PennState
Applied Research
Laboratory

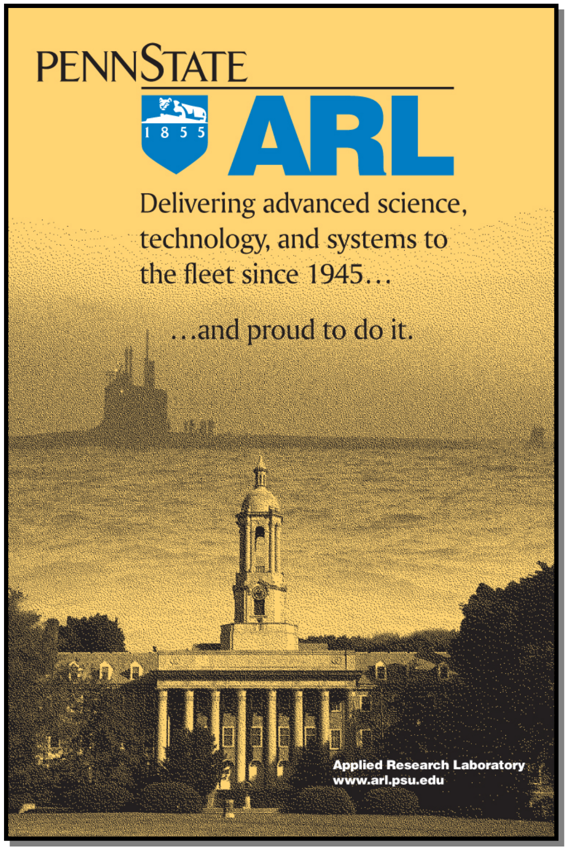
Driving Requirements For Prognostics - How Far In The Future Do We Need to Predict?

NIST Industry Forum: Monitoring, Diagnostics, and Prognostics for Manufacturing Operations

9 May 2018

Dr. Karl M. Reichard
Associate Research Professor
The Applied Research Laboratory
Embedded Systems Department Head
Graduate Program in Acoustics
kmr5@arl.psu.edu
814-863-7681

ARL is a Navy University Affiliated Research Center at the Pennsylvania State University



- **Established in 1945 by the Navy post WW II**
- **Technology Areas**
  - **Undersea Weapons**
  - **Undersea Vehicles/UUV's**
  - **Hydrodynamics and Structures**
  - **Acoustics & Quieting**
  - **Comms and Information**
  - **Power and Energy**
  - **Navigation**
  - **Materials/ Manufacturing**
- **Largest Interdisciplinary Research Unit at Penn State – 1140 faculty/engineers, staff, students**
- **Classified facilities and programs to SCI**
- **FY 17 Funding Expenditures - $220M +**
- **Designated an University Affiliated Research Center in 1996**

PSU/ARL Mission

- **Develop and transition technology solutions**
  - develop and demonstrate advanced S&T
  - mature technology TRL 3/4/5 to TRL6/7
  - transition technology to acquisition and current systems
  - design, deploy, and test new solutions
- **Cost savings for acquisition and lifecycle**
  - new technology solutions and open standards
  - proof of concept before commitment
  - design for manufacturing and affordability
  - cost / performance design trade tools
- **Education and Training**
  - filling pipeline of future engineers & scientists
  - providing tools / expertise for training forces
  - training manufacturers on new technology

PennState
Applied Research
Laboratory

How do we set thresholds and time horizons for predictions in diagnostics and prognostics?

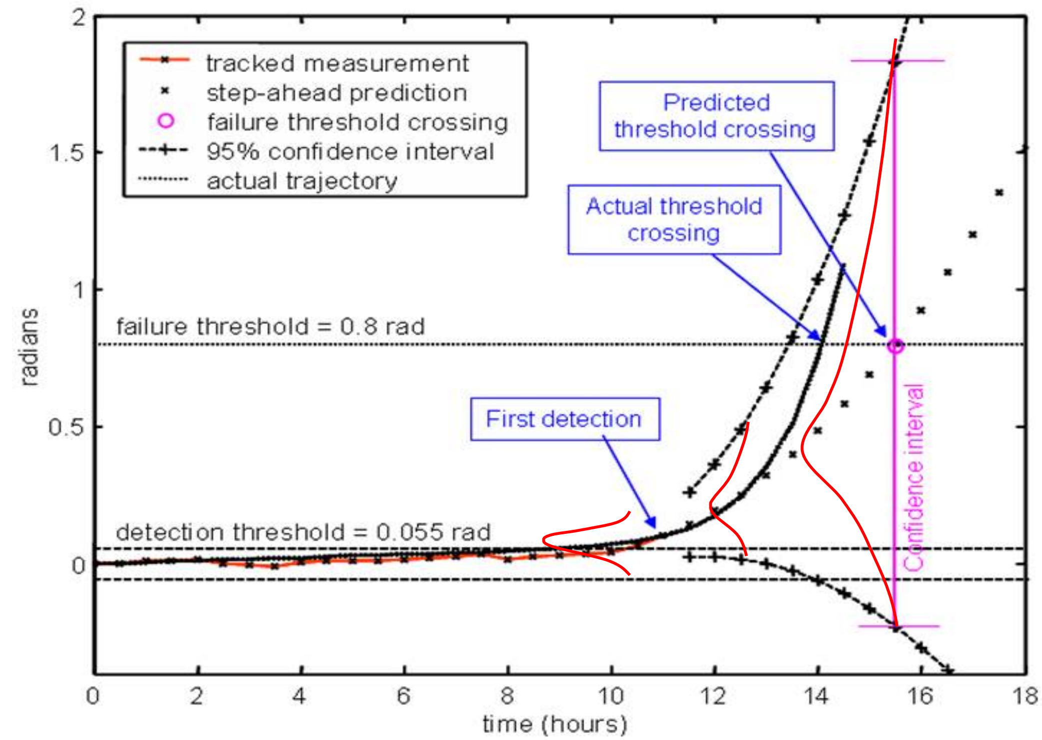
- What do we hope to achieve by predicting the failure, event, or degradation in performance?
- What's the time between detection and the event?
- What do we need to do once we know there is going to be a failure?
- Similar issues for vehicles, manufacturing systems, and other "assets."

PennState
Applied Research
Laboratory

Objective of Predictive/Prognostics Analytics

Reduce Prediction Uncertainty:

- Accurate remaining useful life (RUL) estimate **under variable and unknown future operating conditions**.
- Provide the **earliest predicted failure** indication relative to the maintenance planning/ scheduling needs.

