RDECOM

Prognostics and Diagnostics for Operational Awareness and Condition Based Maintenance

ARL

TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.

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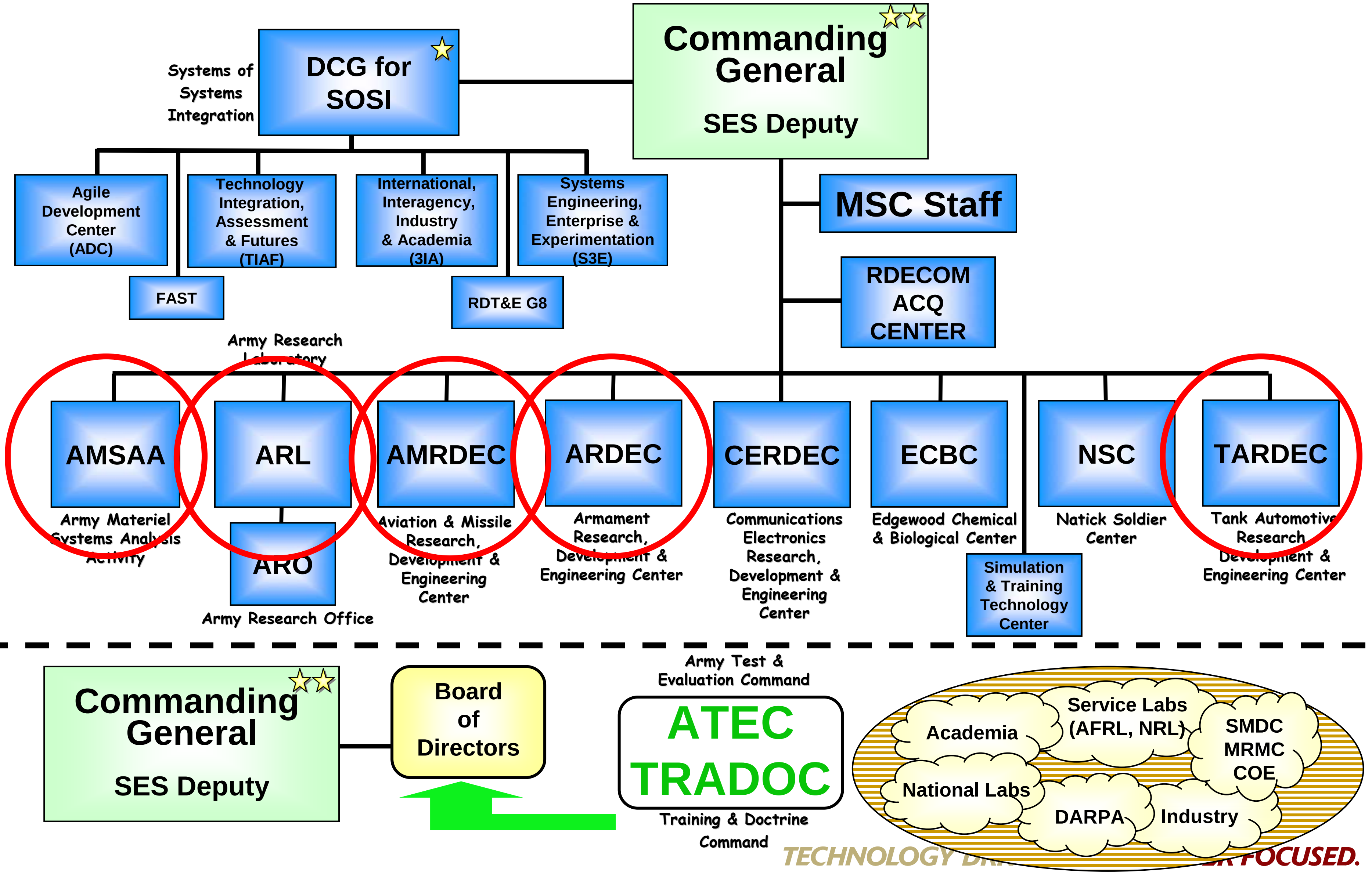
Outline

- Intro
- Definitions
  - Diagnostic
  - Prognostics
- Description of the basic process for developing Prognostics
- Implications
  - Cost / Benefit
  - Data intensity
    - P&D vs. post facto reliability
  - Reliability of the P&D system…
- Path Forward

Research, Development and Engineering Command



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ARL Organization

Director

- Deputy Director
- Deputy Director for Basic Science & Director ARO
- Associate Director for Plans, Programs & Budget

