

# Introduction to Prognostics

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# Outline

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- Prognostics Overview
  - What is Prognostics?
  - How does Prognostics fit into “PHM”?
  - Types of Prognostic algorithms
- Trends, Remaining Useful Life, & Uncertainty
  - What does a prognostic algorithm tell you?
  - How do you manage thresholds?
  - How does uncertainty screw everything up?
- Prognostics Methods
  - Data-Driven Models
  - Physics-Based Models
  - Hybrid Approaches
- Current Challenges in Prognostics
- Q&A



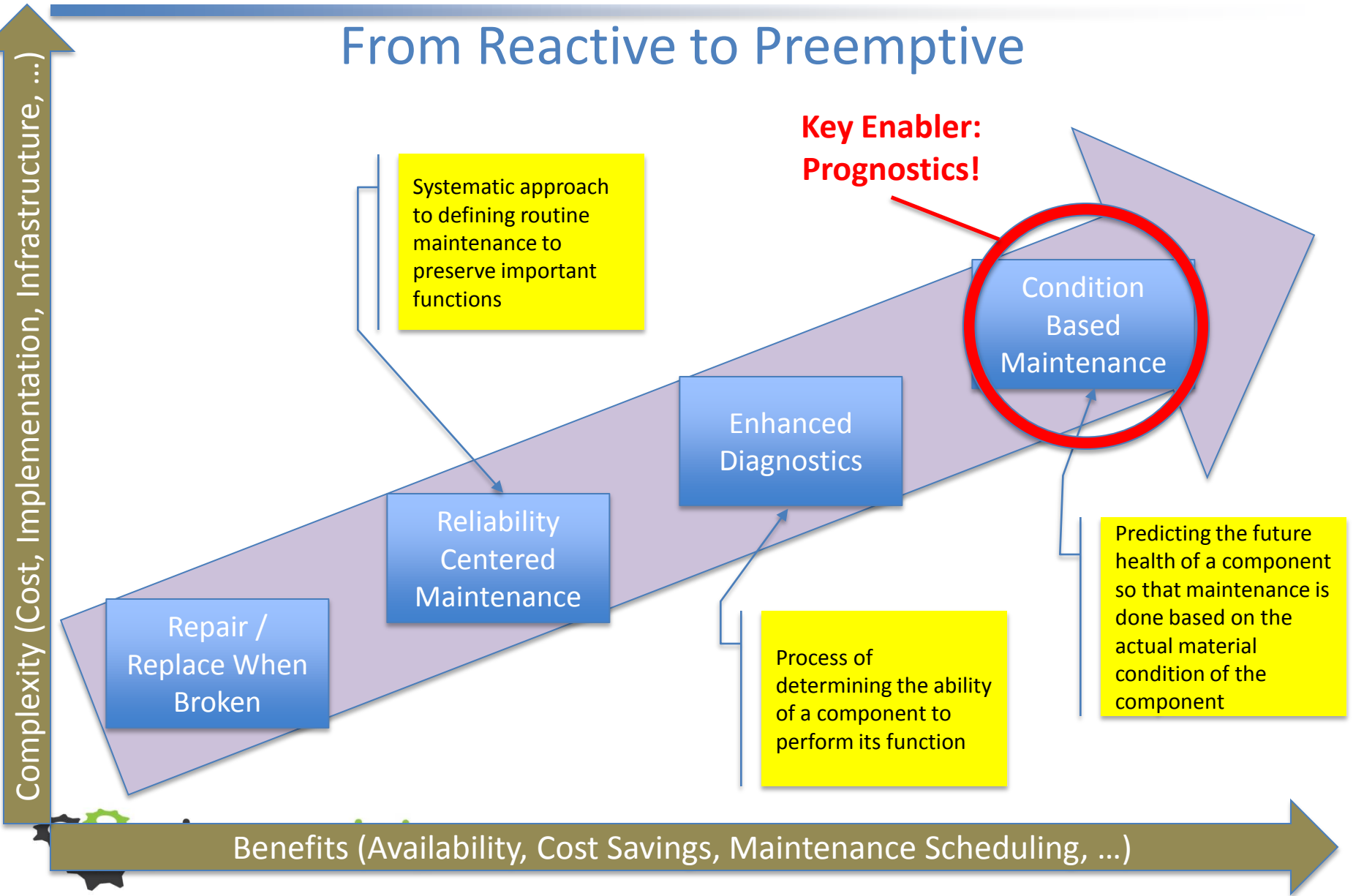
# Prognostics Overview

*“It’s tough to make predictions,  
especially about the future.”*

Yogi Berra

# Evolution of Maintenance Practices

From Reactive to Preemptive





# Prognostics & Health Management

## Putting the "P" in "PHM"

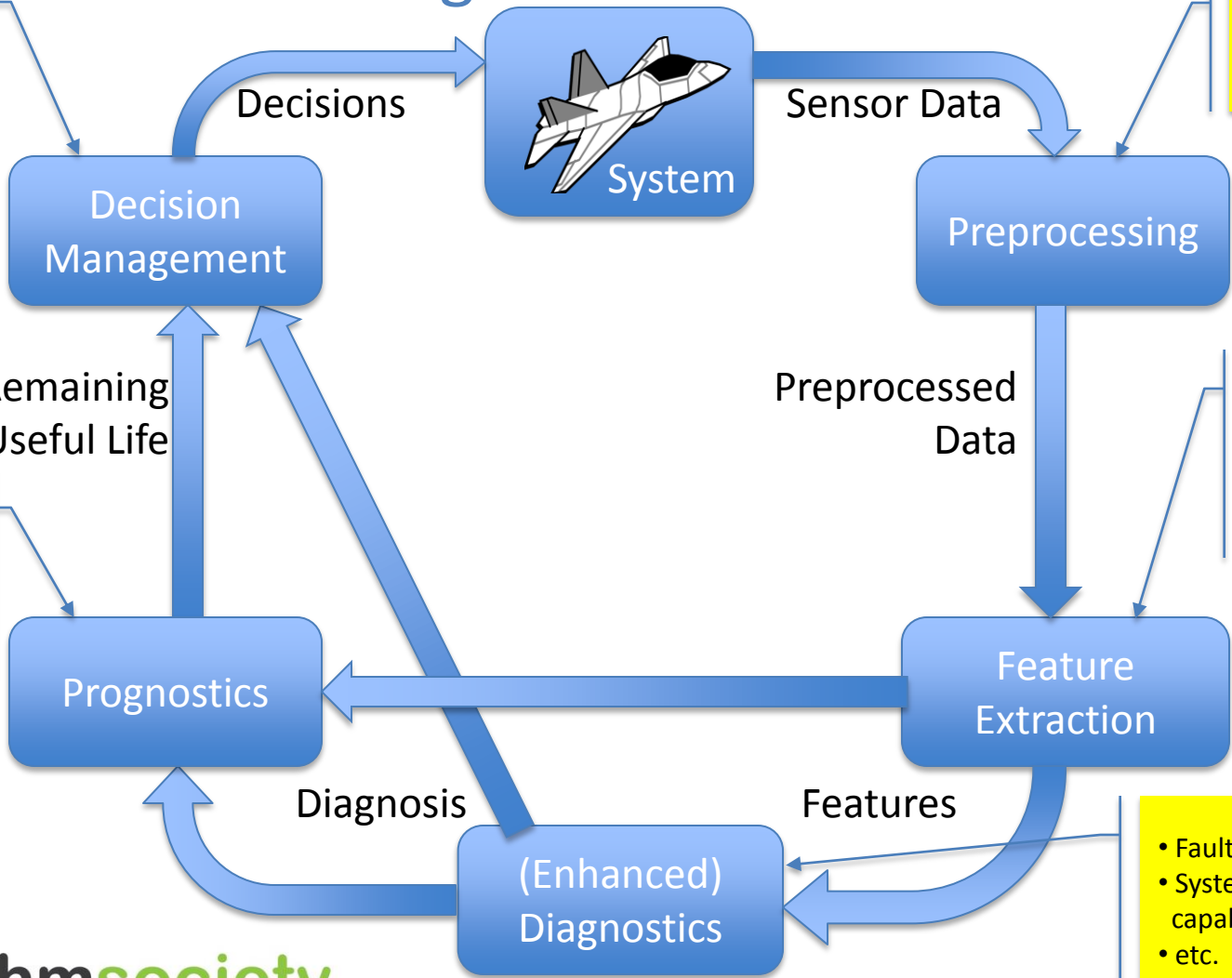
- Maintenance planning
- Mission planning
- etc.

- De-noising
- Filtering
- etc.

- Future capabilities
- Component RUL
- etc.

- Signal statistics
- Estimated parameters
- etc.

- Fault status
- System capabilities
- etc.



# Definitions

## So what is “Prognostics” anyway?

- prog·nos·tic
  - M-W.com – “Something that foretells”
  - PHM Community – “Estimation of the *Remaining Useful Life* of a component”
- Remaining Useful Life (RUL) – The amount of time a component can be expected to continue operating within its given specifications. *Not necessarily to failure!*
  - Dependent on future operating conditions (input commands, environment, and loads)



# Some Different Perspectives

I.e., who cares?