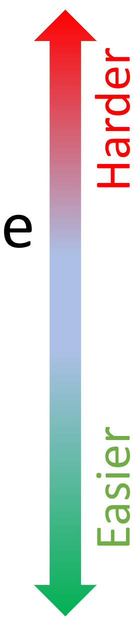


- **Isolate to a specific failure mode** for a specific component to enable the ability plan/schedule the appropriate maintenance before failure.

PennState Applied Research Laboratory

We are all familiar with making short and long term predictions. Consider health care:

- How long am I going to live?
- How much long term care insurance do I need?
- Should I choose the high or low deductible health insurance this year?
- Do I need to buy allergy medicine this week?
  - Am I planning to work outside or inside?
  - Are the oak trees going to bloom?
  - Am I planning to travel to PA, VA, TX, NM or AK?



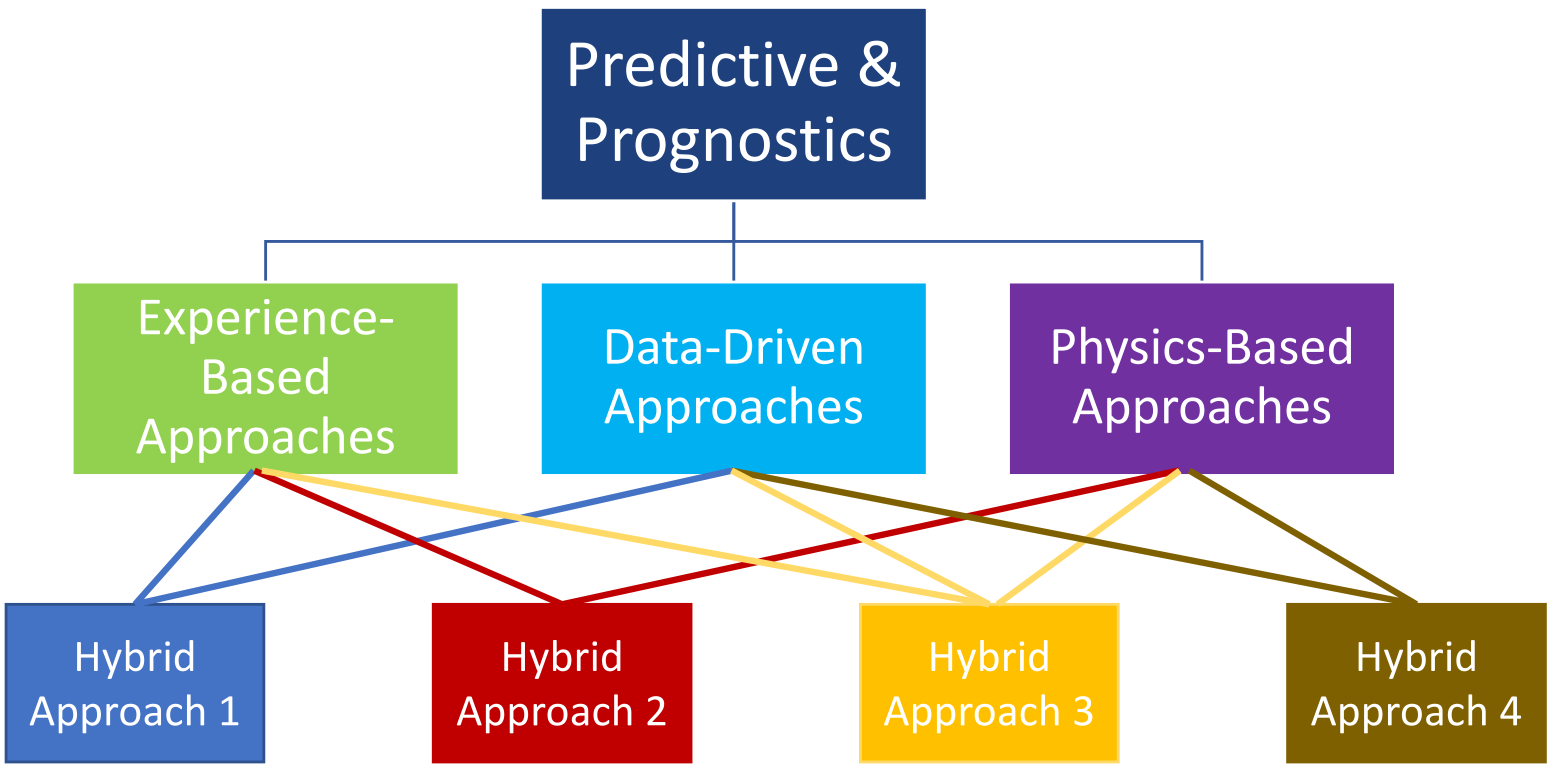
The shorter the prediction horizon, the less uncertainty in our prediction.

PennState Applied Research Laboratory

There are many different drivers for health monitoring and management – different applications have different requirements.

- **Safety** – early work in helicopter HUMS
- **Maintenance** – use HUMS to enable condition based maintenance (CBM)
- **Manning** – reduce manning through CBM and PHM
- **Life Cycle Cost** – reduce total life cycle cost through savings in maintenance, manning, and sustainment
- **Logistics** – extend savings through the enterprise by leveraging CBM and PHM across fleets of assets
- **Asset Capability Management** – manage asset health by matching mission requirements to capability
- **Autonomy and Automation** – enable autonomous and automated response to changing external and internal operating conditions

