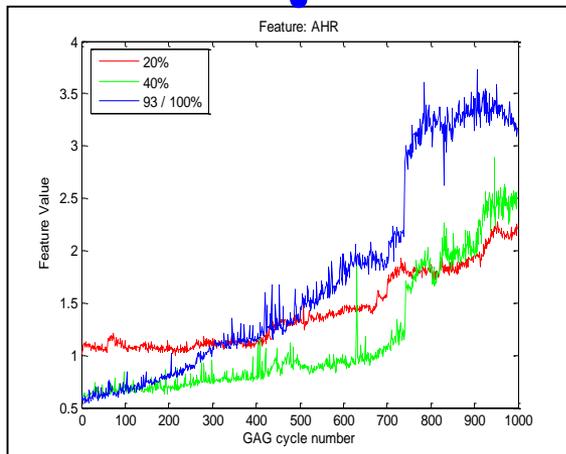
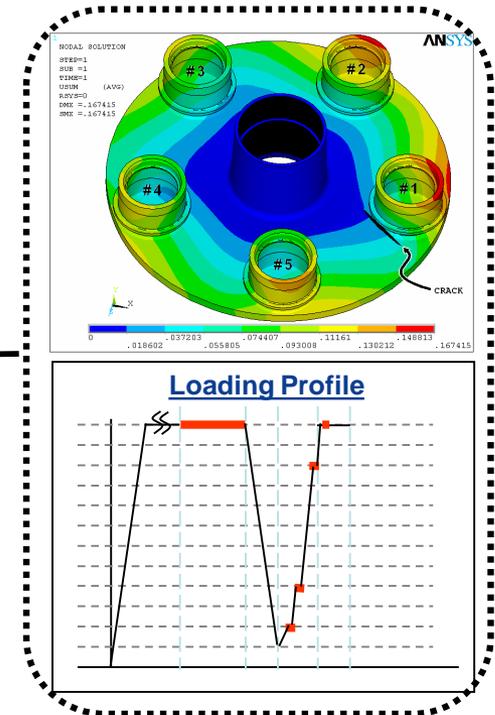
- Particle Filter Fault Detection Module
  - **System:** Gear plate of the main transmission of a helicopter
    - Accelerometers mounted on its frame.
  - **Objective:** Analyze the growth of a crack in a seeded fault test.
    - Normal condition: crack is growing very slowly or not growing at all
    - Faulty condition: abrupt change in the growth rate.



