Empirical Methods for Process and Equipment Prognostics

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Reliability Programs at UT COE

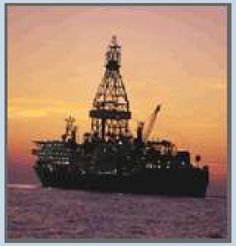
- **Maintenance and Reliability Center (MRC)**
  - University - industry association dedicated to improving industrial productivity, efficiency, safety & profitability through advanced maintenance and reliability technologies and management principles
  - Industrial Center since 1996 with 30 members

- **Reliability and Maintainability Engineering Program (RME)**
  - Interdisciplinary Academic Program
    - Undergraduate Minor in RME
    - Graduate Certificate and/or MS in RME
  - Local or Synchronous, Interactive Distance Delivery

- **Prognostics, Reliability Optimization and Control Technologies (PROaCT)**
  - Interdisciplinary research program with professors and students in industrial, mechanical, and nuclear engineering, and statistics.

Monitoring and Prognostics Research

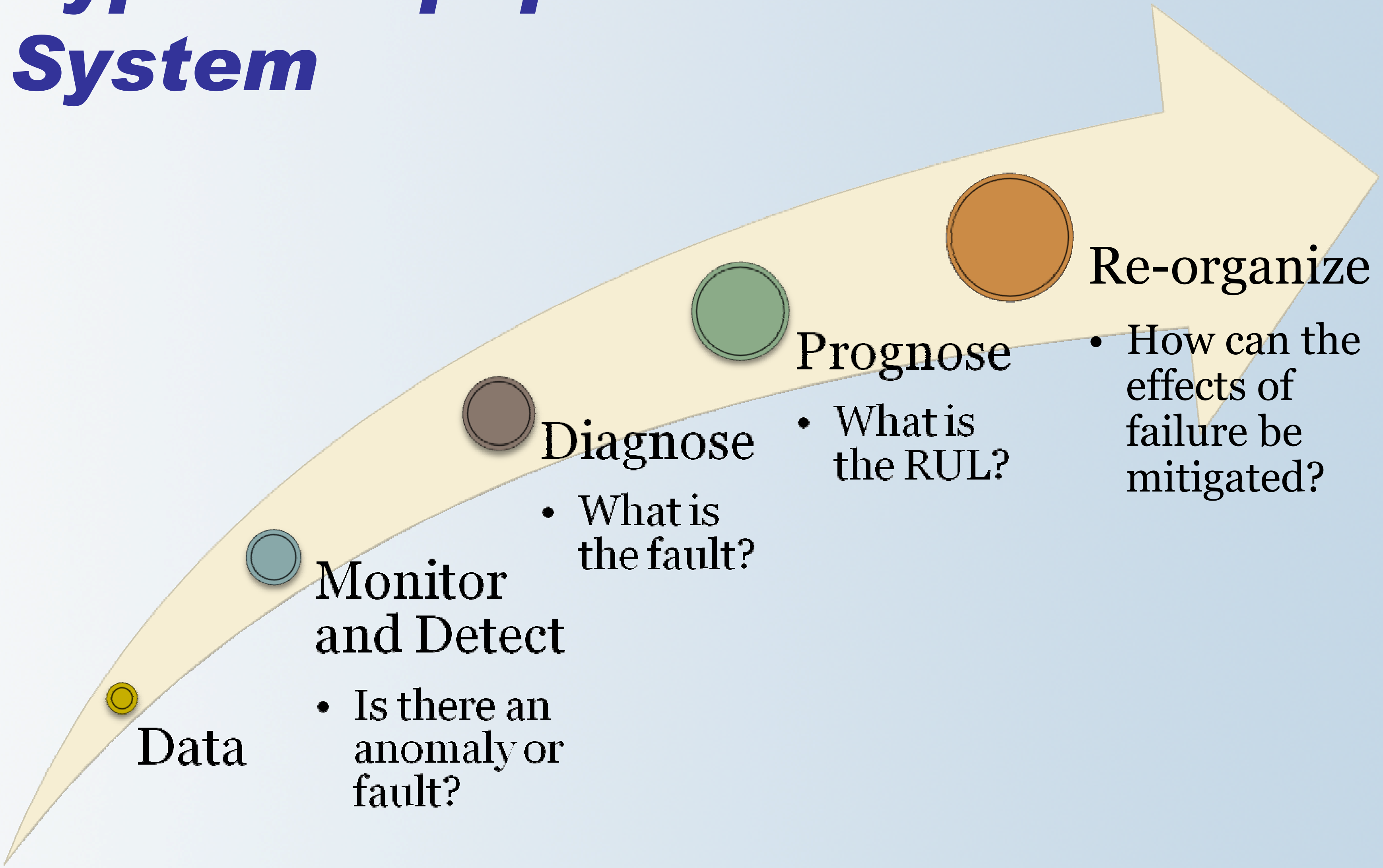
- Experimental Breeder Reactor II, 1989.
- Florida Power Corporation Nuclear Plant Monitoring, 1995.
- Dow Corning Chemical Plant Monitoring, 1996.
- High Flux Isotope Reactor Monitoring, 1997.
- Idaho National Engineering and Environmental Lab, 1998-2000.
- TVA Kingston Fossil Power Plant, 1998-2003.
- SmartSignal Inc. Uncertainty Estimation, Model Regularization and
- Sun Microsystems, Improved Real-time Fault Detection, 2002 - 2003
- EPRI Redundant Sensor Calibration Monitoring and Reduction System, 2003
- Halden Reactor Project, Uncertainty Analysis, 2003.
- Oak Ridge Y-12 Sensor Fault Detection for CAVIS 2003
- DOE Automated On-Line Monitoring and Diagnostics of the Integrity of Nuclear Plant Steam Generators and Heat Exchangers 2002-2005
- NSF Cooperative Research Project on Monitoring and Diagnosis of Process System Components, 2004-2006
- NRC, On-Line Monitoring Regulatory Research Needs, 2005-2006
- Expert Microsystem, Uncertainty Analysis of Empirical Models 2005–2006
- EPRI, Improved Probability of Failure Analysis using Equipment Condition Assessment (ECA) Based on Health Monitoring Technologies, 2005- 2006
- Sun Microsystems, Computer Monitoring and Diagnostics, 2005- 2006.
- Idaho National Laboratory, SCADA System Modeling and Diagnostics, 2005-6.
- BHI, On-Line Monitoring, Diagnostics, and Prognostics of Drilling Operations, 2006-2007.
- Global Strategic Solutions, Advanced Prognostic and Health Management (PHM) and Model Based Prognostic Useful Life Remaining Capabilities for Aircraft Tactical Information and Communication Systems for the U.S. Navy SBIR 2007.1 - Topic N07-010, 2007-2009
- EPRI, Prognostics Methods for Power Plants 2008-2009.
- Halliburton, Monitoring Drilling Operations, 2008-2009.
- Ridgetop, Prognostics and Health Management (PHM) for Digital Electronics Using Existing Parameters
  and Measurands for the U.S. Navy, 2007-2009
- DOE, Advanced Instrumentation and Control Methods for Small Export Reactors , 2007-2010.
- US Dept of Justice, Improved Facial Reconstruction Techniques, 2009.



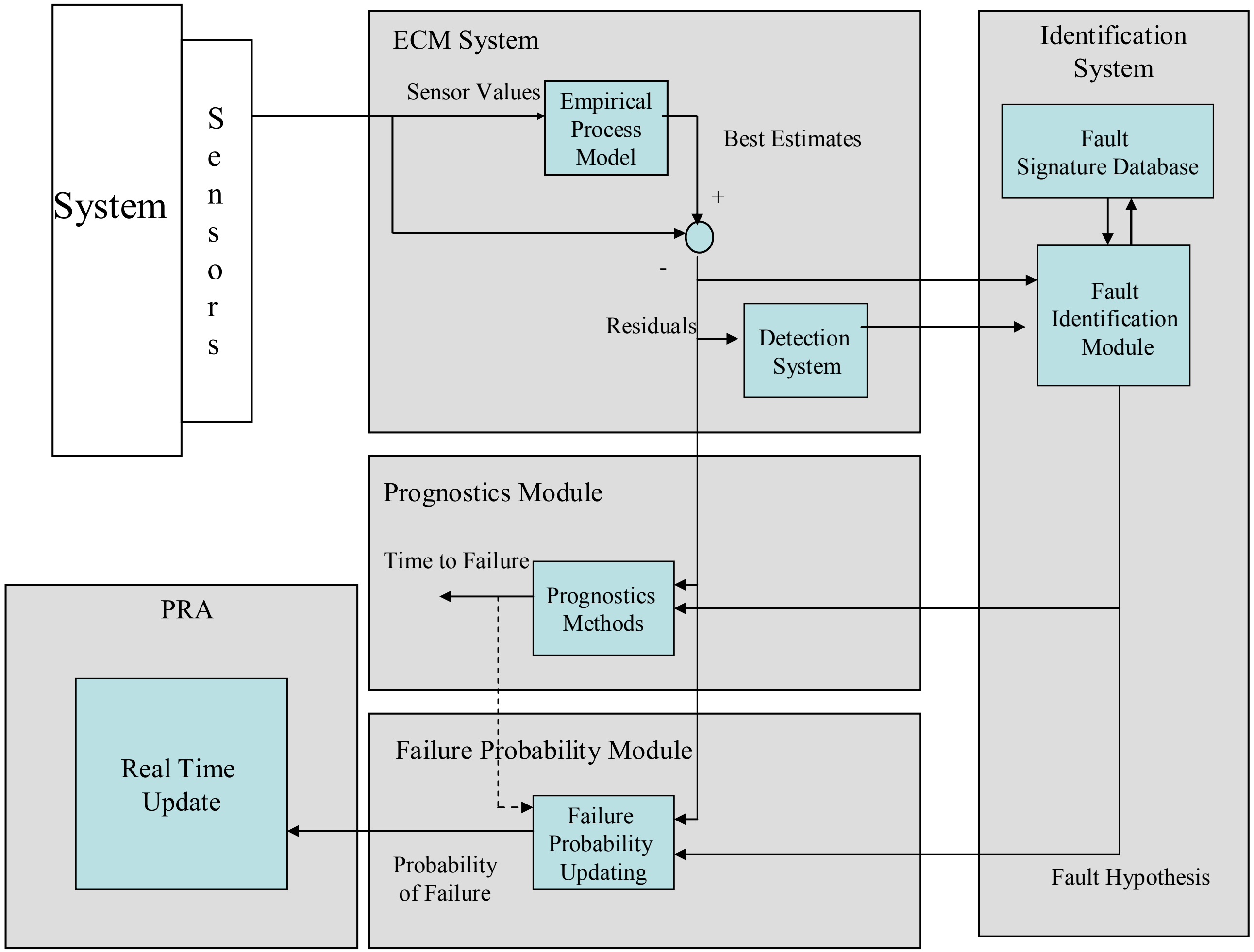
Overview

- Overview of Equipment Surveillance
- Introduction to Equipment Prognostics
- Prognostic Methods
- Prognostic Case Studies

Typical Equipment Surveillance System

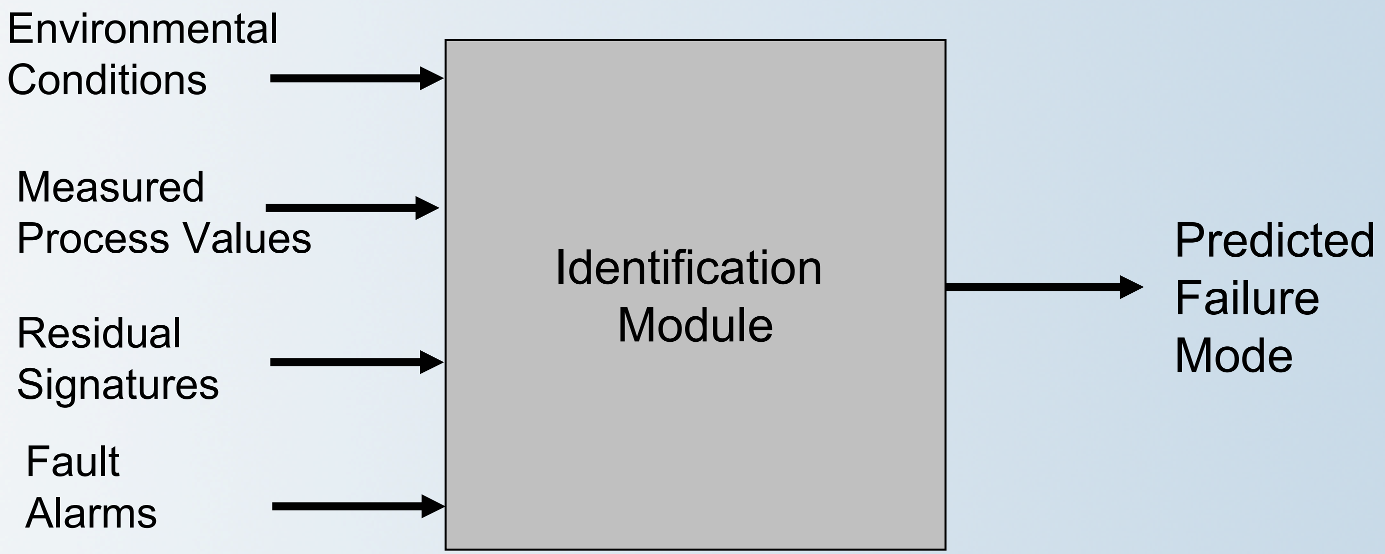


System Interaction Diagram



Basic Identification Architecture

- **Use information in environmental and operational conditions, measured process values, and monitored residuals, and fault alarms to identify the fault mode.**
- **Different fault modes progress to failure differently and thus will require different prognostic models.**



Prognostics 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 to Failure (TTF): **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.**

Prognostics Motivation

- **Improved prognostic and predictive capabilities using existing monitoring systems, data, and information will enable more accurate equipment risk assessment for improved decision-making.**

  - **Reduce needless maintenance through lengthened (optimized) maintenance intervals.**
  - **Reduce unplanned maintenance and associated costs.**
  - **Improve safety and reduce environmental impacts.**

- **Operational Decisions:**
  - **Should we continue to operate or immediately shutdown for maintenance?**
  - **Can we change operations (speed, load, stress) to make it to the next maintenance opportunity?**
  - **Will the equipment have high probability of safe operation for the planned mission?**

Constant Failure Rate

- **What if the failure mode has a constant failure rate: truly random failures? (no wear-out)**
- Can you do prognostics?

- **Yes you can: If you can detect failures before they occur, you can take action.**

- **Eg. Getting a nail in your tire is a random event, you can't predict it, so Weibull analysis, planned replacement, and overhaul have no value; but, if you measure pressure or look at your tires frequently, you may be able to detect the fault and replace it before it fails.**

Decision Time

- **We routinely hear that if there is a very short time between detection and failure, monitoring is useless.**
- Do you agree?