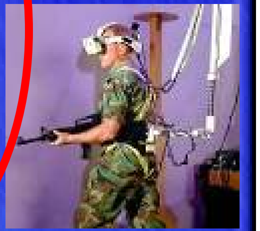
Associate Director for Laboratory Operations

European Research Office

Far East Research Office

Vehicle Technology Directorate

Human Research & Engineering Directorate



Survivability/ Lethality Analysis Directorate

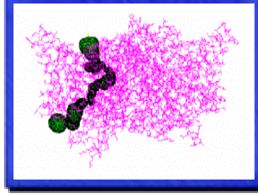
Computational & Information Sciences Directorate

Sensors & Electron Devices Directorate

Weapons & Materials Research Directorate

Army Research Office

Mathematical & Information Sciences Directorate



Physical Sciences Directorate

Engineering Sciences Directorate

Definitions: Formal

- **Reliability** - *the ability of a system or component to perform its required functions <u>under stated conditions for a specified period of time</u>*.

- **Diagnostic** –
  - sensor + measurement + interpretation=>
  - immediate assessment of health/status of a particular attribute
  - Valid at the time of measurement

- **Prognostic** - the capability to predict time to repair/failure of device/ component/ system (Remaining Useful Life)

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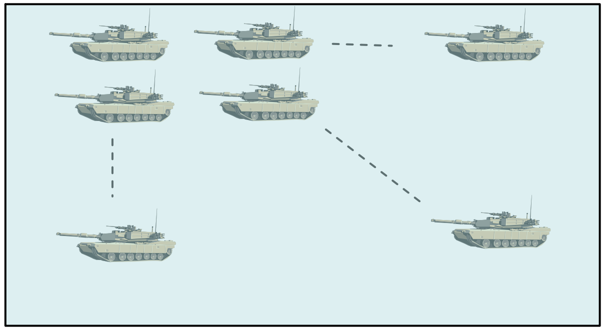
Definitions: Practical

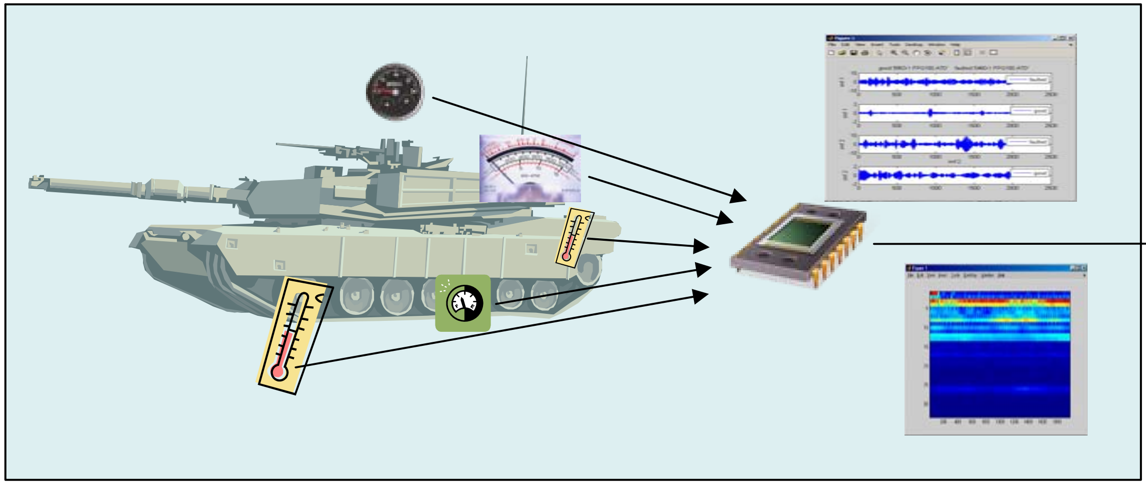
- **Reliability** -

Ao ?



- **Diagnostic** – measure of <u>current</u> health
- **Prognostic** -

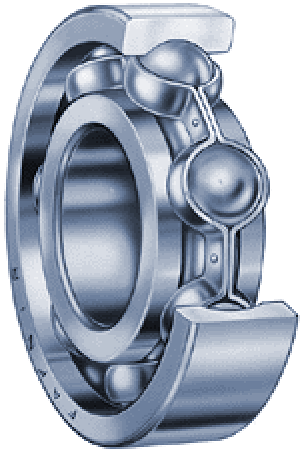
Ao ?