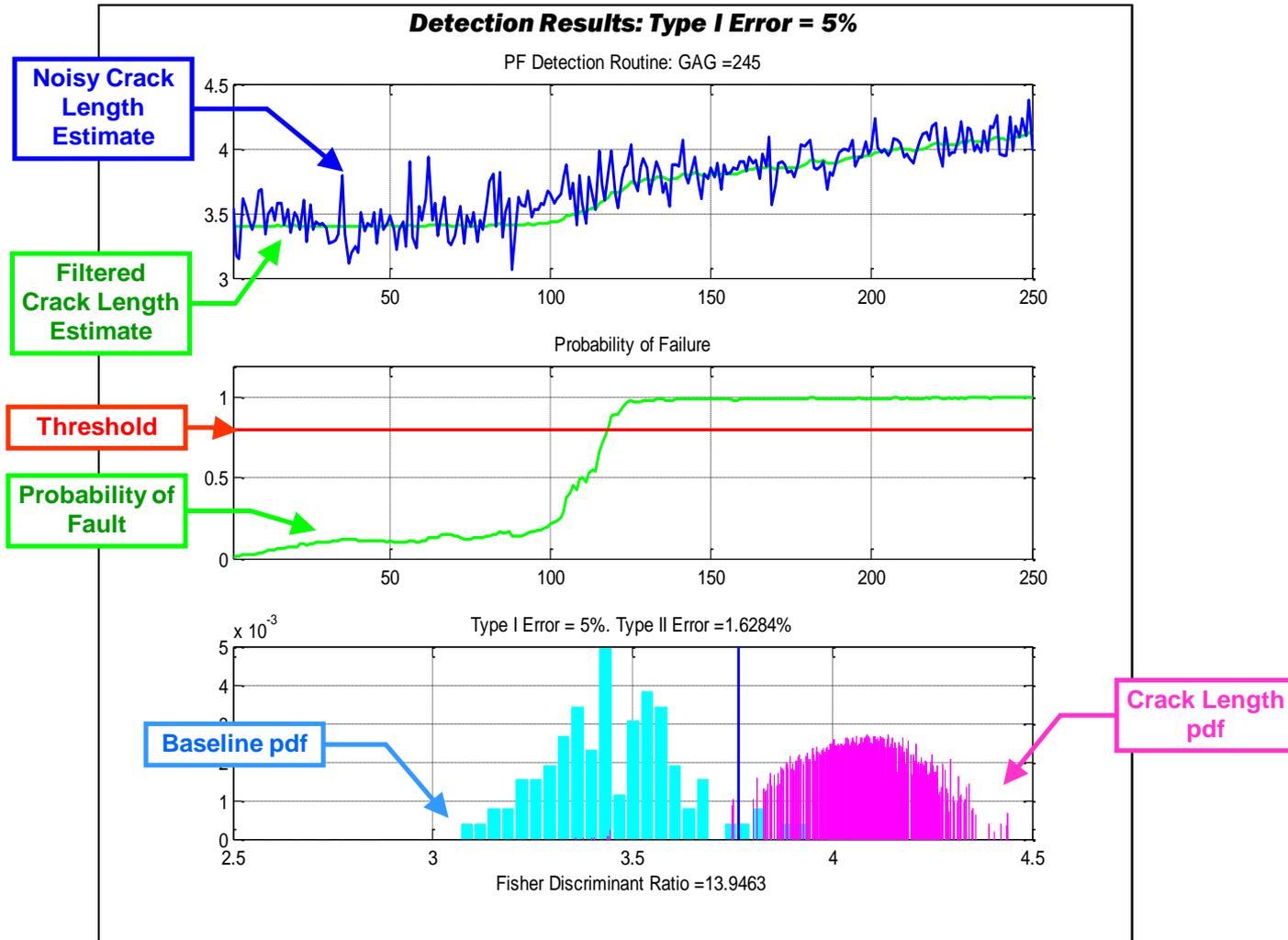
# The Particle Filter Framework

$$\begin{cases} L(t+1) = L(t) + C \cdot \alpha(t) \cdot \left\{ (\Delta K_{inboard}(t))^m + (\Delta K_{outboard}(t))^m \right\} + \omega_1(t) \\ \alpha(t+1) = \alpha(t) + \omega_2(t) \\ \Delta K_{inboard}(t) = f_{inboard}(\text{Load}(t), L(t)) \\ \Delta K_{outboard}(t) = f_{outboard}(\text{Load}(t), L(t)) \end{cases}$$

Feature(t) = h(L(t)) + v(t)

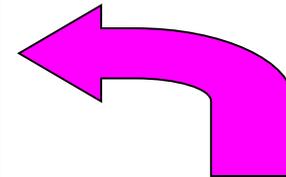


# FDI Case Study: Cracks in Planetary Carrier Plate

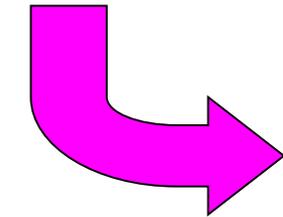
