An Introduction to Data-Driven Prognostics of Engineering Systems

Jamie Coble

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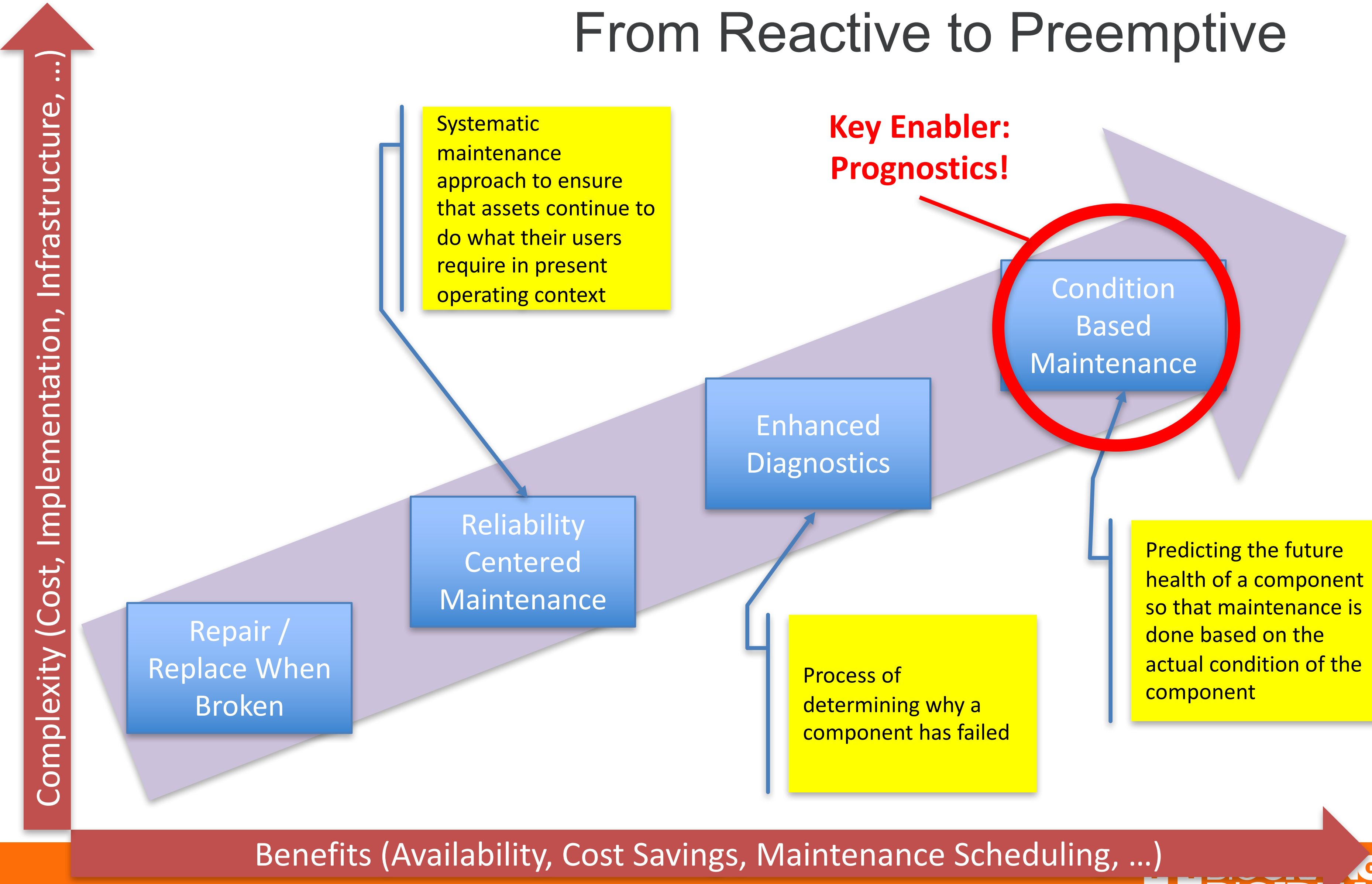
Evolution of Maintenance Practices

From Reactive to Preemptive



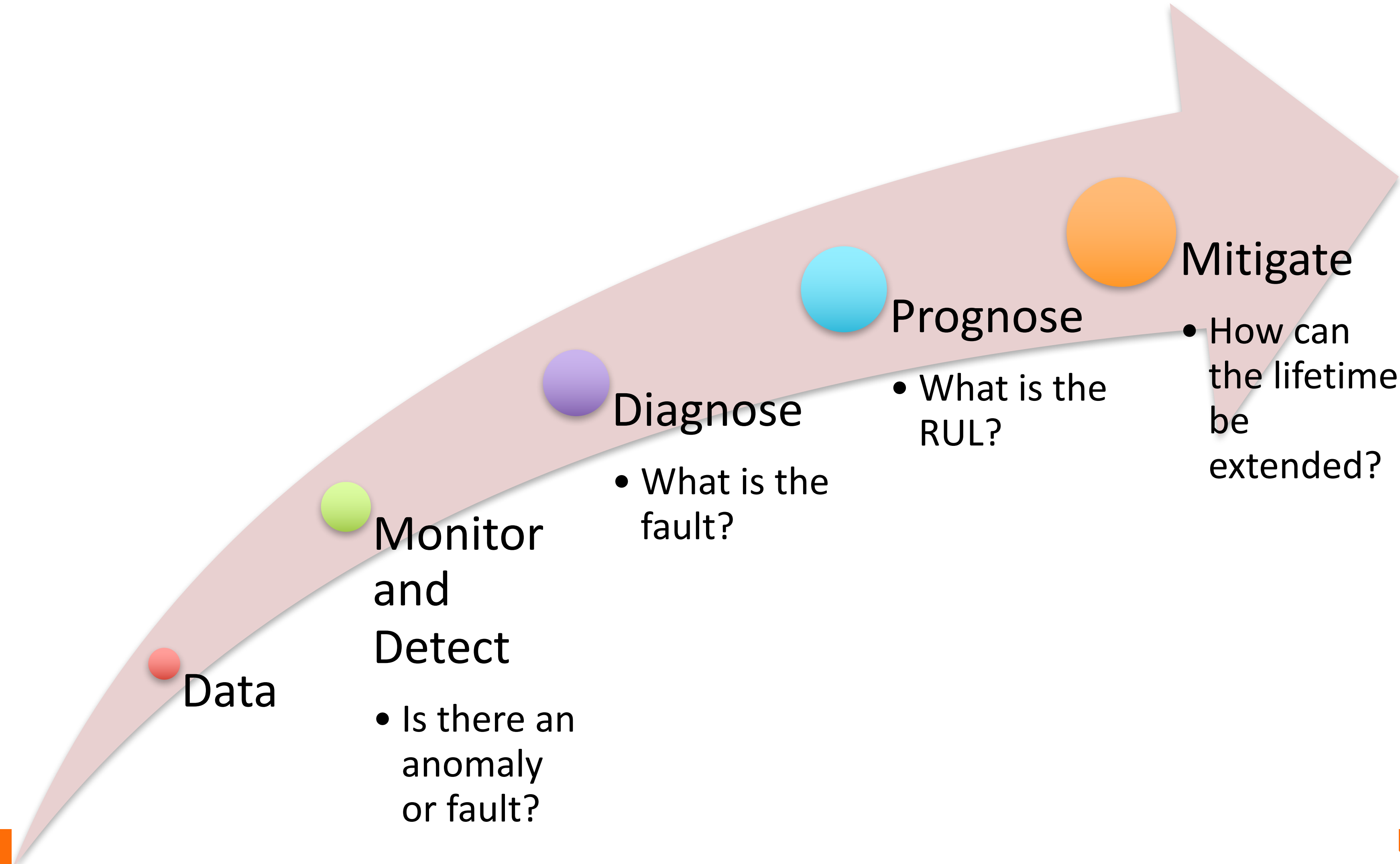
Reliability and Prognostics

- Reliability analysis gives us information about the failure of a population of similar systems or components
- Prognostics extends this to a specific system or component
  - When will it fail?
  - What's the probability that it will fail in the next 5 minutes?
  - What's the probability that we can complete the mission before something fails?
- The potential benefits of early warning of impending failure are significant
  - Improved availability
  - Reduced equipment damage
  - Improved safety

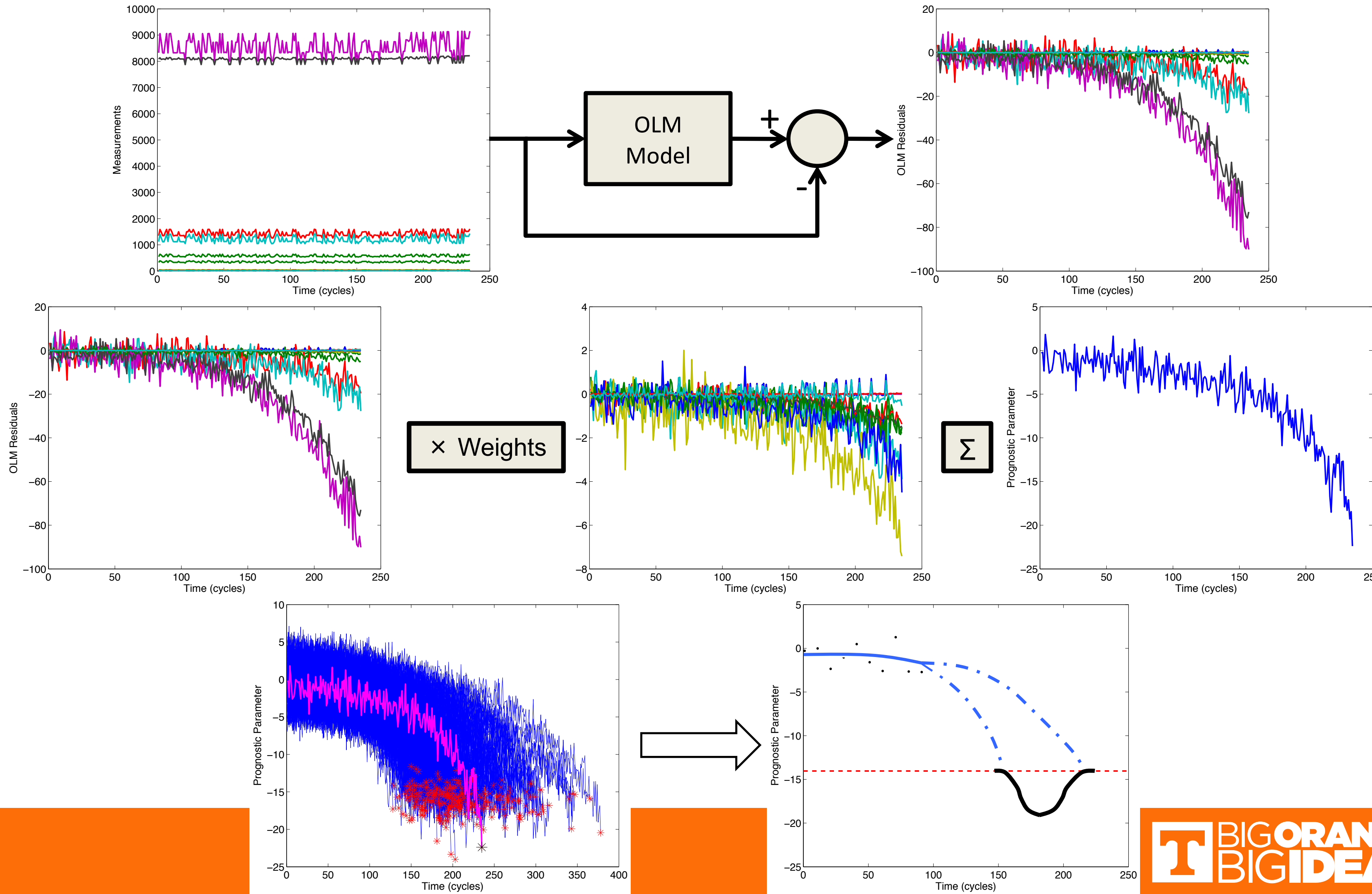
Fully realized PHM systems have four key components

- Nondestructive **measurement** methods and analyses to detect degradation and anomalies
- **Algorithms** to characterize and monitor the degradation state of the component
- **Prognostics** that use the degradation state information to determine remaining useful life (RUL) and probability of failure (POF) of components
- Methods to **integrate prognostic estimates** into risk estimates and advanced control algorithms

Prognostics is one component of a larger surveillance system.