## Maintainers

- Scheduling Mx
- Opportunistic Mx
- System Uptime
- Min. unnecessary Mx
- Training

## Logisticians

- Spares Positioning
- Reduced Spares Count
- Logistics Footprint

## Engineers

- Requirements Satisfaction
- Improved Capabilities for Future Programs
- Robustness

## Safety

- Avoid Catastrophic Failures
- Min. impact to other (healthy) systems

## Mission Planners

- Mission Capability
- Mission Assignment

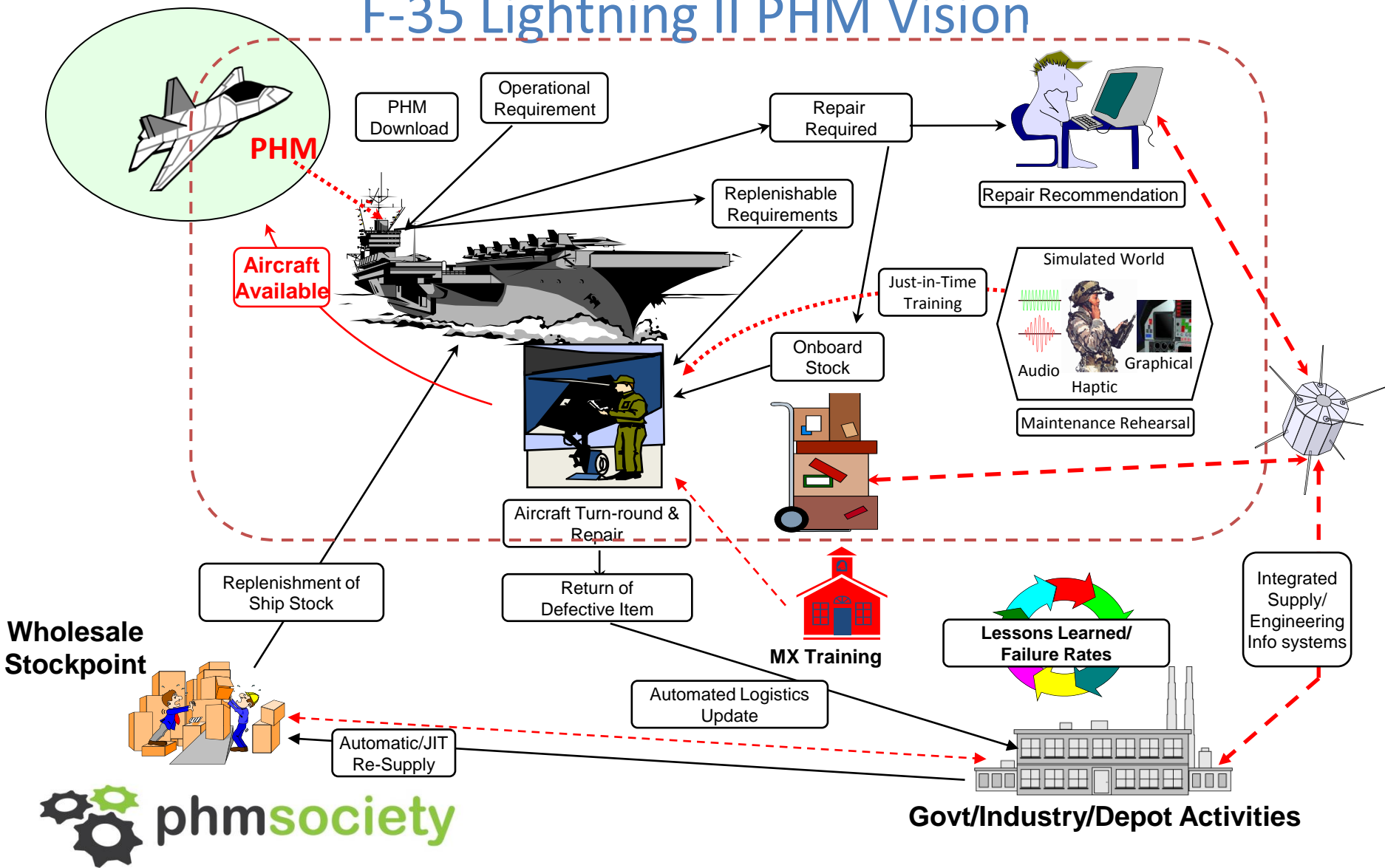
## Program Mgmt

- Meeting customer expectations
- Proposals

*Not Just for Maintenance!*

# An Example PHM System

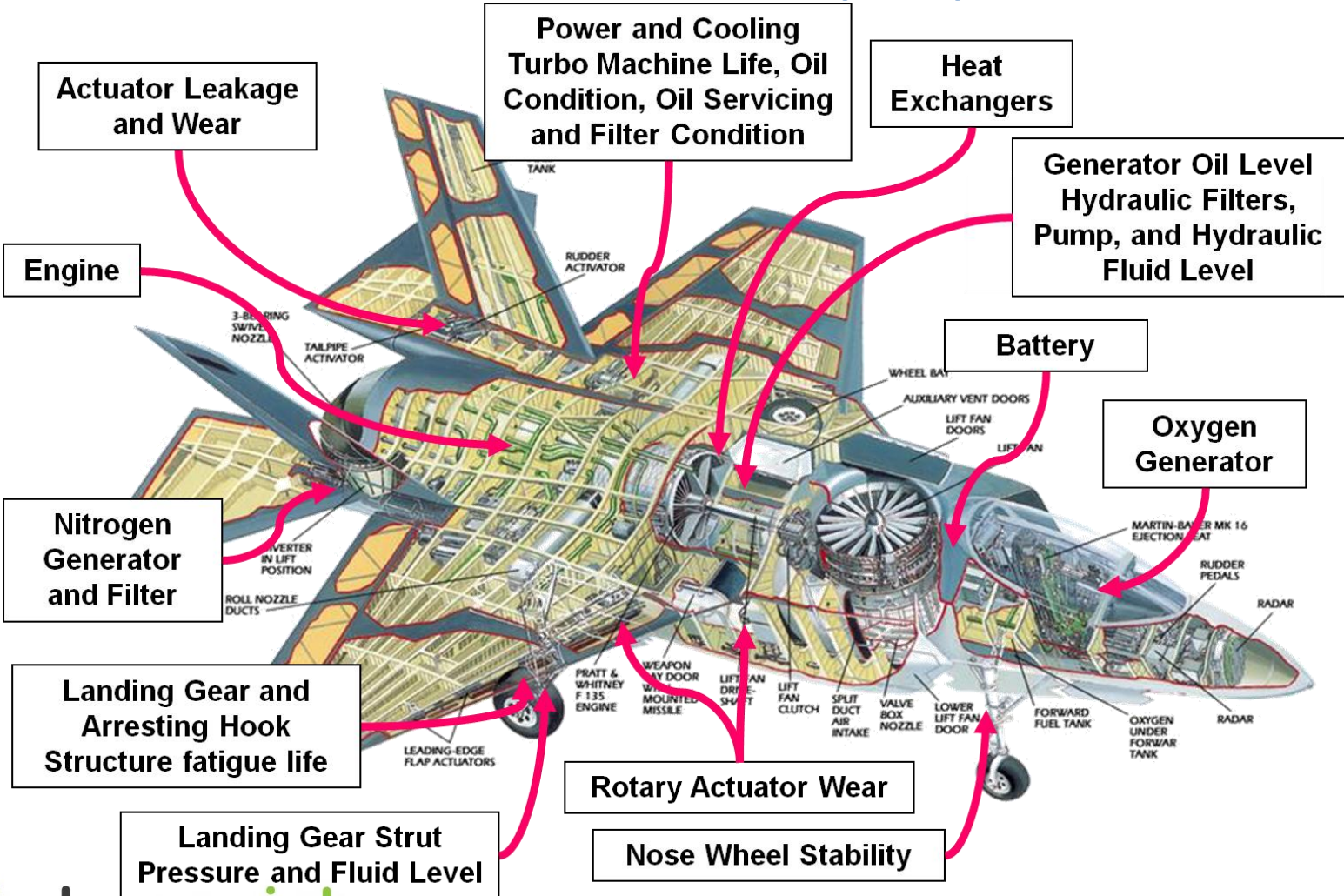
## F-35 Lightning II PHM Vision





# F-35 Prognostic Candidates

(Some of them, anyway)





# Prognostic Algorithm Categories

- **Type I: Reliability Data-based**
  - Use population based statistical model
  - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of a typical component under nominal usage conditions.
  - Ex: Weibull Analysis
- **Type II: Stress-based**
  - Use population based fault growth model – learned from accumulated knowledge
  - These methods also consider the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions.
  - Ex: Proportional Hazards Model
- **Type III: Condition-based**
  - Individual component based data-driven model
  - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions.
  - Ex: Cumulative Damage Model, Filtering and State Estimation