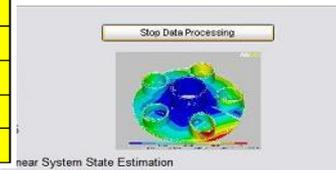


• Prognosis Case Study: Crack in Planetary Carrier Plate

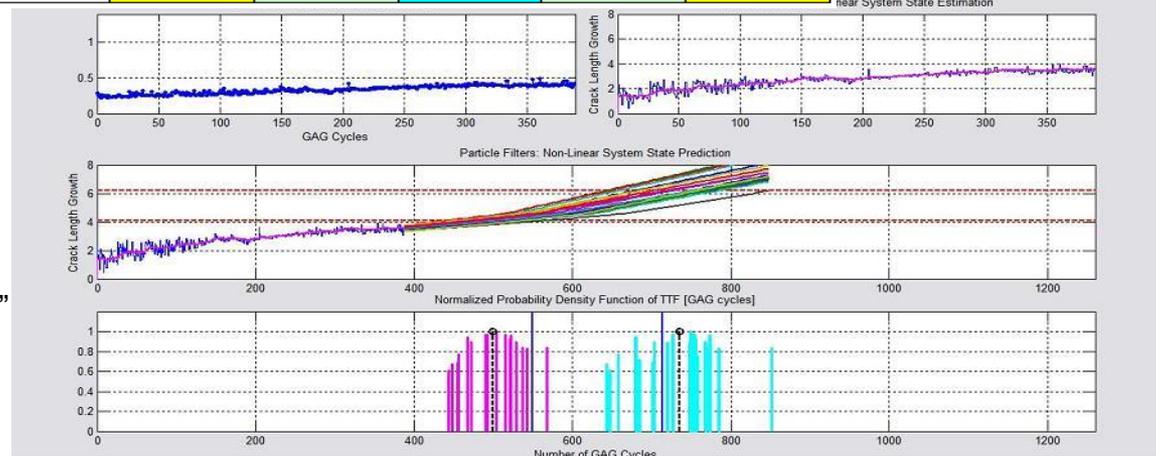
Measured Crack Length		GaTech Predictions				
GAG	Total Crack Length (inches)	- 3 sigma	- 95%	Mean	+ 95%	+ 3 sigma
0	1.34	N/A	N/A	1.34	N/A	N/A
36	2.00	0.74	1.03	1.60	2.17	2.46
100	2.50	1.93	2.09	2.40	2.71	2.87
230	3.02	2.73	2.79	2.90	3.01	3.07
400	3.54	3.41	3.54	3.80	4.06	4.19
550	4.07	3.85	4.11	4.30	4.60	4.75
<b>650</b>	<b>4.52</b>	4.20	4.48	4.71	5.08	5.70
714	6.21	5.27	5.36	5.55	5.74	5.84
750	6.78	6.38	6.42	6.61	6.76	6.84