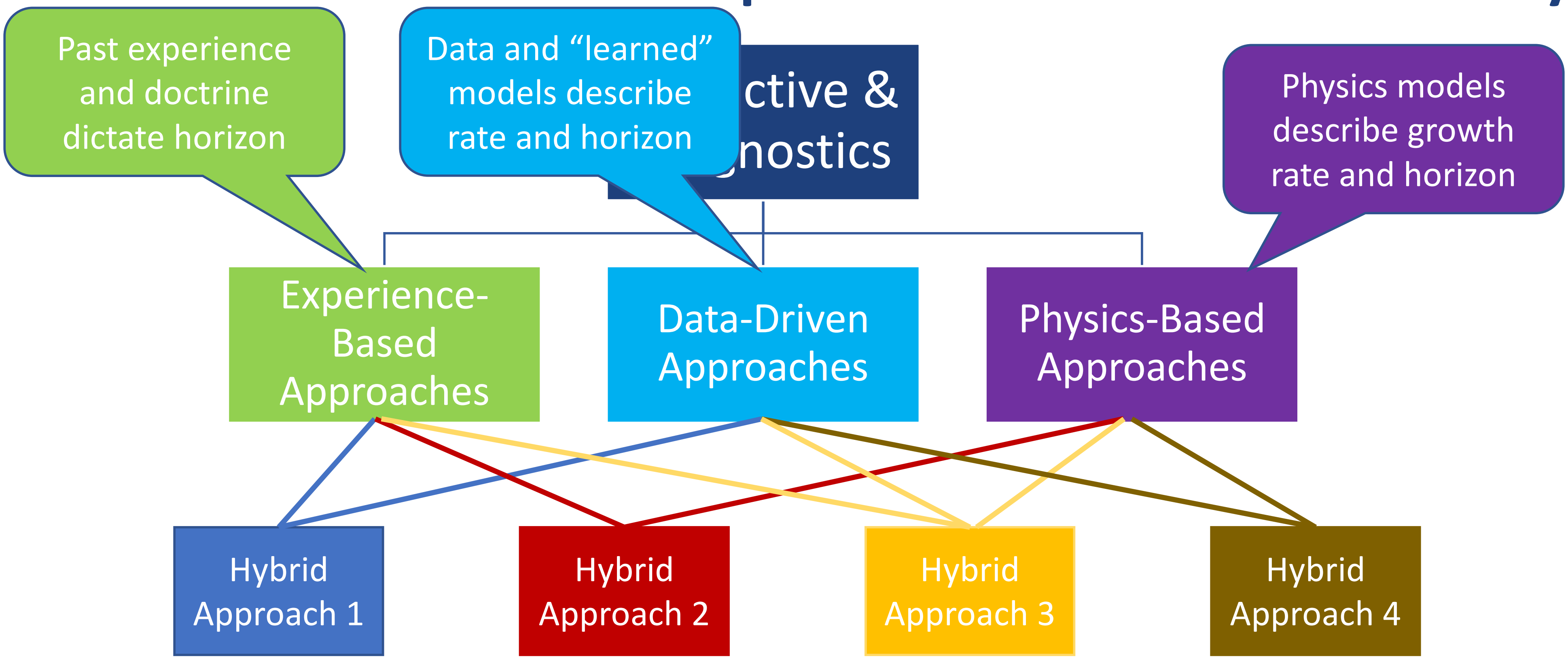
Different prognostics approaches derive their prediction thresholds and timelines differently



PennState Applied Research Laboratory

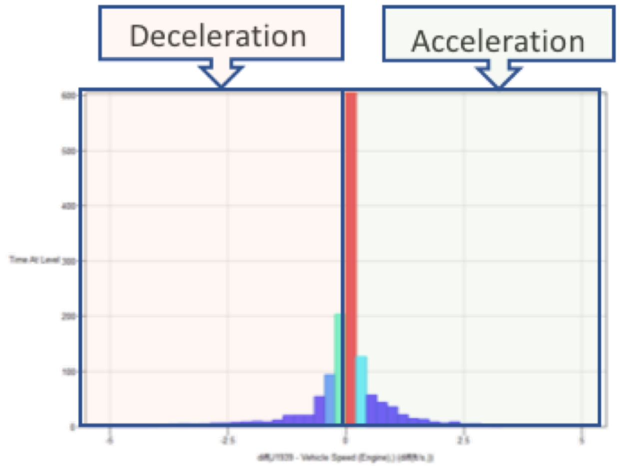
Reference: Linxia Liao and Felix Kottig, 'Review of Hybrid prognostics Approaches for Remaining Useful Life Prediction of Engineered Systems, and an Application to Battery Life Prediction', 2014 IEEE Transactions on Reliability, Vol.63, No.1, 1 March 2014

Different prognostics approaches derive their prediction timelines differently



Reference: Linxia Liao and Felix Kottig, 'Review of Hybrid prognostics Approaches for Remaining Useful Life Prediction of Engineered Systems, and an Application to Battery Life Prediction', 2014 IEEE Transactions on Reliability, Vol.63, No.1, 1 March 2014

Experience/Data driven PHM Example: Brake Wear RUL



High Break Wear Value → Low Break Wear Value | No Break Wear Value

BIN	Time in Bin
-5	1.173
-4	2.176
-3	13.81
-2	39.36
-1	78.19
0	752
1	108.6
2	45.5
3	6.067
4	0.169
5	0

Histogram Bins

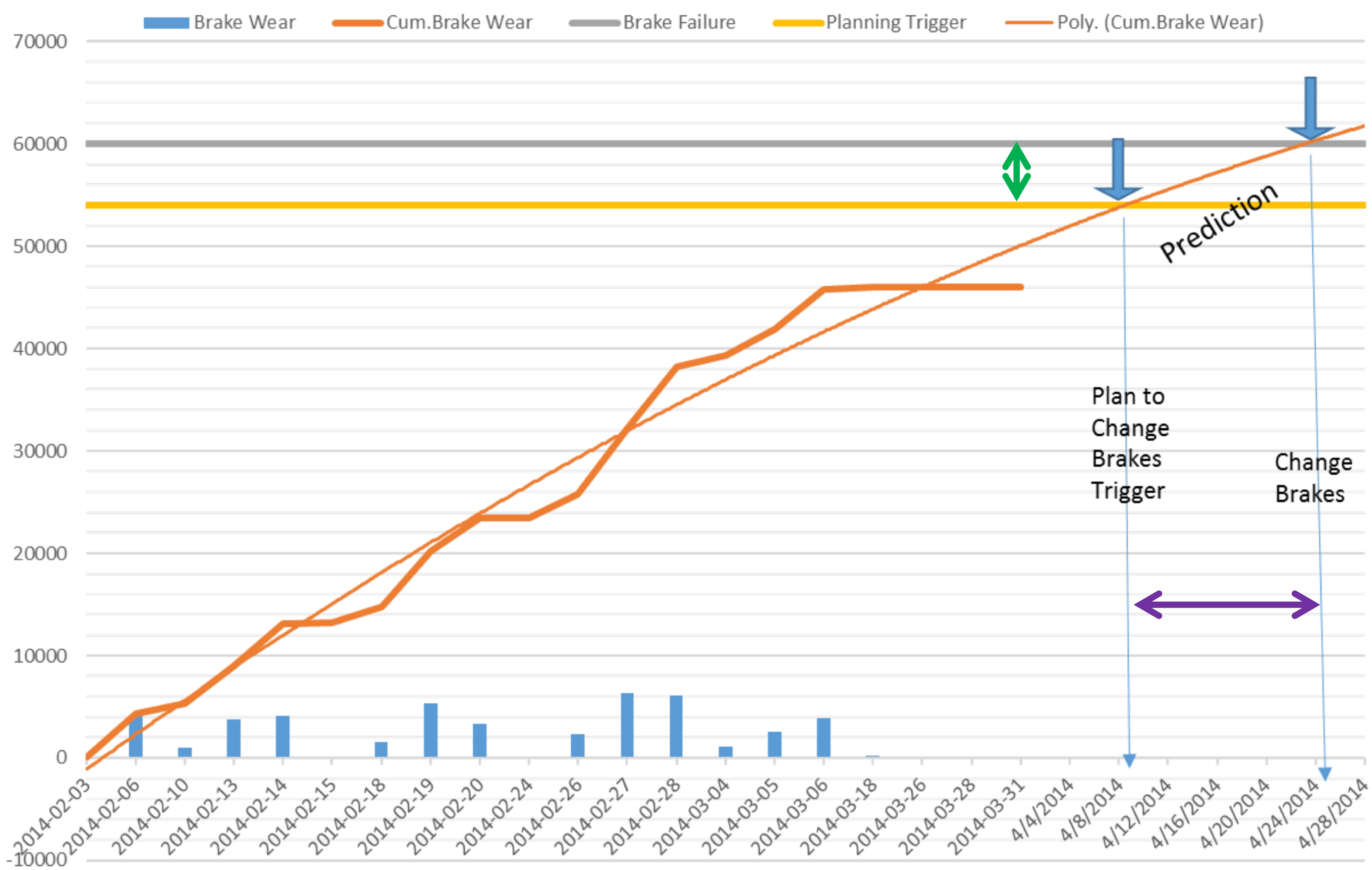
X High Brake Wear Value ↓ Low Brake Wear Value = Brake Wear Value of Run