- **If you can detect and identify a failure, then reconfigure, you may improve availability.**

- **Eg: Multi Level Inverter Drives**
  - **Automated fault detection and accommodation.**

Prognostics Data Hurdle

- **In many fields failure data may be difficult to obtain.**

WHY?

1. **When components are found to be degraded they are repaired or replaced.**
   - **Unexpected vibration levels of a nuclear power plant reactor coolant pump will prompt an immediate response.**

2. **When important failure modes are discovered, they are designed out of the system.**
   - **When several failures of a truck's steering system are discovered, a redesign and recall may be initiated.**

Basic Prognostics Methodology

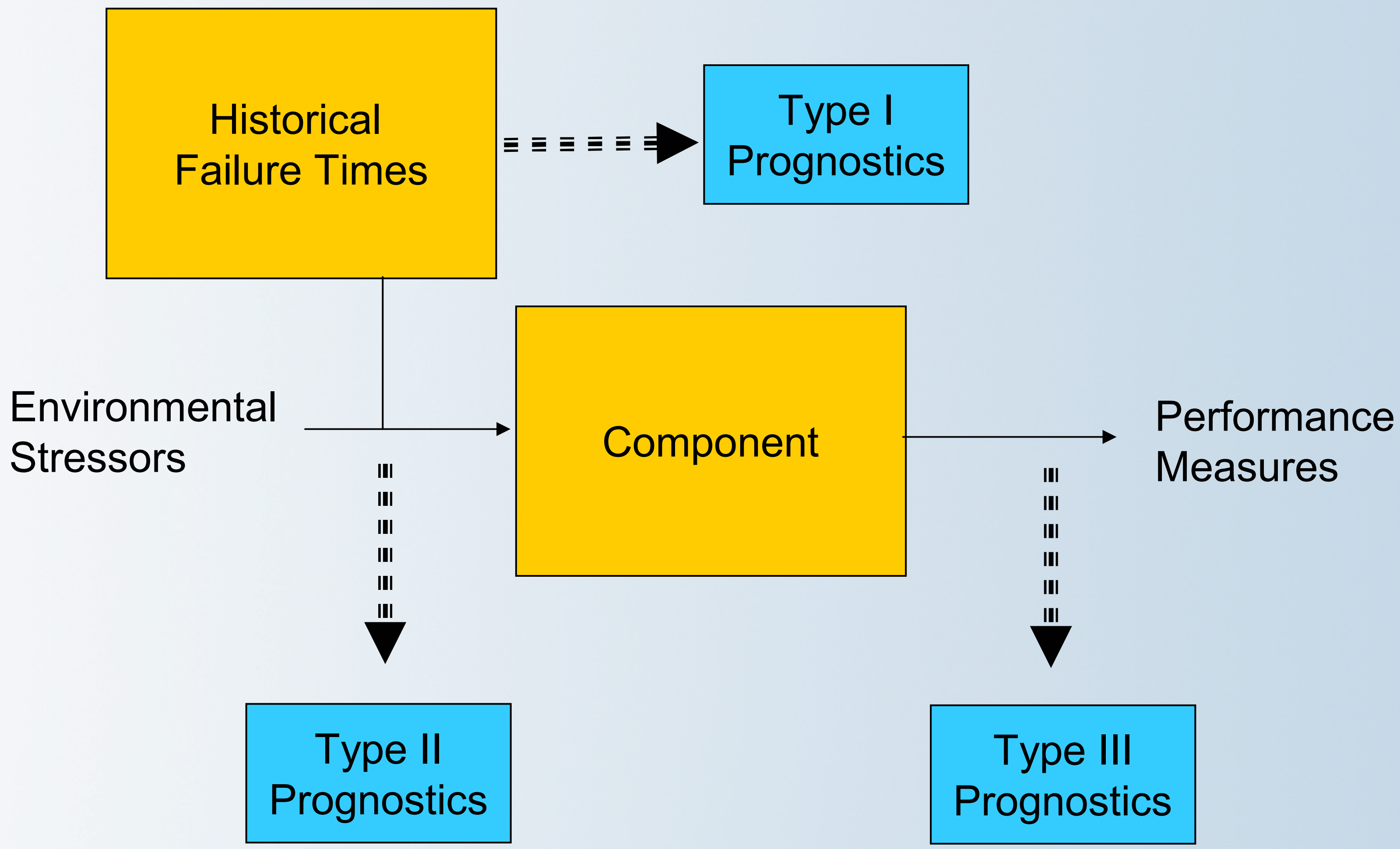
1. **Collect historical failure data and related information.**
2. **Perform a Failure Modes Effects and Criticality Assessment (FMECA) of the system of interest.**
   - **A FMECA++ also identifies sensor information that changes with degradation.**
3. **Perform Accelerated Life Testing**
   - **Collect degradation data identified in FMECA++**
4. **Develop Prognostic Model**
   - **Many types are available.**
5. **Validate Prognostic Model**

Note: Each failure mode may require its own prognostics model.

Prognostic Method Categories

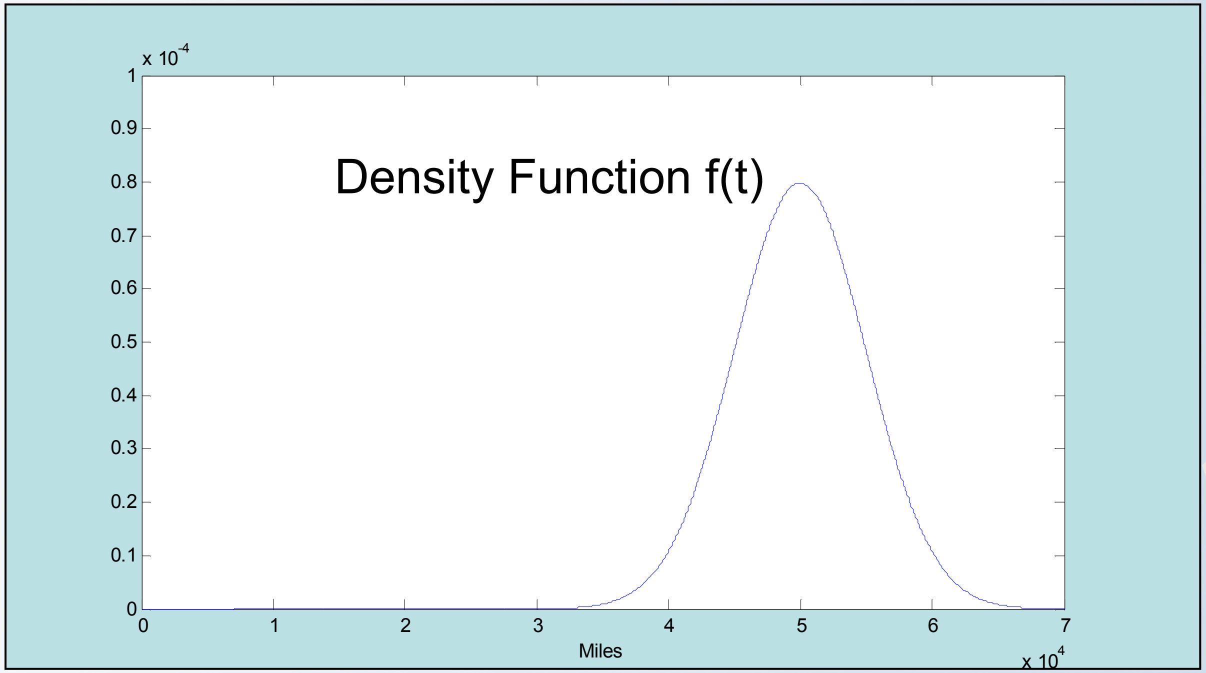
- **Type I: Reliability Data-based (population)**
  - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of an average component under average usage conditions.
  - Example Method: Weibull Analysis
- **Type II: Stress-based (population)**
  - 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.
  - Example Method: Proportional Hazards Model.
- **Type III: Effects-based (individual)**
  - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions.
  - Example Method: Cumulative Damage Model

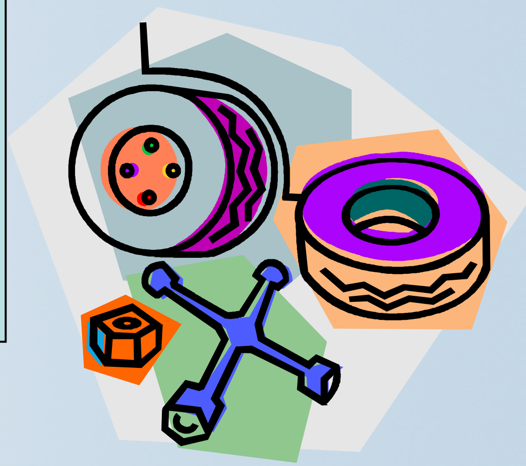
Prognostic Method Types



Tire Prognostics Example

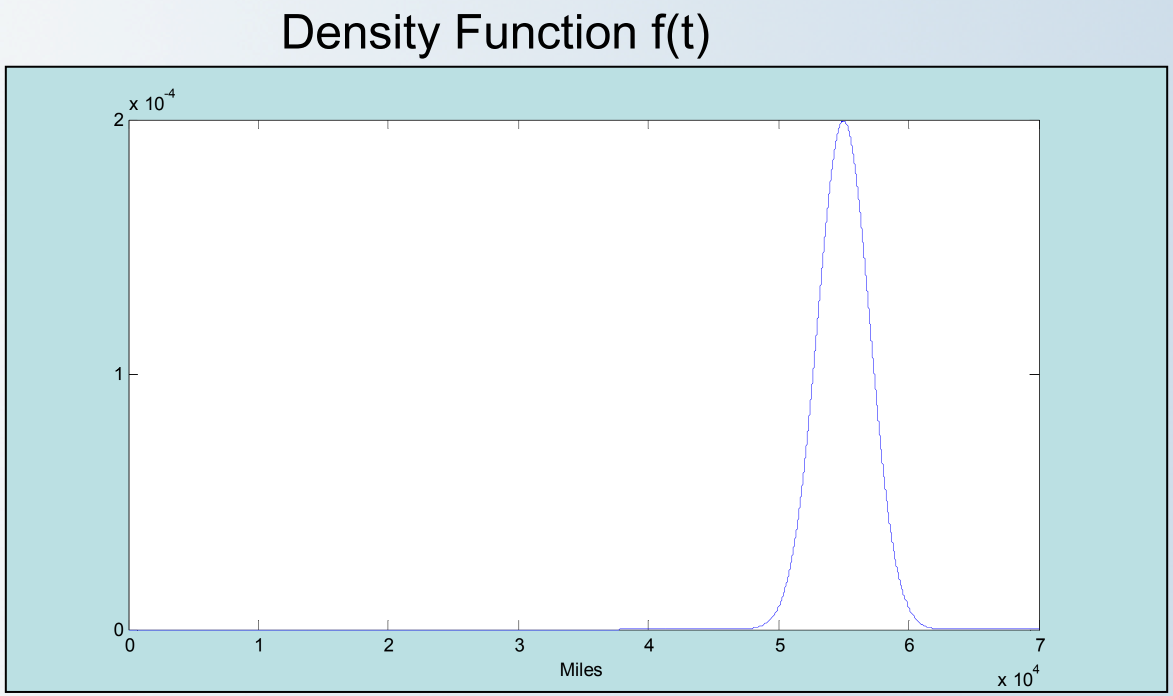
- **Type I: Tire failure distribution is normally distributed with a mean of 50,000 miles and standard deviation of 5,000 miles.**

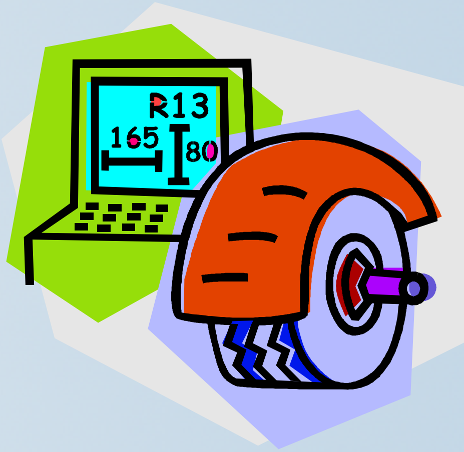




Tire Prognostics Example

- **Type II: Tire failure is estimated by knowing the number of miles driven and the tire conditions for each mile driven: temperature, slippage, inflation, etc.**
  - **This results in a new distribution for that particular tire.**

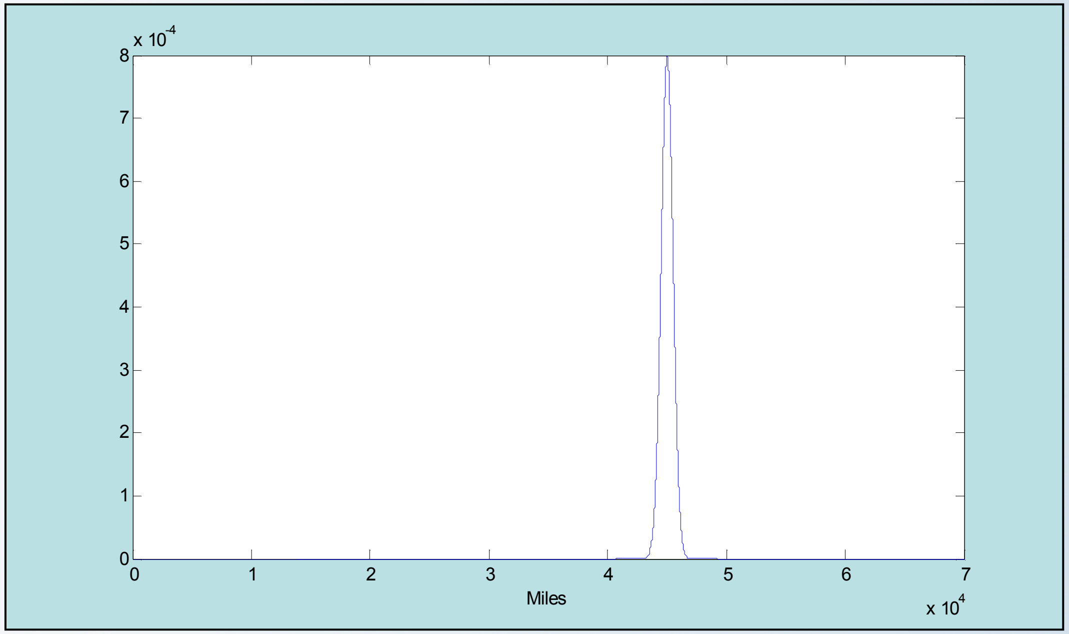




Tire Prognostics Example

- Type III: Tire failure is estimated by knowing the actual condition (tread depth, dry rot) of the tire.
  - This results in a new distribution for that particular tire.