Initial Prognosis Results:  
(No Ground Truth data available)  
Hazard Zone around 4.5"



Final Prognosis Results:  
Several Hazard Thresholds i.e. 4.1"  
6.2", etc.



# Prognosis Case Study: Crack in Planetary Carrier Plate



**GA Tech On-line FDI/Prognosis GUI**

**Feature Extraction with De-Noising**

**Feature Values**: Feature Value (PORTRING) vs. Hours of Operation. Shows a noisy blue line and a filtered red line.

**Estimates of Crack Length Progression**: Crack Length (SBR, 40%, PORTRING) vs. Hours of Operation. Shows a noisy blue line and a filtered red line.

**Mapping of Feature Values vs. Crack Length**: Crack Length vs. Feature Value. Shows a scatter plot with a fitted curve.

**User choices for display (on-line selectable)**: Sensor: PORTRING, Torque: 40%, Delta Feature Off: [dropdown].

**Baseline PDF (Healthy conditions)**: PDF of Crack Length [inches] for healthy conditions, shown as a green bar at approximately 0.5 inches.

**Current State PDF**: PDF of Crack Length [inches] for the current state, shown as a red bar at approximately 2.0 inches.

**FDI Results**: PF Detection Routine: Cycle# = 57. Shows the current state PDF and baseline PDF.

**Detection Parameters**: Prob. False Alarm: 1%, Prob. Detection: 80%.

**Earliest Detection Results**: Time of Detection: 0.65 hrs, Crack Length at Detection: 0.85".

**Fault Identification**: Crack Length Estimate: 2.00", 95% Confidence: [1.87, 2.14].

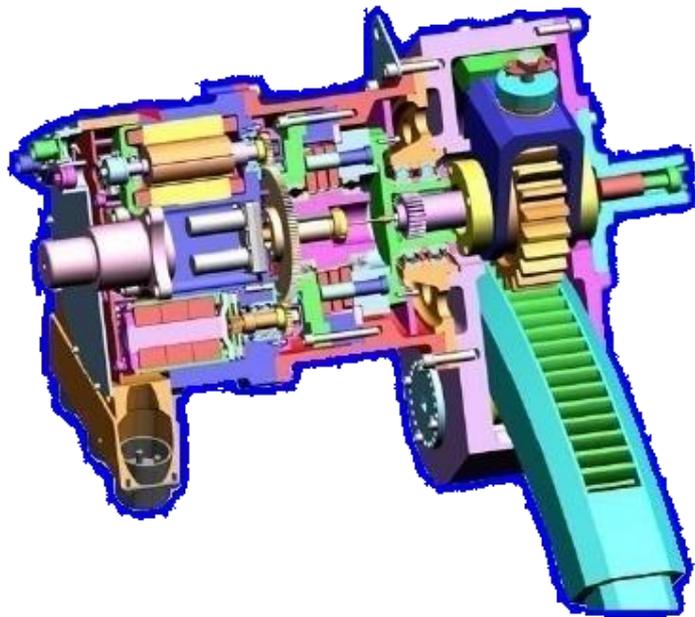
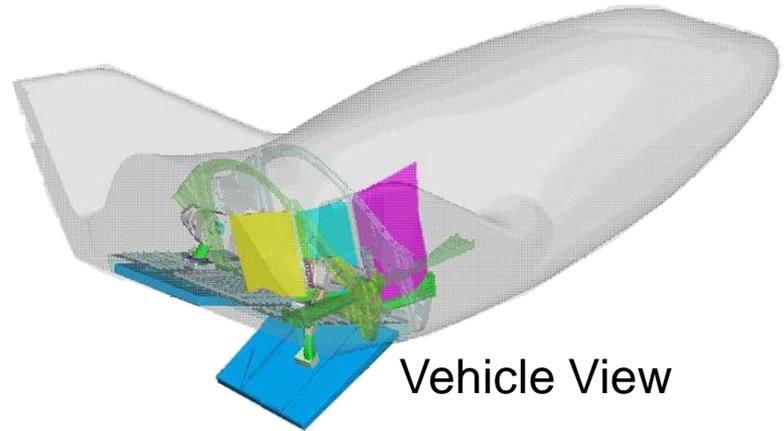
**Fault Detection Indicators corresponding to different features and operating conditions**: Sideband Ratio (40%, 100%) and RelSX (40%, 100%) all show "Fault!".