$$\frac{\sum Brake\ Wear\ Value\ Per\ Run\ for\ Each\ Vehicle}{Brake\ Wear\ Value\ at\ Failure\ for\ Vehicle\ Type}$$

Vehicle	Family	Location	Date Since Last Break Change	Brake Wear Value
10TGJAM129S105740	LHS-A4	KANDAHAR AIR BASE, AFGHANISTAN, ABS	11/17/13	95%
10TGJAM189S105659	LHS-A4	KANDAHAR AIR BASE, AFGHANISTAN, ABS	12/01/13	94%
10TGJAM159S107272	LHS-A4	KANDAHAR AIR BASE, AFGHANISTAN, ABS	01/01/14	85%
10TGJAM189S103300	HEMTT-A4	KANDAHAR AIR BASE, AFGHANISTAN, ABS	05/16/14	50%
1FUJATCG58PZ87895	Line-Haul-A3	KANDAHAR AIR BASE, AFGHANISTAN, ABS	08/21/14	22%

PennState Applied Research Laboratory

Experience/Data driven **PHM Example: Brake Wear RUL**



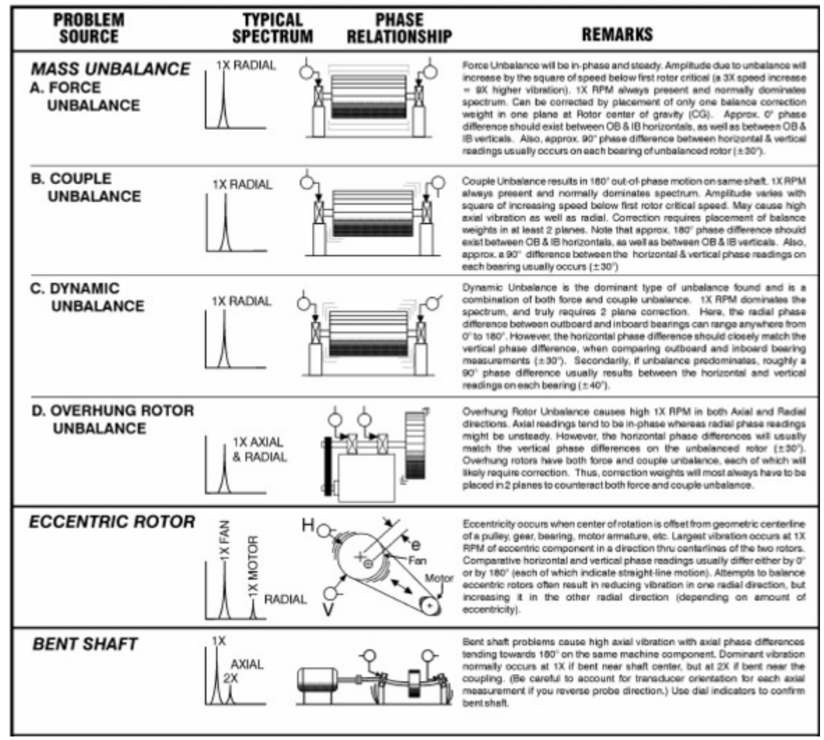
- Difference in thresholds are based on expert experience (safety factor, etc.).
- Minimum time between the plan to change brakes and the actual repair depends on the nature and duration of planned usage
- Actual time depends on parts and maintainer availability

PennState Applied Research Laboratory

Physics-based Example – Vibration monitoring

- The physical relationships between machinery component (i.e. bearings, gears, shafts, etc.) faults and vibration measurements are well understood.
- In addition, it is also well understood what vibration frequencies are generated for basic imbalance, misalignment conditions that lead to excessive degradation.