Density Function f(t)



Some Basic Prognostic Data Requirements

- For Type I, failure modes must be related to measurable stressors for historical data to be beneficial.
  - Failures cannot be random (characterized by an exponential failure model)
- For Type II, environmental effects that drive the failure modes must be measurable.
- For Type III, degradation severity must be related to a measurable parameter such as tread depth or bearing vibration level or temperature.
  - Degradation growth must be slow enough for decisions to be made and actions to be taken.

Type I. Reliability Data-Based Prognostics

(population based)

- **This group of methods attempts to 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 useful in predicting the failure density.**
- **Example parametric models include exponential, normal, log-normal, and Weibull.**

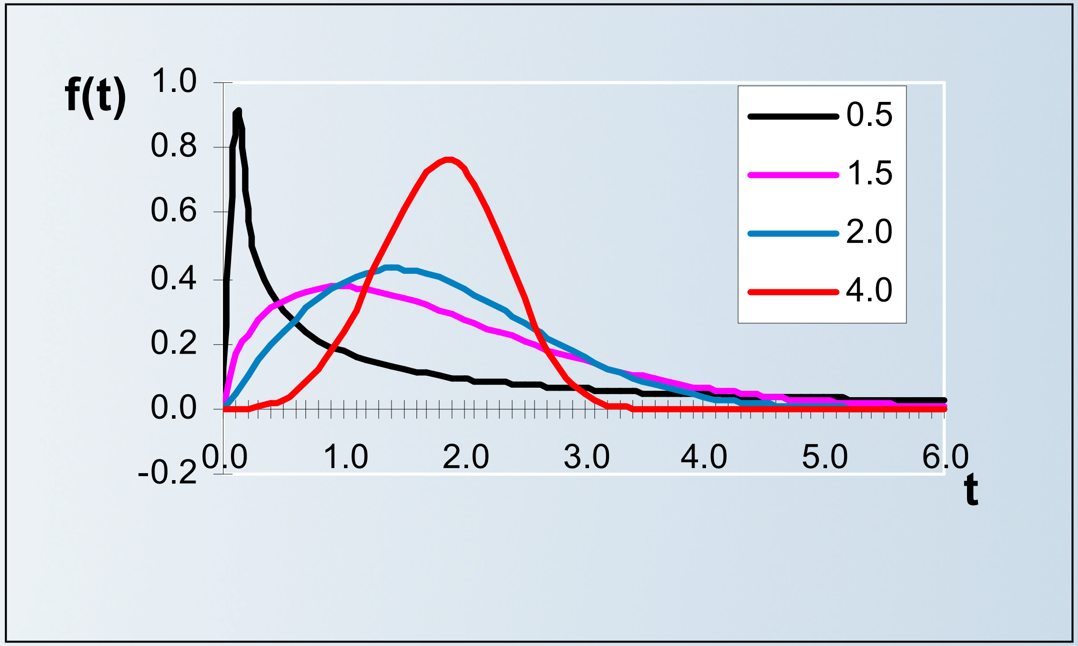
Weibull Model

- 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).**
- **the Weibull distribution does a good job of modeling failure data with exponential, normal, or Rayleigh distributions.**



Reliability Data-Based 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.
- It provides a failure distribution for the average component operating under average conditions (population-based).
- Shortcomings
  - Failures observed during lifetime tests may not be useful for different operating conditions.
    - Equipment setups may be different for different applications and the amount of failure data may not be sufficient.

Type II: Stress-Based Prognostics

- **General Covariate Model**
  - **One or more of the failure distribution parameters (such as hazard rate) is a function of explanatory or covariate variables.**
  - **Usually there is a physical cause and effect**
    - **If cause and effect exist, then one can use covariates to** control **reliability**
    - **Otherwise, can only use covariates to** predict **reliability.**
    - **Use design of experiments to establish cause and effect**

Stress-Based Prognostics Models

- The simplest class of methods for stress-based prognostics is failure-time, linear regression models.
- These methods use prior observations of explanatory variables such as temperature, load, voltage, etc. and the response variable, which is usually the failure time, to model relationship between the stressors and life of a component.
- The stressors are regressed onto the response variable to optimize the regression coefficients:

$$\text{Failure Time} = \beta_0 + \beta_1 * Temp + \beta_2 * Load + \ldots + \beta_n * Stress_n$$

Proportional Hazards Model (PHM)

- **The proportional hazards model (PHM) [Cox 1984] is a technique that merges failure time data and stress data.**
- **The model uses environmental condition information, termed covariates (z_j), to modify a baseline hazard rate ($\lambda_0(t)$) to form a new hazard rate:**

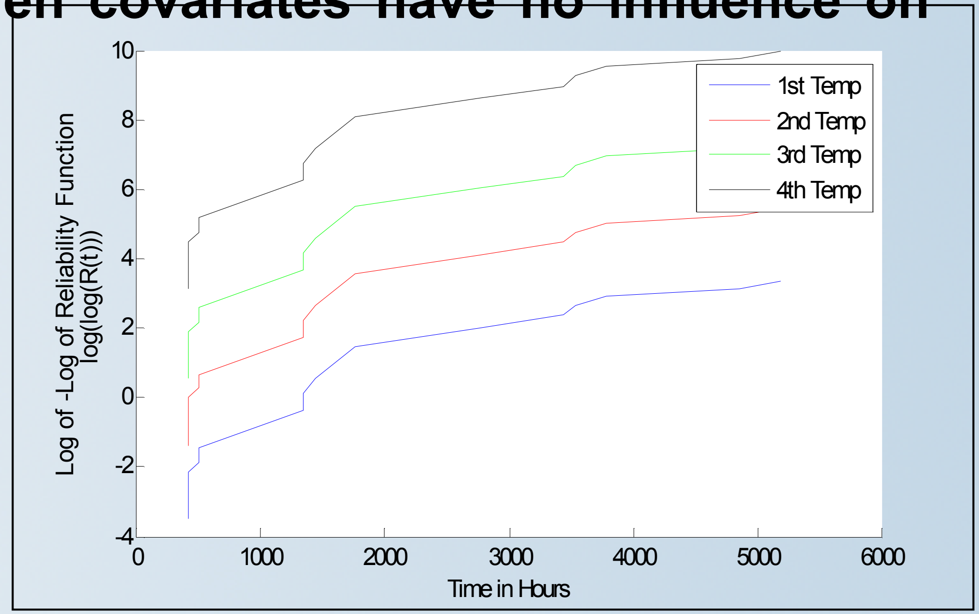
$$\lambda(t;z) = \lambda_0(t)\exp\left(\sum_{j=1}^{q} \beta_j z_j\right)$$

$\lambda_0(t)$ is an arbitrary baseline hazard or function
z_j is a multiplicative factor, explanatory variable or covariate
β_j is a model parameter

PHM Assumptions

- **Failure data collected at covariate operating conditions are used to solve for the parameters (β_j) using an ordinary least squares algorithm.**
- **A basic assumption of the PHM is that the covariates are multiplicative.**
- **The baseline hazard is when covariates have no influence on the failure rate.**

Reliability functions, after logarithmic transformations, will resemble parallel lines.



Proportional Hazards Model Example

- PHM has the property that individual component hazard rate functions are proportional to each other.

- Example (Ebeling's book): Time to failure of a motor is Weibull with a shape parameter of 1.5 and characteristic life $\theta(x) = e^{23.2 - .134x}$
- where x = load placed on the motor.
- Find the .95 design life if a motor has a load of 115. What if the load is reduced to 100?

Solution: $\theta(115) = 2416.3$

and $t_{.95} = 2416.3\,(-\ln .95)^{.6667} = 333.5$ hr.

$\theta(100) = 18033.7$

and $t_{.95} = 18{,}033.7\,(-\ln .95)^{.6667} = 2489.3$ hr.

Type III: Effects-Based Prognostics

- **Effects-based prognostics uses degradation measures to form a prognostic prediction.**
- **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.**

Degradation Parameter

- **The degradation measure does not have to be a directly measured parameter.**
- **It could be a function of several measured variables that provide a quantitative measure of degradation.**
- **It could also be an empirical model prediction of the degradation that cannot be measured.**

- **Example: pipe wall thickness may be an appropriate degradation parameter but there may not be an unobtrusive method to directly measure it. However, there may be related measurable variables (corrosion, etc.) that can be used to predict the wall thickness. In this case the degradation parameter is not a directly measurable parameter but a function of several measurable parameters.**

Type III Model Types

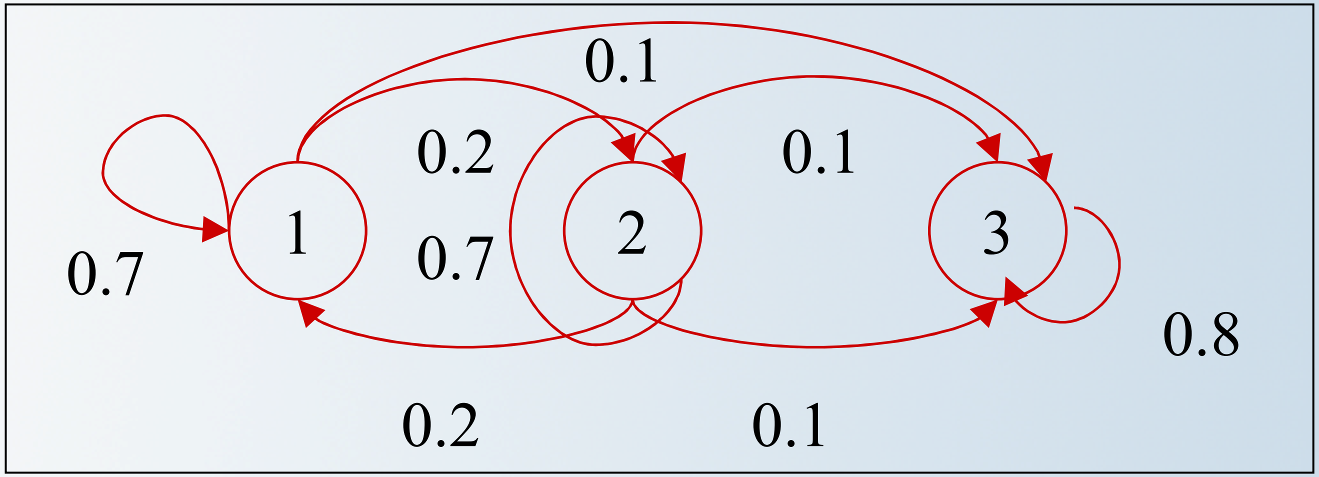
- Many effects-based prognostics models track the degradation (damage) as a function of time and predict when the total damage will exceed a predefined threshold that defines failure.
- Cumulative damage is defined to be irreversible accumulation of damage in components under cyclical loadings.
- There are several mathematical approaches to model cumulative damage:
  - Markov Chain-based Models
  - Shock Models
  - General Path Models

Markov Chain-based Models

- **Markov Chain (MC) models can be used as Type II or Type III prognostic models.**
  - **The Type II (stressor) case is when one is not able to observe the individual component's response to the influence of the dominant failure mechanism.**
    - **Degradation is not directly measurable.**
    - **Degradation may be inferred through measured stressors.**
  - **The Type III (effects) case is when one is able to directly observe a numerical quantity characterizing the component's ability to function in accordance with its specifications.**
    - **Degradation is directly measurable or inferred through other degradation parameters.**

Markov Chain Models

- **MC models explain the equipment degradation as a transition of states.**
  - **The states can be the environmental conditions that cause degradation or the degradation state itself.**
  - **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 Chain Prognostic Models

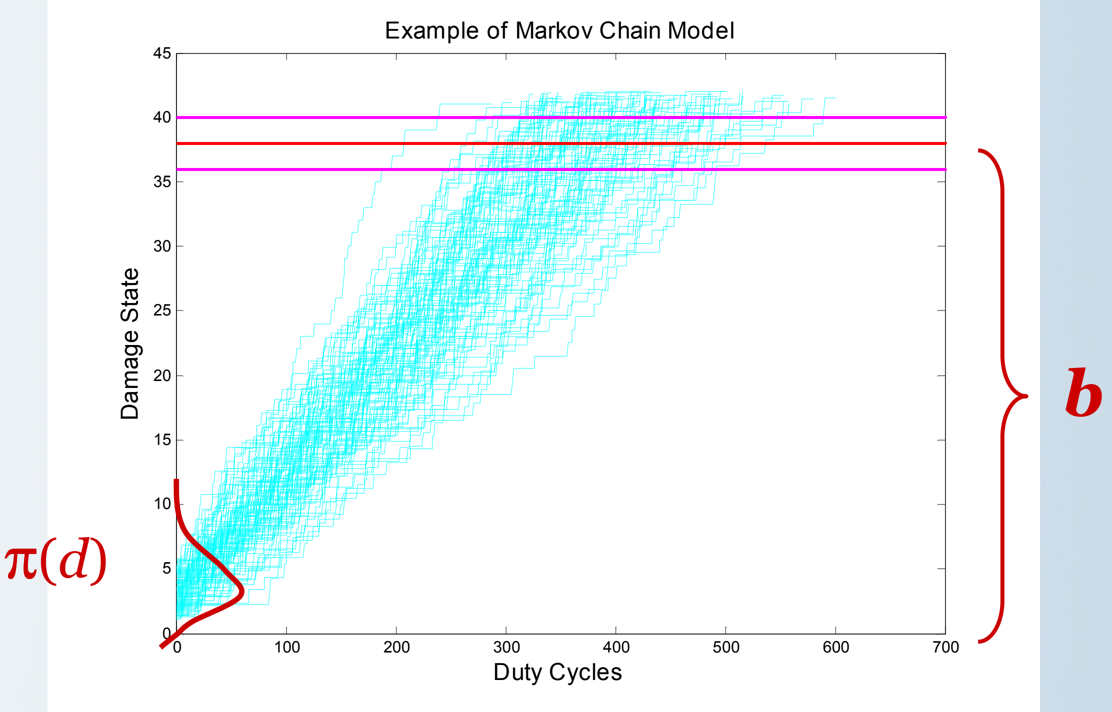
- *Markov Chain Prognostic Models* are discrete in the time domain and in the degradation measure domain.
- For each duty cycle, there is a non-zero probability of receiving a unit-size damage.
- The model is usually formulated as a probabilistic simulation of past and future degradation.
  - If the degradation is directly measurable, then the simulation is only performed for the future.
- The model has several parameters which can be estimated from historical degradation and failure data:
  - Probability of a damage occurrence in a duty cycle
  - The magnitude of the damage (usually a unit-size damage is assumed)
  - The critical damage level (Failure Threshold)