# Trends, RUL, & Uncertainty

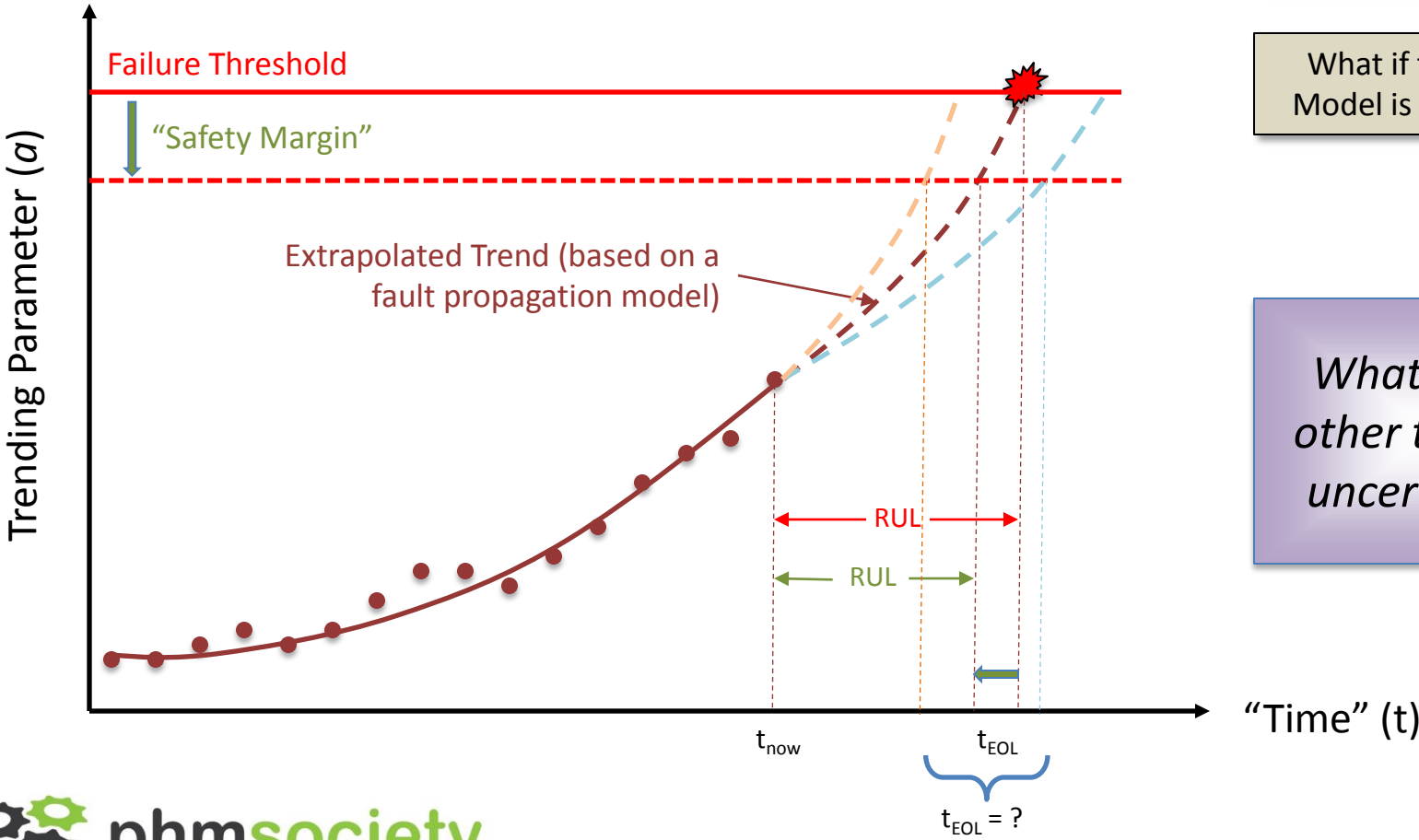
*“In theory there is no difference  
between theory and practice. In  
practice, there is.”*

*Yogi Berra*



# Trends and Thresholds

First, the basics ...



How much do you trust the Threshold?

What if the Fault Model is "wrong"?

*What about other types of uncertainty?*



# Types of Uncertainties

You just had to go and make things difficult!

- Model uncertainties – Epistemic
  - Numerical errors
  - Unmodeled phenomenon
  - System model and Fault propagation model
- Input uncertainties – Aleatoric
  - Initial state (damage) estimate
  - Manufacturing variability
- Measurement uncertainties – Prejudicial
  - Sensor noise
  - Sensor coverage
  - Loss of information during preprocessing
  - Approximations and simplifications
- Operating environment uncertainties
  - Unforeseen future loads / environment
  - Variability in the usage history data

Systematic uncertainties due to things we could know in principle, but don't in practice.

Statistical uncertainties that may change every time the system is run.

Unknown uncertainties due to the way data is collected or processed.

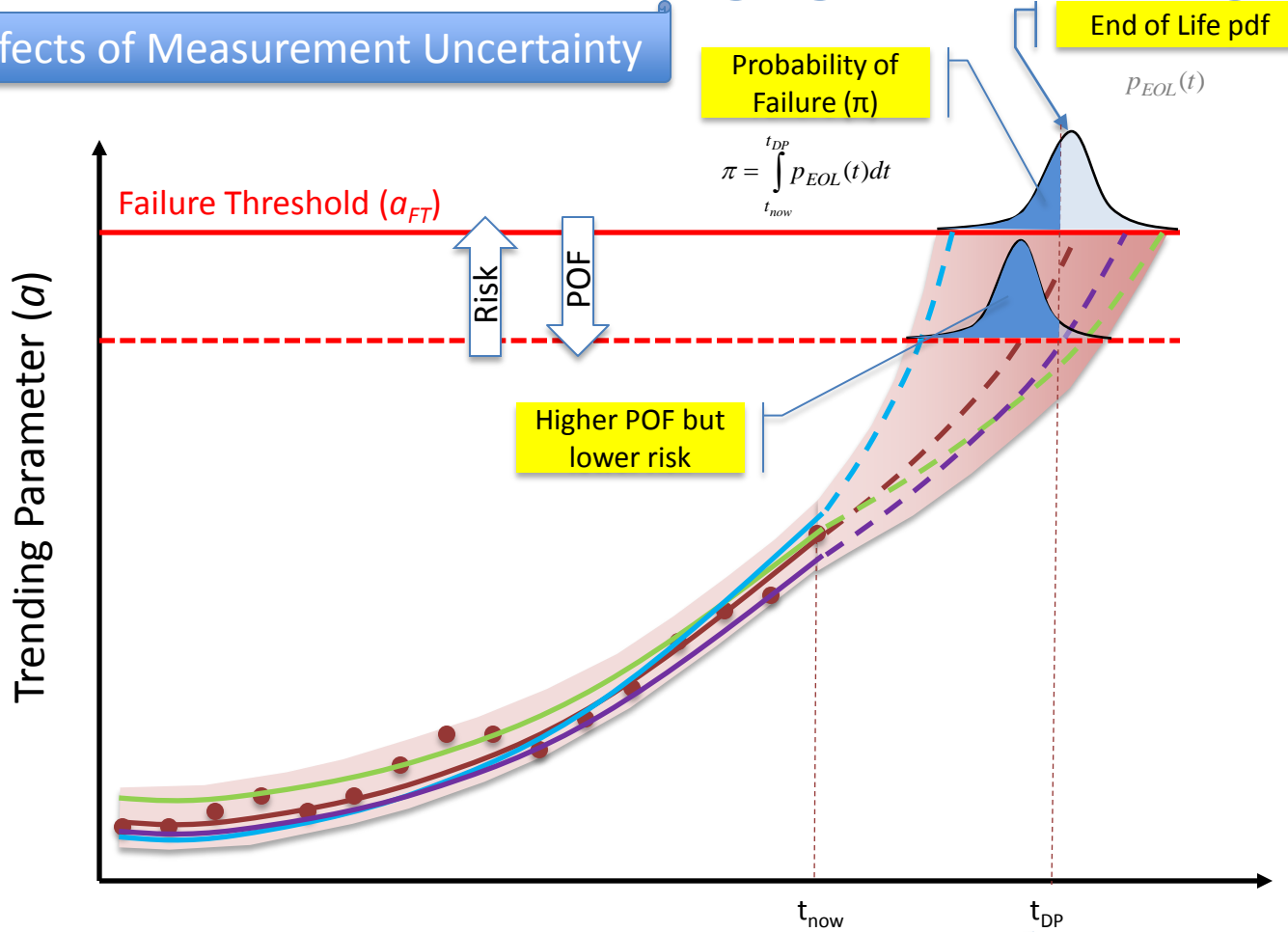
Can be a mix of any of the above.



# Trends and Thresholds Revisited

... now things get interesting!