Remaining Useful Life….

P&D looks complex and expensive…

Motivation



Results of Helicopter Accident Survey

• During 1937-1981 - 32% of fatigue related accidents were caused damaged engine and transmission components.

•During 1990-1996 - structural failures was the 2nd most common cause of accidents.

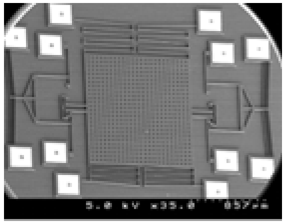
•During 1998-2004 - failure of the propulsion system was the primary cause of vehicle related accidents.

•During 1999 - 28 from a total of 192 accidents were directly due to mechanical failures - the gearbox drive train most common.

Earliest adopters have been NASA and Aviation

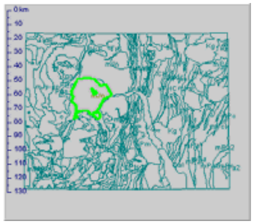
Overview of the Process for Developing Prognostics

- Transduction (sensing)

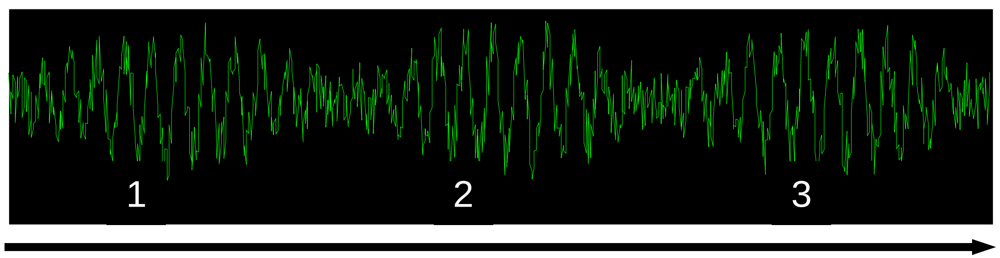


- Feature Extraction & Selection

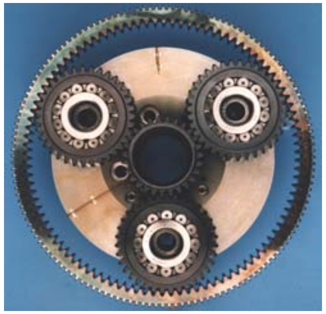
$$K = \frac{N\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left[\sum_{i=1}^{N}(x_i - \bar{x})^2\right]^2} \qquad NA4^* = \frac{N\sum_{i=1}^{N}(r_i - \bar{r})^4}{\left\{\frac{1}{M}\sum_{j=1}^{M}\left[\sum_{i=1}^{N}[(gr)_{ij} - (\overline{gr}_j)]^2\right]\right\}^2}$$



- Data Fusion (Classification/Reasoning)



Time

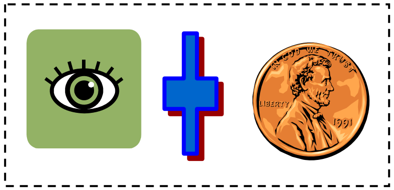


- Prognosis (Model-based)

Prognostics: Transduction

- Transduction is the means of measuring the physical characteristic to be used for the diagnostic
  - Physical dimensions
  - Vibration
  - Temperature
  - Humidity
  - Shock

Example: How long will this tire last?



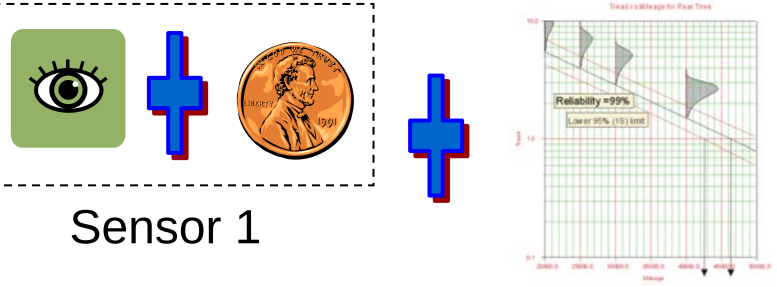
Sensor 1

Raw sensor data is only the start of the process

Prognostics: Feature Extraction

- Once we have obtained a signal from the transducer, applying math gets us a diagnostic

Example: How long will this tire last?