Cumulative Damage Model

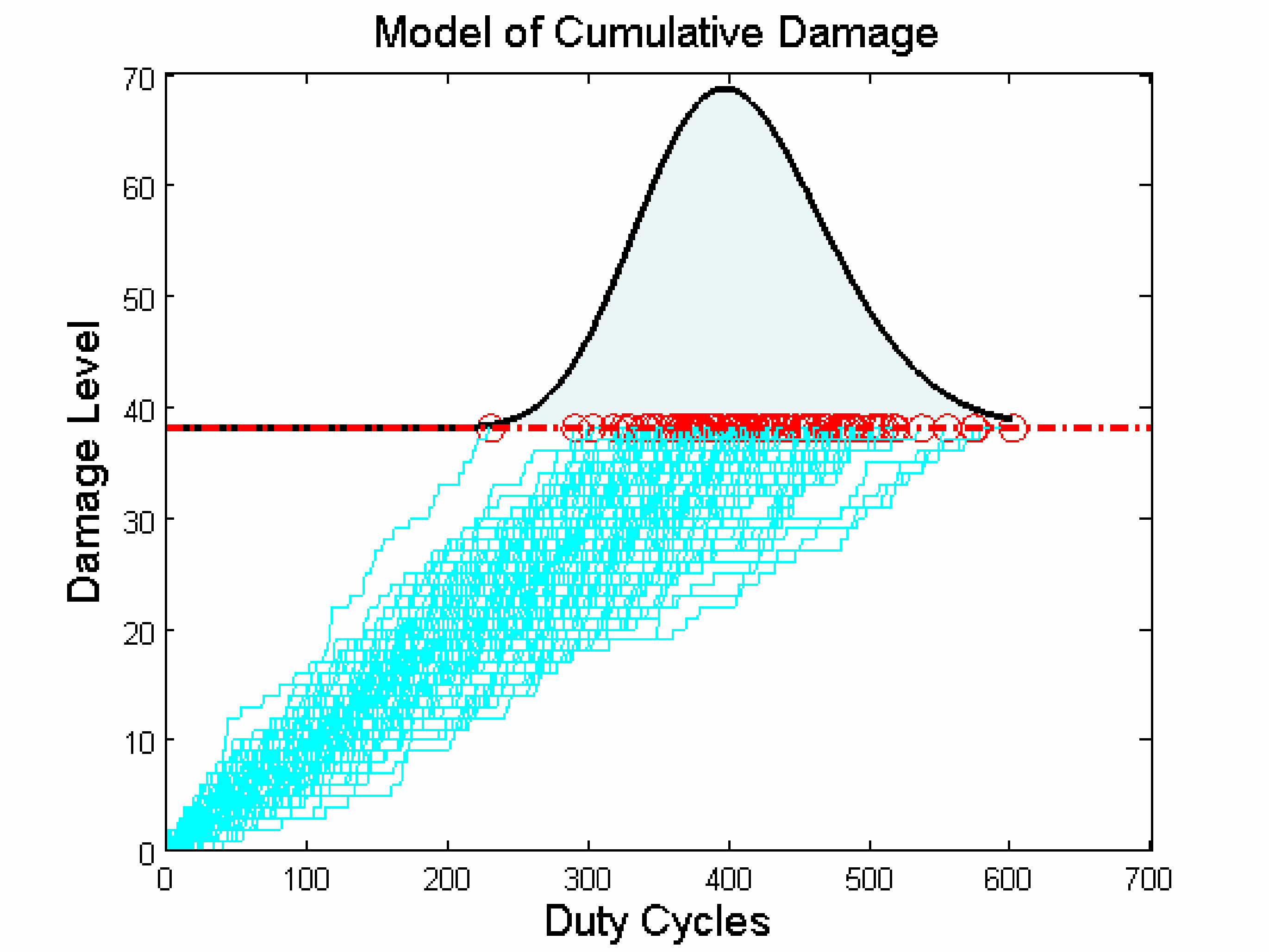
- Cumulative Damage model was originally proposed by Kozin and Bogdanoff in "*Probabilistic Models of Cumulative Damage*" (1985)
- Cumulative Damage is defined to be irreversible accumulation of damage in components under cyclical loadings
- A discrete time Markov Chain (MC) was used to model the damage accumulation process
- The MC-based model can naturally account for different sources of uncertainty in reliability data.
  - Random initial level of damage
  - Different severity and order of the loads in successive duty cycles.
  - Variable states of damage at the moments of retirement.
  - Imperfections in measurements

Stochastic Cumulative Damage Model

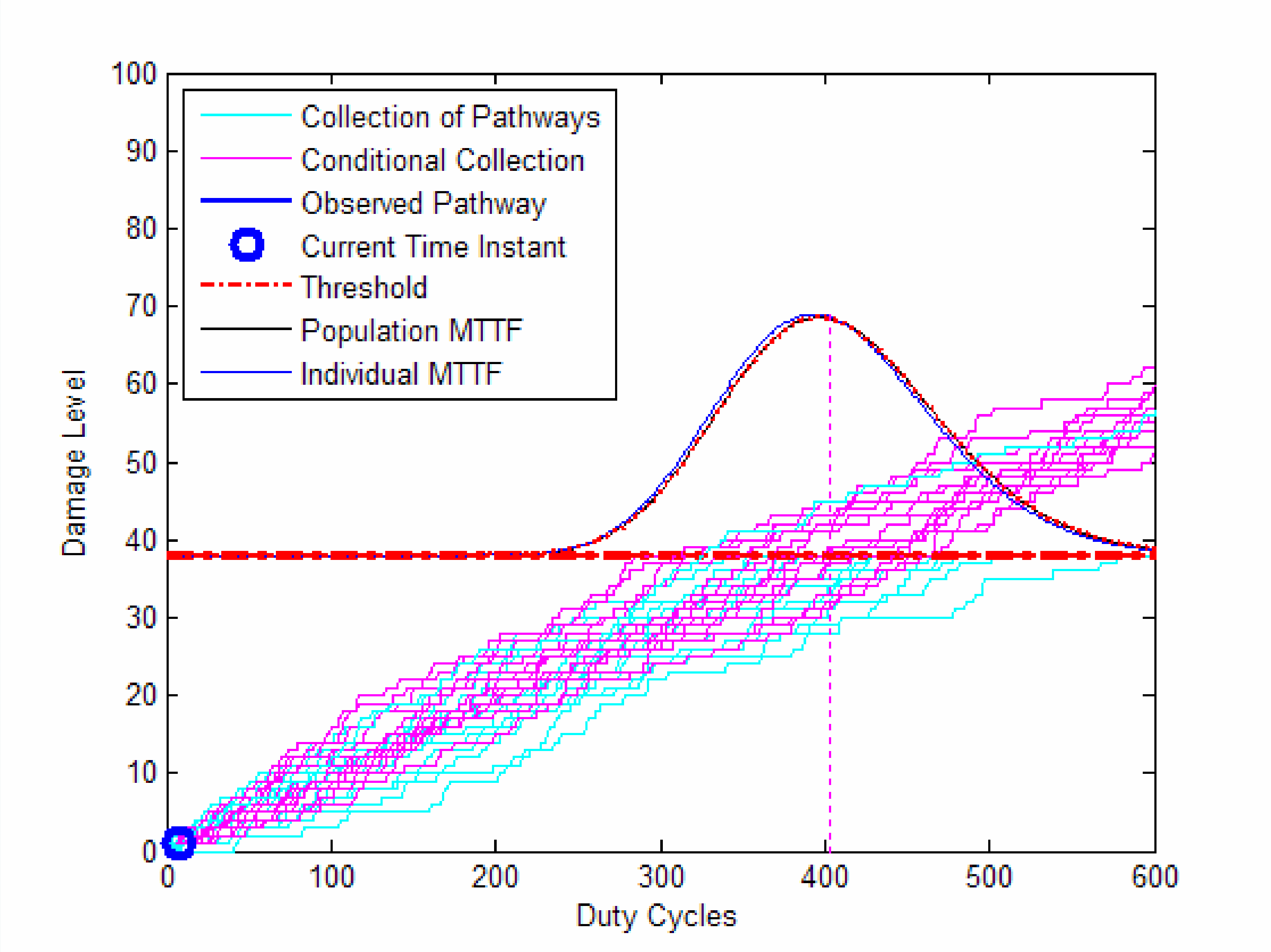
- **Parameters of the model**
  - **Number of possible damage states (levels),** b
  - **Distribution of Initial Damage,** $\pi_0(d)$
  - **Transition Matrix,** $Q = \{q_{ij}\}$, **where** $q_{ij} = P(y_k=i \mid y_{k-1}=j)$



Stochastic Cumulative Damage Model



Cumulative Damage Model



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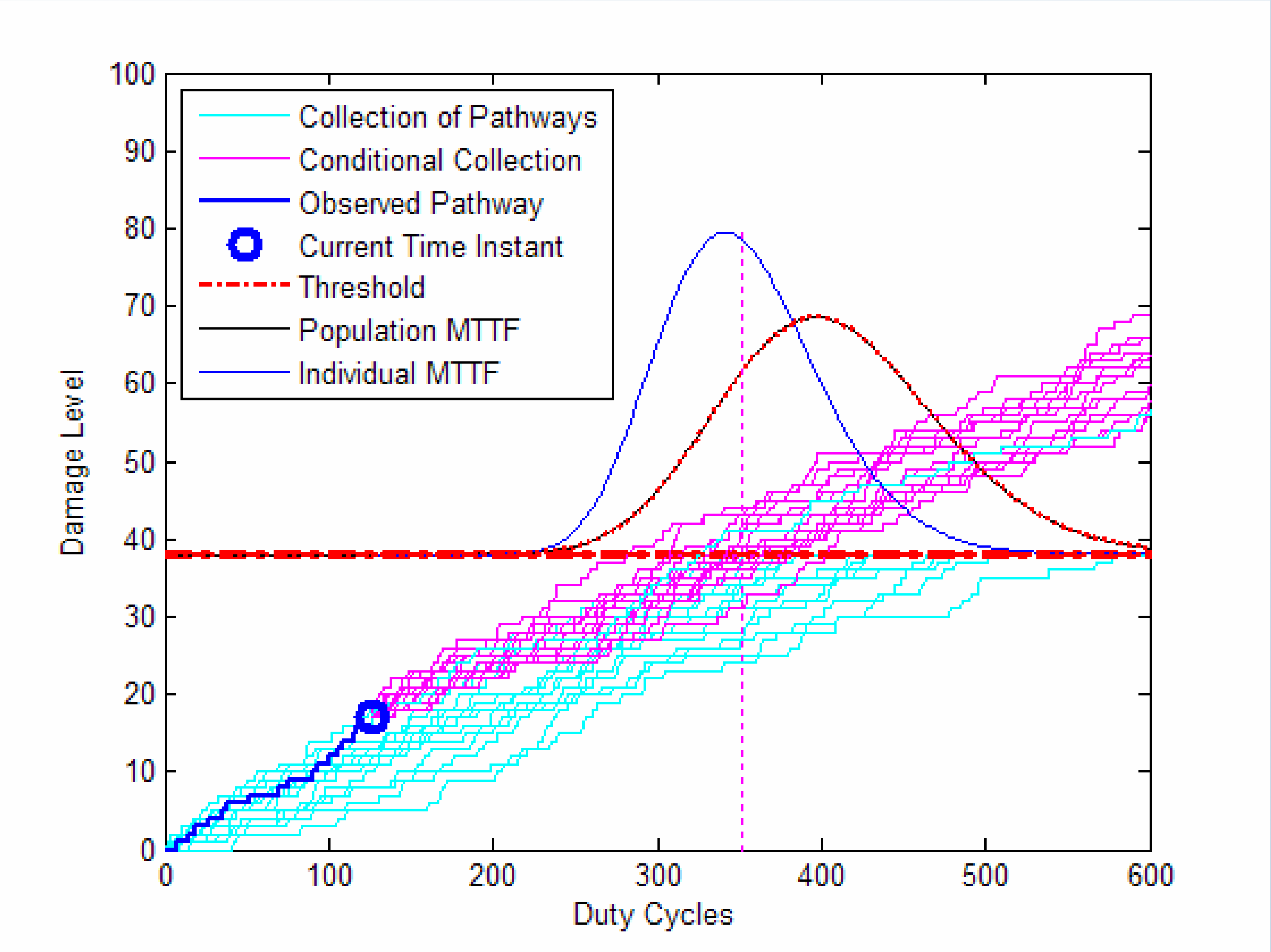