Online condition assessment provides information about the evolving degradation of components



Asset surveillance systems extract knowledge from data

- Sensed data contains degradation information and should be used to improve operational reliability through:
  - Optimizing maintenance scheduling (condition-based)
  - Improving operations (equipment state knowledge)
- Several methods exist, the selection is based on
  - Data availability: failure, causal, effects
  - Knowledge of degradation modes (physical model)
- Each prognostic application may have its own specific needs requiring new and creative solutions

Prognostic Term Definitions

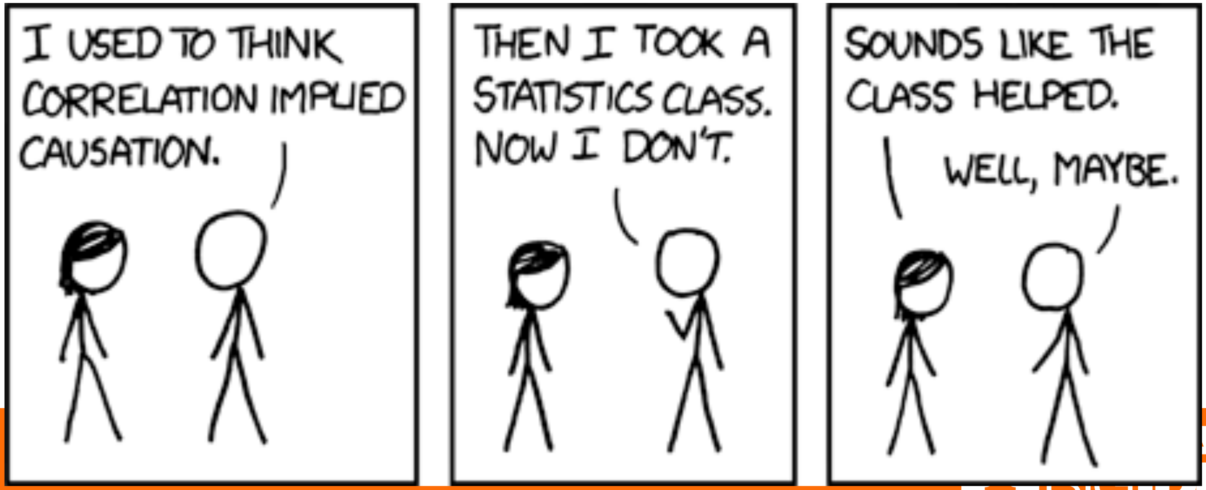
- Methods used to predict:
  - Remaining Useful Life (RUL): the amount of time, in terms of operating hours, cycles, or other measures the component will continue to meets its design specification.
  - Time of Failure (TOF): the time a component is expected to fail (no longer meet its design specifications).
  - Probability of Failure (POF): the failure probability distribution of the component.

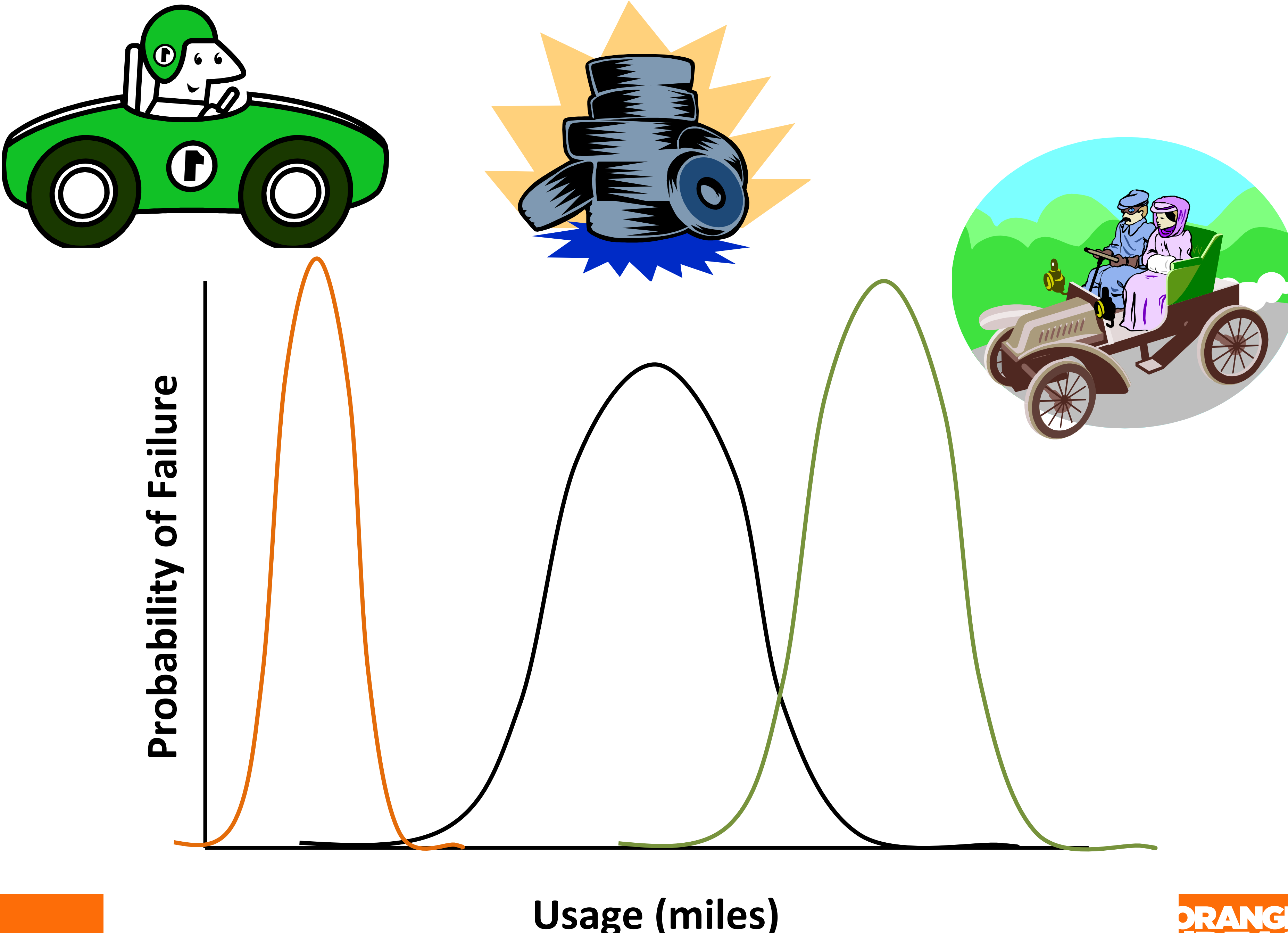
So what is data-driven prognostics?

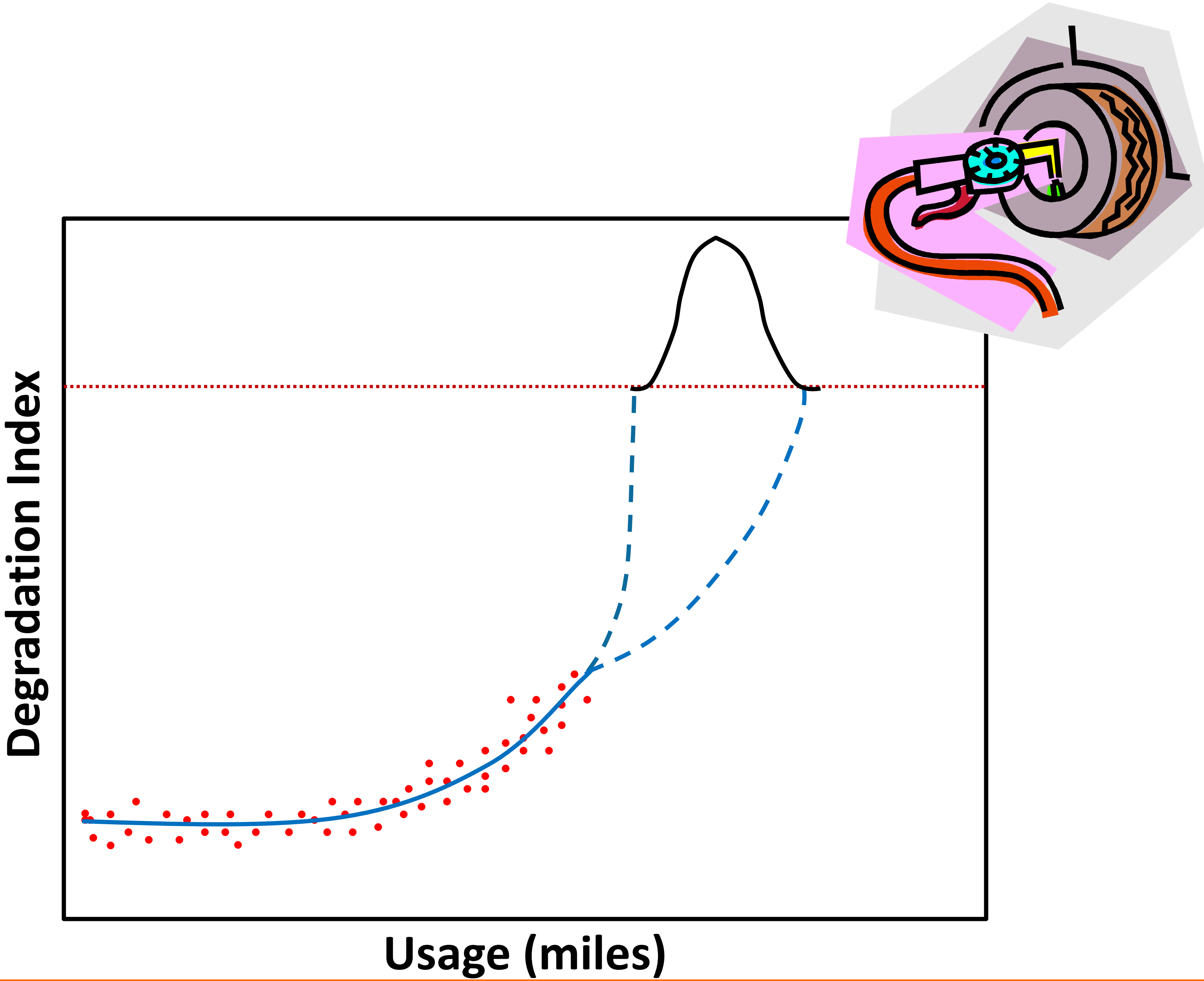
- Prognostic models developed and derived from historic run-to-failure data
- Models are typically “black boxes” with no explicit system knowledge
- Data are typically preprocessed to extract useful information
  - Feature extraction
  - System monitoring
  - Detection, isolation, and diagnostics

Sensed data contain information about the condition of components, systems, and processes

- A lot of data are being collected all the time
  - Equipment data, process parameters, operating conditions …
- We want to
  - discover the underlying relationships in data
  - exploit these relationships to make predictions or decisions about new data




Probability of Failure
Usage (miles)


Degradation Index
Usage (miles)

Some Basic Prognostic Data Requirements

- For Type I, we need a population of historical failure times that include the expected operation
- For Type II, environmental and stressor conditions that drive the failure modes must be measurable
- For Type III, degradation must be related to a measurable parameter such as tread depth or bearing vibration level or temperature or inferred from available measurements

2008 PHM Challenge Data

- Develop a data-based prognostics algorithm with no knowledge of the system being monitored
- Provided 24 variables
  - 3 operating condition indicators
  - 21 sensed variables
- Provided simulated data for model development and testing
  - 218 training cases (run to failure)
  - 218 test cases (censored)
  - 435 final test cases (censored)

Saxena, A., K. Goebel, D. Simon, N. Eklund, "Prognostics Challenge Competition Summary: Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation," PHM '08, Denver CO, Oct 6-9, 2008.

Type I – Reliability-based Prediction

- Type I prognostics characterize the expected lifetime of the **average** component operating in historically **average** conditions
- Major Assumption: Future components will operate in similar conditions and degrade in similar ways to those seen in the past
- May be applied when data collection of stressor or component condition measures is not possible
  - At beginning of life, these things may be unknown or unavailable

Type I – Reliability-based Prediction

- Estimate failure density functions with parametric or non-parametric models
  - A population of components is tracked and their failure times are noted
  - Components that have not failed are called censored data and that information is also used to predict the failure density
- Example parametric models include exponential, normal, log-normal, and Weibull

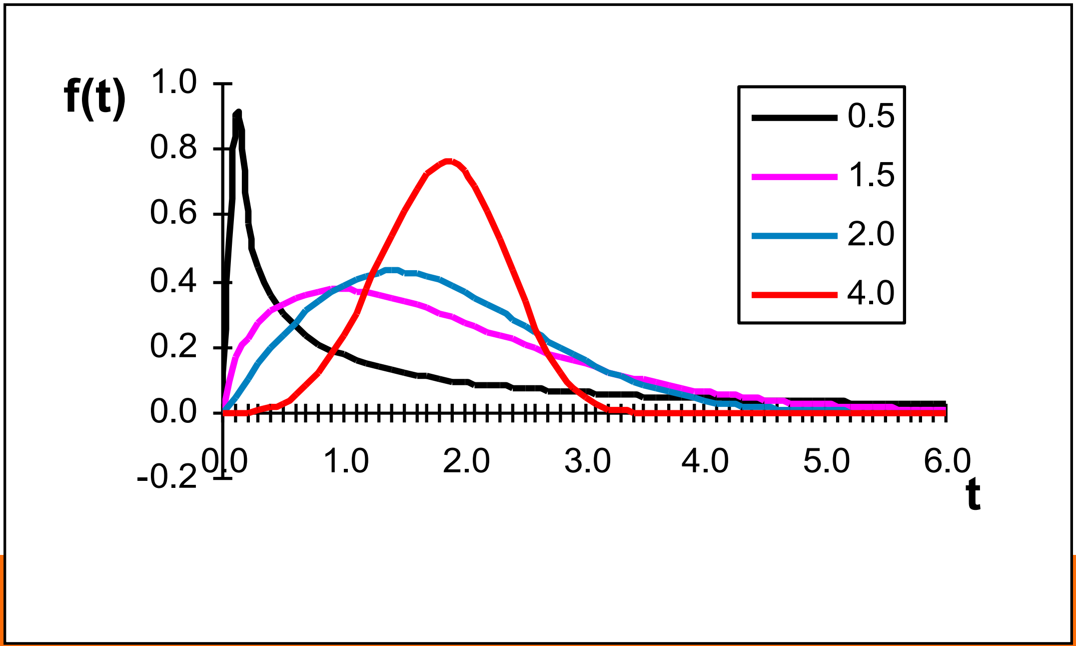
Weibull Model

- Probably the most common parametric model is the Weibull distribution.
- This model is used because it is flexible enough to model a variety of failure rate profiles.
- The failure rate is modeled with two parameters
  - a shape parameter (β) and
  - a characteristic life (θ)

$$\lambda(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1}$$

Two Parameter Weibull

- Increasing failure rate (β>1), a constant failure rate (β=1), and a decreasing failure rate (β<1)
- Does a good job of modeling failure data with exponential, normal, or Rayleigh distributions