Sensor 1

Diagnostic 1

-Prior reliability work helps
-Our crude depth gauge and
Simple math tells us the tire should last
~30K miles

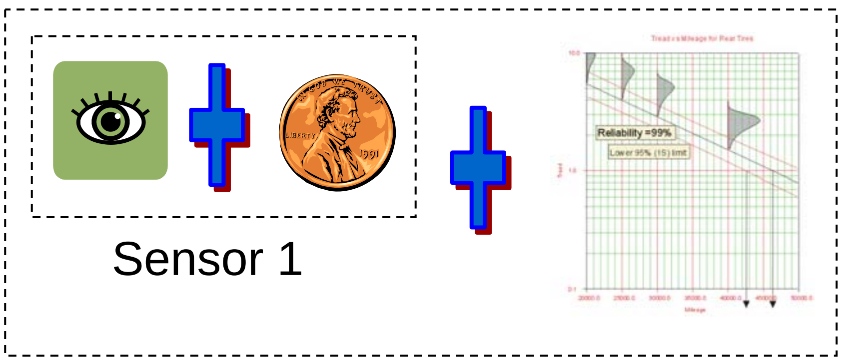
<u>(under very specific conditions)</u>

There are simple useful predictions that can be made.
The operative question is confidence level.

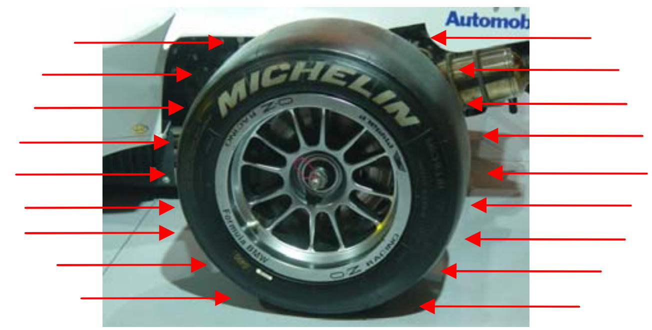
Prognostics: Feature Selection*

- Challenging

Example: **NO, really, how long will this tire last?**



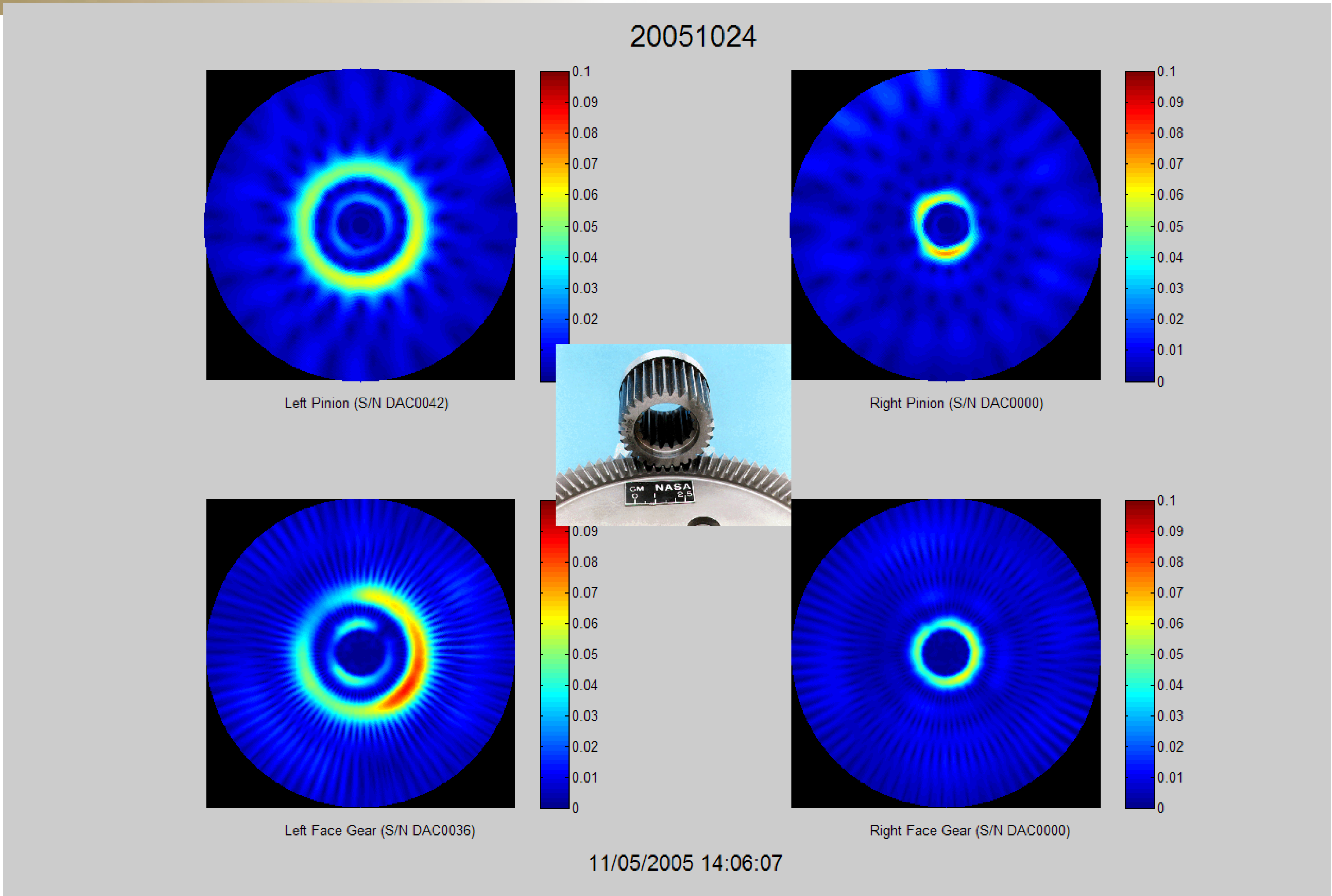
Diagnostic 1



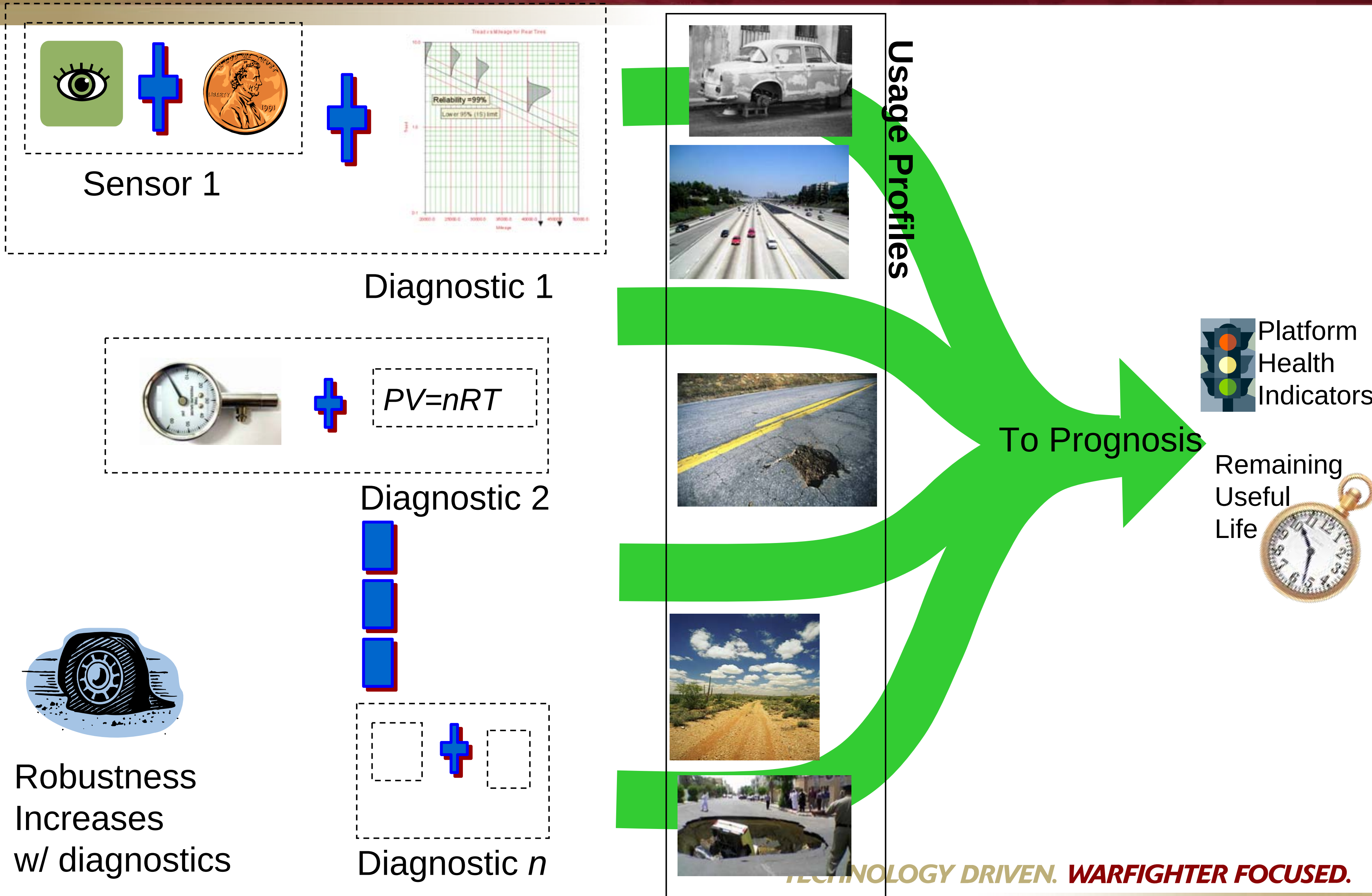
For a better RUL estimate we will need higher resolution measurements