## Effects of Measurement Uncertainty



Band of uncertainty around measurement points

Many possible Models may "fit" the measurements

Use statistics to extrapolate the uncertainty into the future

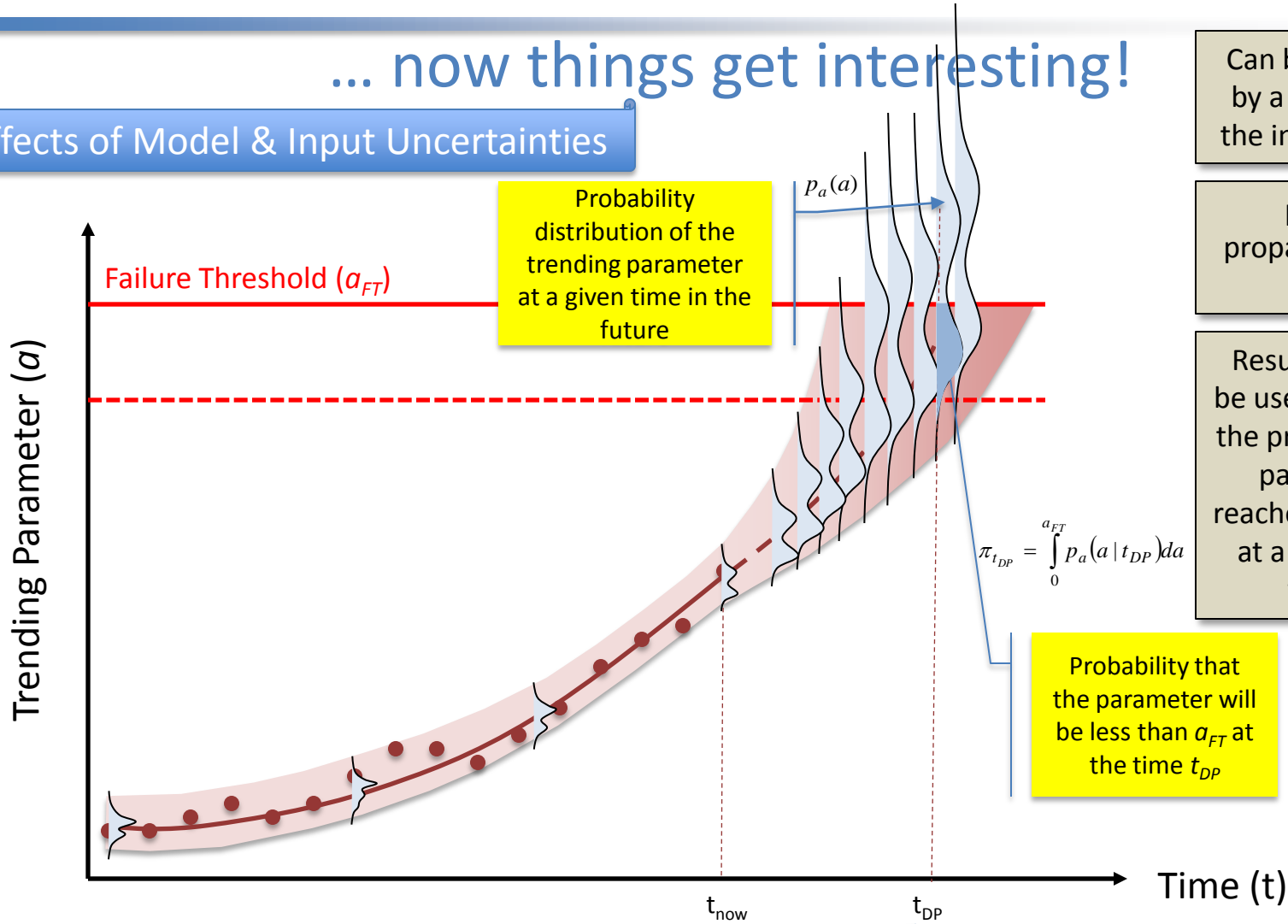
Resulting pdf can be used to determine the probability of EOL occurring between two future time points

Risk vs POF

# Trends and Thresholds Revisited

... now things get interesting!

Effects of Model & Input Uncertainties



Can be represented by a pdf describing the initial conditions

pdf is then propagated forward in time

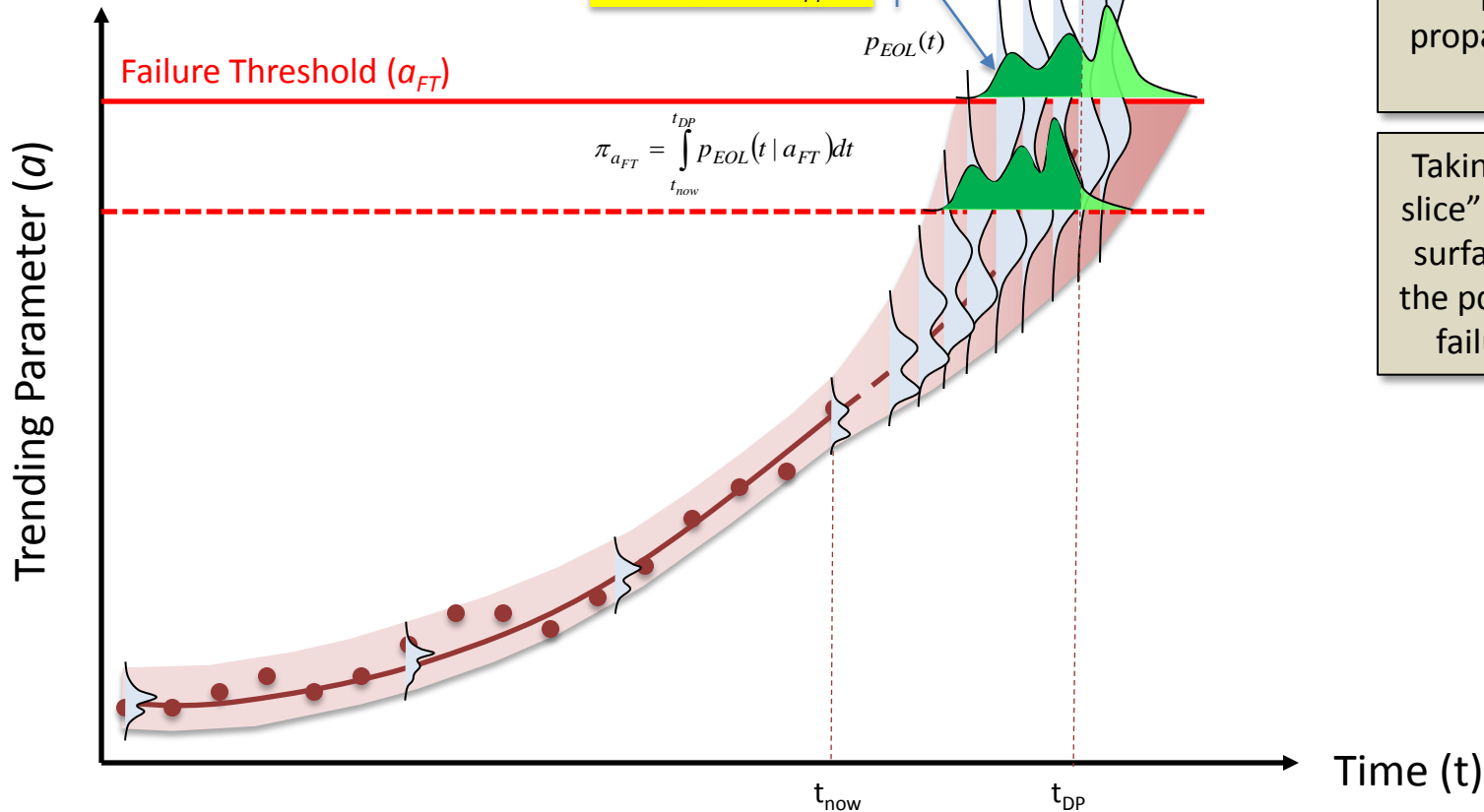
Resulting pdf's can be used to determine the probability that a parameter has reached a given value at a given point in the future



# Trends and Thresholds Revisited

... now things get interesting!