**Prognosis Results**: Expected TTF (in cycles) and 95% Confidence Interval for different thresholds.

Threshold	Expected TTF (in cycles)	95% Confidence Interval
Threshold #1: 2.0"	8.00	[1.00, 34.00]
Threshold #2: 4.5"	487.00	[456.00, 542.00]

# Electromechanical Actuator (EMA) Anomaly Detection

- Avionics flight actuator
- Controls flap and rotor position
- Critical system component
- High reliability required



Actuator Assembly



Flap Actuator

# Case Study: Actuator Fault Modes

## Fault Modes Identified

- Stator windings shorts (turn to turn/ turn to ground)/ open faults
- Bearings (friction induced faults), spalling, cracks, etc.
- Resolver winding insulation faults (shorts / open faults)



**Brushless Motor**

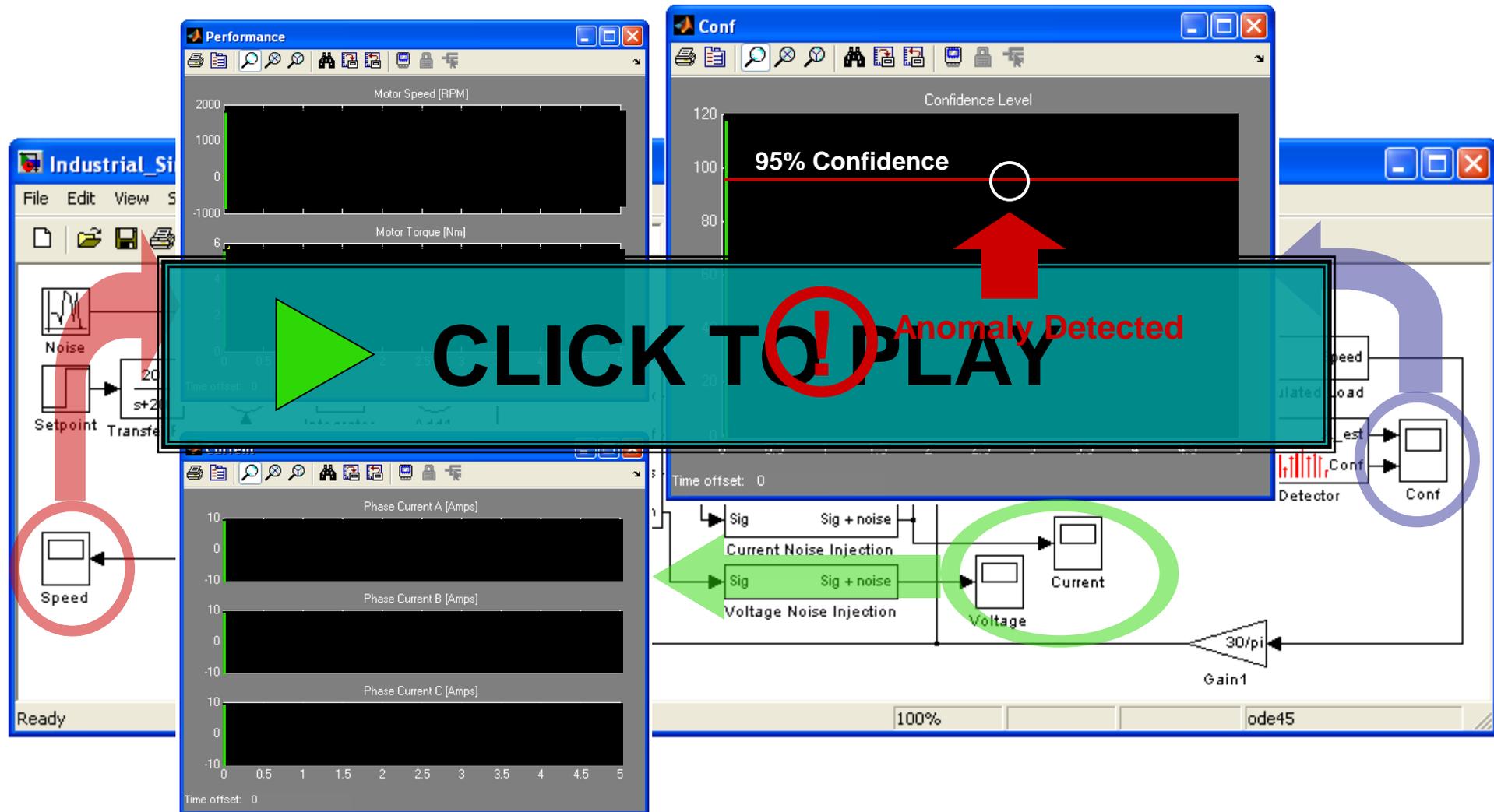


**Resolver Sensor  
(w/ Electronics)**



**Motor Bearing**

# Anomaly Detection of EMA Winding Fault (Simulink Demo)



## The Opportunity

Condition Based Maintenance (CBM) promises to deliver improved maintainability and operational availability of military assets while reducing life-cycle costs

## The Challenge

Prognostics is the Achilles heel of CBM systems - predicting the time to failure of critical systems/components requires new and innovative methodologies that will effectively integrate diagnostic results with maintenance scheduling practices

*“Prediction is rather difficult particularly when  
it concerns the future”  
- Niels Bohr*

# Failure Progression Timeline

## Prognostics

**Need:** To Manage Interaction between Diagnostics and Prognostics

## Diagnostics

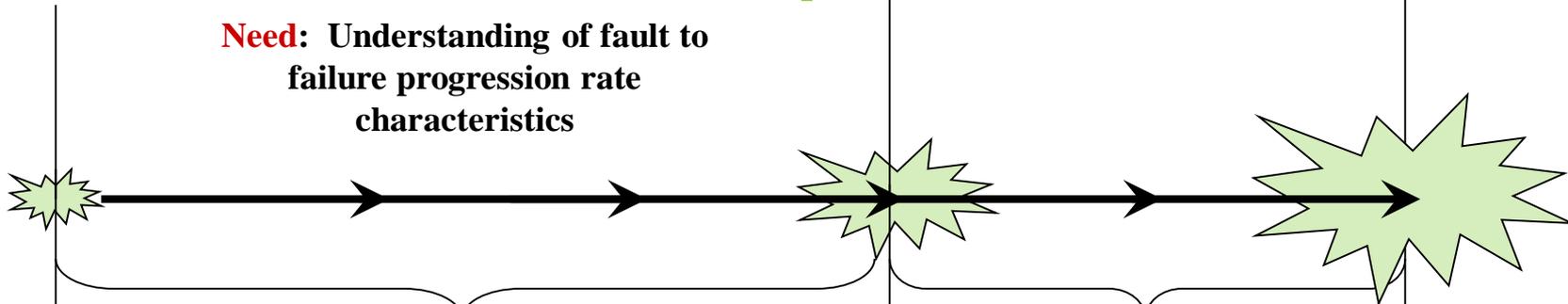
System, Component, or Sub-Component Failure

Secondary Damage, Catastrophic Failure

Very early incipient fault

Proper Working Order - New

**Need:** Understanding of fault to failure progression rate characteristics



Predicted useful life remaining

Determine effects on rest of aircraft



**Desire:** Advanced Sensors and Detection Techniques to “see” incipient fault

**Develop:** Useful life remaining prediction models – physics and statistical based

**Need:** Better models to determine failure effects across subsystems

The Goal is To Detect “State Changes” as Far to the Left As Possible

# Prognosis: A Model-based and Measurements Approach

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## **Our Approach:**

Utility of a fault model, a feature vs. fault dimension mapping, streaming data and a particle filtering framework (Bayesian estimation) for long-term prediction