Features represent a small portion of the data,
but a lot of data must be taken to create the features.

Development of new features: Stockwell Transform

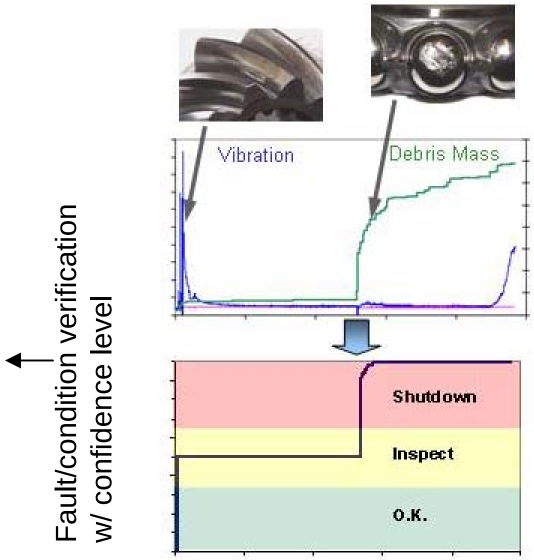


Prognostics: Data Fusion (Classification/Reasoning)

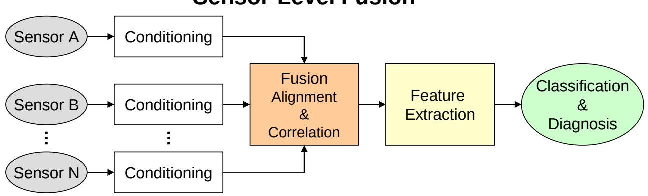


Prognostics: Data Fusion (Classification/Reasoning)

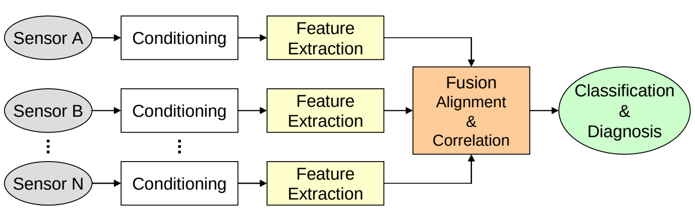
Fusion Level	Fusion Methods	Algorithms and Techniques
Sensor-Level and Feature-level	Pre-Processing	Kalman filter, Wavelet, STE Principal components analysis, Pruning Embedded modeling technique
Feature-Level (Component)	Classification	Neural networks, Fisher's Linear Discriminant, Singular-value-decomposition, min-max, cluster algorithms
Decision-Level (Platform)	Inference	Bayesian inference, Markov Chain Monte Carlo (MCMC), Dempster-Shafer method, Particle Swarm
Decision-Level (Platform)	Artificial Intelligence	Fuzzy logic, expert systems, Blend Heuristic methods (e.g., voting methods, consensus methods, and scoring methods)