Effects of Model & Input Uncertainties



Can be represented by a pdf describing the initial conditions

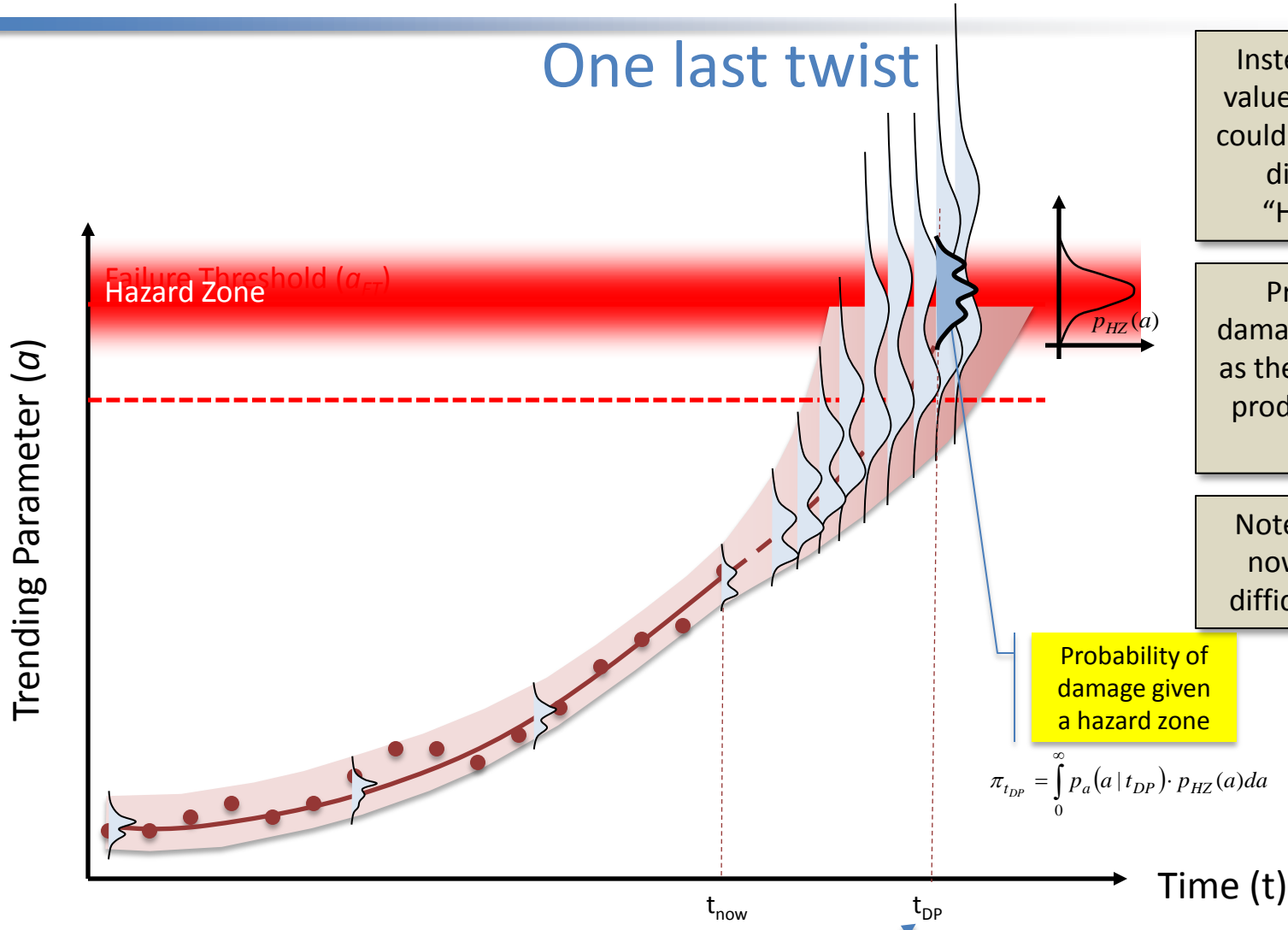
pdf is then propagated forward in time

Taking a “horizontal slice” of the resulting surface at  $a_{FT}$  yields the pdf of EOL at that failure threshold



# Trends and Thresholds Revisited

One last twist



Instead of a single value, the threshold could be defined as a distribution – “Hazard Zone”

Probability of damage is now taken as the integral of the product of the two pdf's

Note that “Risk” is now much more difficult to quantify

Probability of damage given a hazard zone

$$\pi_{t_{DP}} = \int_0^{\infty} p_a(a | t_{DP}) \cdot p_{HZ}(a) da$$

Decision Point

# Prognostic Methods

Data-Based or Physics-Based  
Models? – That is the question!

# Sources of Knowledge

## How we know the things we know

- FMEA / FMECA
  - What the failure modes are
  - Effects (and Criticality) – which failure modes to go after
- Fault Tree Analysis
  - Propagation Models
- Designers / Reliability Engineers
  - System knowledge and insight
  - Expected / nominal behavior of the system
- Seeded Failure Testing / Accelerated Life Testing
  - Data (and lots of it if you're lucky)
  - Failure signatures
  - Effects of environmental conditions
- Fielded Systems
  - Sensors measurements
  - Maintenance logs

# Data-Driven Methods

## When you want to give your PC a task all night

- Model is based solely on data collected from the system
- Some system knowledge may still be handy:
  - What the system ‘is’
  - What the failure modes are
  - What sensor information is available
  - Which sensors may contain indicators of fault progression (and how those signals may ‘grow’)
- *General* steps:
  - Gather what information you can (if any)
  - Determine which sensors give good trends
  - Process the data to “clean it up” – try to get nice, monotonic trends
  - Determine threshold(s) either from experience (data) or requirements
  - Use the model to predict RUL
    - Regression / trending
    - Mapping (e.g., using a neural network)
    - Statistics

# Data-Driven Method Example

## PHM2008 Data Challenge

- No knowledge of system (just a bunch of data)
- 218 sets of data (“runs”)
- 24 Signals
  - 3 described as “operational settings”
  - 21 described as “sensor measurement  $n$ ”
- At the start of each run, the system is healthy
- At some point during each run, a fault develops and grows to ‘failure’ at the end of the run