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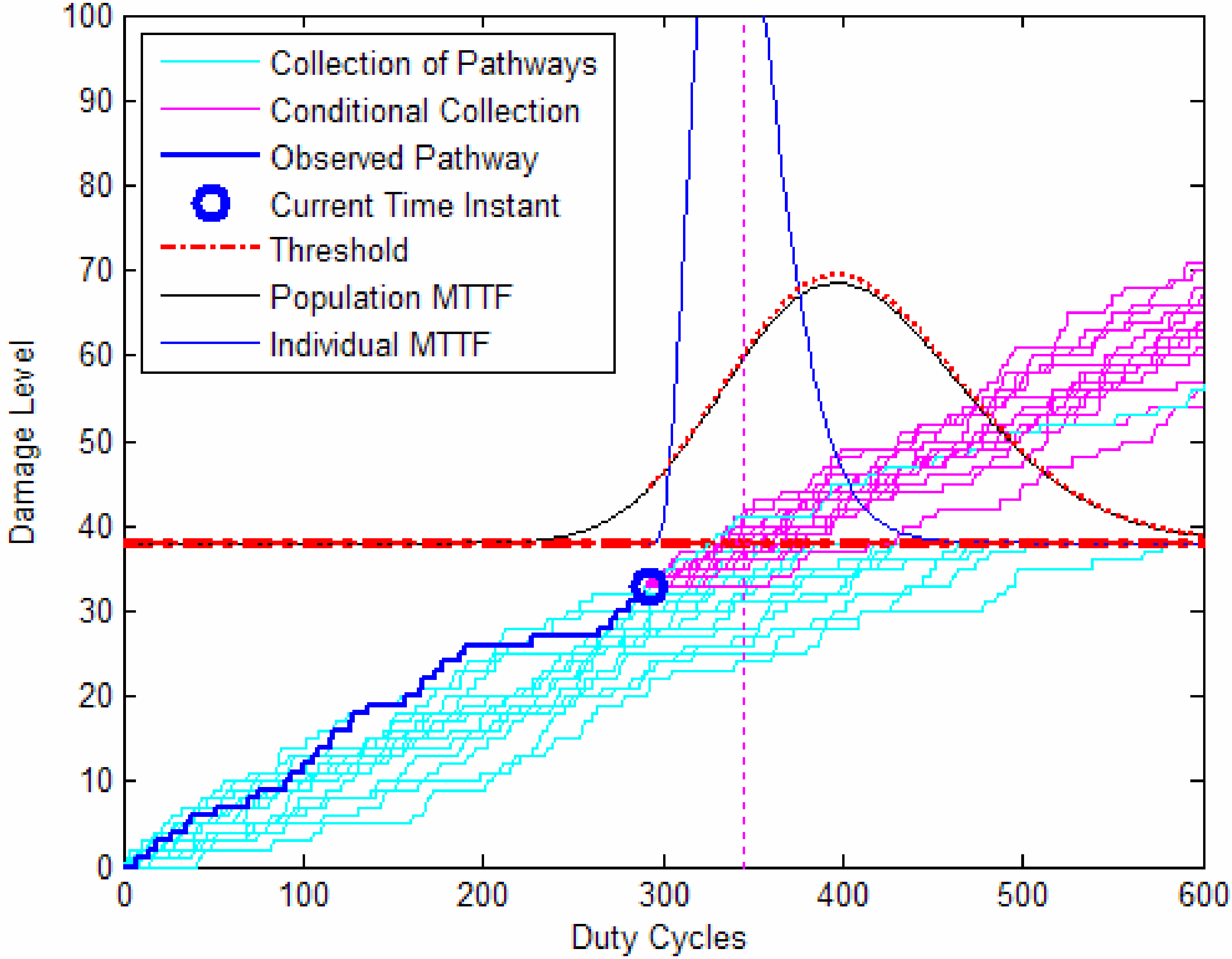
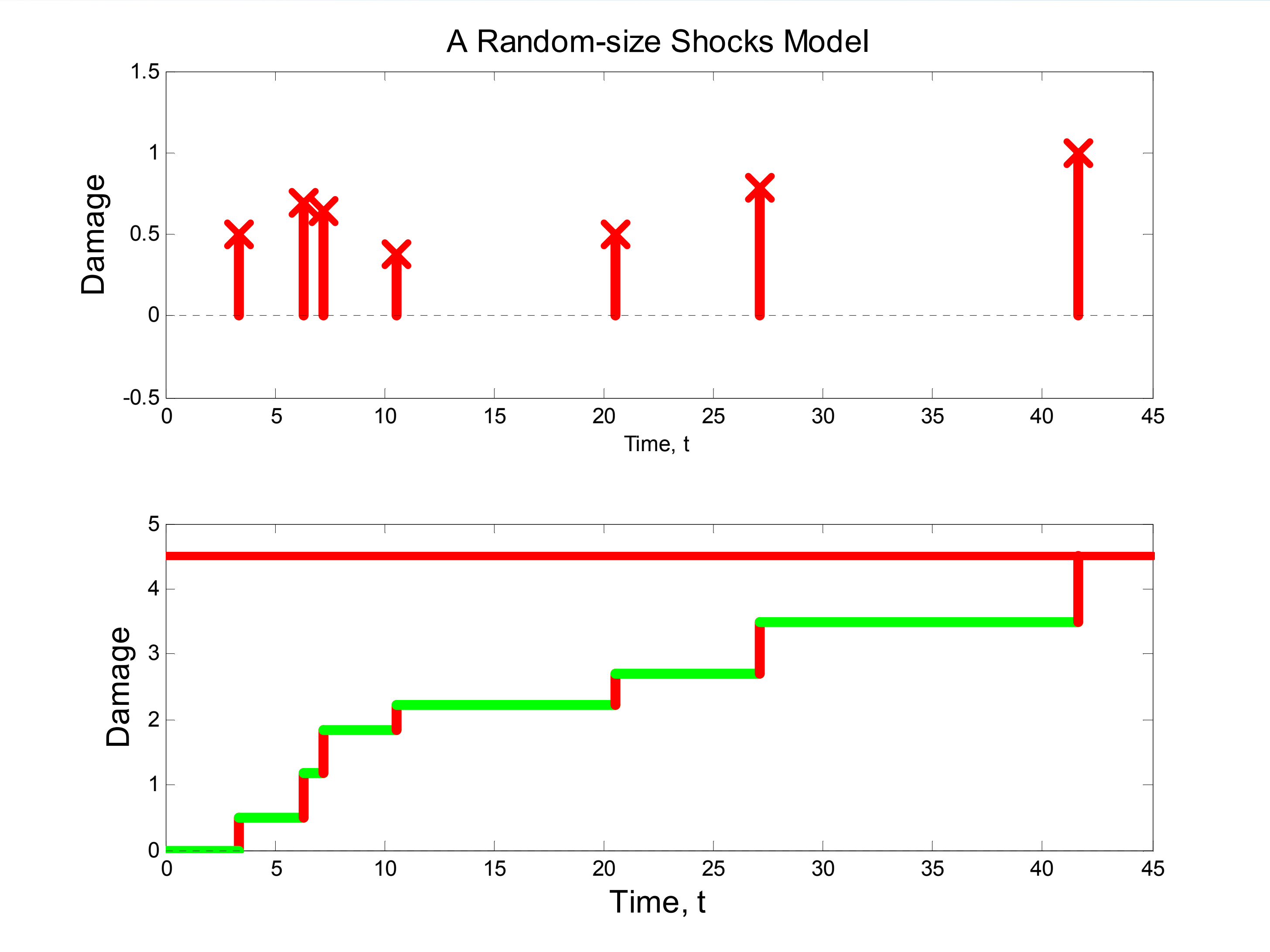


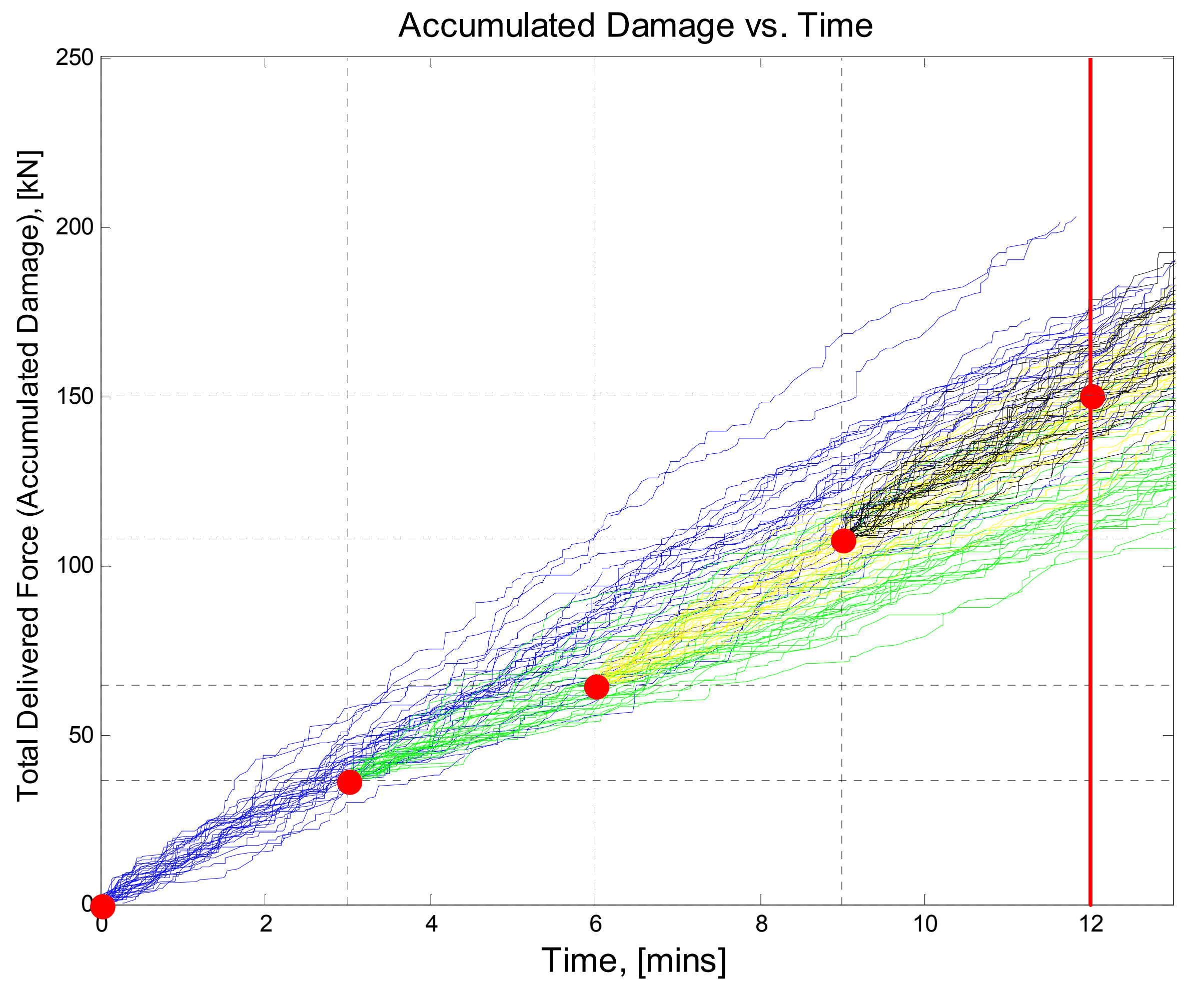
Shock Models

- ***Shock Models*** **are used predict the RUL for systems which are subject to randomly arriving shocks, which deliver some damage of a random magnitude.**
- **They are continuous in the time and the degradation measure domains.**
- **Shock models have several important parameters that are estimated from historical failure data:**
  - **Time between successive shocks, t ~ Exp(λ)**
  - **The magnitude of shocks, *x* ~ F(x)**
  - **The critical failure threshold**
- **The method is similar to the Markov Chain model but the time between shocks and the shock magnitudes are continuous random variables.**

Shock Model Example



Shock Accumulation Pathways



General Path Models

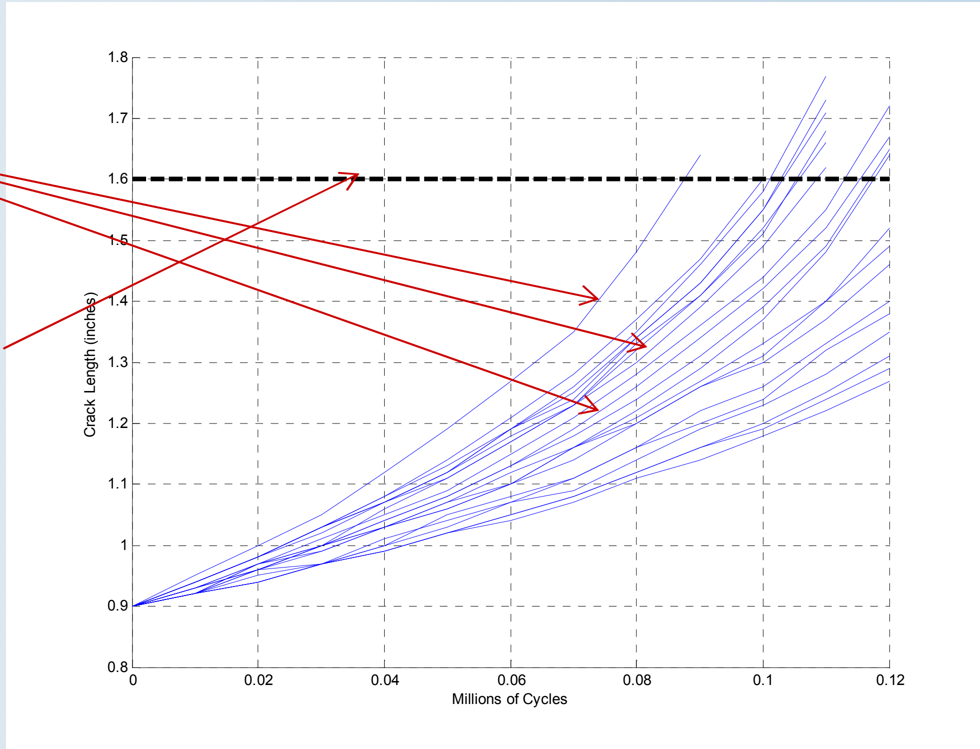
- GPM was originally proposed by Lu and Meeker [1993] as a statistical method for using degradation measures to estimate a time-to-failure distribution
  - Some systems result in few or no failures during accelerated testing.
  - Degradation measurements may contain useful information about product reliability.

- The GPM assumes that the degradation is a function of time, duty cycles, or some other measure.
- Extrapolation of this degradation function has been used to predict remaining useful life.

GPM has two main assumptions

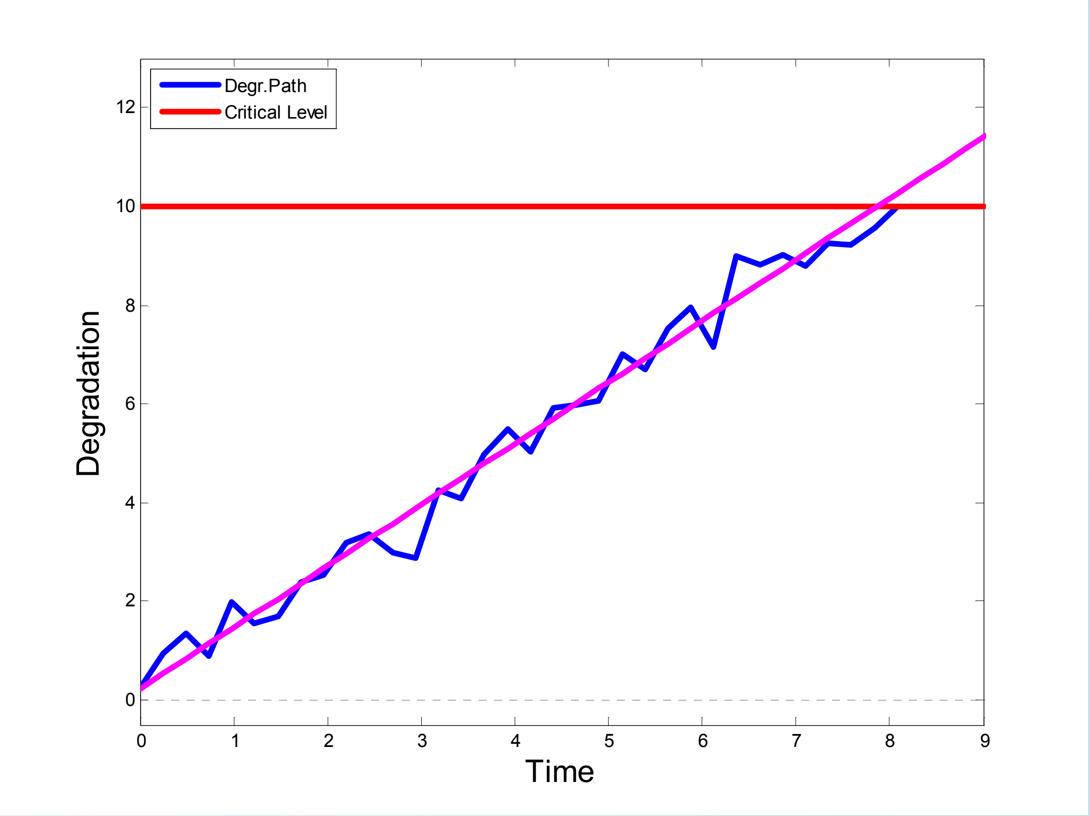
- The degradation signal for each individual device is unique