Using a Type I model to do prognostics

- The failure criterion is some value of reliability (*R(t|T)*)
- For some desired α,
  we can calculate the
  value of t such that
  R(t|T) = α

$$R\left(t|T\right) = \frac{R(t,t>T)}{R(T)} = \alpha$$

$$R(t,t>T) = \alpha * R(T)$$

$$note \quad R(t) = 1 - F(t)$$

$$\Rightarrow 1 - F(t,t>T) = \alpha * R(T)$$

$$F(t,t>T) = 1 - \alpha * R(T)$$

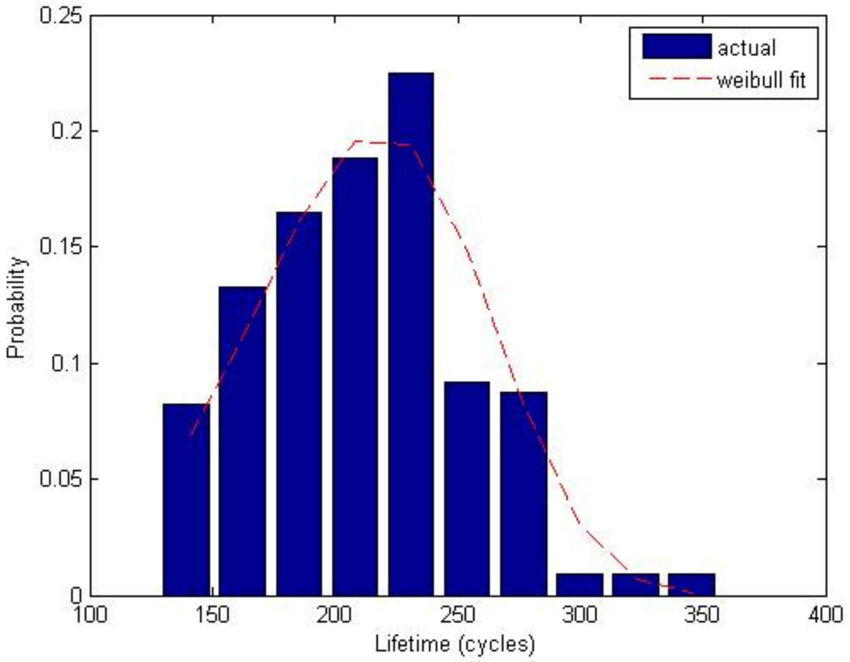
$$t = F^{-1}(1 - \alpha * R(T)), t > T$$

$$RUL_\alpha = t - T$$

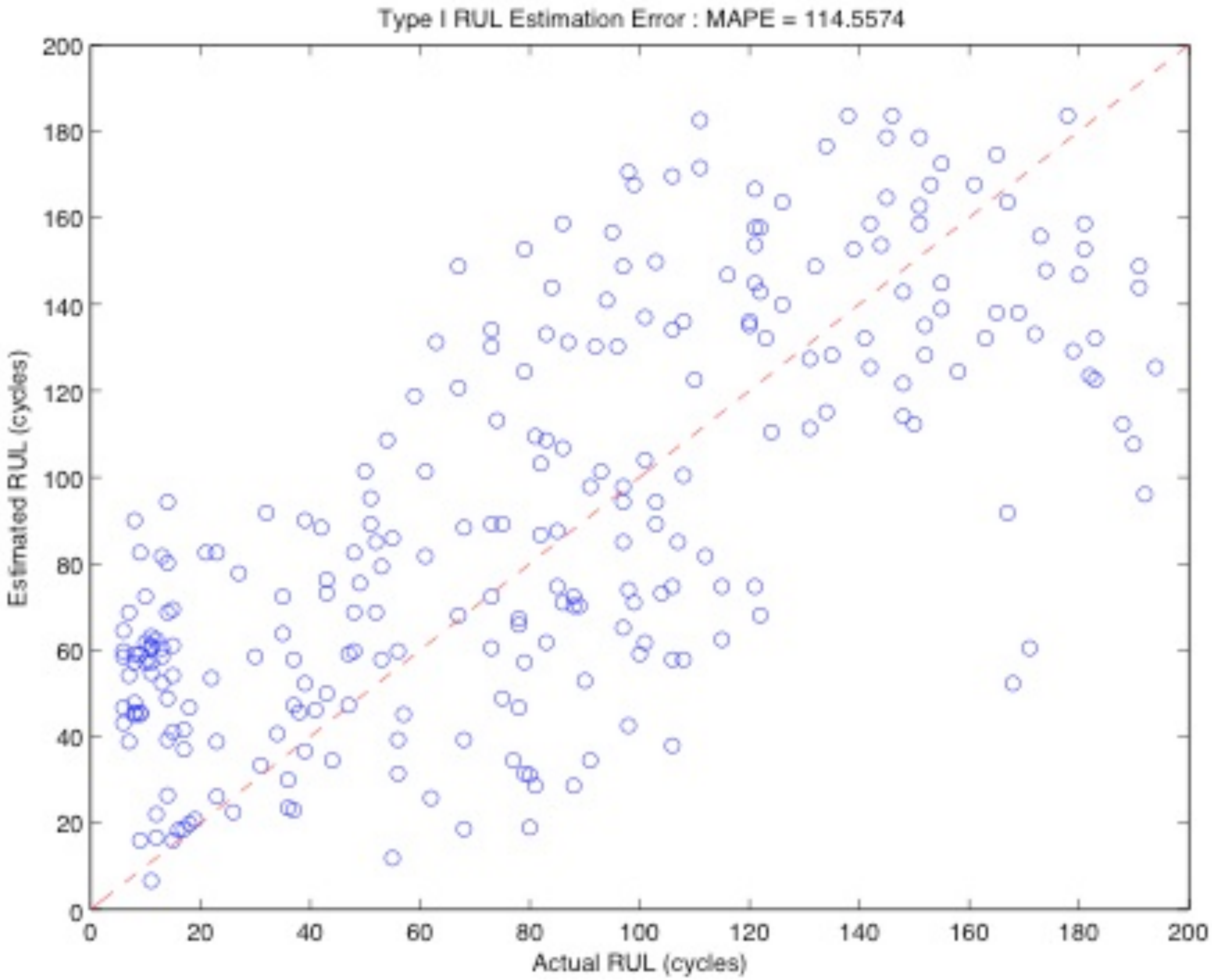
Type I Results – Weibull Analysis

- Calculate failure time for all failed cases, then fit a Weibull model to the histogram

- ML estimates
  - $\beta = 4.38$
  - $\theta = 225.66$



Type I Results – Weibull Analysis



Type I prognostics have many limitations.

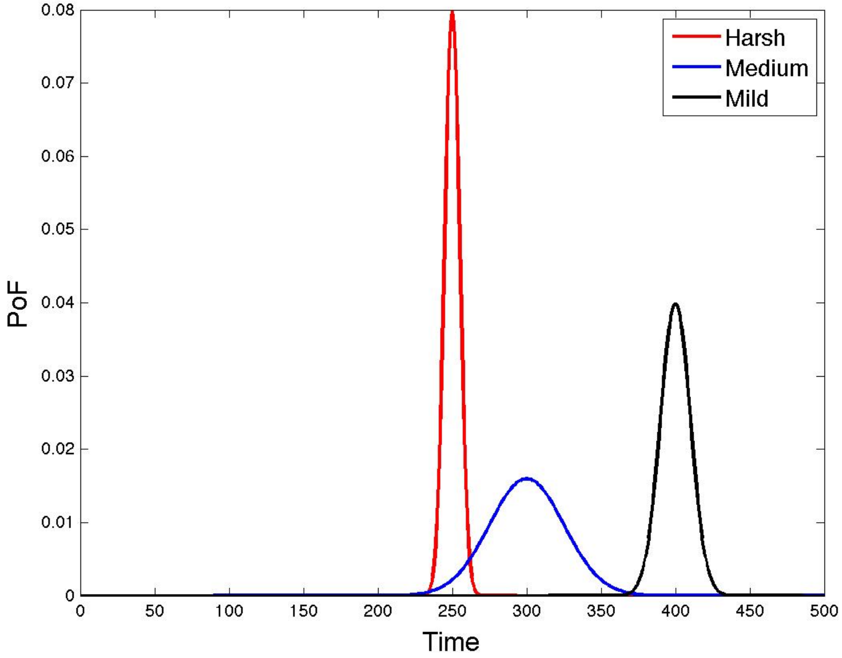
- A readily apparent disadvantage of reliability data-based prognostics is that it does not consider the operating condition of the component
  - Components operating under harsh conditions would be expected to fail sooner and components operating under mild conditions to last longer
- Failures observed during lifetime tests may not be useful for different operating conditions
  - Multiple fault modes are often merged into one distribution
- Operation of a specific component may be very different from historic operation

Type II – Stressor-based Prediction

- Type II prognostics estimate the lifetime of the **average** component in a **specific** environment
- Major Assumption: Components operating in similar conditions will degrade in similar ways; unit-to-unit variation is not significant
- Type II can be applied if stressor variables are measureable and well-correlated to component degradation
- Stressor-based reliability models, Proportional hazards models, life consumption models, Markov chain Monte Carlo models

Type II Reliability Models

- Instead of lumping all your failure data in to one reliability model, you can have separate PoF (or *R* or *F*) models for each operating condition



Proportional Hazards Model

- Similar equipment may have dissimilar operating conditions or histories because of different factors such as loads and stresses
  - Called “covariates”
- Modeling the failure data requires isolating the effects of these covariate factors
- Proportional Hazard model assumes hazard rate can be divided separated into two functions
  - Baseline hazard rate depending only on time
  - A second function only dependent on the covariates
- Factors are assumed to be multiplicative rather than additive
  - Maintains that each condition is relative to some baseline

$$\lambda(t, Z_1, \ldots, Z_n) = \lambda_0 \exp(\beta_1 Z_1, \ldots, \beta_n Z_n)$$

Fitting the regression parameters

$$\lambda\left(t,z\right) = \lambda_o(t)\psi(z;\beta)$$

- *z* is a row vector of covariates
- *β* is a column vector of regression parameters
  - Defines the effects of the covariates
- Different functional forms of ψ may be used
  - Typically exponential: $\psi(z;\beta)=exp(z\beta)$
- Use maximum likelihood method to estimate the values of *β* given the observed failure times (and censored times) and covariates

Estimating RUL

- PH model gives the survival function (reliability function, *R*) as a function of both time and covariates

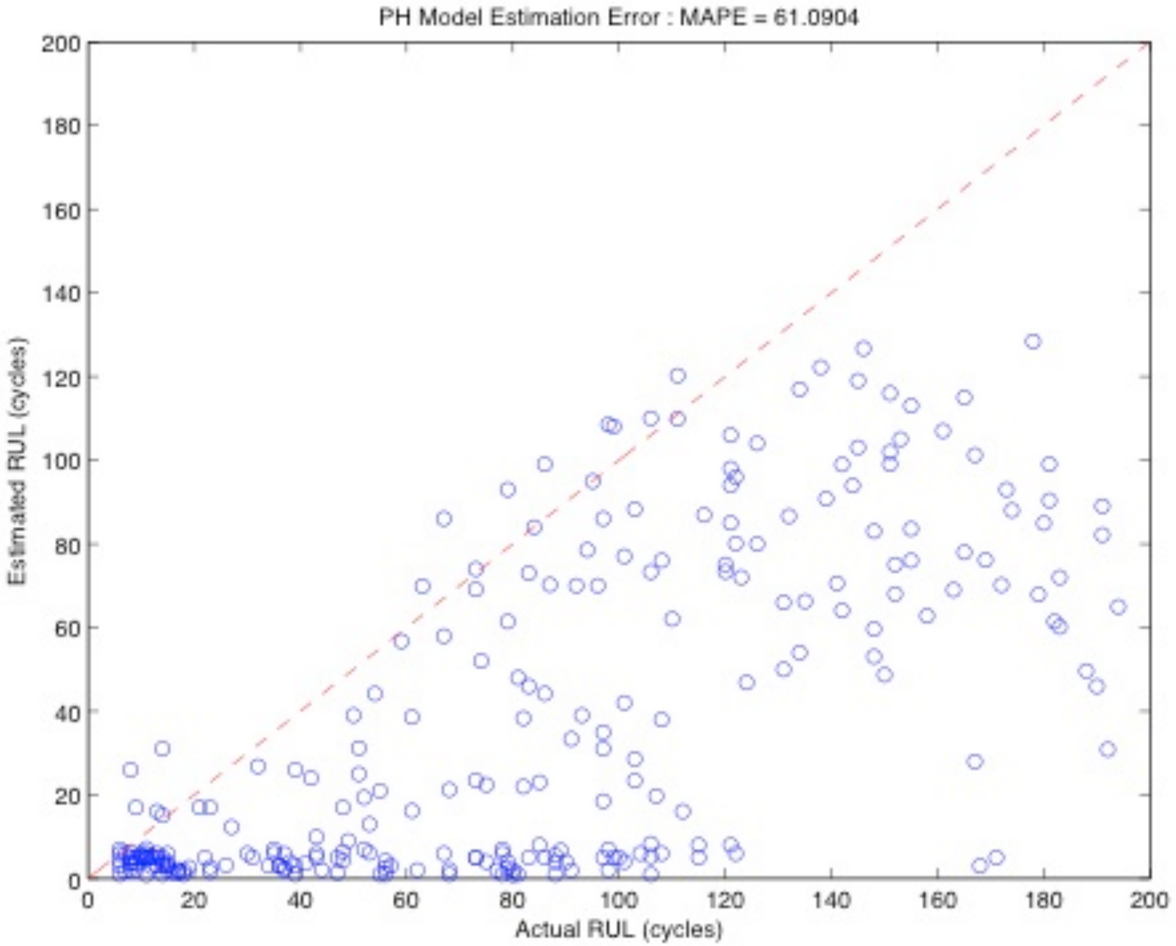
$$H(t,z) = \int_0^t \lambda(u,z)\,du$$

$$R(t,Z) = \exp\left(-H(t,z)\right)$$

- Once you have *R*, you can solve for the RUL just like we did with standard (type I) reliability models