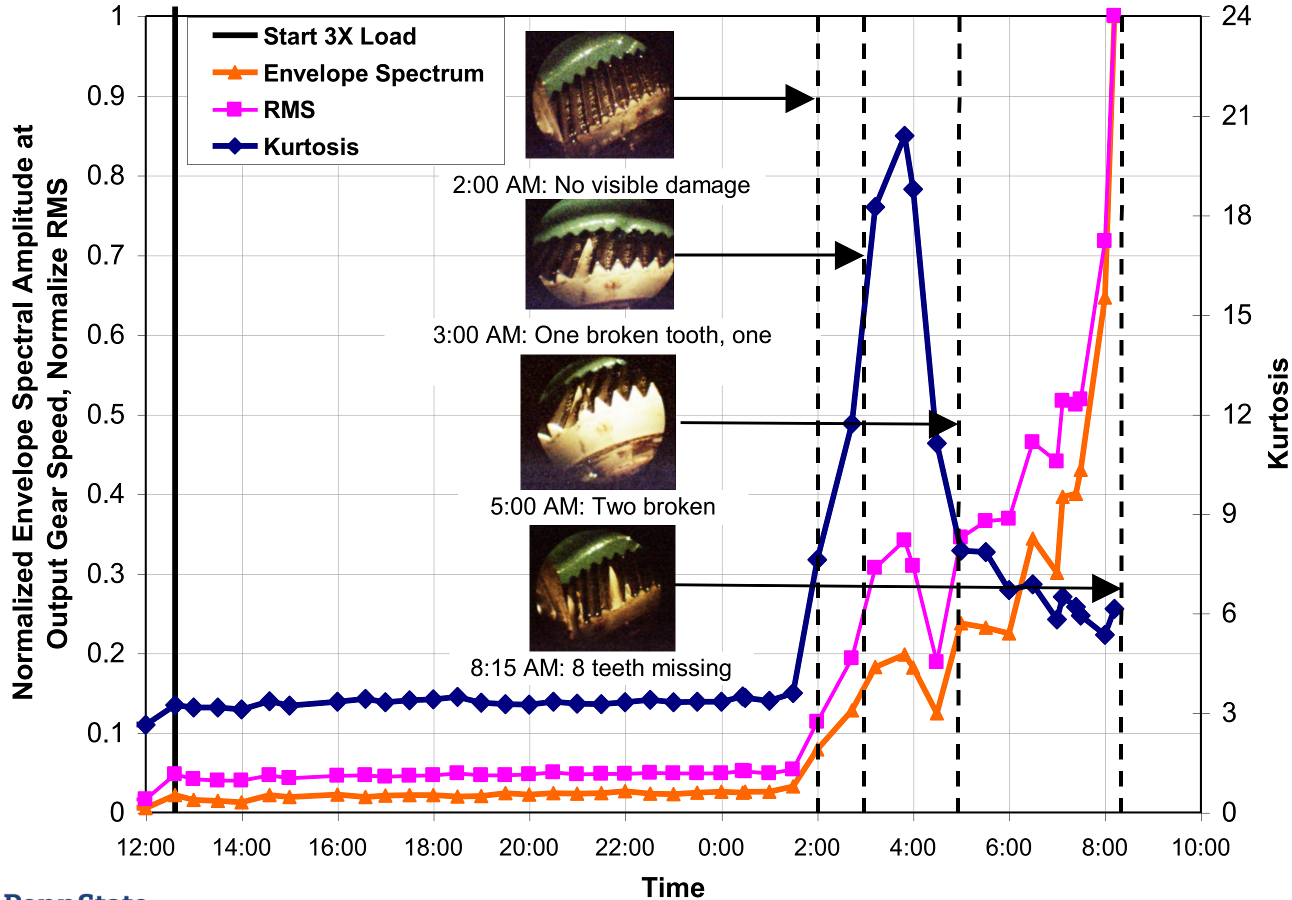
Vibration Control Chart



PROBLEM SOURCE	TYPICAL SPECTRUM	PHASE RELATIONSHIP	REMARKS
MASS UNBALANCE A. FORCE UNBALANCE	1X RADIAL		Force Unbalance will be in-phase and steady. Amplitude due to unbalance will increase by the square of speed below first rotor critical (a 3X speed increase = 9X higher vibration). 1X RPM always present and normally dominates spectrum. Can be corrected by placement of only one balance correction weight in one plane at Rotor center of gravity (CG). Approx. 0° phase difference should exist between OB & IB horizontals, as well as between OB & IB verticals. Also, approx. 90° phase difference between horizontal & vertical readings usually occurs on each bearing of unbalanced rotor (±30°).
B. COUPLE UNBALANCE	1X RADIAL		Couple Unbalance results in 180° out-of-phase motion on same shaft. 1X RPM always present and normally dominates spectrum. Amplitude varies with square of increasing speed below first rotor critical speed. May cause high axial vibration as well as radial. Correction requires placement of balance weights in at least 2 planes. Note that approx. 180° phase difference should exist between OB & IB horizontals, as well as between OB & IB verticals. Also, approx. a 90° difference between the horizontal & vertical phase readings on each bearing usually occurs (±30°)
C. DYNAMIC UNBALANCE	1X RADIAL		Dynamic Unbalance is the dominant type of unbalance found and is a combination of both force and couple unbalance. 1X RPM dominates the spectrum, and truly requires 2 plane correction. Here, the radial phase difference between outboard and inboard bearings can range anywhere from 0° to 180°. However, the horizontal phase difference should closely match the vertical phase difference, when comparing outboard and inboard bearing measurements (±30°). Secondarily, if unbalance predominates, roughly a 90° phase difference usually results between the horizontal and vertical readings on each bearing (±40°).
D. OVERHUNG ROTOR UNBALANCE	1X AXIAL & RADIAL		Overhung Rotor Unbalance causes high 1X RPM in both Axial and Radial directions. Axial readings tend to be in-phase whereas radial phase readings might be unsteady. However, the horizontal phase differences will usually match the vertical phase differences on the unbalanced rotor (±30°). Overhung rotors have both force and couple unbalance, each of which will likely require correction. Thus, correction weights will most always have to be placed in 2 planes to counteract both force and couple unbalance.
ECCENTRIC ROTOR	1X FAN 1X MOTOR RADIAL	H V e Fan Motor	Eccentricity occurs when center of rotation is offset from geometric centerline of a pulley, gear, bearing, motor armature, etc. Largest vibration occurs at 1X RPM of eccentric component in a direction thru centerlines of the two rotors. Comparative horizontal and vertical phase readings usually differ either by 0° or by 180° (each of which indicate straight-line motion). Attempts to balance eccentric rotors often result in reducing vibration in one radial direction, but increasing it in the other radial direction (depending on amount of eccentricity).
BENT SHAFT	1X AXIAL 2X		Bent shaft problems cause high axial vibration with axial phase differences tending towards 180° on the same machine component. Dominant vibration normally occurs at 1X if bent near shaft center, but at 2X if bent near the coupling. (Be careful to account for transducer orientation for each axial measurement if you reverse probe direction.) Use dial indicators to confirm bent shaft.

PennState Applied Research Laboratory

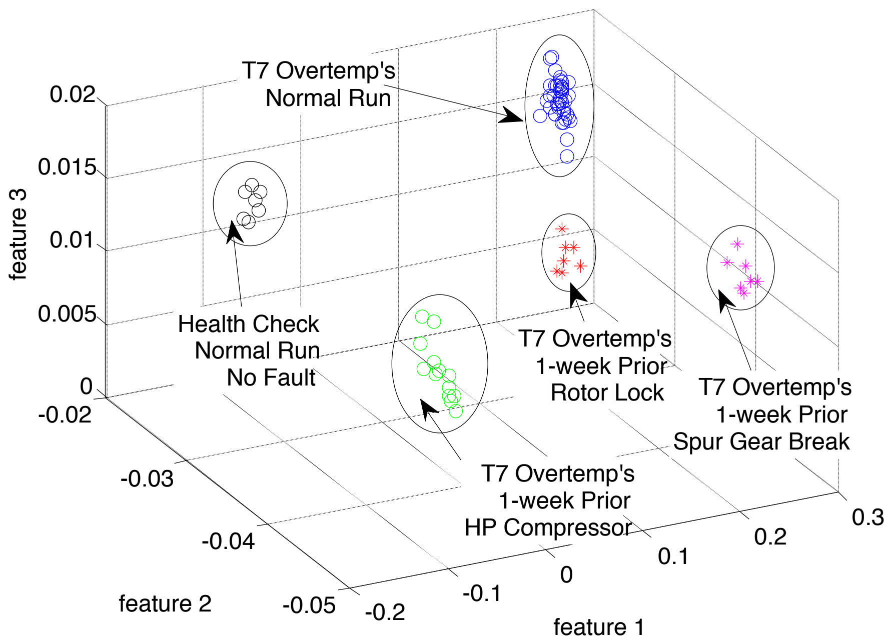
Physics-Based Example: Vibration Analysis