# Fault Tolerant Control

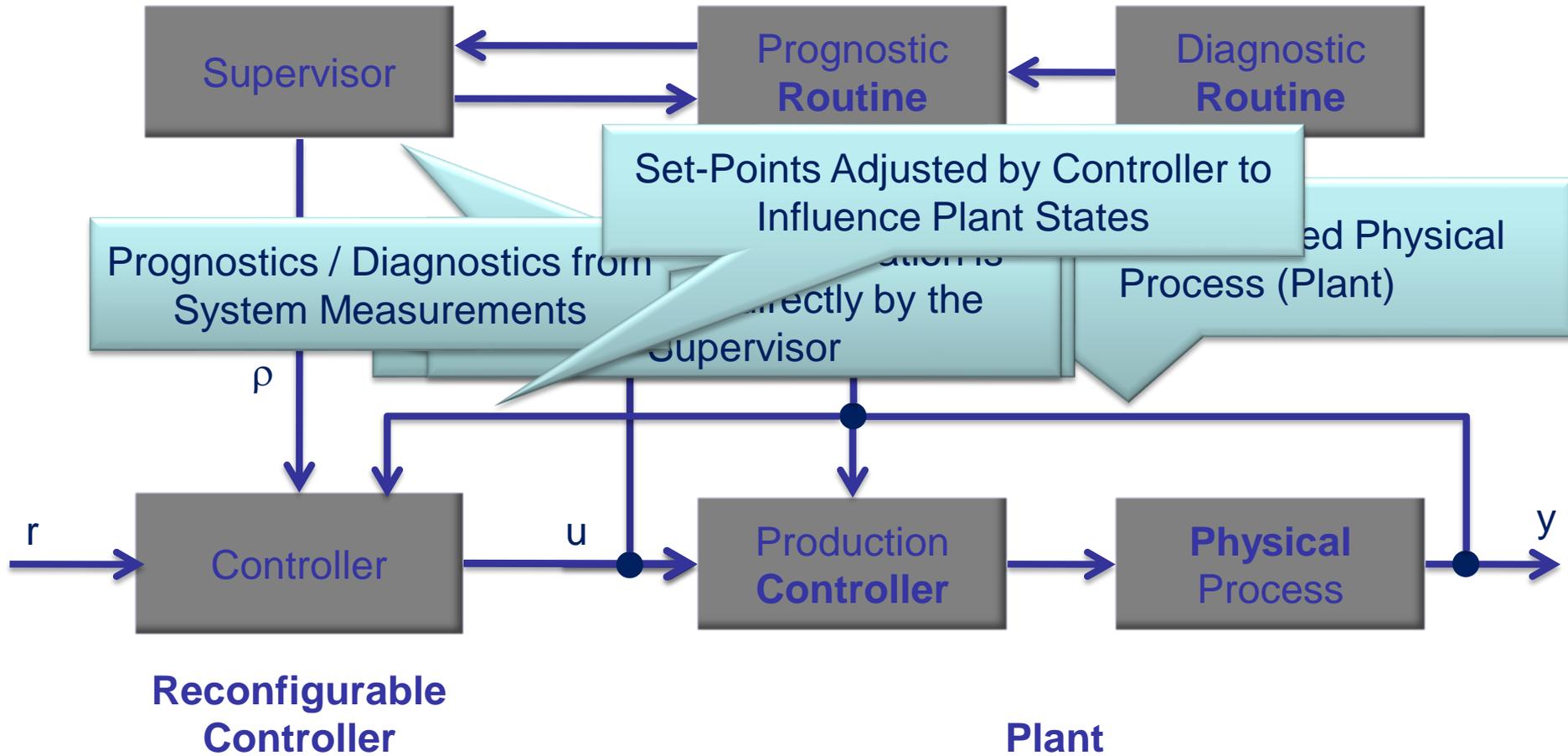


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*Designing High-Confidence and Reliable  
Dynamic Systems*

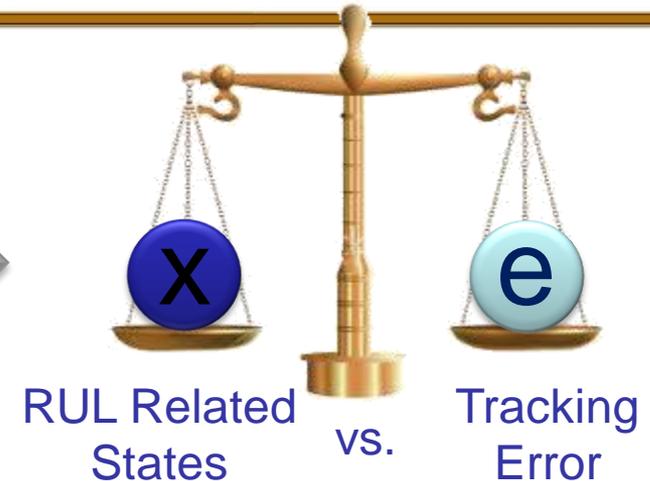


# Control Architecture - Reconfigurable Control



# The Control Architecture

## Optimization Criteria for MPC



Adaptation parameter  $\rho$  adjusts cost

- The cost function:

$$J = \min_{\Delta \mathbf{u}} \int_{t_0}^{t_0+T} [(\mathbf{x} - \mathbf{x}^*)^T \mathbf{Q} (\mathbf{x} - \mathbf{x}^*) + \Delta \mathbf{u}^T \mathbf{R} \Delta \mathbf{u}] dt$$