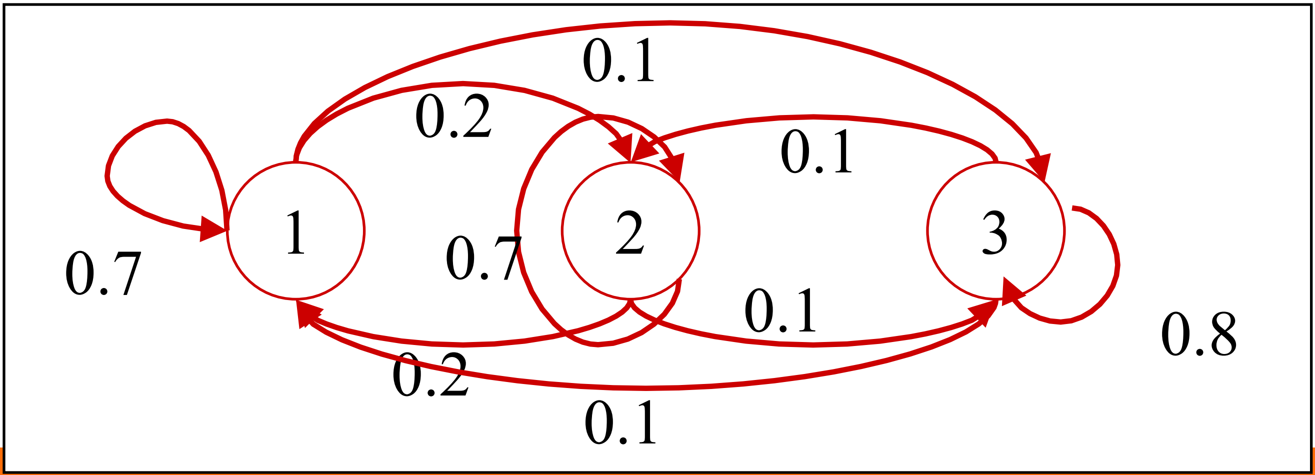
PH Model Results

- Covariates are mean value of each of the 3 environmental sensors
- Reliability cutoff of 0.95 used



Markov Chain Models

- MC models explain the equipment degradation through a transition of states
  - The states can be the environmental conditions that cause degradation
  - Transition probabilities control state movement through a transition matrix Q



$$Q = \begin{bmatrix} .7 & .2 & .1 \\ .2 & .7 & .1 \\ .1 & .1 & .8 \end{bmatrix}$$

Markov Chains

- A Markov chain is a process that consists of a finite number of states and some known probabilities P_{ij}, where P_{ij} is the probability of moving from state j to state i

- This process is independent of all previous states, only the current state has any bearing on the transition probabilities

$$P(X_t = j \mid X_0 = i_0, X_1 = i_1, \ldots, X_{t-1} = i_{t-1})$$
$$= P(X_t = j \mid X_{t-1} = i_{t-1}) = P_{ij}(t-1)$$

Type II Markov chain models really consist of two models

- The first model, the Markov chain, generates a possible future progression of operating conditions

- The second model maps these operating conditions onto a degradation parameter with some defined threshold value

State to degradation mapping

- In general, the mapping can be any function of the states

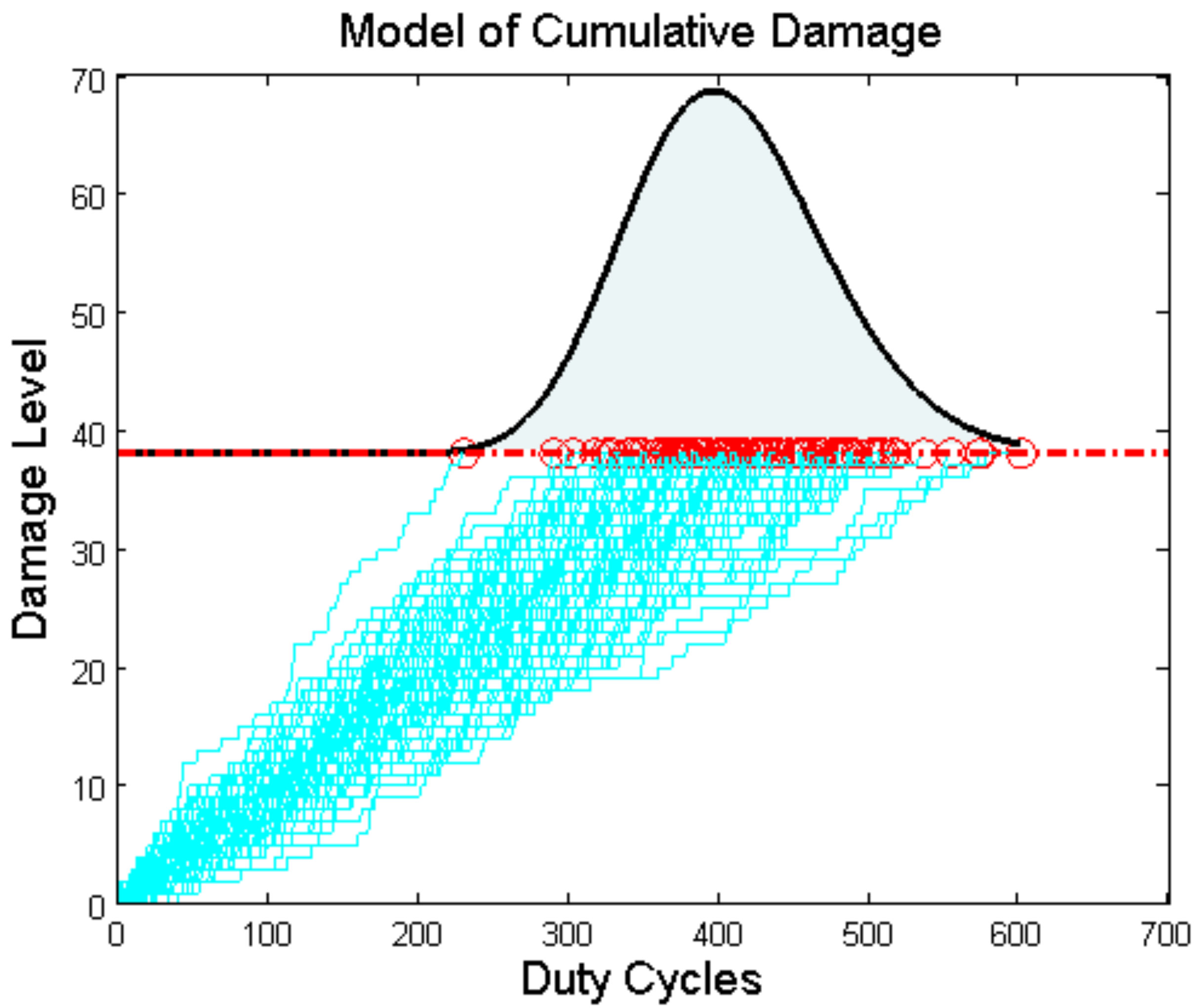
$$D(t = n) = f\left(x_0, x_1, \ldots, x_n\right)$$

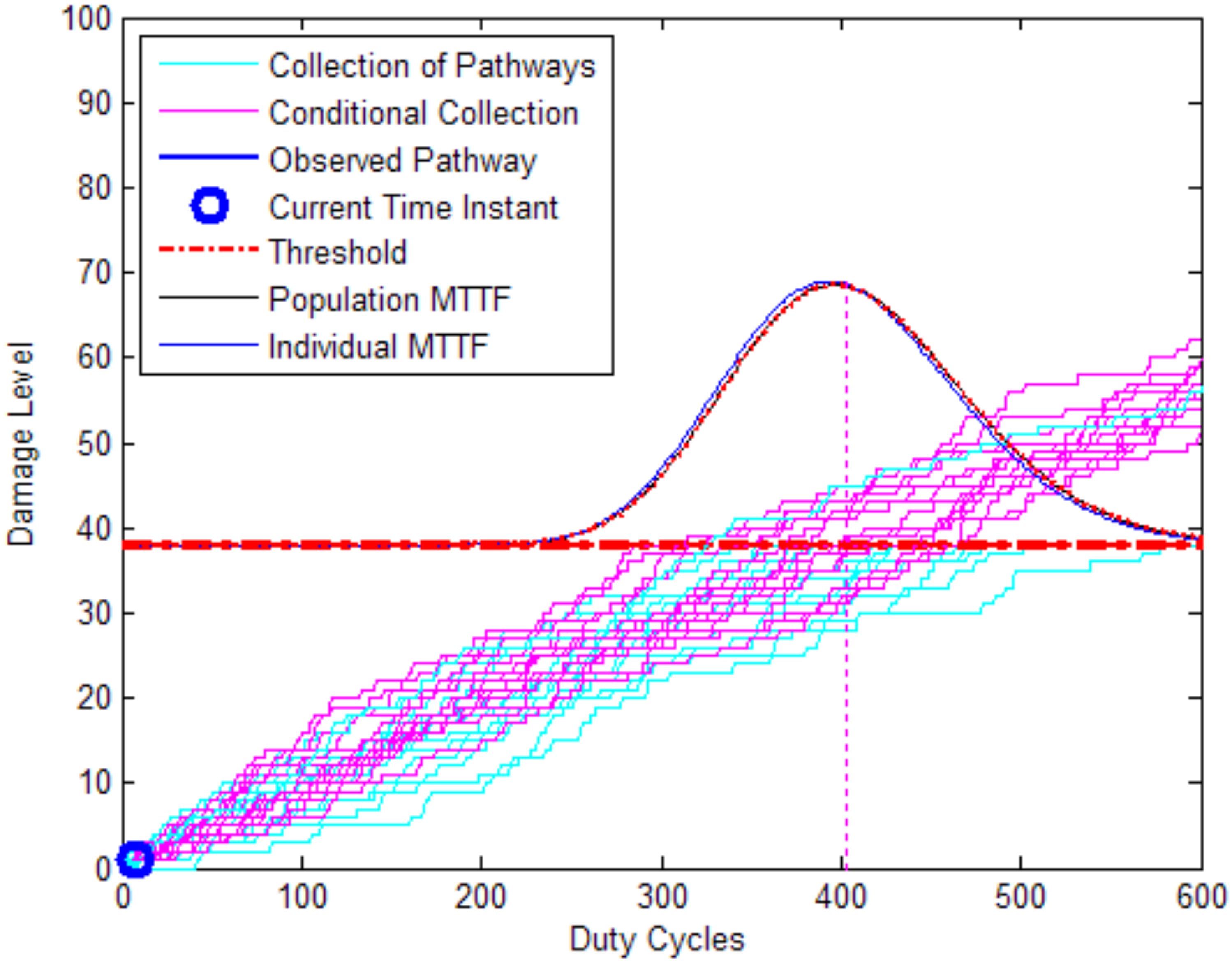
- One simple approach is to assume each state contributes some deterministic amount of degradation
  - If state *i* contributes d_i degradation, then:

$$D(t = n) = \sum_{k=1}^{n} d_{x_k}$$

  - We can easily extend this to probabilistic degradation amounts

Markov chain prognosis, t = 0




Collection of Pathways
Conditional Collection
Observed Pathway
Current Time Instant
Threshold
Population MTTF
Individual MTTF
Damage Level
Duty Cycles
0
10
20
30
40
50
60
70
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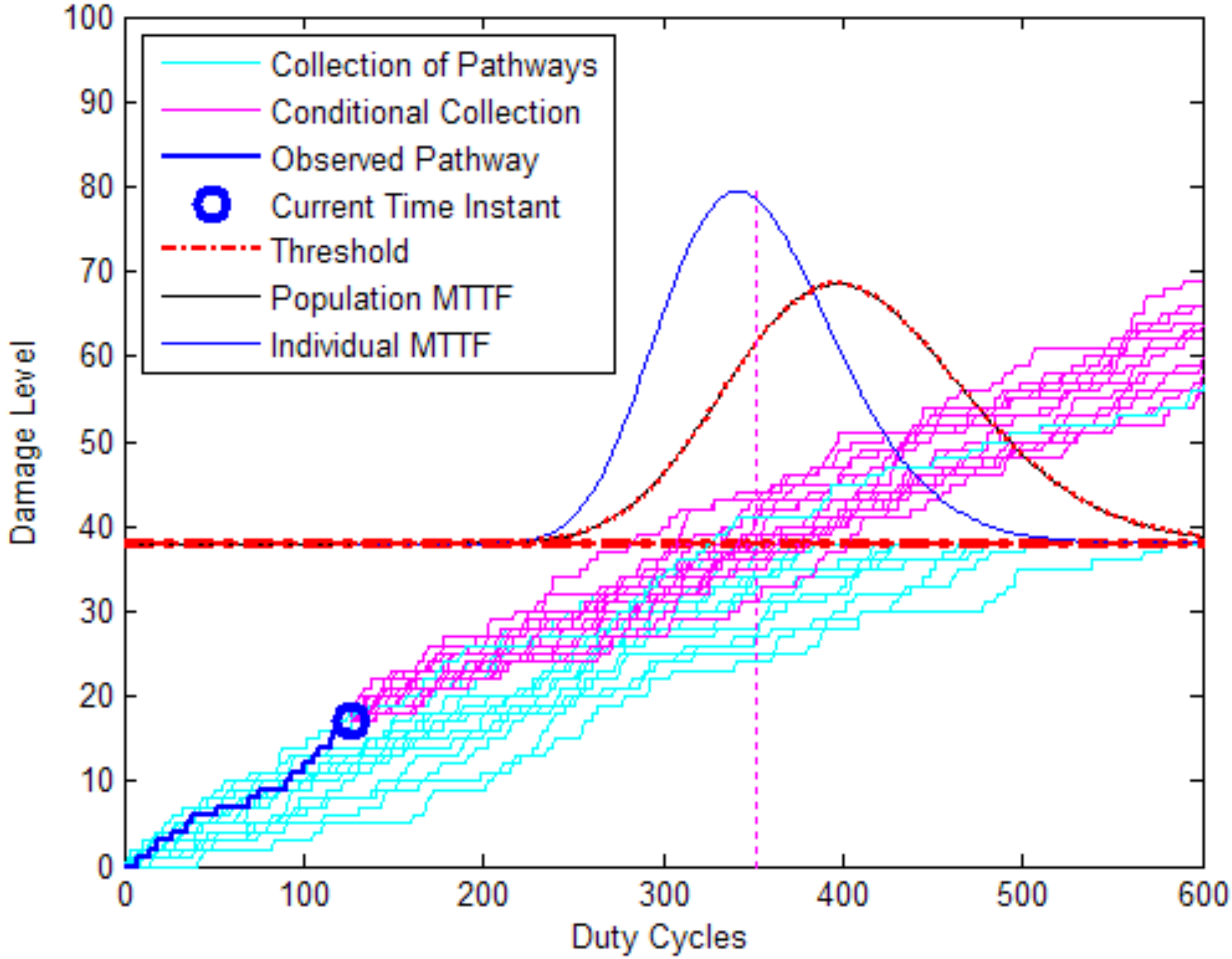

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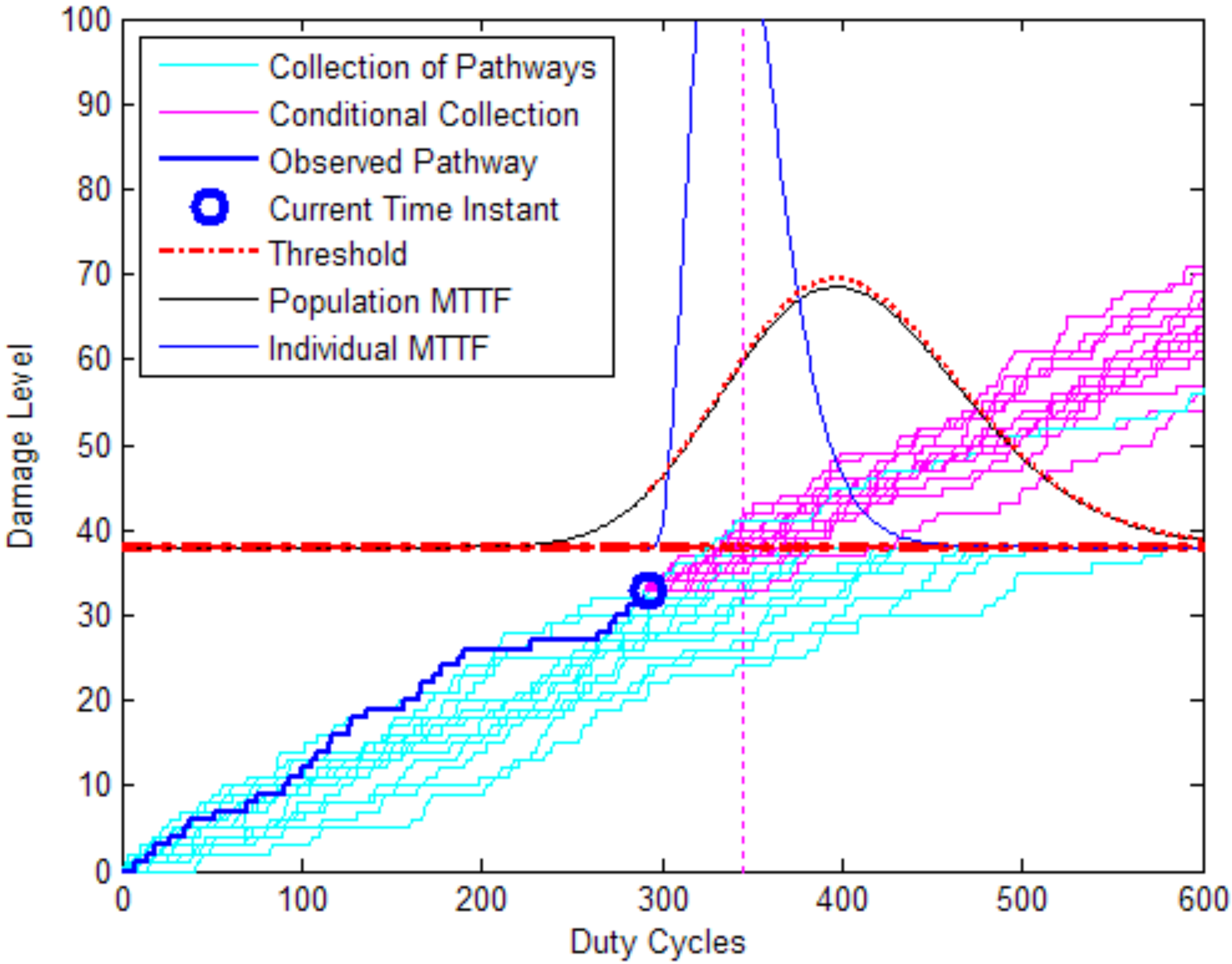

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Type II Results – Markov Chain Model

- Data divided into six operating conditions according to the three condition variables
- Used historic paths to determine condition transfer probabilities
  - Assume we have static transfer probabilities
  - Can be made time-dependent

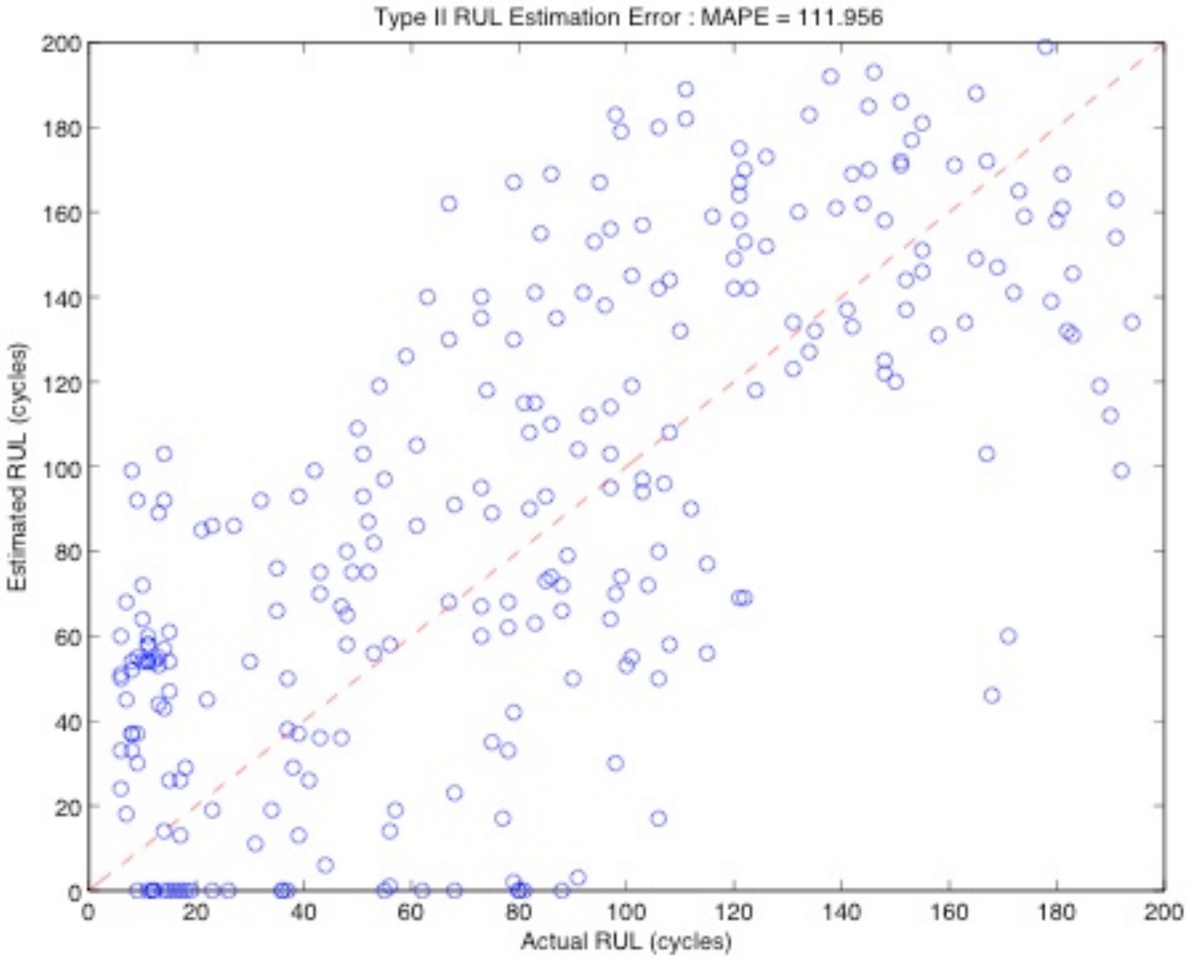
From \ To	1	2	3	4	5	6
1	0.14	0.16	0.15	0.16	0.15	0.24
2	0.16	0.15	0.14	0.14	0.15	0.25
3	0.15	0.14	0.15	0.15	0.15	0.26
4	0.16	0.15	0.15	0.15	0.15	0.24
5	0.15	0.15	0.15	0.15	0.15	0.26
6	0.15	0.14	0.15	0.15	0.15	0.26

Type II Results – Markov Chain Model

- Operation condition evolutions can be generated (MC Model I)
- However, this cannot easily be related to a deterministic degradation measure (MC Model II)