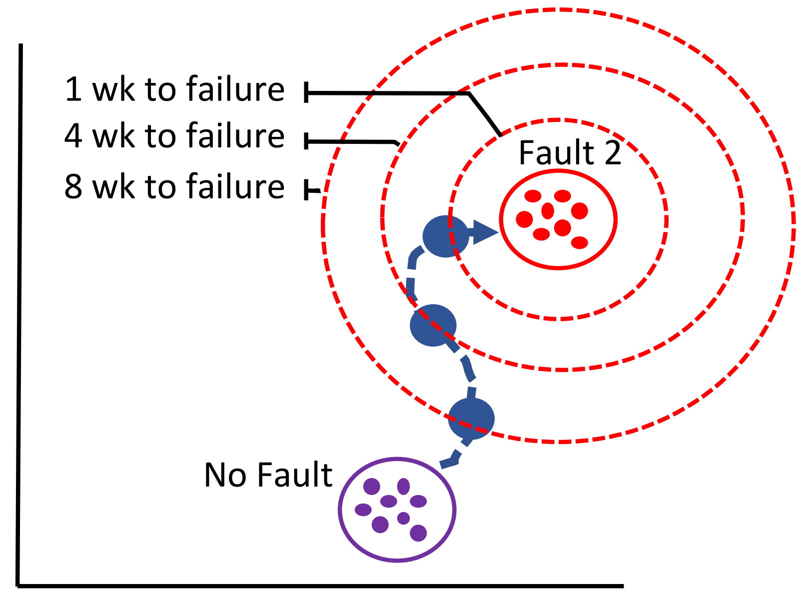
Growth rate based on physical model. Time horizon based on time to repair, logistics delays, manufacturing delays,

PennState Applied Research Laboratory

Data Analytics-based Prognostics: Turbine Engine Data



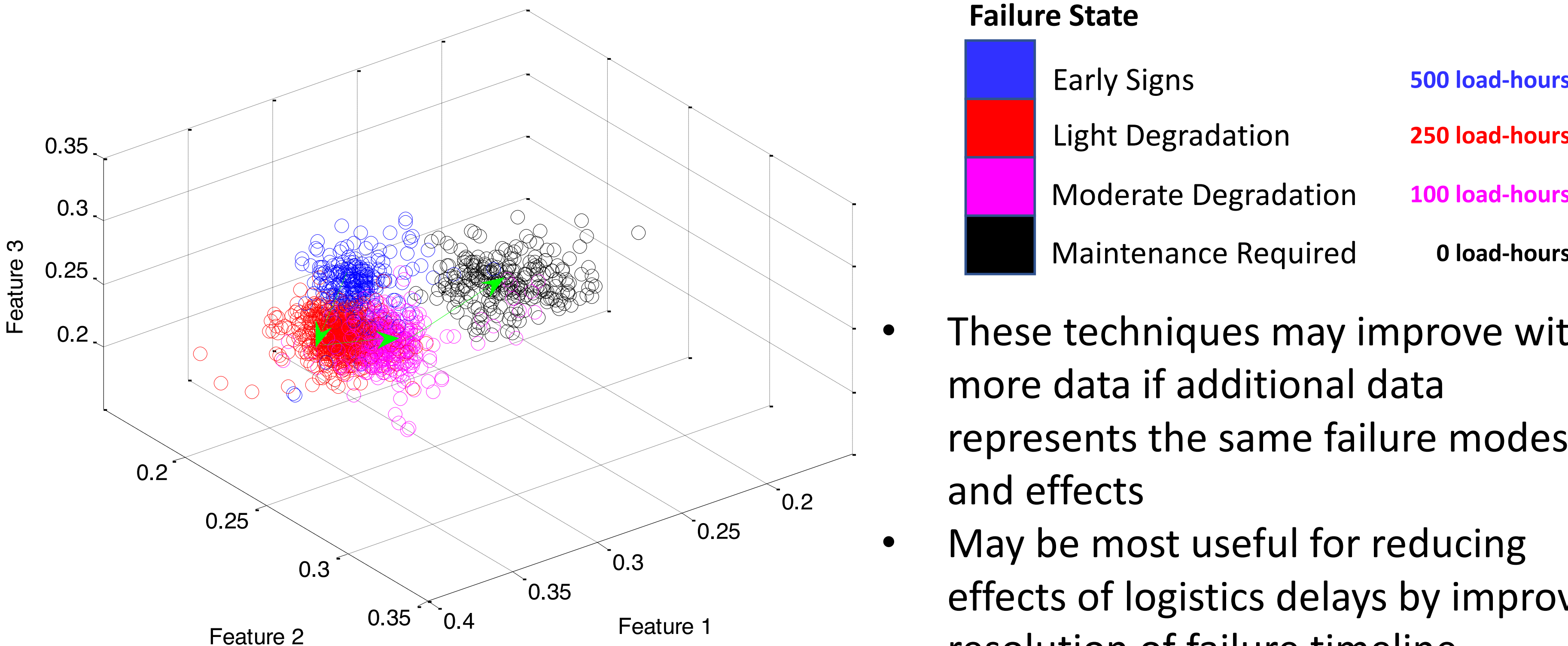
Classify engine data behavior based on operational parameters and maintenance records across "fleet"



Predict fault by understanding data migration from no fault condition to one failure mode