# Data-Driven Method Example

## PHM2008 Data Challenge

Operational Settings



*Use Op Settings to determine different modes of operation*

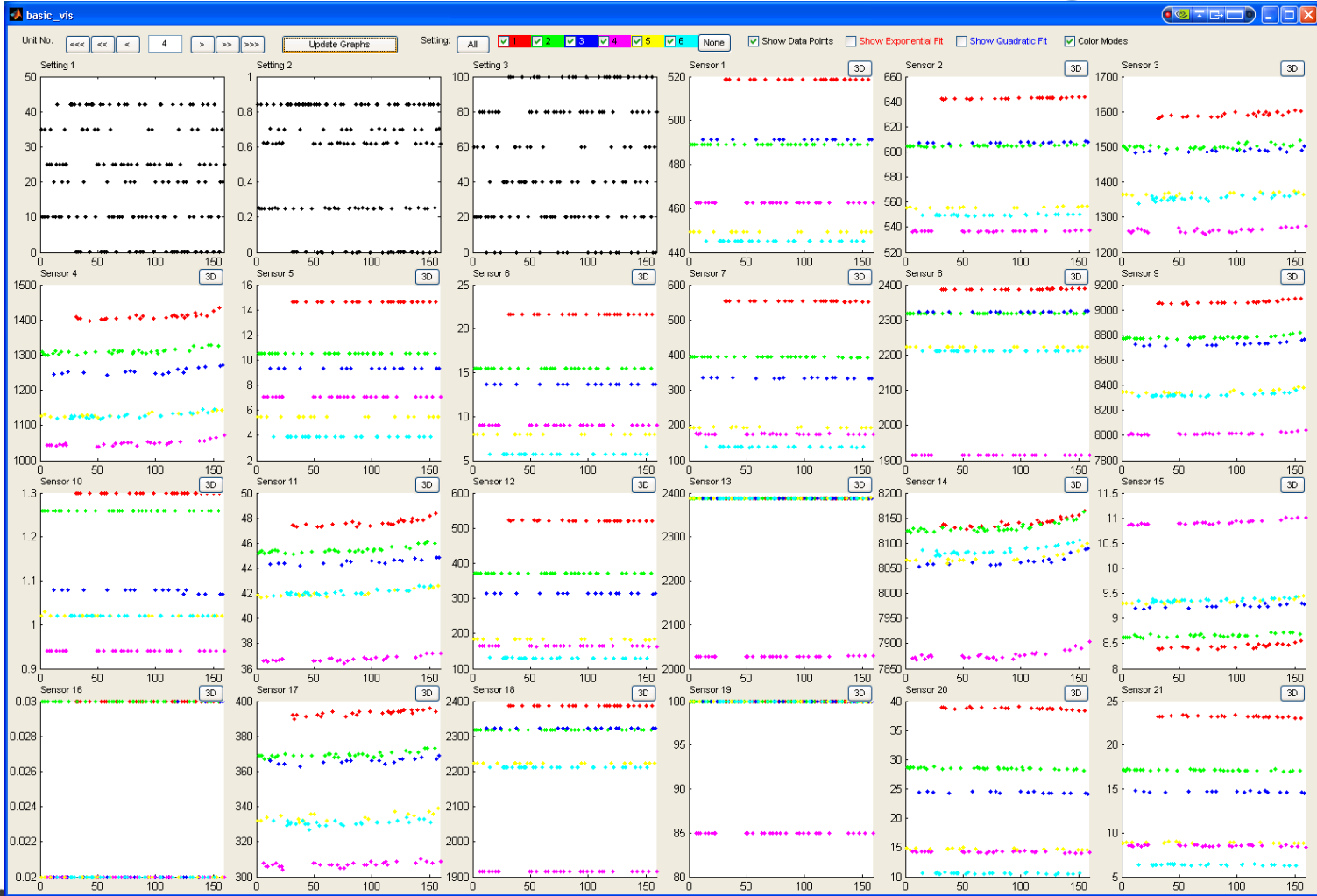


Raw Data Plots for a Single Run



# Data-Driven Method Example

## PHM2008 Data Challenge

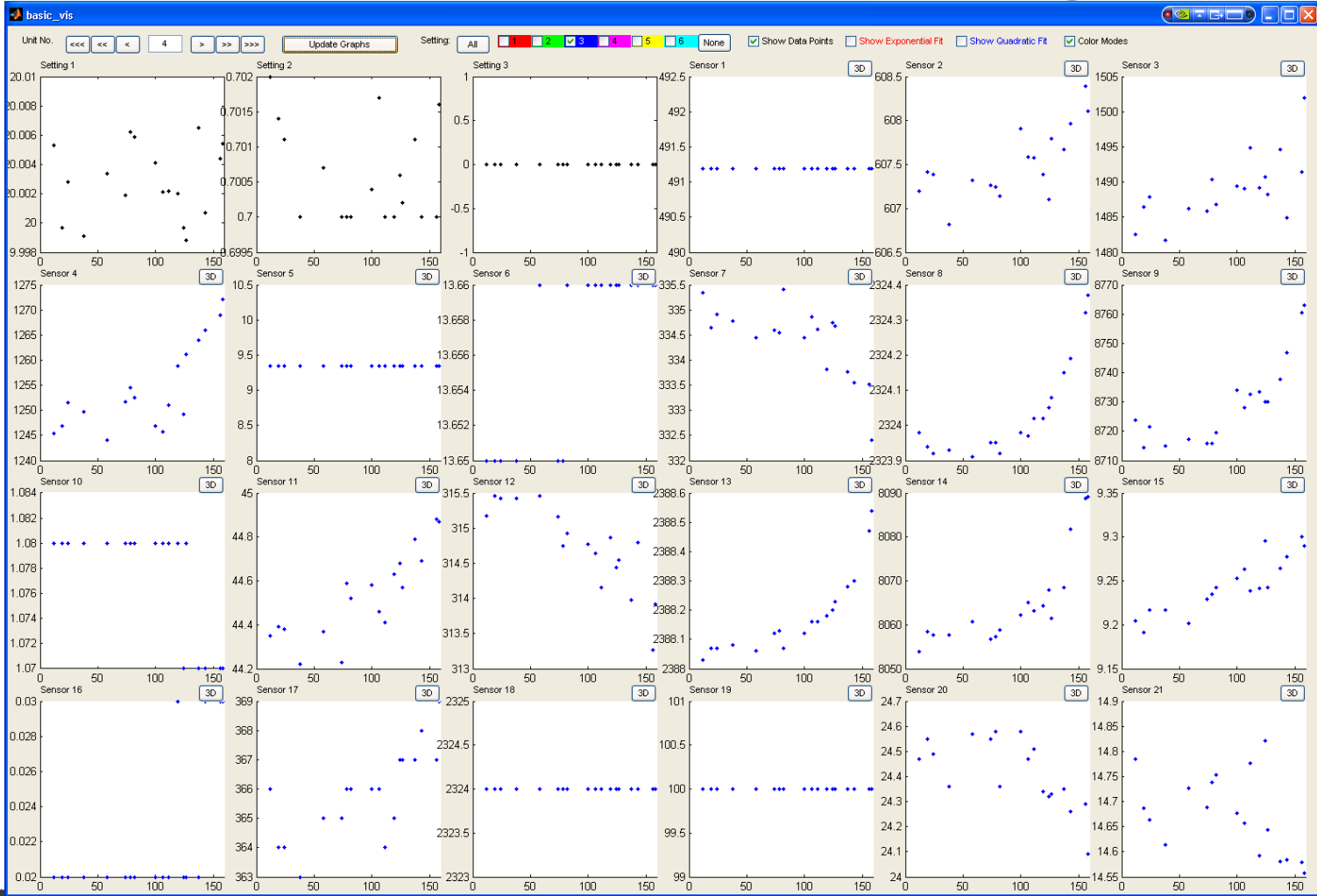


*Consider a single mode*



# Data-Driven Method Example

## PHM2008 Data Challenge



*Let's look at a single sensor*



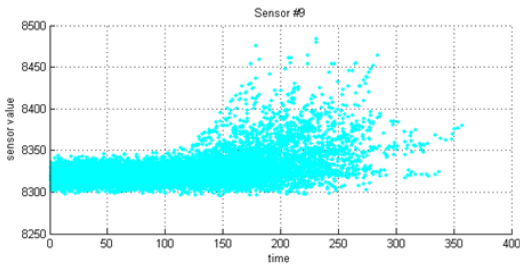
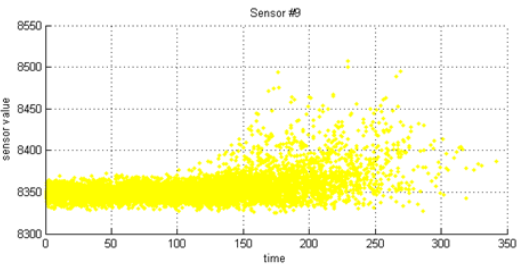
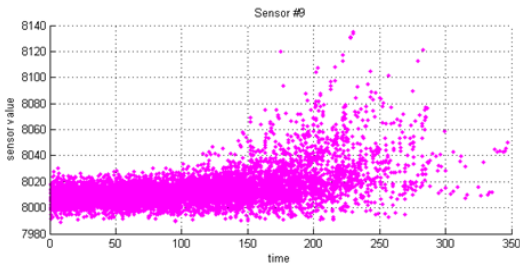
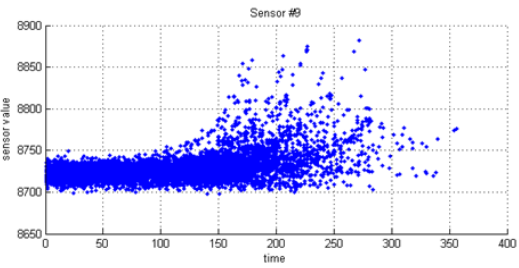
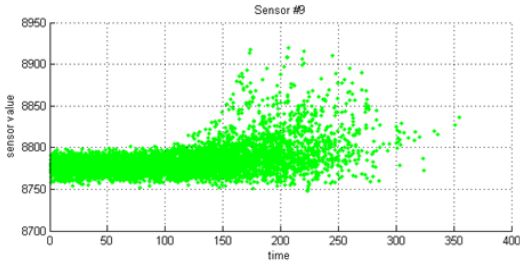
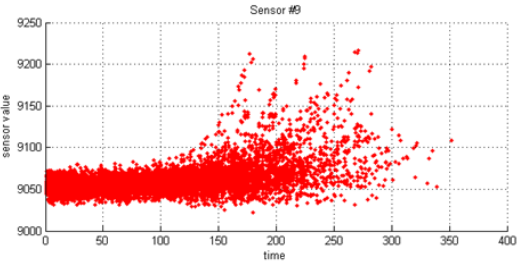