Correlation to Lifetime	
1	0.12
2	-0.037
3	0.041
4	0.021
5	-0.064
6	-0.046

Markov Chain Results



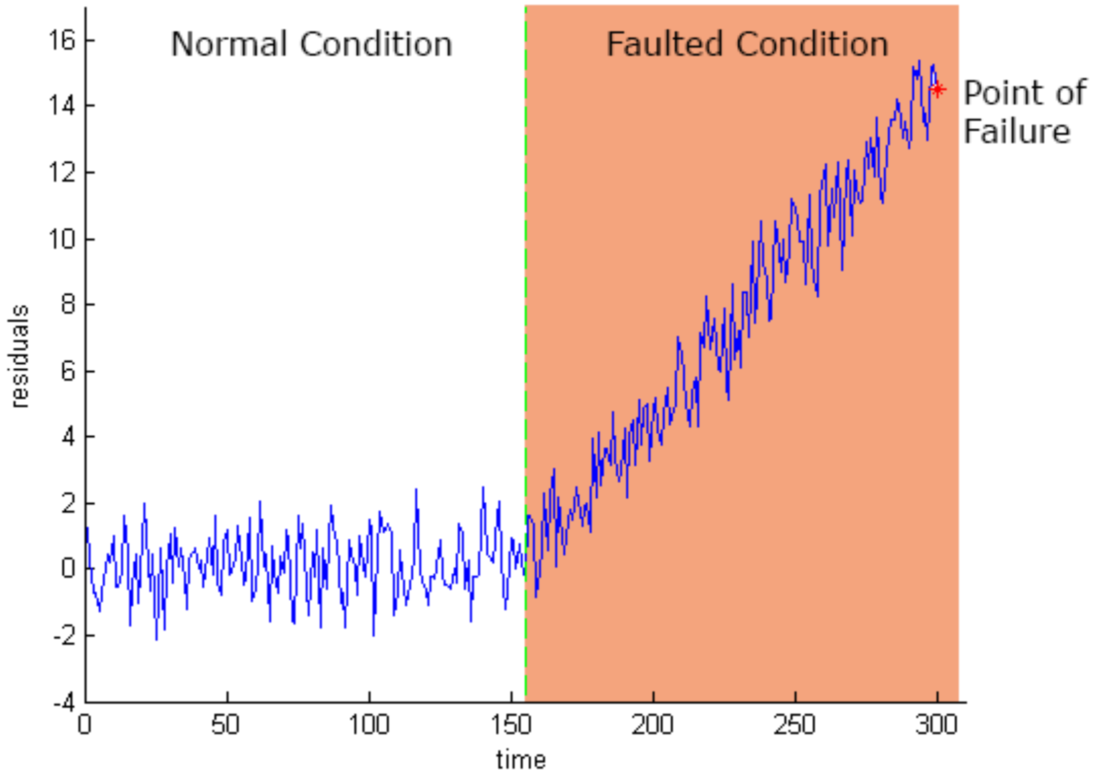
Type III – Degradation-based Prediction

- Type III prognostics estimate the lifetime of the **specific** component in its **specific** operating environment
- Type III algorithms track the degradation (damage) as a function of time and predict when the total damage will exceed a predefined threshold that defines failure
- Damage is generally assumed to be cumulative (irreversible)
- Markov chain Monte Carlo model, shock model, general path model, particle filter-based model

BIG ORANGE BIG IDEAS

Type III – Degradation Based Prognostics

- Direct measurements of the individual can be monitored to detect when a fault occurs
- A fault progresses until failure is reached



Type III: Degradation-Based Prognostics

- A **degradation measure** is a scalar or vector quantity that numerically reflects the current ability of the system to perform its designated functions properly. It is a quantity that is correlated with the probability of failure at a given moment.
- A **degradation path** is a trajectory along which the degradation measure is evolving in time towards the critical level corresponding to a failure event.

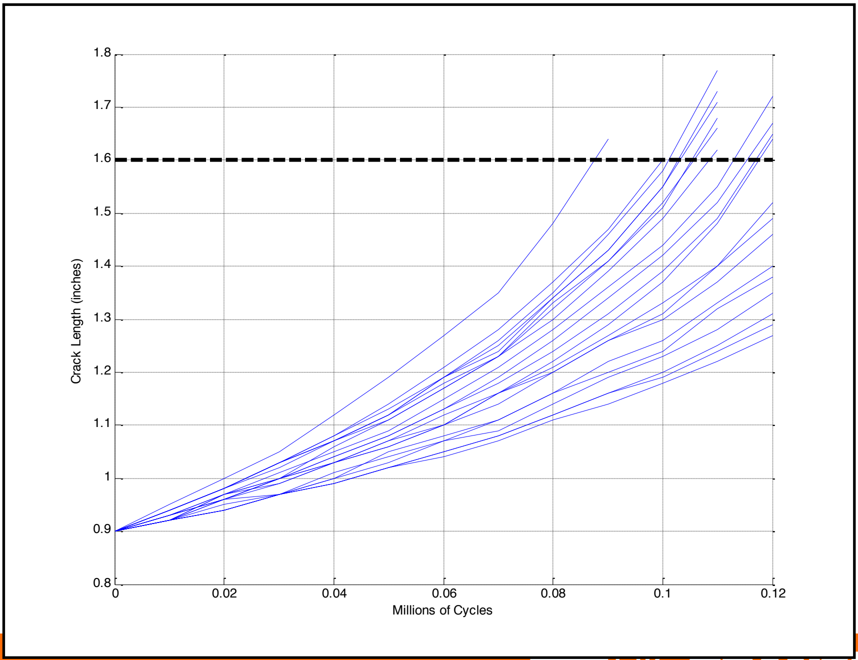
General Path Models

- Traditional reliability methods use only time-to-failure data to estimate failure distributions
- Some systems result in few or no failures during accelerated life testing
- Degradation measurements may contain useful information about product reliability

GPM to enhance reliability analysis

- The GPM was originally developed to estimate the failure density for censored data.
  - Lu, C.J. and W.Q. Meeker, "Using Degradation Measures to Estimate a Time-to-Failure Distribution," *Technometrics*, Vol 35, No 2, May 1993, pp. 161-174.

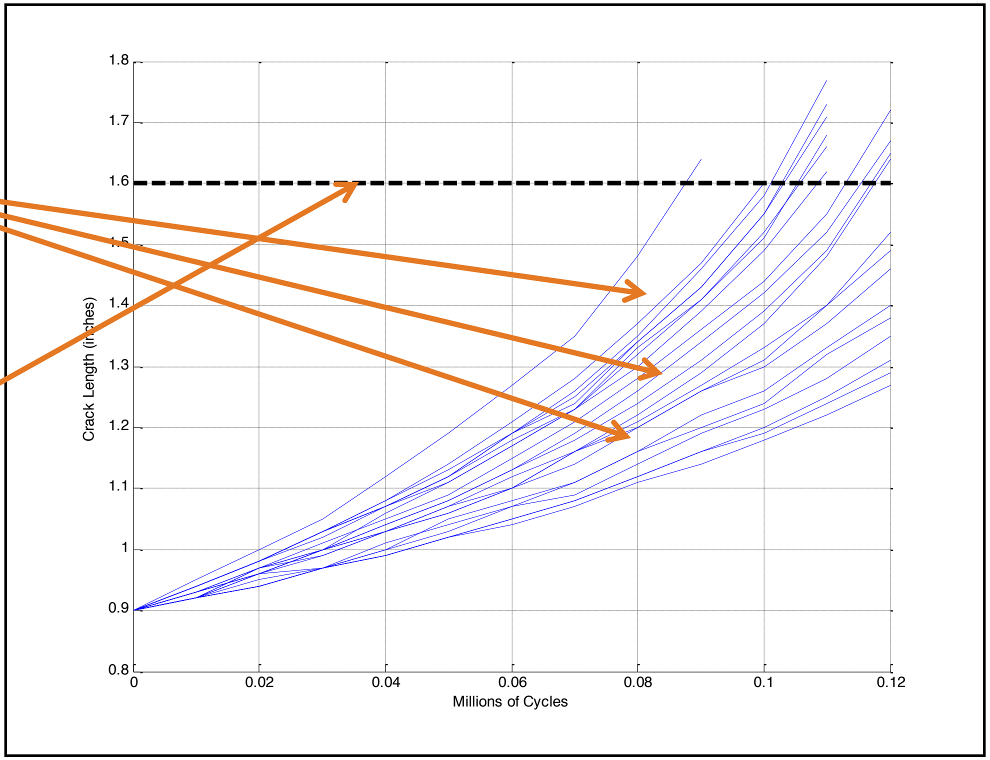
- Degradation paths were extrapolated to find estimated failure times
- The distribution was estimated from measured and estimated failure times



BIG ORANGE BIG IDEAS

General Path Models

- Degradation signal for each individual device is unique
- There is a critical threshold at which failure occurs



"Unique Path" assumption introduces individual-based TOF estimates

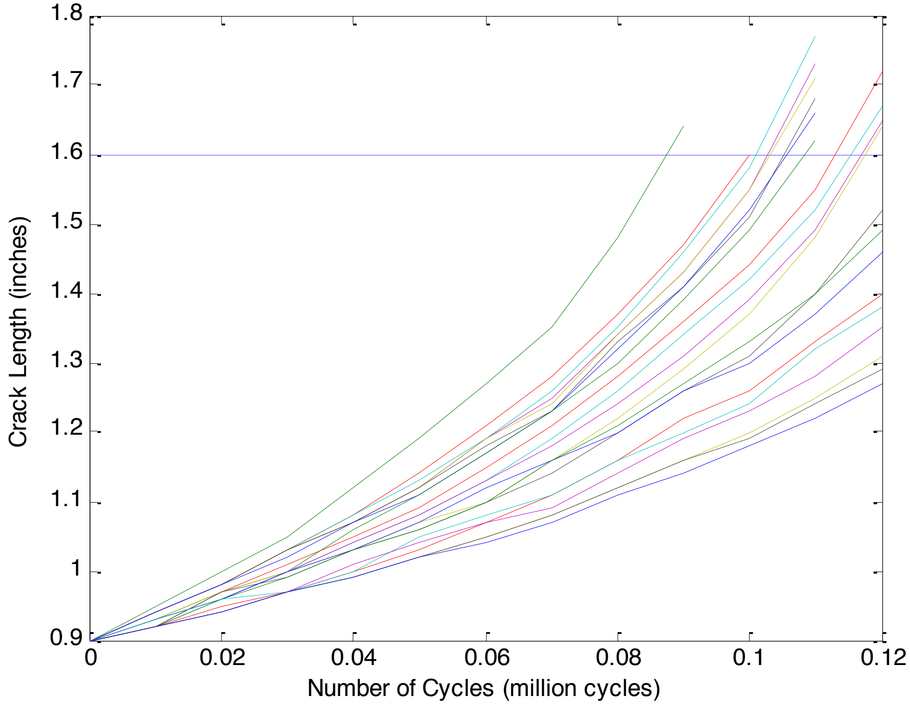
- The observed degradation path, *y*, is modeled by

$$y_i = \eta(t, \varphi, \Theta_i) + \varepsilon$$

- where φ is the vector of fixed effects (population) parameters and Θ_i is the vector of random (individual) effects for unit *i*
- The function, *η*, can be any type of model
  - Regression, spline, nonparametric, neural network, etc.
- It's convenient and straightforward to use linear models and OLS regression

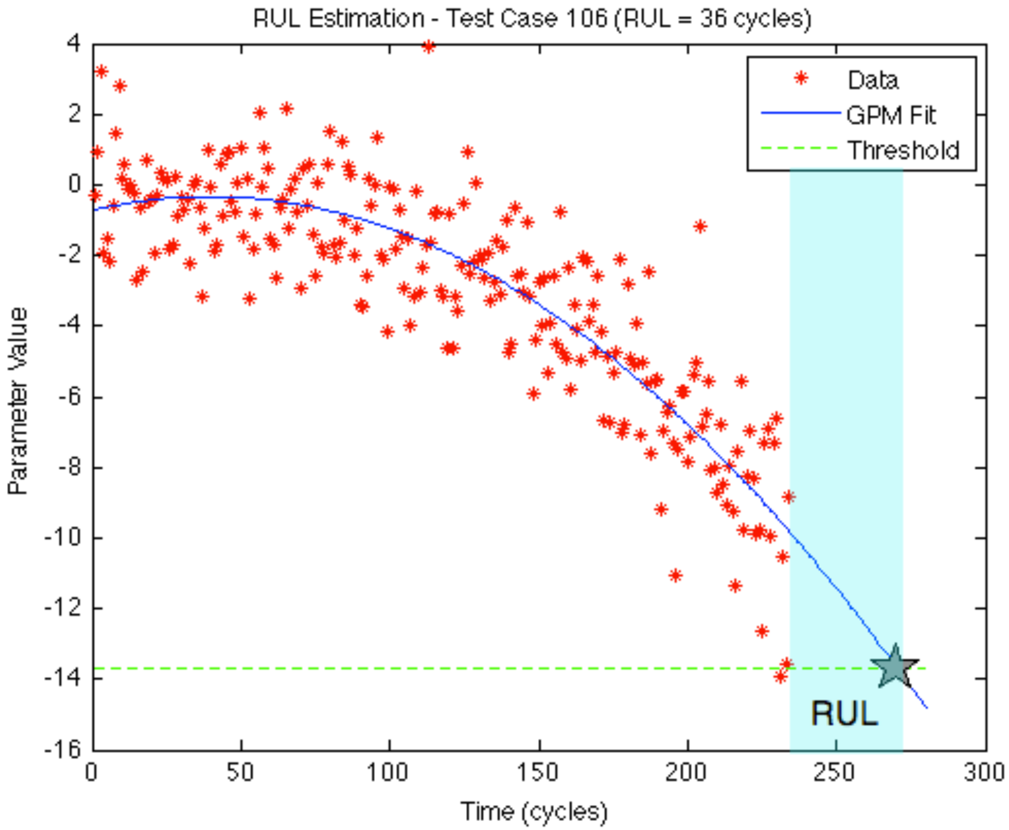
Using the GPM to estimate RUL

- Step 1: Fit a parametric model to the exemplar degradation paths; quantify mean and covariance values to describe individual, random parameters
  - Censored data can be used
  - Physical models can be used when available