PennState Applied Research Laboratory

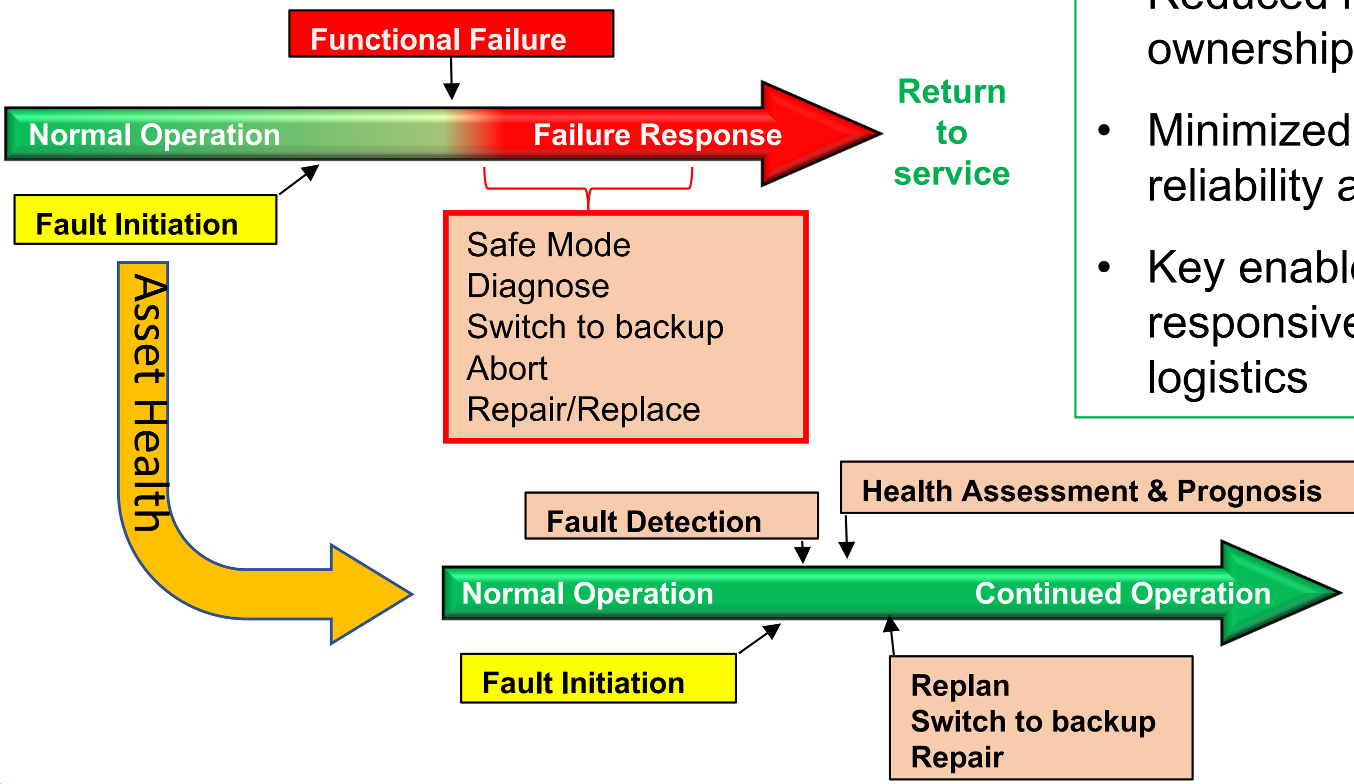
Data Analytics-based Prognostics: Diesel Engine Data



- These techniques may improve with more data if additional data represents the same failure modes and effects
- May be most useful for reducing effects of logistics delays by improving resolution of failure timeline – preemptive logistics.

PennState Applied Research Laboratory

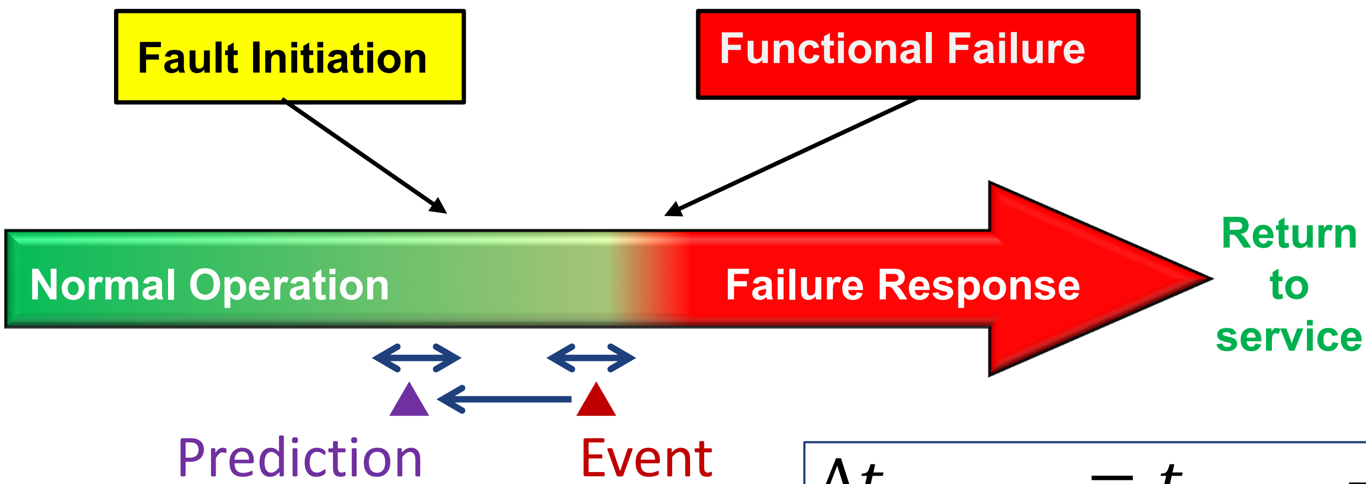
Let's look at a typical usage timeline for an asset:



- Reduced manning and total ownership cost
- Minimized down time and improved reliability and availability
- Key enabler for operationally responsive space and autonomic logistics

PennState Applied Research Laboratory

We need to predict failure or future state with enough time to take the necessary action



$$\Delta t_{Horizon} = t_{Event} - t_{Predict}$$

- What are we trying to predict?
- How much advanced knowledge do we need of the event or change in system state?