Sensor-Level Fusion

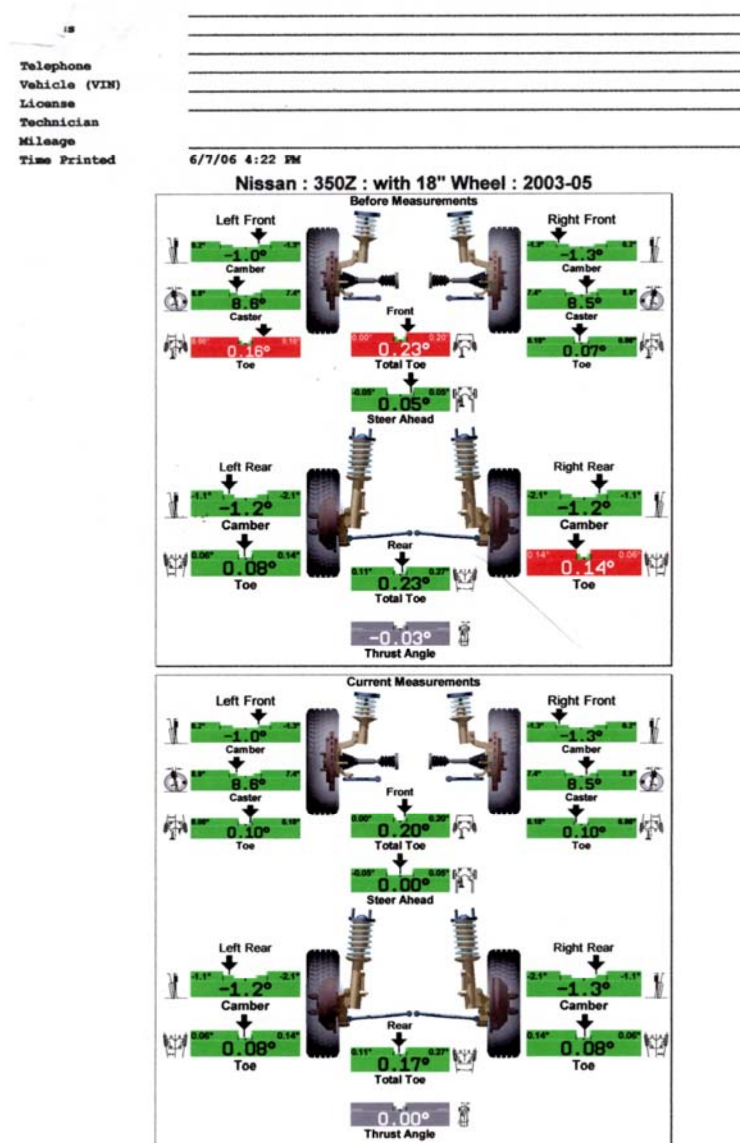


Feature-Level Fusion



Category	Sensor-Level Fusion	Fusion Method			
		Estimation	Classification	Inference	AI
Sensor Type Applicability	Commensurate	Commensurate	Commensurate or noncommensurate	Commensurate or noncommensurate	Commensurate or noncommensurate
Information Loss	No loss	Low	Medium	Potentially High	Potentially High
Performance Loss	No loss	Low	Medium	Potentially High	Potentially High
Communication Bandwidth	Large	Large	Medium	Small	Small
Computational Requirements	High	High	Medium	Medium	Medium
Processing Complexity	High	High	Medium	Low	Low
Reference/ Training Data Requirements	Low	Low	High	High	High