# Data-Driven Method Example

## PHM2008 Data Challenge

- Mode 1
- Mode 2
- Mode 3
- Mode 4
- Mode 5
- Mode 6

Sensor 9



*Different sensors show different trends – Op mode and Failure mode dependent*



# Data-Driven Method Example

## PHM2008 Data Challenge

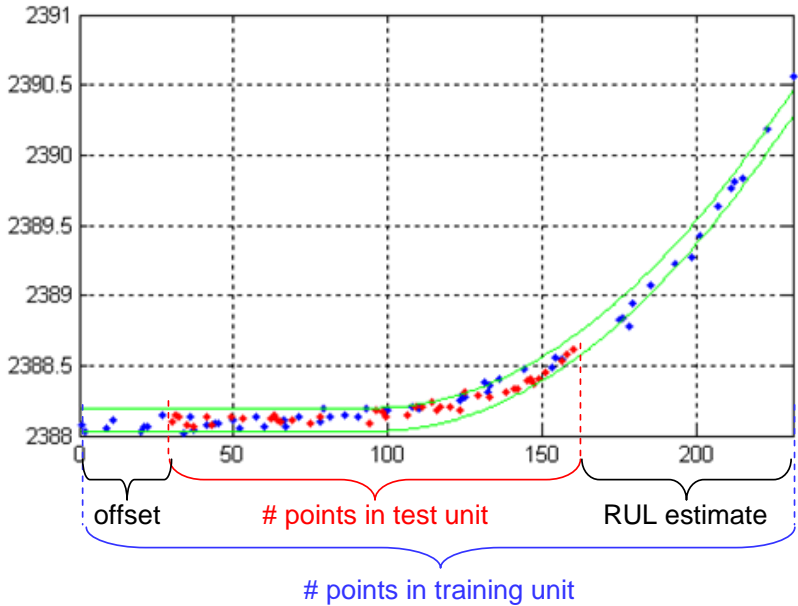
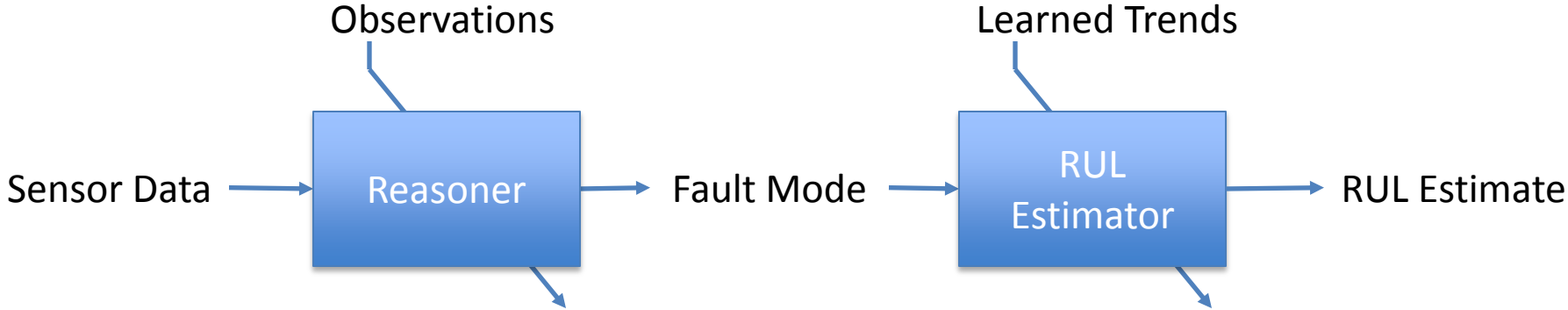
Sensor	Observations
1	Single-valued for each operational setting across all units. No useful information.
2	All operational settings tend to show slight “up” trend as failure progresses.
3	All operational settings tend to show slight “up” trend as failure progresses.
4	All operational settings tend to show slight “up” trend as failure progresses.
5	Single-valued for each operational setting across all units. No useful information.
6	Dual-valued for each operational setting across all units. The lower value (in each operational setting) appears to be confined to the earlier cycles of each unit.
7	All operational settings tend to show slight “down” trend as failure progresses, perhaps slightly more pronounced in operational setting 1.
8	Operational settings 1, 2, and 3 show “up” trend as failure progresses for all units. Operational settings 4, 5, and 6 show a mix of “up” and “down” trends as failure progresses. Many curves appear to be rather pronounced (i.e., sharp up or down trend as failure progresses).
9	All operational settings show “up” trend as failure progresses for most units, though some units appear flat. Many curves appear to be rather pronounced (i.e., sharp up or down trend as failure progresses).
10	Operational settings 1 and 2 are single-value across all units. Operational settings 3, 4, 5, and 6 are dual-valued across all units.
11	All operational settings tend to show slight “up” trend as failure progresses.
12	All operational settings tend to show slight “down” trend as failure progresses, perhaps slightly more pronounced in operational setting 1.
13	Operational settings 1, 2, and 3 show “up” trend as failure progresses for all units. Operational settings 4, 5, and 6 show a mix of “up” and “down” trends as failure progresses. Many curves appear to be rather pronounced (i.e., sharp up or down trend as failure progresses).
14	All operational settings show “up” trend as failure progresses for most units, though some units appear flat. Many curves appear to be rather pronounced (i.e., sharp up or down trend as failure progresses).
15	All operational settings tend to show slight “up” trend as failure progresses.
16	Operational settings 1, 2, 4, 5, and 6 are single-valued across all units. Operational setting 3 is dual-valued across all units with the lower value confined to the earlier cycles of each unit.
17	All operational settings tend to show slight “up” trend as failure progresses. Signals are discrete valued (no fractional values, only integral).
18	Single-valued for each operational setting across all units. No useful information.
19	Single-valued for each operational setting across all units. No useful information.
20	All operational settings tend to show very slight “down” trend as failure progresses, perhaps slightly more pronounced in operational setting 1.
21	All operational settings tend to show very slight “down” trend as failure progresses, perhaps slightly more pronounced in operational setting 1.





# Data-Driven Method Example

## PHM2008 Data Challenge



# Data-Driven Methods

## Pros & Cons

- Pros
  - Easy and Fast to implement
    - Several off-the-shelf packages are available for data mining
  - May identify relationships that were not previously considered
    - Can consider all relationships without prejudice
- Cons
  - Requires lots of data and a “balanced” approach
    - Very real risk of “over-learning” the data
    - Conversely, there’s also a risk of “over-generalizing”
  - Results may be counter- (or even un-)intuitive
    - Correlation does not always imply causality!
  - Can be computationally intensive, both for analysis and implementation
- Example techniques
  - Regression analysis
  - Neural Networks (NN)
  - Bayesian updates
  - Relevance vector machines (RVM)

# Physics-Based Methods

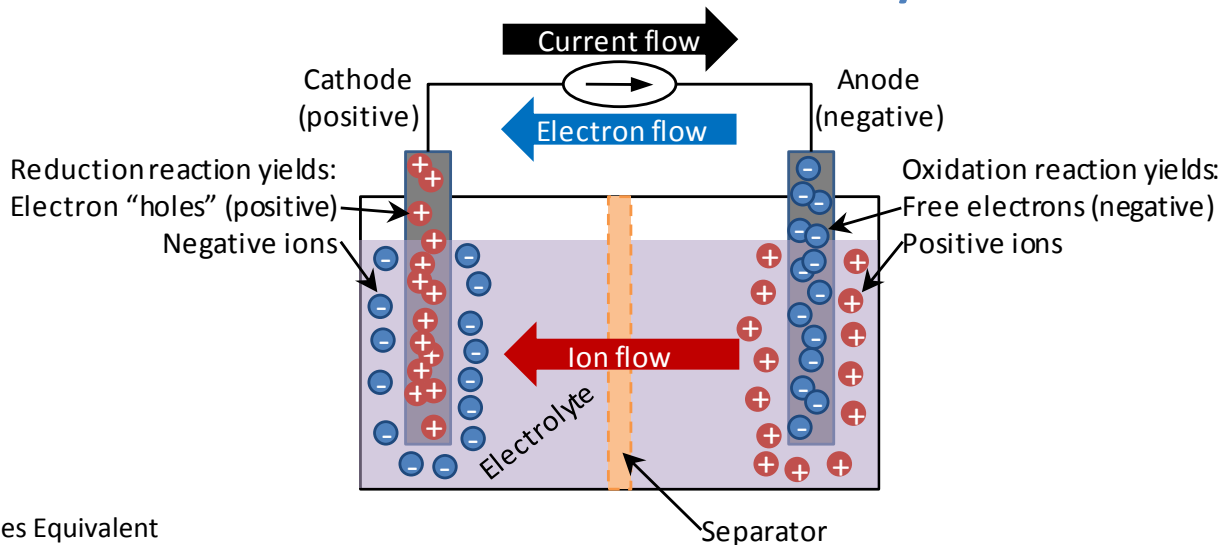
For those who prefer the “pen and paper” approach

- What is a “Physics-Based” Model?  
Some examples:
  - Model derived from “First Principles”
    - PDEs
    - Euler-Lagrange Equations
  - Empirical model chosen based on an understanding of the dynamics of a system
    - Lumped Parameter Model
    - Classical 1<sup>st</sup> (or higher) order response curves
  - Mappings of stressors onto damage accumulation
    - Finite Element Model
    - High-fidelity Simulation Model
- Something in the model correlates to the failure mode(s) of interest

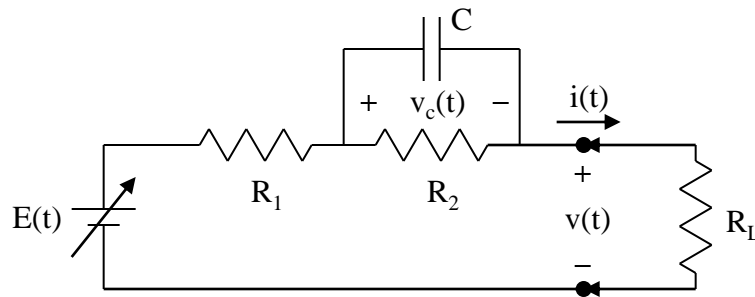
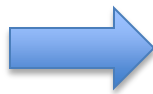
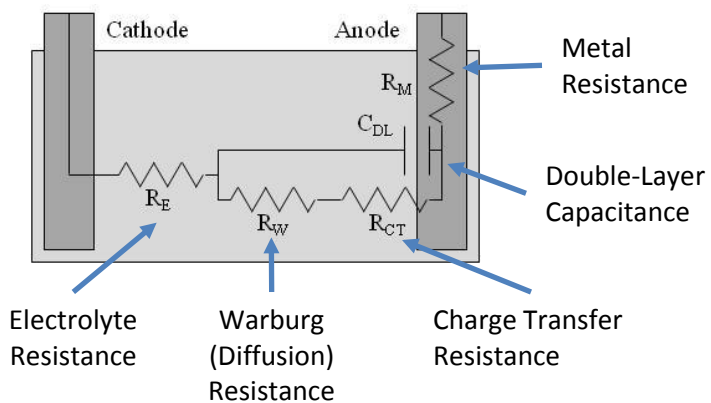