PennState Applied Research Laboratory

We need to look at what contributes to time horizon and threshold requirements

- Fault growth rate – function of planned/actual use <u>and</u> health (nonlinear effect)

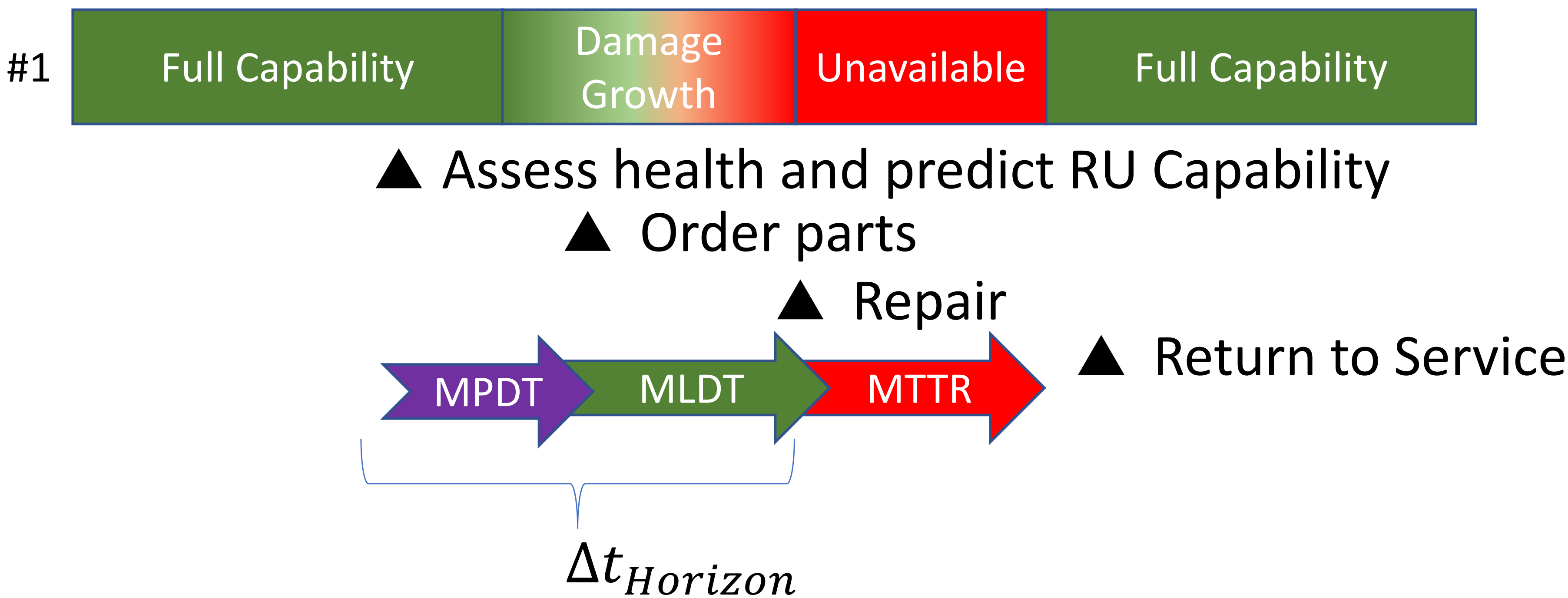
- Mean Time to Repair
  - Mean repair time
  - Personnel/facility availability
- Mean Logistics Delay Time
  - Time to order materials
  - Time to manufacture parts
  - Time to ship/deliver parts

- Mean Prognostic Delay Time
  - Time to collect data
  - Time to compute health assessment
  - Time to generate health prediction
- Mean Reconfiguration Delay Time
  - Time to replan
  - Time to retask/reschedule assets
  - Time to reconfigure system(s)

PennState
Applied Research
Laboratory

Time Horizon Calculation

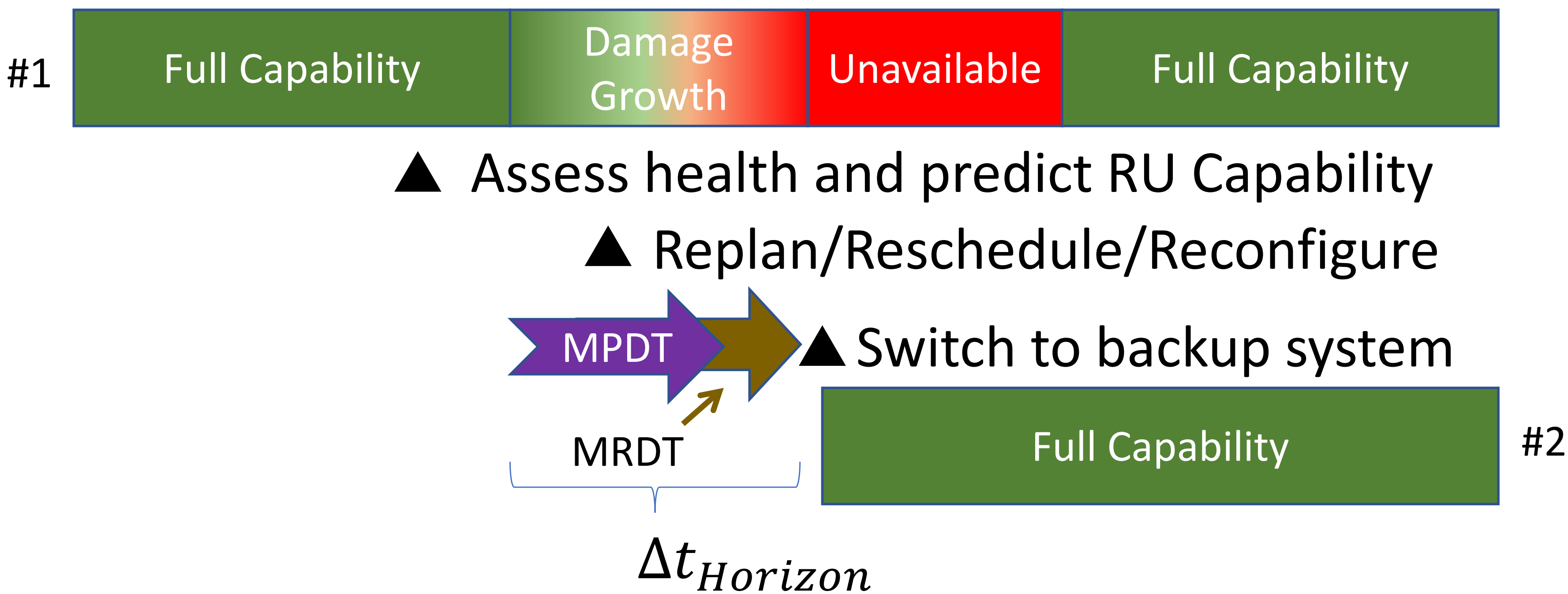
Use Case #1 – No redundancy



PennState Applied Research Laboratory

Time Horizon Calculation

Use Case #2 – Redundant or Backup Systems



Closing Thoughts

- We can reduce uncertainty in health predictions by reducing the prediction time horizon
- The options to respond to degraded health or performance affect how far ahead we need to predict system health and capability – response time drives the prediction horizon
- Approaches to PHM (embedded/on-platform versus cloud-based/analytics-based) influence responsiveness of the PHM system and therefore can also drive time horizon requirements