- Subject to the constraints,

$$\begin{cases} \Delta \mathbf{u}_{\min} \leq \Delta \mathbf{u}(t) \leq \Delta \mathbf{u}_{\max} \\ \mathbf{u}_{\min} \leq \mathbf{u}(t) \leq \mathbf{u}_{\max} \end{cases}$$

# Complex Systems (Complexity Theory)

- Complex systems can be considered “system of systems” with hierarchical sets of subsystems or components
  - Overall system behavior results from the interaction of subsystems
- Increasing complexity may result in:
  - More unpredictable emergent behaviors
  - Increasing vulnerability to severe disturbances (failures)



# Fleet of Aircraft – the Enterprise Level

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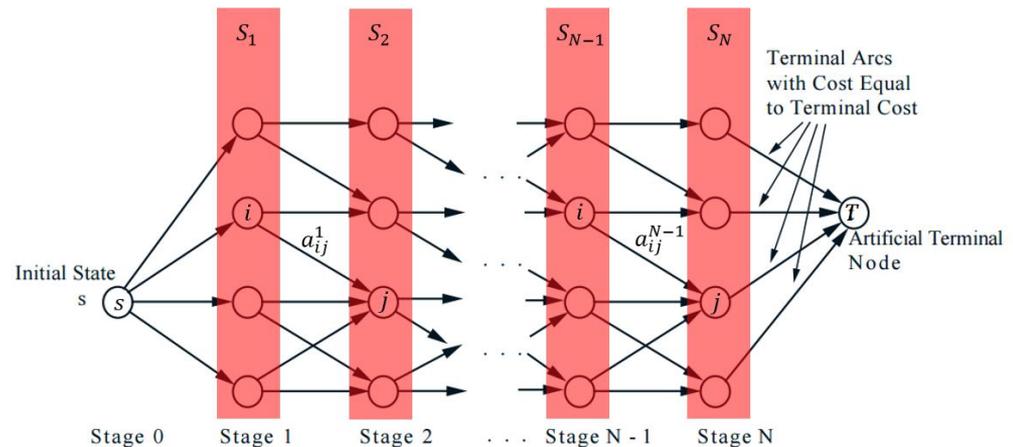


- Data acquisition and data analytics from a fleet of aircraft
- Prognostics and Health Management at the fleet level
- Objective: Which assets are ready to fly the next five missions?
- Data aggregation from multiple vehicles
- Data fusion at all levels
- Decision making from multiple asset sources
- Uncertainty representation and management

# Dynamic Programming

- The optimal path will be evaluated by finding the path with maximum total expected reward using the Bellman equation in a finite horizon window
  - Value function is defined as:

$$V(s) = \max(R(s, a) + \gamma \sum T(s'|s, a)V(s'))$$



- Reliability analysis tools/methods:
- Data and data mining, modeling tools/methods
- Prognosis of remaining useful life or time to failure of failing systems/components
- First order and higher order reliability methods
- Optimization tools
- Risk assessment and management

➤ *Probabilistic methods for reliability analysis*

# Lifecycle Management- The Main Modules

**Reliability Analysis  
(Life Distribution)**



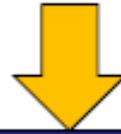
**Life Decision  
(MTBR, etc.)**

**Stage I: Long-term  
Planning**

- Physics-based Life Modeling
- Reliability Analysis

**Past**

**CBM & PHM**

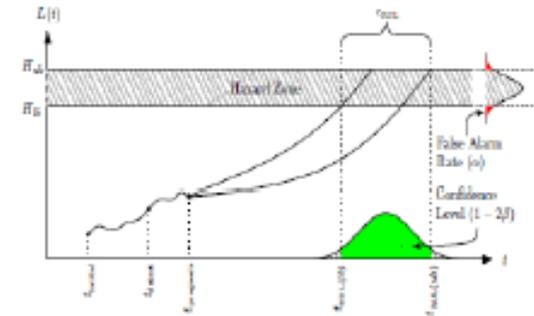


**Adjusted Life  
Decision  
(Maintenance Options)**

**Stage II: Short-term  
Planning**

- Condition-based Monitoring
- Risk-based Inspection
- Degradation Prognostics

**Present**



**Maintenance  
Execution**

**Future**

## Objective:

- ❖ Given critical component failure(s), build a system lifecycle model for optimizing system performance: lifespan, maintenance cost, safety, etc.
- ❖ Optimize system design on the basis of safety/reliability analysis methods
- ❖ Concepts of envelope protection make use of on-line learning adaptive neural networks to generate on-line dynamic models exploited to estimate limits on controller commands.