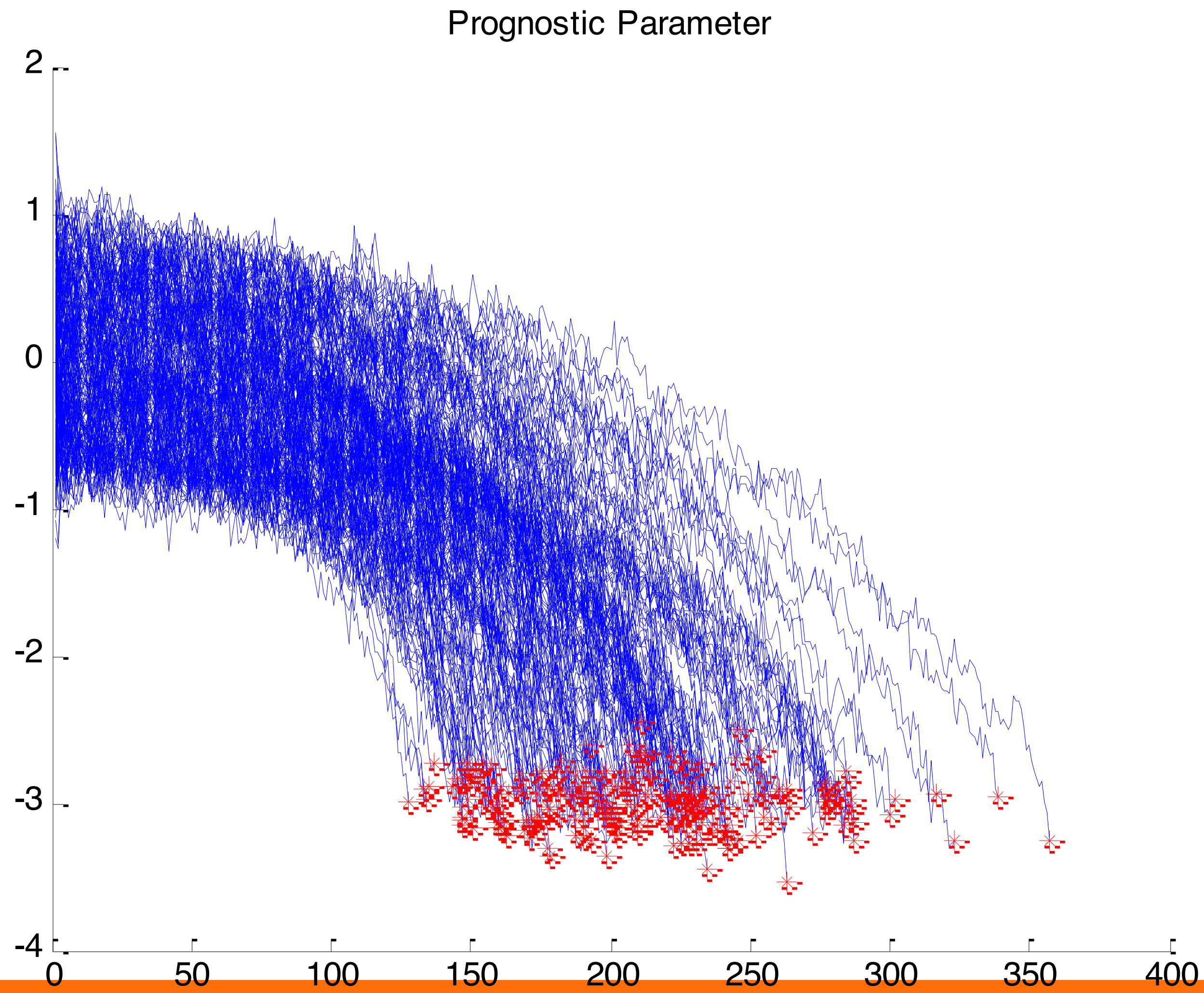


Using the GPM to estimate RUL

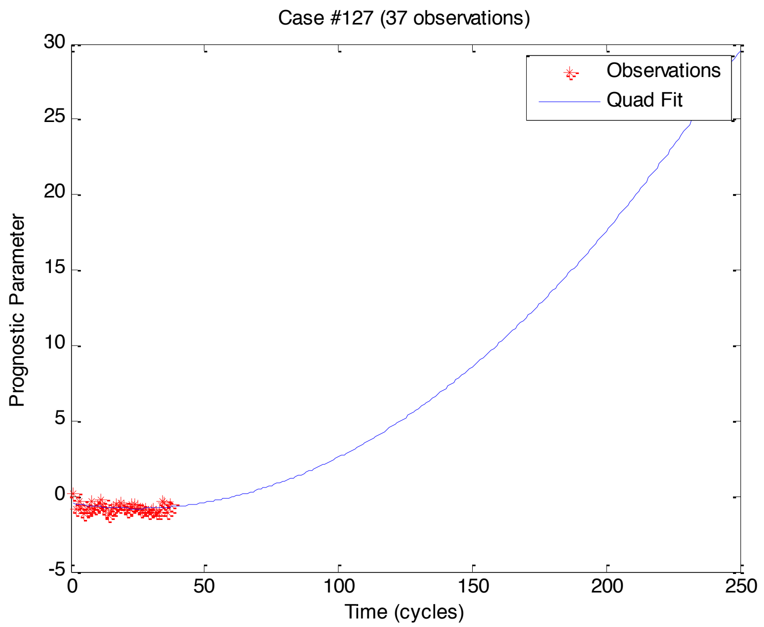
- Step 2: Use the model from step 1 and existing degradation measurements to fit a model to the current individual
- Step 3: Extrapolate this model to the critical failure threshold to estimate RUL

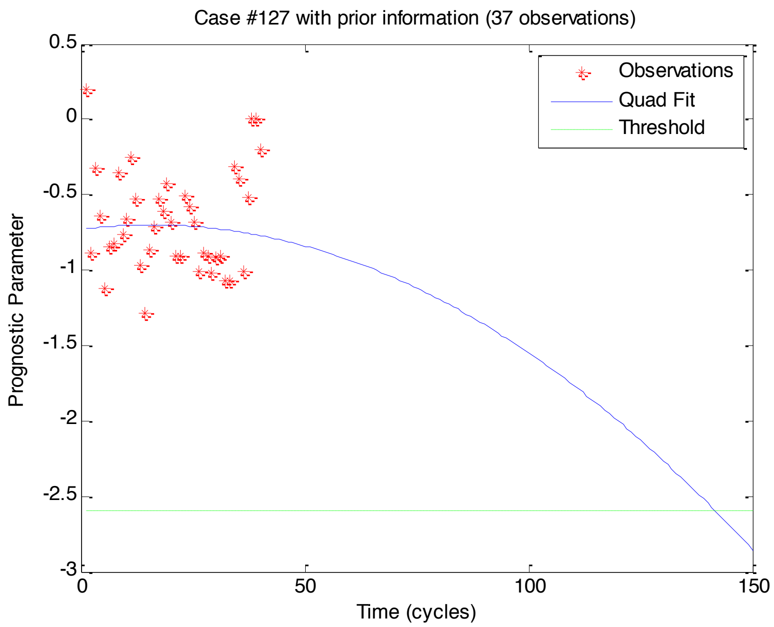


If this is your population of historic prognostic parameters …

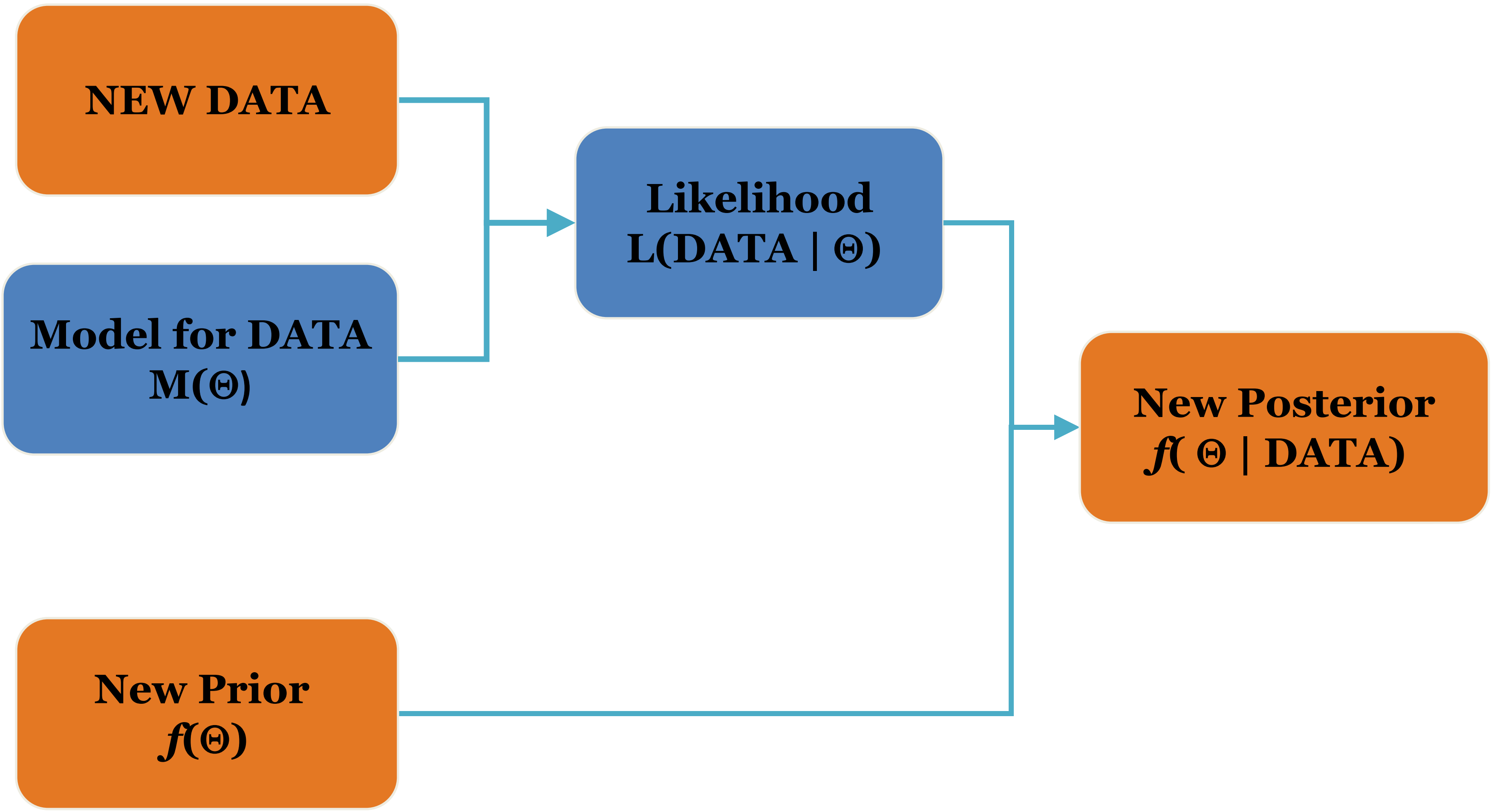


… which would you expect to be the correct prognostic trend for a new system?





We can use Bayesian methods to incorporate our prior expectations into the GPM fit



Conjugate prior methods can be used with linear regression models

- Bayesian methods for linear regression can be used to incorporate prior information
- The standard linear regression model is given by

$$Y = X\beta$$

- The model parameters are estimated as:

$$\beta = \left(X^T \Sigma_y^{-1} X\right)^{-1} X^T \Sigma_y^{-1} Y$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \quad X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad \Sigma_y = \begin{bmatrix} \sigma_y^2 & 0 & \cdots & 0 \\ 0 & \sigma_y^2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_y^2 \end{bmatrix}$$

Prior Information About Regression Coefficients

- Assume the parameters are normally distributed: $\beta_j \sim N\left(\beta_{j_o}, \sigma^2_{\beta_j}\right)$
- The prior information on β_j is treated as another observation in the regression

$$Y^* = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \\ \beta_{j_o} \end{bmatrix} \quad X^* = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \\ 0 & \cdots & 1 & 0 \end{bmatrix} \quad \Sigma^*_y = \begin{bmatrix} \sigma^2_y & 0 & \cdots & 0 & 0 \\ 0 & \sigma^2_y & \ddots & \vdots & 0 \\ \vdots & \ddots & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \sigma^2_y & 0 \\ 0 & 0 & \cdots & 0 & \sigma^2_{\beta_j} \end{bmatrix}$$

- New parameter estimates become the prior information for the next data observation