- There is a critical threshold at which failure occurs

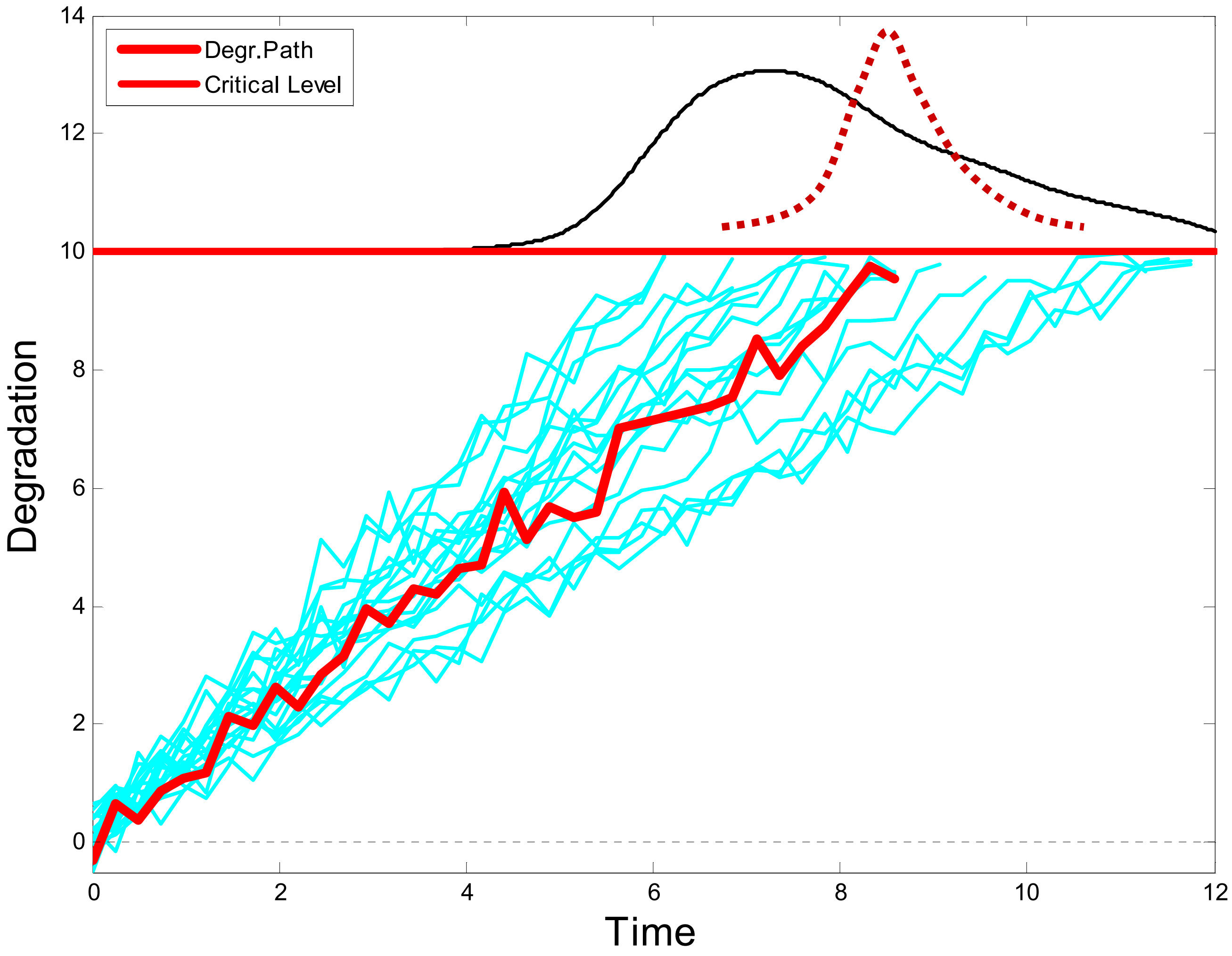


Linear Damage Accumulation Model

- **The constant degradation rate zone takes the longest time in the item's lifespan.**
- **The primary interest is the item's degradation within this zone.**

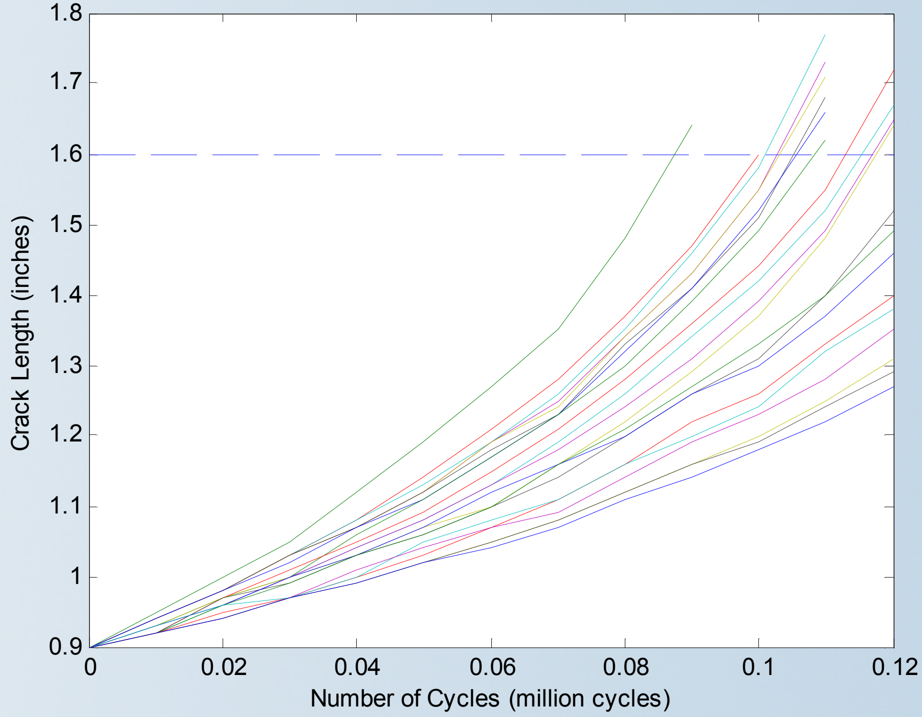


Linear Damage Accumulation Model



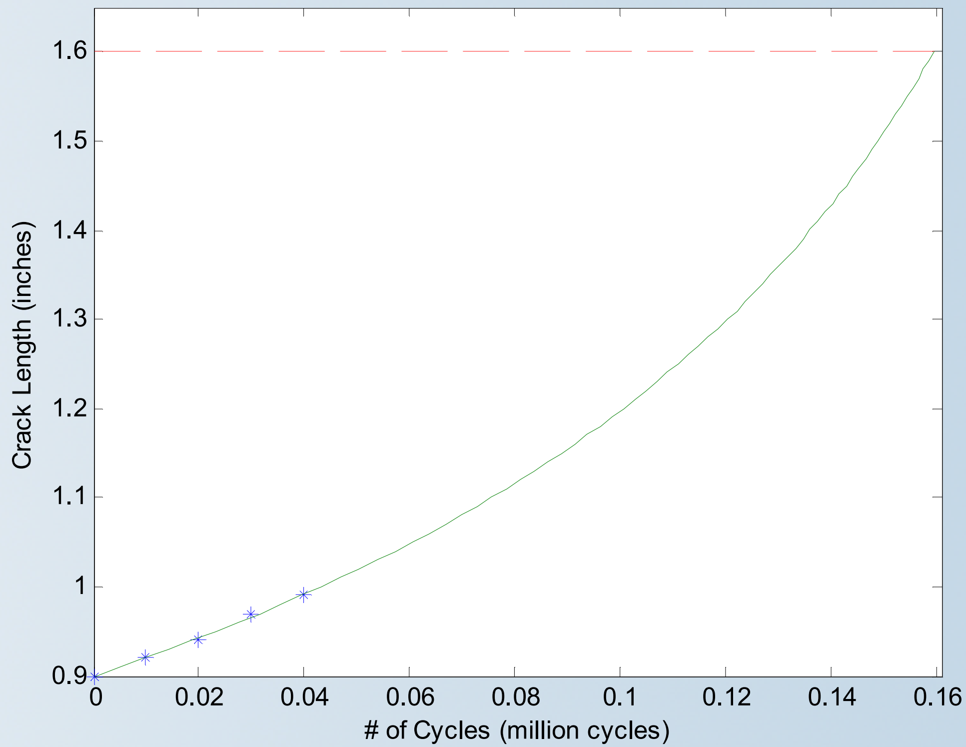
Using the GPM to estimate RUL

- **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**



Quantifying uncertainty in RUL

- **Because parameters (or an appropriate reparameterization) are normally distributed, 95% CIs can be constructed for each parameter**

$$\theta \in \left[\hat{\theta} - t_{n-1,\alpha/2} s\sqrt{1+1/n}, \hat{\theta} + t_{n-1,\alpha/2} s\sqrt{1+1/n}\right]$$

  where *s* is the standard deviation of the parameter

- **s can be estimated from the prior distributions for each operating condition**

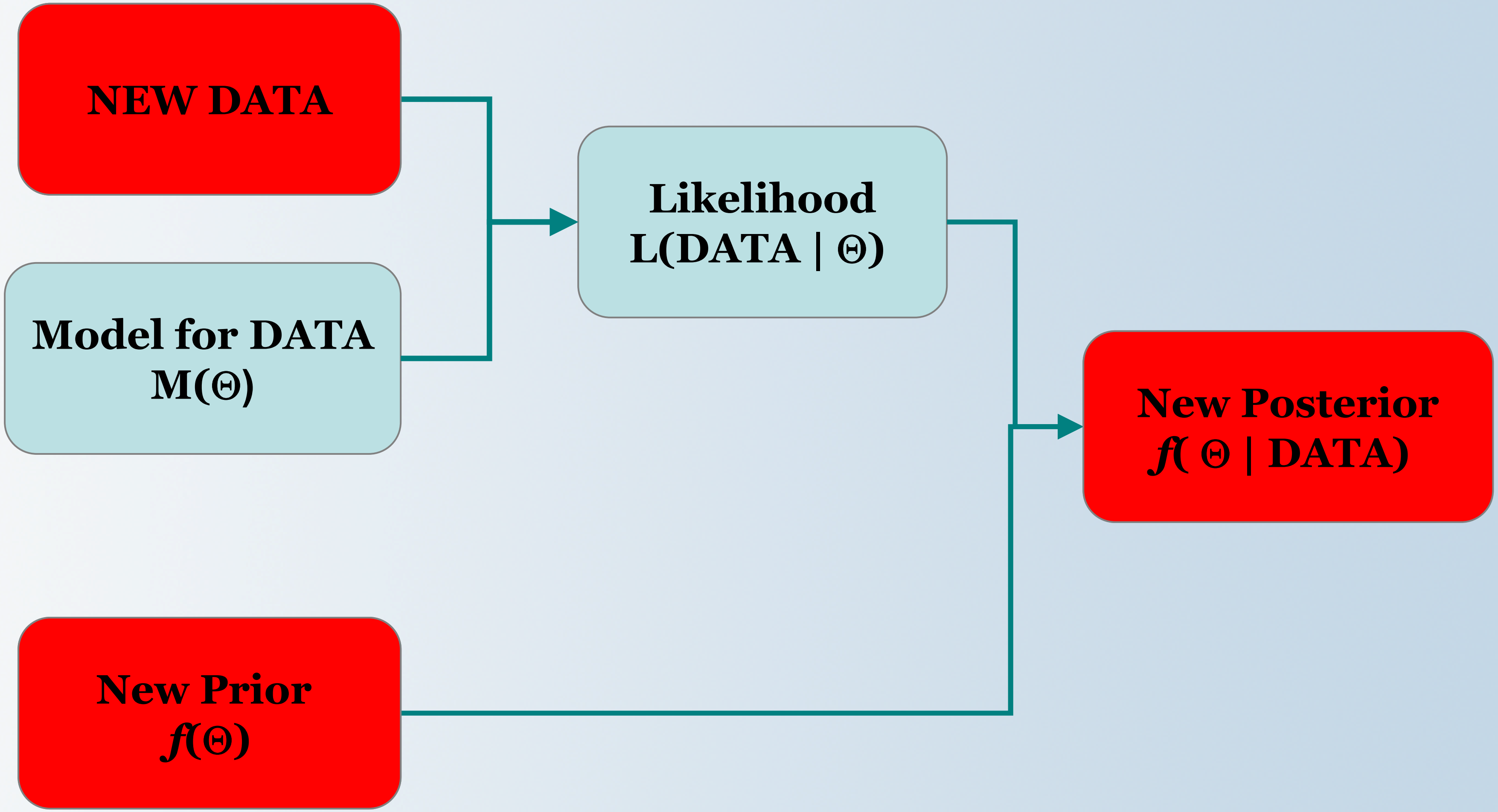
Bayesian Regression

- Can be used to incorporate prior information or beliefs about the model parameters.
- Can be used to update model parameter predictions using observations.