# Safety Assurance – A Probabilistic Design Approach

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- Define safety margins
- Probability of failure
- First-order safety/reliability analysis
- Risk index
- Risk control
- Risk is quantified in terms of the scenario of events leading to hazard exposure, the likelihood of the scenario and a measure of its consequences

# Safety Margins

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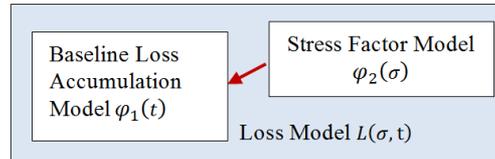
- ❖ **Safety Margins** - Safety margins are designed as an automatic envelope protection system.
- ❖ The system's behavioral modes may escape from the stable region of operation, under severe stress conditions, endangering its safety and survivability.
- ❖ Concepts of envelope protection make use of on-line learning adaptive neural networks to generate on-line dynamic models exploited to estimate limits on controller commands.

# Overall Architecture

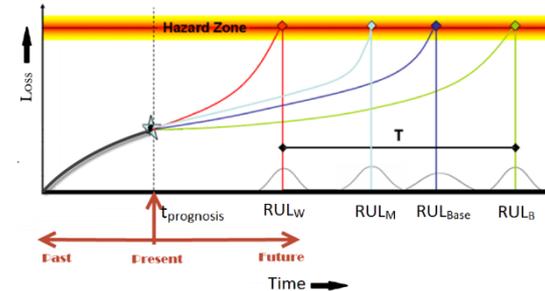
## Engineering System



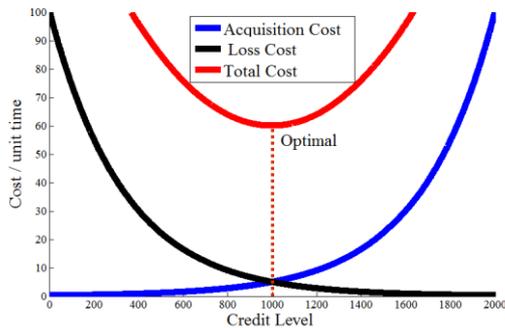
## Life Loss Modeling under Stressors



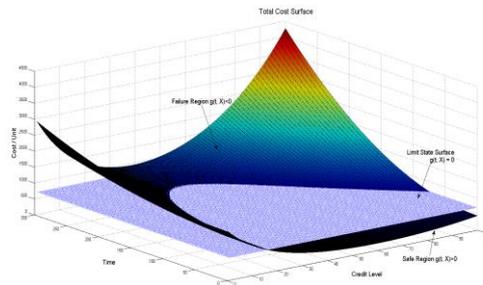
## Long-term Prognosis



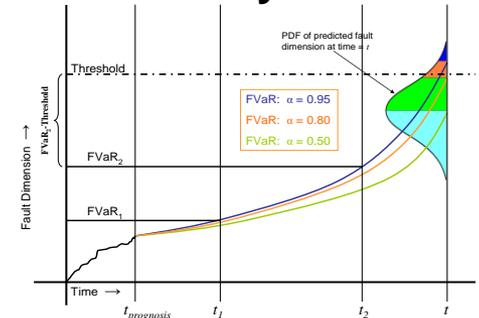
## Life Cycle Optimization



## Safety Analysis



## Prognosis-based Risk Analysis



# Potential Benefits

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- Provide exactly the functionality needed, exactly when needed
- Optimum life cycle management via tools/methods for modeling, detection, prediction and fault-tolerant control of critical assets
- An open-ended architecture so that it can be improved, upgraded, and reconfigured, rather than replaced
- Application domains: autonomous systems, aerospace assets, industrial and manufacturing processes

**A new paradigm in the way we design and operate complex systems**

- The need: Data! Data! Data!
- Seeded Fault Testing
- Data Warehousing / Knowledge Bases
- Prognosis-The Achilles' Heel of CBM/PHM
- The Expanding Customer Base: Maintainer, Field Commander Manager, Designer
- The Business Case: ROI

## **Where do we go from here?**

- Improved coupling between design, health management and fault-tolerant control
- The human-system interface
- The uncertainty issue
- Probabilistic design methods
  
- **DESIGN OF FAULT-TOLERANT HIGH-CONFIDENCE SYSTEMS**