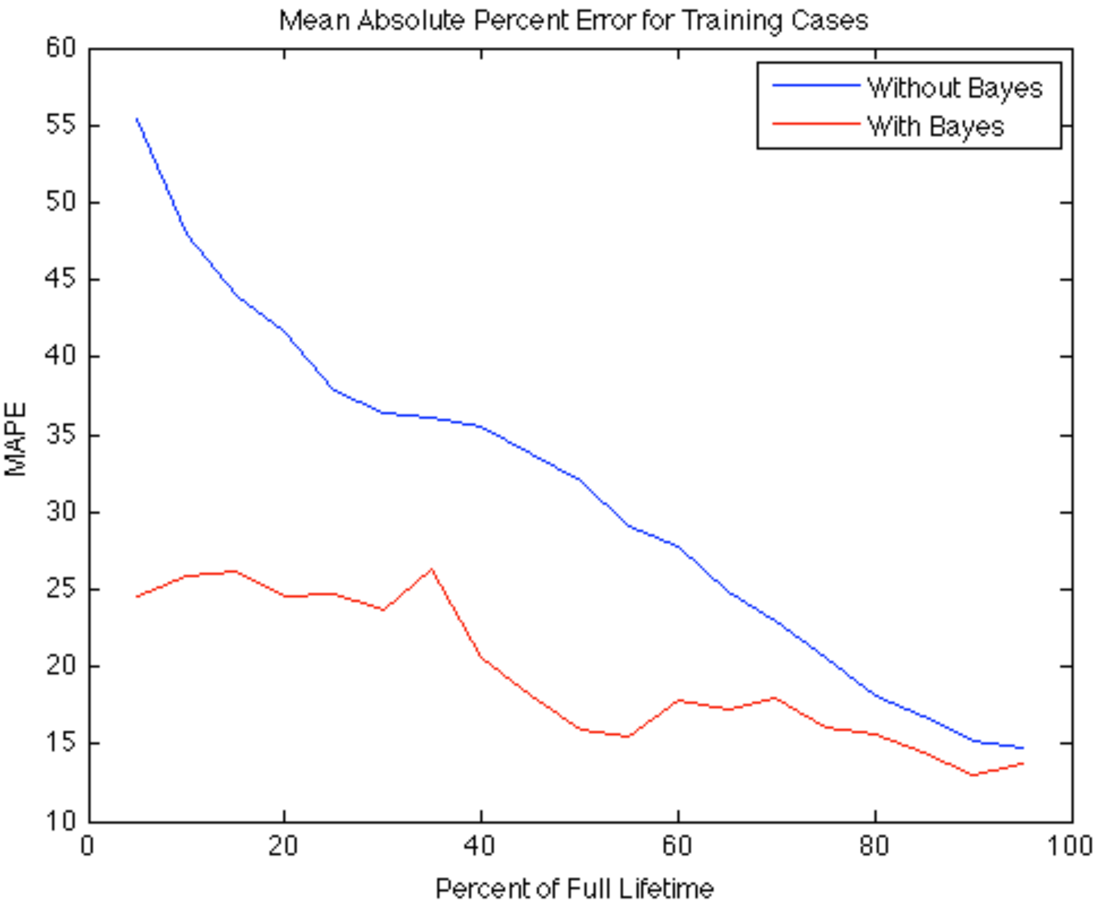
Prior Information About All Regression Coefficients

$$\beta \sim N(\beta_0, \Sigma_\beta)$$

$$Y^* = \begin{bmatrix} Y \\ \beta_0 \end{bmatrix} \qquad X^* = \begin{bmatrix} X \\ I_k \end{bmatrix} \qquad \Sigma^* = \begin{bmatrix} \Sigma_y & 0 \\ 0 & \Sigma_\beta \end{bmatrix}$$

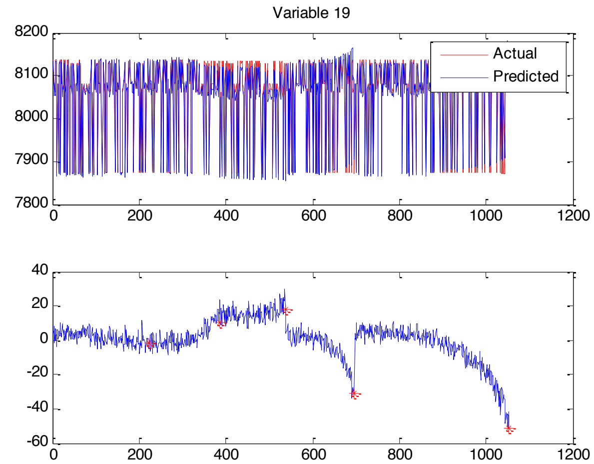
$$\hat{\beta} = (X^{*T}\ \Sigma^{*\,-1} X^*)^{-1}\ X^{*\,T} \Sigma^{*\,-1} Y^*$$

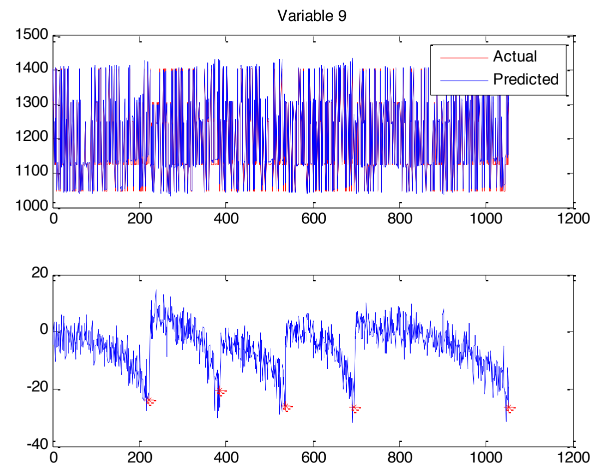
Comparison of GPM and GPM/Bayes RUL Predictions



Type III Results – General Path Model

- Monitoring system residuals as prognostic parameters
  - Same shape for every case
  - Same value at failure
- Six residuals were identified and combined (weighted average) as the prognostic parameter

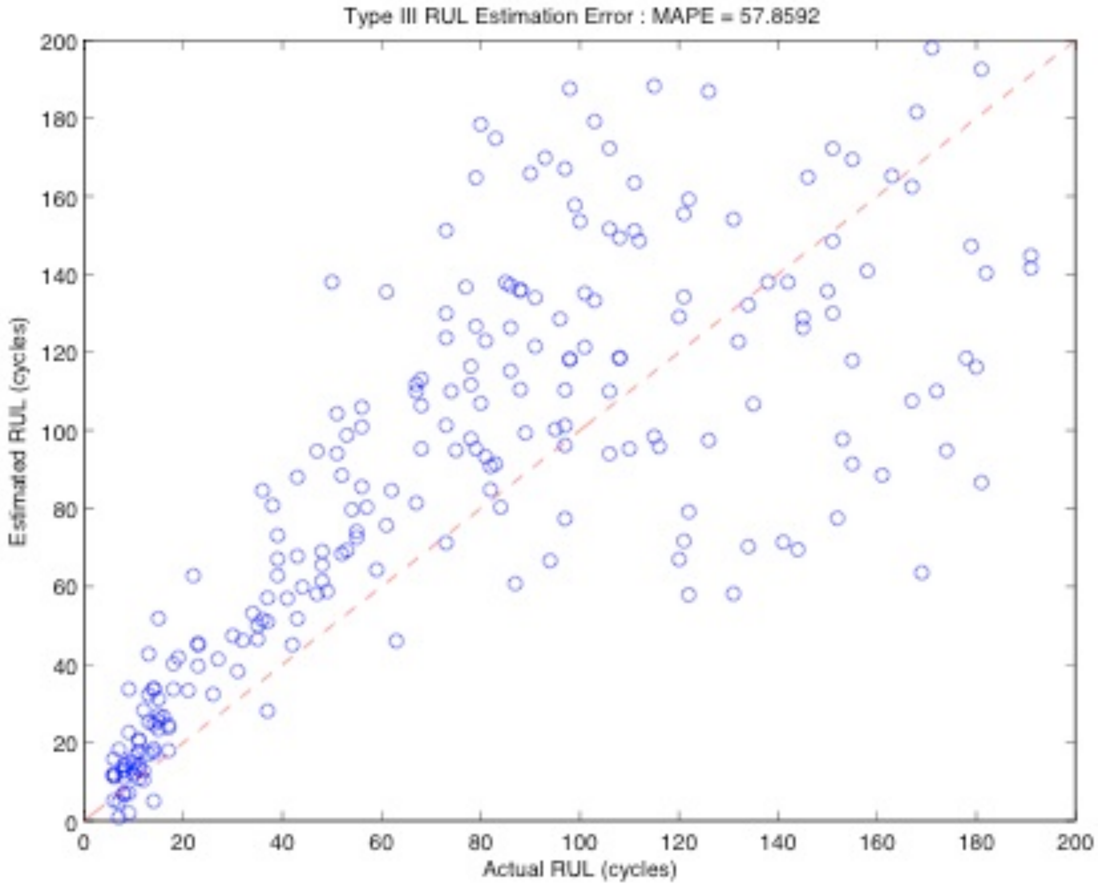




Type III Results – General Path Model

- Used Bayesian priors estimated from historic failure cases
- Quadratic fit

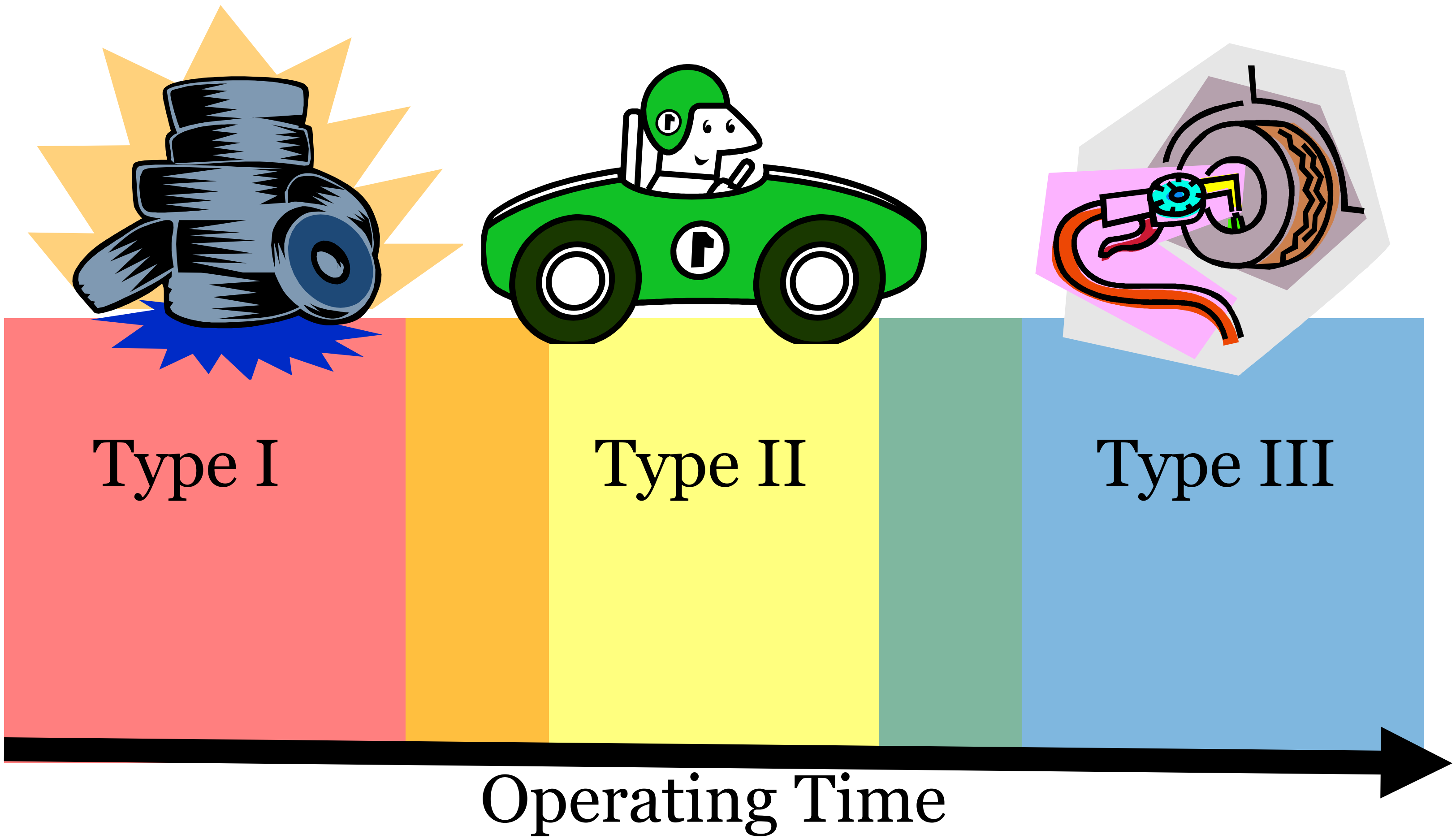
$$f(t) = \beta_1 t^2 + \beta_2 t + \beta_3$$



Data Requirements for each Type

- For Type I, failure modes must be related to usage time or number of operating cycles for historical data to be beneficial.
  - Failures cannot be random (characterized by an exponential failure model), we don't replace our tires for fear of hitting a nail.
- For Type II, environmental effects that drive the failure modes must be measurable.
  - Must measure temperature, load, cavitation, etc.
- For Type III, degradation severity must be related to a measurable or inferable degradation parameter such as tread depth, bearing vibration level, or impeller thickness.
  - Degradation growth must be slow enough for decisions to be made and actions to be taken.

Lifecycle Prognostics



Questions left unanswered

- How do we propagate uncertainty through our prognostics?
- How do we assess and compare the performance of prognostic models?
- What about physics-based models?
- What do we do if we don't have a large history of degradation and failure data?
  - How can we combine physics-based and data-driven approaches?

To summarize data-driven prognostics …

- There is no one-size-fits-all solution to prognostics!
  - Different data may be available
  - Different algorithms may be best for different systems or fault modes
- Several approaches and algorithms exist; selection is based on
  - Data available: failure, causal, effects.
  - Knowledge of degradation mode (physical model)
- Sensed data contains degradation information and should be used to improve operational reliability through:
  - Optimizing maintenance scheduling (condition-based)
  - Improving operations and asset utilization (equipment state knowledge)

Research Opportunities

- Online performance metrics for prognostics
- Data analysis during non-stationary operation
- Online performance metrics
- Verification and validation methodologies
- Algorithms to mine information from **large data**
  - Identify important degradation correlations
  - Uncover significant maintenance relationships
  - Optimize data usage to improve safety and reliability
- Integration of PHM results into operations and maintenance planning, risk assessment, and optimal control

Questions?

jamie@utk.edu

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