Notation

Θ	-	the parameter to estimate
DATA	-	available observations
L(DATA | Θ)	-	Likelihood of DATA
$f(\Theta)$	-	the prior density of Θ
$f(\Theta$ | DATA)	-	the posterior PDF of Θ

Bayesian Inference



GPM Prior Parameter Distribution can be used for better model fitting

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

$$Y = bX$$

- **The model parameters are estimated as:**

$$b = (X^T \Sigma_y^{-1} X)^{-1} X^T \Sigma_y^{-1} Y$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \quad X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad \Sigma_y = \begin{bmatrix} \sigma_y^2 & 0 & \cdots & 0 \\ 0 & \sigma_y^2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_y^2 \end{bmatrix}$$

Prior Information About Regression Coefficients

- $\beta_j \sim N(\beta_{j0}, \sigma^2_\beta)$
- The prior information on β_j is considered to be another "data point" in the regression.

$$Y^* = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \\ \beta_{jo} \end{bmatrix} \quad X^* = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ 0 & \cdots & 1 & 0 \end{bmatrix} \quad \Sigma_y^* = \begin{bmatrix} \sigma_y^2 & 0 & \cdots & 0 & 0 \\ 0 & \sigma_y^2 & \ddots & \vdots & 0 \\ \vdots & \ddots & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \sigma_y^2 & 0 \\ 0 & 0 & \cdots & 0 & \sigma_\beta^2 \end{bmatrix}$$

$$b = (X^T \Sigma_y^{-1} X)^{-1} X^T \Sigma_y^{-1} Y$$

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

Prior Information About All Regression Coefficients

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

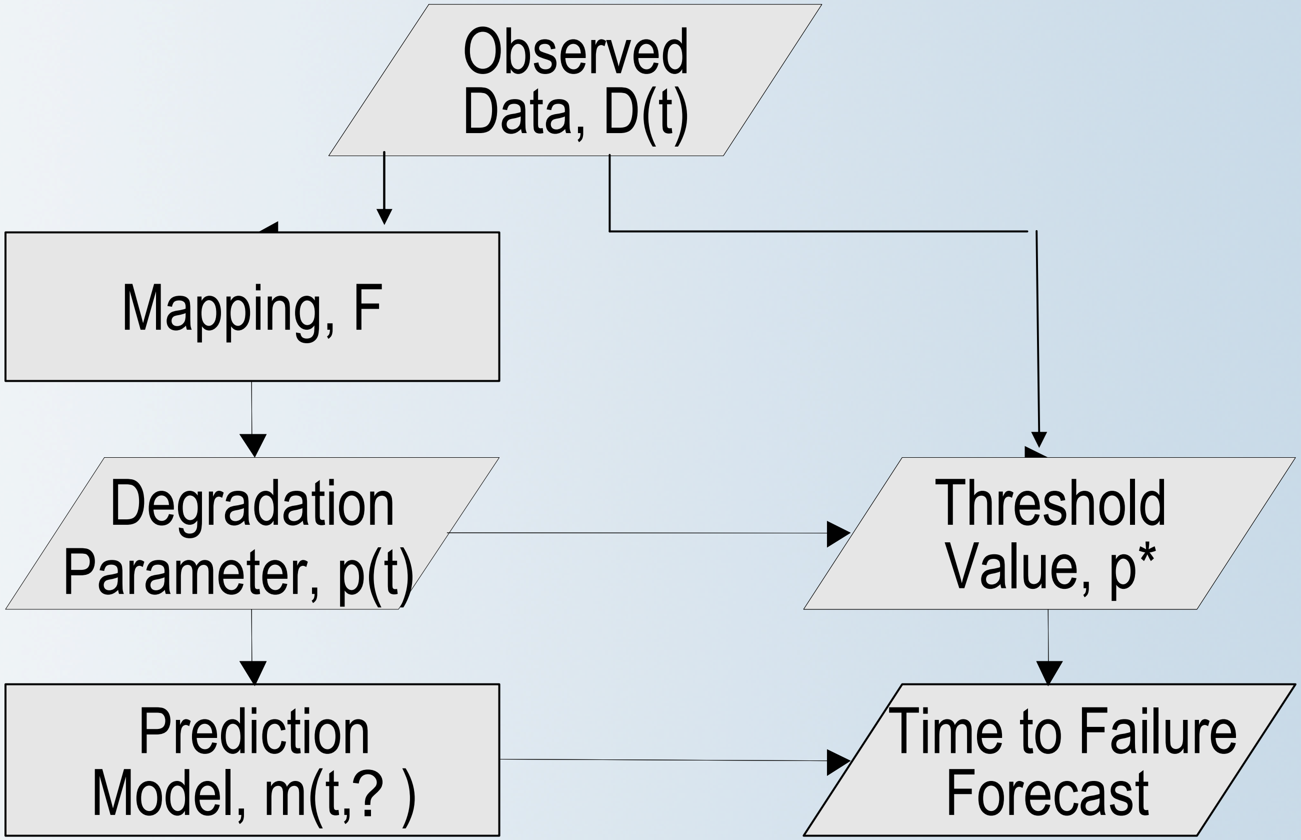
$$Y^* = \begin{bmatrix} Y \\ \beta_0 \end{bmatrix} \qquad X^* = \begin{bmatrix} X \\ I_k \end{bmatrix} \qquad \Sigma^* = \begin{bmatrix} \Sigma_y & 0 \\ 0 & \Sigma_\beta \end{bmatrix}$$

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

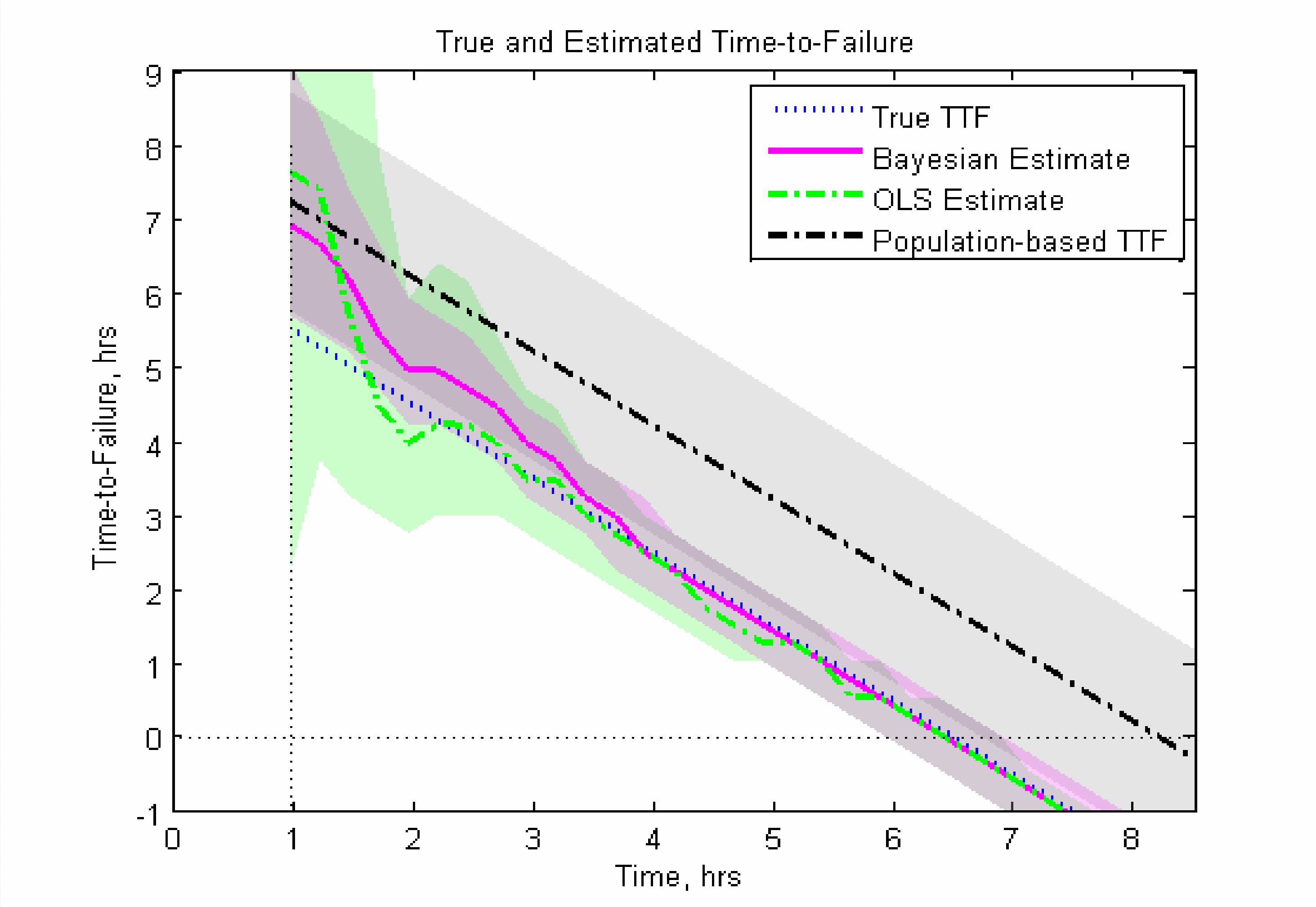
Hybrid Prognostics Approach

- **Always begin with a Failure Modes Effects and Criticality Assessment (FMECA)**
  - **Historical failure data will be used to estimate the population POF.**
  - **Covariates (e.g. speeds, currents, pressures, vibration, etc.), or covariate residuals with the use of empirical models, will be used to develop a degradation parameter and used to augment population POF to provide individual POF.**
  - **A Bayesian framework has been developed to update RUL or POF predictions based on new data.**

Example Basic Prognostics Framework



Prognostics Comparison Example



GPM Tire Case Study

- A case study involving the simulation of tire degradation data was chosen to demonstrate the main prognostic models.
- Tire degradation is assumed to come only from wear
- Three possible environmental operating conditions
  1. *Normal*
  2. *Off-road*
  3. *High Slip*
- The tires are assumed to have negligible initial wear and one duty cycle is equal to 100 miles.
- Tires will be simulated as operating in one environmental condition for the life of the tire or as operating in one condition for a duty cycle but allowing the condition to change between duty cycles.
  – The simulation method will depend on the prognostic method applied.

Reliability Assumptions

- **The functional form of the TTF probability density function for each mode is assumed to be Gaussian.**
- **The mean time to failure and standard deviation for different environmental conditions are provided in Table 1.**
- **The typical usage pattern is also given in Table 1 where p_i is the probability of a tire operating in the i^{th} condition.**
- **The three individual distributions can be combined using this usage pattern to get a mean and standard deviation of the population of tires; these values are also included in Table 1.**

Tire Degradation Parameters			
Env. Condition	**μ_{TTF}, [DC]**	**σ_{TTF},[DC]**	**p_i**
Z_1, Normal	**400**	**40**	**0.7**
Z_2, Off road	**300**	**30**	**0.2**
Z_3, High Slip	**200**	**20**	**0.1**

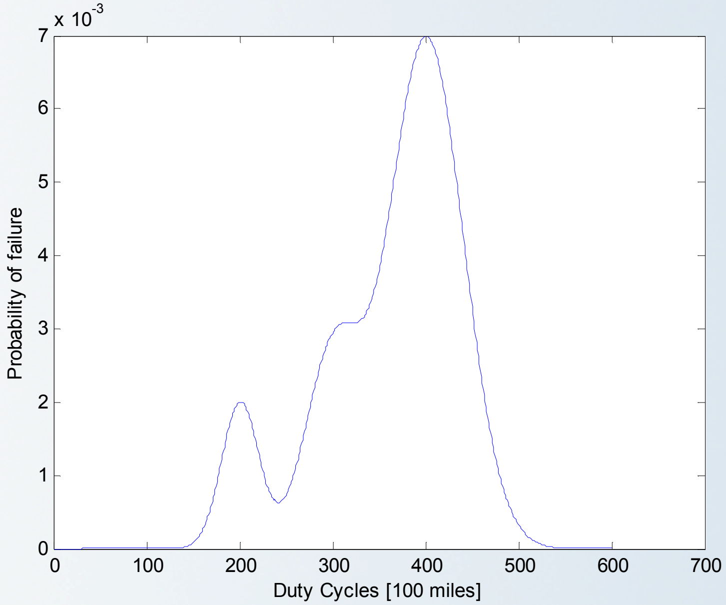
Simulation Experiments

- **Type I: distributions for the population of tires will be constructed and population based methods will be used to calculate the predicted distribution.**
- **Type II: the PHM case will be evaluated in which it is assumed that the tire is operated in one mode for its life and that the mode is known.**
- **Type III: In the GPM case, it is assumed that the tire is operated in one of the modes and that measurements with noise can be made, but that the mode is not known.**
- **Finally, two Markov Chain simulations will be given in which the mode can change at each duty cycle.**

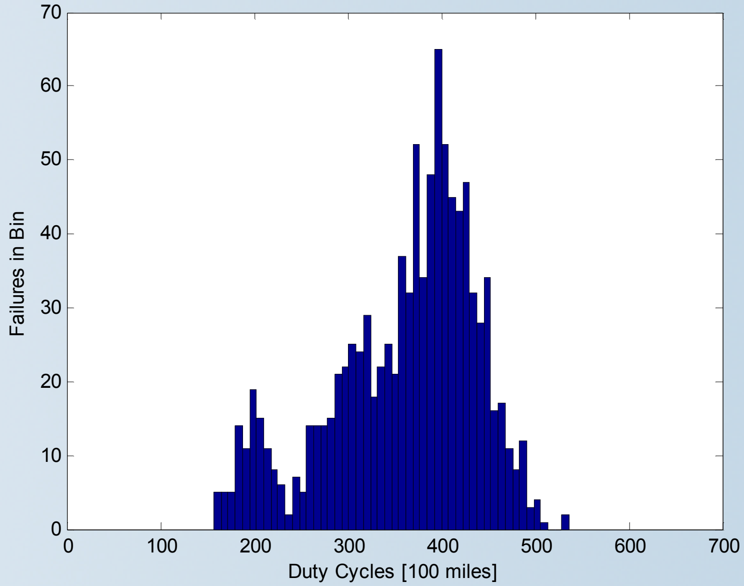
Type I: Reliability data based

- **Population based prognosis.**
- **Tires are expected to operate in one condition for the life of the tire.**
- **One thousand tires are simulated and a Weibull model is used to predict the population mean time to failure.**

Actual Population Density

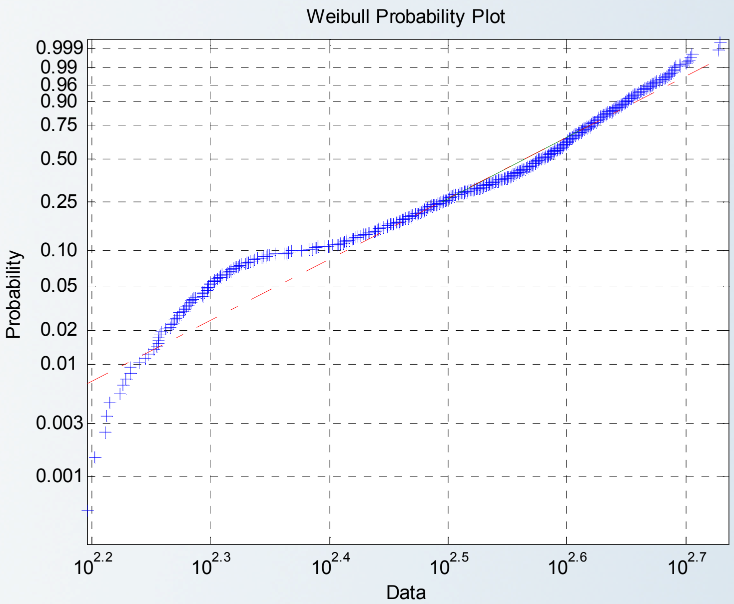


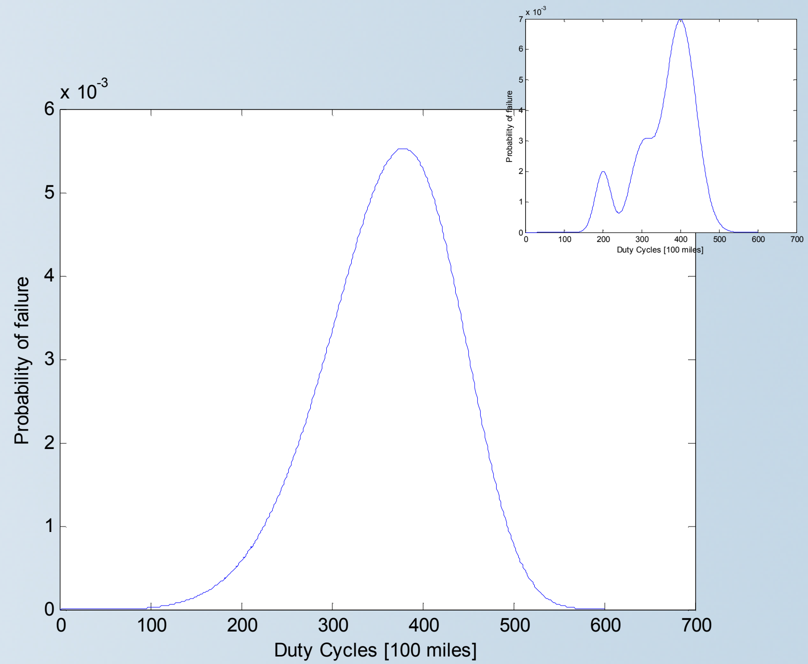
Histogram of Simulated Failures



Weibull Analysis

- **Because the failure times are a composition of three normal distributions with significantly different means, the Weibull plot does not fit the population exceptionally well.**
- **The mean of the plot is 36,200 miles with a standard deviation of 7,259 miles.**
- **This is very close to the true mean of 36,000 miles and standard deviation of 7,580 miles.**