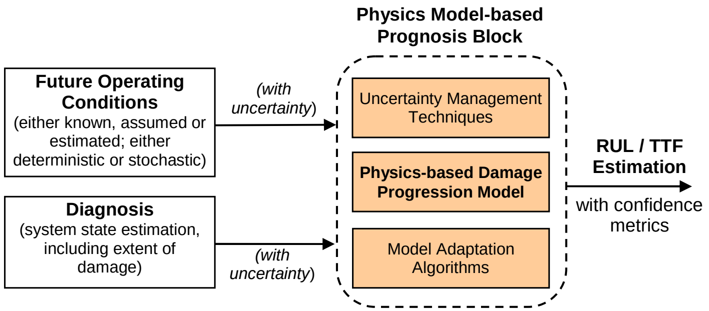
Classification: Practical example



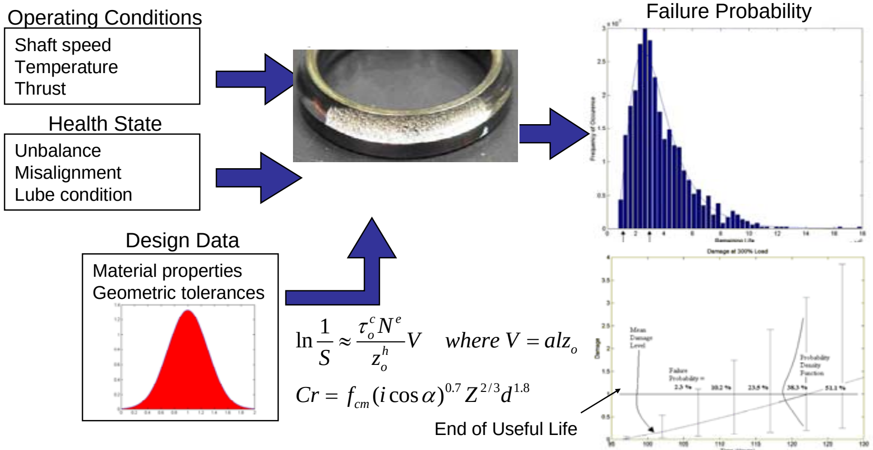
Prognostics: (Physical) Model-based Approach

Physics-based prognosis predicated on:

- Fault Initiation model (e.g. Lundberg-Palmgren)
- Fault propagation model (e.g. Kotzalas-Harris)
- Dynamic updates from on board monitoring

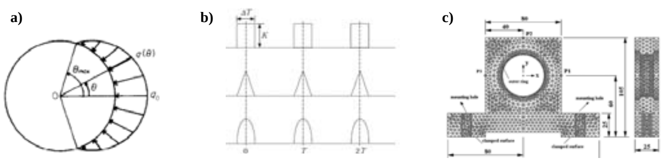


Spall Damage Progression Model



$$\ln\frac{1}{S} \approx \frac{\tau_o^c N^e}{z_o^h} V \quad \text{where } V = alz_o$$

$$Cr = f_{cm}(i\cos\alpha)^{0.7} Z^{2/3} d^{1.8}$$

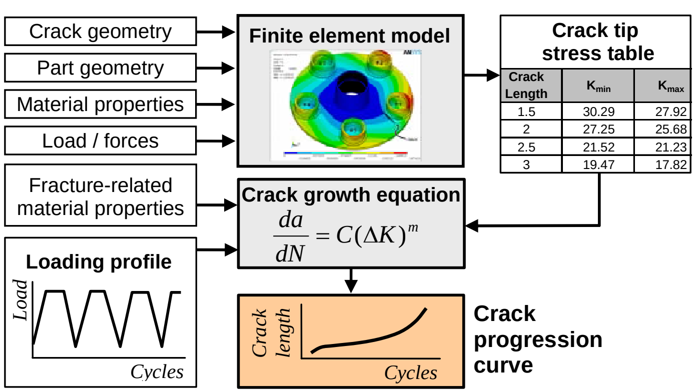


$$\frac{dSp}{dN} = C(W_{sp})^m$$

$$W_{sp} = (\sigma_{\max} + \tau_{avg})\sqrt{\pi Sp}$$

$$x(t) = x_f(t)\cdot x_q(t)\cdot x_{bs}(t) + x_s(t) + n(t)$$

Crack Damage Progression (modeled)



Crack tip stress table

Crack Length	K_{min}	K_{max}
1.5	30.29	27.92
2	27.25	25.68
2.5	21.52	21.23
3	19.47	17.82

Crack growth equation

$$\frac{da}{dN} = C(\Delta K)^m$$

Implications

- Data, Data, Data…

Complexity of fault propagation
X # of critical components (or desired fault coverage)
X # of assets

= data rates > 1MB/min per platform

  – Transport & storage periods may also require monitoring
  – Form factor for on-board data storage
  – Limits of comms architectures
    - Throughput
    - Security

- Enables/enhances condition based maintenance
  – P&D augmentations to platforms will lead to higher reliability and Ao
  – Current Reliability data expedites P&D development
  – Reduced lifecycle cost*
- Cost

  $ New sensors*
  $$ Monitoring systems
  $$ Data infrastructure
  $$ Algorithm Development -requires training data
  ¢ Computational (offboard) hardware
  ¢ Diagnostics (recoverable)

Commercial Sector:
-Privacy Issues
-Safety
-Insurance/liability
-Warranties

Path Forward

- Demonstrate prognostics on a ground platform
- Continue HUMS advancement (Health and Usage Monitoring Systems)
- Aviation work provides substantial benefit
  - Fault seeding & on-rig testing
  - Seeded faults - test stand

- Integration of data flow into AMCOM LCMC CBM enterprise architecture
- Differences in the commodity areas will require flexible adaptation of those technical approaches
  - Data acquisition
    - Hardware
    - Methods for obtaining in-situ data

- Current ROI challenges do not preclude a solution