# Physics-Based Method Example

## Lithium Ion Battery



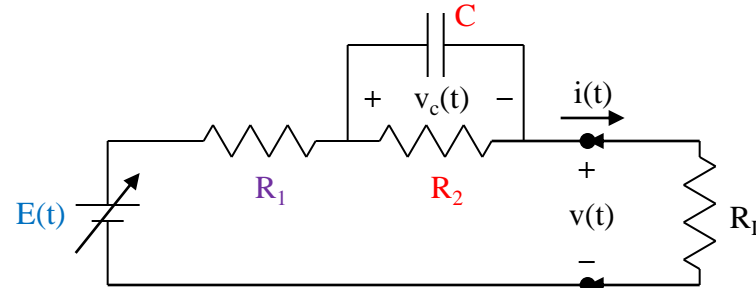
Randles Equivalent Impedance Model



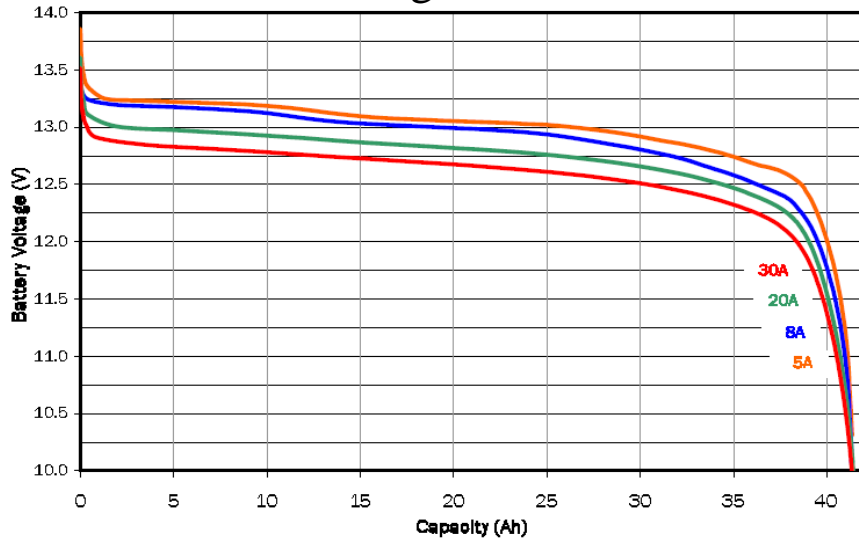
1<sup>st</sup> Order Lumped Parameter Model

# Physics-Based Method Example

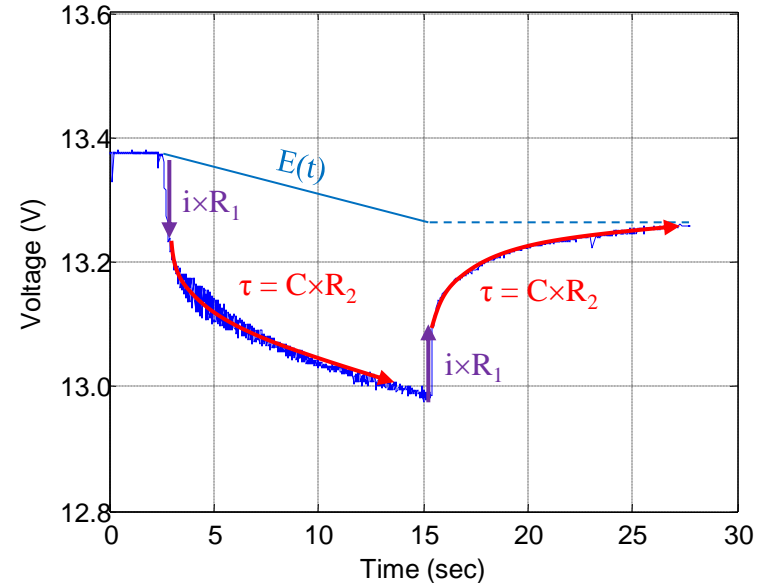
## Lithium Ion Battery



Discharge Curves

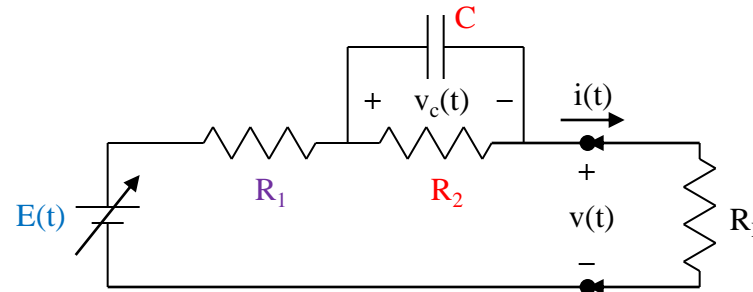


Battery Pulse Data



# Physics-Based Method Example

## Lithium Ion Battery



- As the battery ages, changes in the electro-chemical properties manifest in changes to  $R_1$ ,  $R_2$ , and  $C$
- Usage and/or BIT data is used to continuously estimate the impedance values
- Regression analysis is used to correlate the impedance values to battery capacity (State of Health)



# Physics-Based Models

## Pros & Cons

- Pros
  - Results tend to be intuitive
    - Based on modeled phenomenon
    - And when they're not, they're still instructive (e.g., identifying needs for more fidelity or unmodeled effects)
  - Models can be reused
    - Tuning of parameters can be used to account for differences in design
  - If incorporated early enough in the design process, can drive sensor requirements (adding or removing)
  - Computationally efficient to implement
- Cons
  - Model development requires a thorough understanding of the system
  - High-fidelity models can be computationally intensive
- Examples
  - Population Growth Models
  - Paris-Erdogan Crack Growth Model

# Hybrid Models

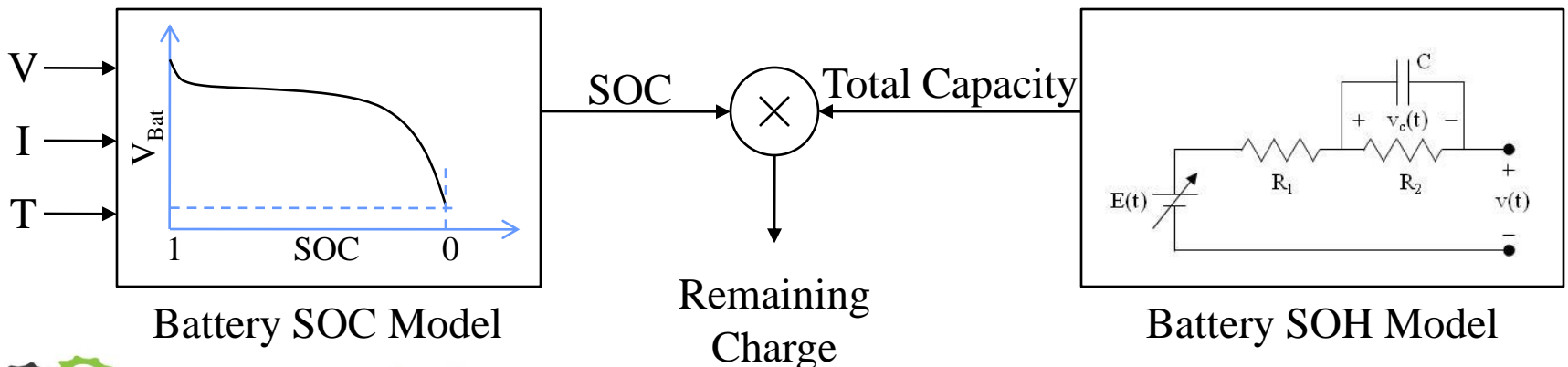
## The best of both worlds

- In practice, many implementations pull from both Data-Driven and Physics-Based Model methods
  - Use data to learn model parameters
  - Use knowledge about the physical process to determine the type of regression analysis to apply (linear, polynomial, exponential, etc.)
  - Data-Driven System Model in conjunction with a Physics-Based Fault Model (or vice-versa)
  - Identify potential correlations physics model and correlate using a data-based approach
  - Data fusion – have one of each!

# Hybrid Example

## Lithium Ion Battery Revisited

- Regression analysis used to trend circuit parameters ( $R_1$ ,  $R_2$ ,  $C$ )
- Battery State of Health (SOH) Model
  - Correlates total charge capacity to SOH
- Battery State of Charge (SOC) Model
  - Correlates voltage, current, and temperature to SOC
- Together they can yield both the life remaining on the current charge as well as when the battery will need to be replaced



# Hybrid Models

## Pros & Cons

- Pros
  - Combines the strengths of each approach
  - Robustness in design
    - Use data where system knowledge is lacking
    - Use physics where data is lacking
  - Results are both intuitive and match observations
  - Can “mix and match” approaches to customize for the current situation
- Cons
  - Though the goal of a hybrid approach is to pull the best from each approach, where each approach is used, it still carries its disadvantages
    - Need for data
    - Portions may still be computationally intensive
    - Need for in-depth system knowledge
- Examples
  - Particle Filters, Kalman Filters, etc.
  - Be creative and clever - The sky's the limit!



# Current Challenges in Prognostics

Where do we go from here?

# Some Open Questions

Stick around for a few more days and see!

- Requirements Specification
  - With all of the pdf's floating around, how do you write a meaningful requirements statement?
    - Confidence, RUL, Risk avoidance
- Validation and Verification (V&V)
  - In order for a requirement statement to be valid (or at least realistic), you must be able to apply a rigorous V&V methodology to show that the requirement is being met
  - However, in a perfect prognostic system, parts are always replaced before they fail
  - Though limited post-mortem analyses may be made, it is infeasible to determine the actual SOH of all pulled components
  - Even if you did know the actual SOH of all pulled components, its difficult to know the RUL pdf of the pulled component
- Uncertainty Management
  - Quantification, representation, propagation, and management
    - We've come a long way, but there's still more to be achieved!

# Questions?

Thank you!