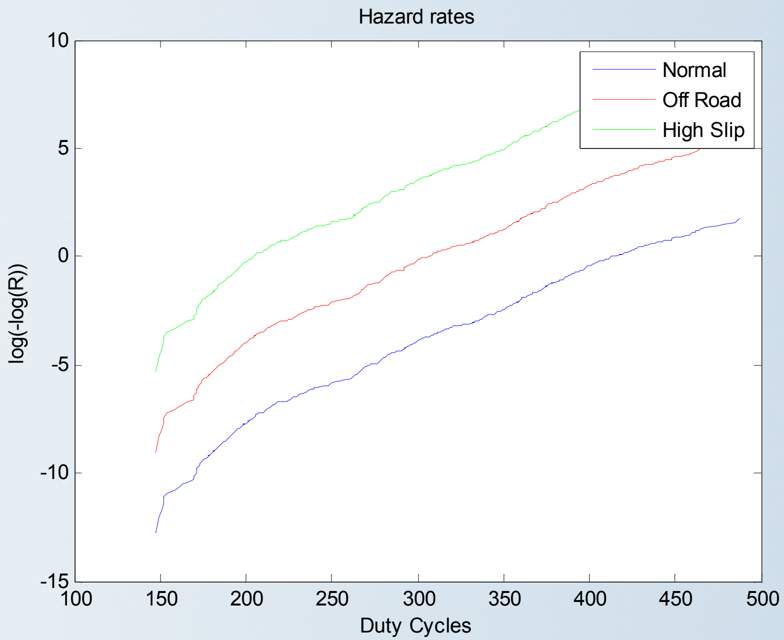
Type II: Proportional Hazards Model

- It is assumed that the tire only operates in one mode and that the mode is known.
- Simulated data is used to solve for the parameter β in the PHM and then the model is used to predict the failure distribution for each mode.
- Covariate values
  - Normal condition z=0
  - Off road z=1
  - High slip z=2

$$\lambda(t;z) = \lambda_0(t)\exp\left(\sum_{j=1}^{q} \beta_j z_j\right) = \lambda_0(t)\exp(\beta z)$$

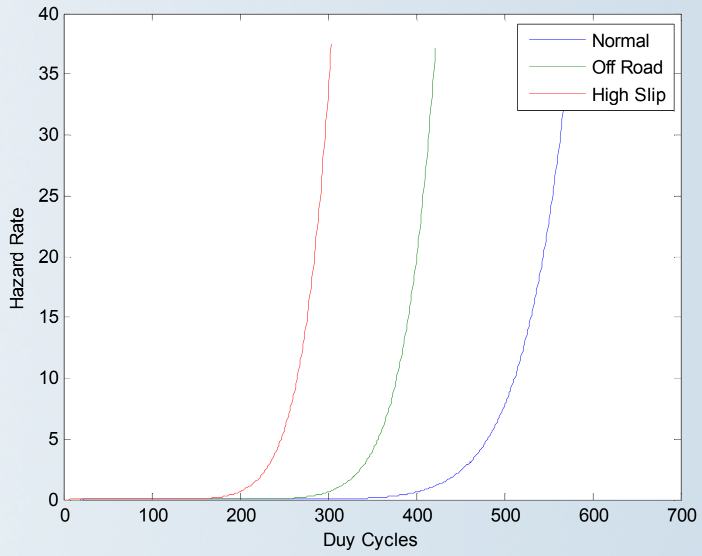
Proportionality Check

- It is important that the covariates be proportional for the PHM to be used effectively.
- To check this, the hazard rates and reliability functions for all three modes are estimated from the data and a log(-log((R(t))) plot is made (Figure 14).
- The plot shows the appearance of proportionality between the different models as all three of the lines appear parallel



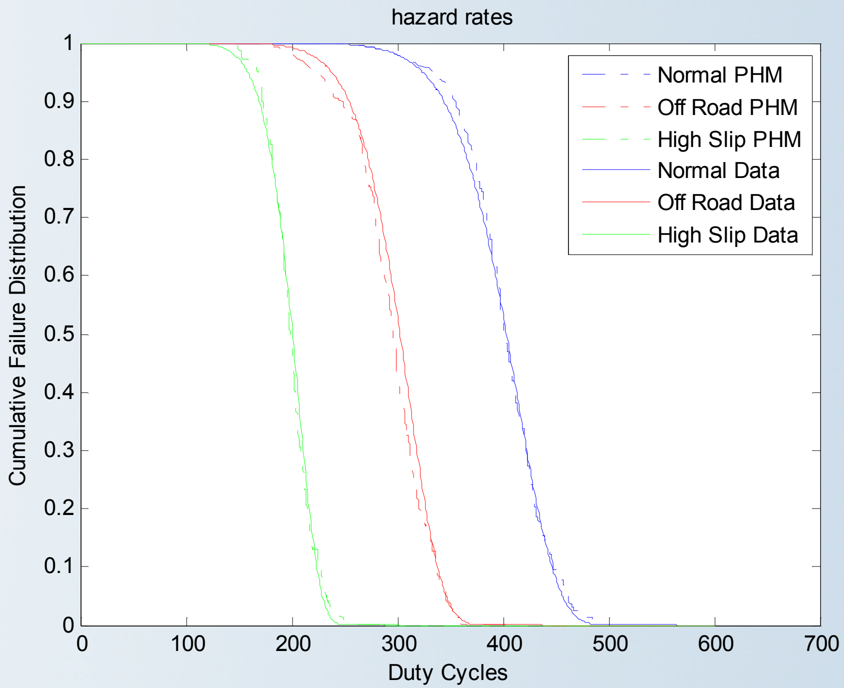
Baseline Hazard Rate

- The baseline hazard rate is estimated as a function of duty cycle.
- The normal condition hazard rate be used for the baseline hazard rate and that the covariate value for normal is 0
  - This results in $\lambda(t;z) = \lambda_0(t)\exp(\beta * 0) = \lambda_0(t)$
- The distributions are modeled with Weibull distributions.



PHM Results

- The PHM results in a regression coefficient of 3.7090 with a standard error of 0.1567.
- PHM results in a reduction of the standard deviation of failure time estimates from that of the population (7,592 miles from Weibull) to that predicted for the three conditions: 4,840 miles for normal, 3,243 miles for off road and 2,351 miles for high slip.



Type III. General Path Model

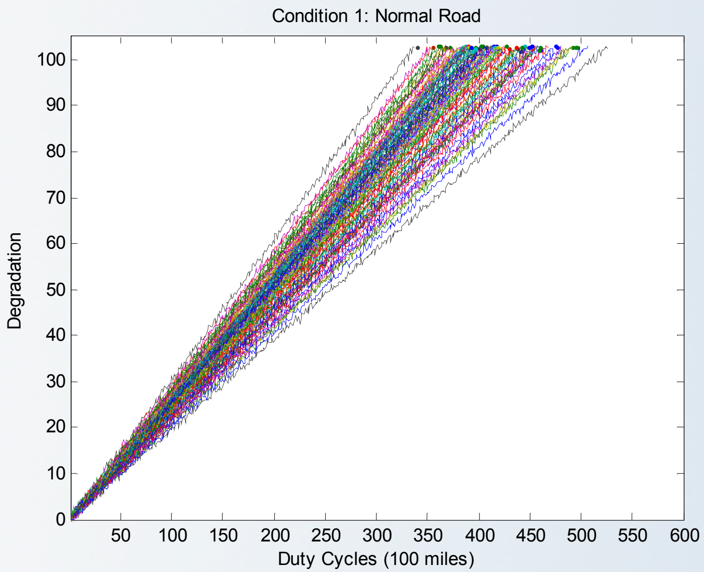
- A tire degradation path is assumed to be of linear form

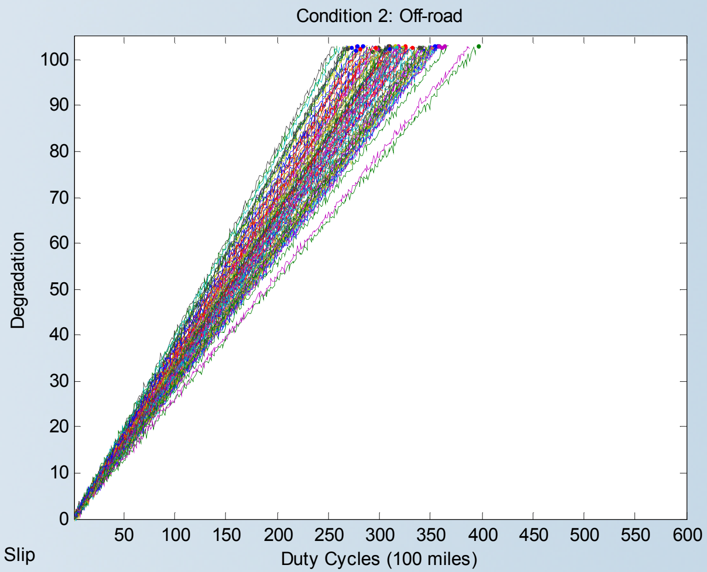
$$y = rx + \varepsilon$$

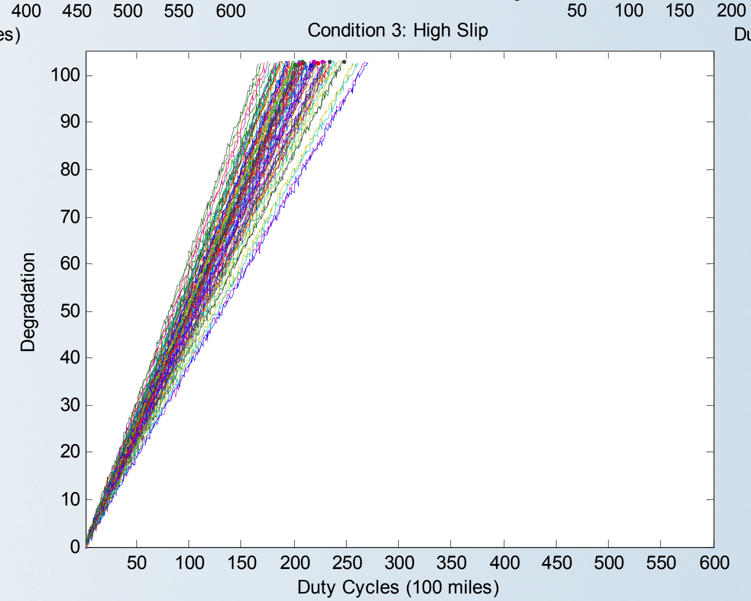
  - where $r = N(\mu_{dr}, \sigma_{dr})$ is the random degradation rate,
  - ε is 1% random measurement error,
  - and x is the number of duty cycles (100 miles)

Environment	μ_{dr} (%/DC)	σ_{dr} (%/DC)	σ^2_{noise} (%^{2})
Normal	0.25	0.0217	0.25
Off-Road	0.33	0.0314	0.25
High Slip	0.50	0.0478	0.25
Population	0.28	0.0171	0.25

Historical Degradation Paths







Obtaining Prior Information

- **Historical paths were used to estimate distribution parameters and noise variance for each condition**
- **A typical usage pattern is given as**

$$[p_1 \quad p_2 \quad p_3] = [0.7 \quad 0.2 \quad 0.1]$$

- **This pattern is used to estimate distribution parameters for the population**

Environment	μ_{dr} (%/DC)	σ_{dr} (%/DC)	σ^2_{noise} ($\%^2$)
Normal	0.251	0.0217	0.252
Off-Road	0.329	0.0314	0.252
High Slip	0.496	0.0478	0.251
Population	0.291	0.0171	0.252

GPM/Bayes algorithm has 7 steps

- Compose *X* and *Y* matrices with all *m* observations.

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \quad X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$$

- Compose the Σ_y matrix with noise variance-covariance values for each observation. For the present case, the covariance between observations is zero, and the noise variance is assumed to be constant and equal to 0.252 %^{2}.

$$\Sigma_y = \begin{bmatrix} 0.252 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0.252 \end{bmatrix}$$

- Augment the *X*, *Y*, and Σ_y matrices with prior information.

$$Y^* = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \\ \hat{r} \end{bmatrix} \quad X^* = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \\ 1 \end{bmatrix} \quad \Sigma_y^* = \begin{bmatrix} 0.252 & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 0.252 & 0 \\ 0 & \cdots & 0 & \sigma_{\hat{r}}^2 \end{bmatrix}$$

GPM/Bayes algorithm has 7 steps (cont'd)

- **Estimate the degradation rate.**

$$\hat{r} = (X^{*T}\Sigma_y^{*-1}X^*)^{-1}X^{*T}\Sigma_y^{*-1}Y^*$$

- **Estimate the uncertainty of the fitted degradation rate.**

$$\sigma_{\hat{r}} = \sqrt{\sum (p_i \sigma_i)^2}$$

where p_i is the probability that r belongs to the i^{th} environment.

- **Estimate 95% PI for r and use these values to estimate a 95% PI for the time of failure.**

$$r \in \left[\hat{r} - t_{m,\alpha/2}\sigma_{\hat{r}}\sqrt{1+1/(m+1)}, \hat{r} + t_{n-1,\alpha/2}\sigma_{\hat{r}}\sqrt{1+1/(m+1)}\right]$$

This PI form is adjusted by substituting *n = m+1*, because estimation of *r* is performed with *m* observations and the one prior information "observation". The time to failure and corresponding 95% PI can be estimated as:

$$\widehat{ttf} = \frac{100}{\hat{r}} \qquad ttf \in \left[\frac{100}{r_{max}}, \frac{100}{r_{min}}\right]$$

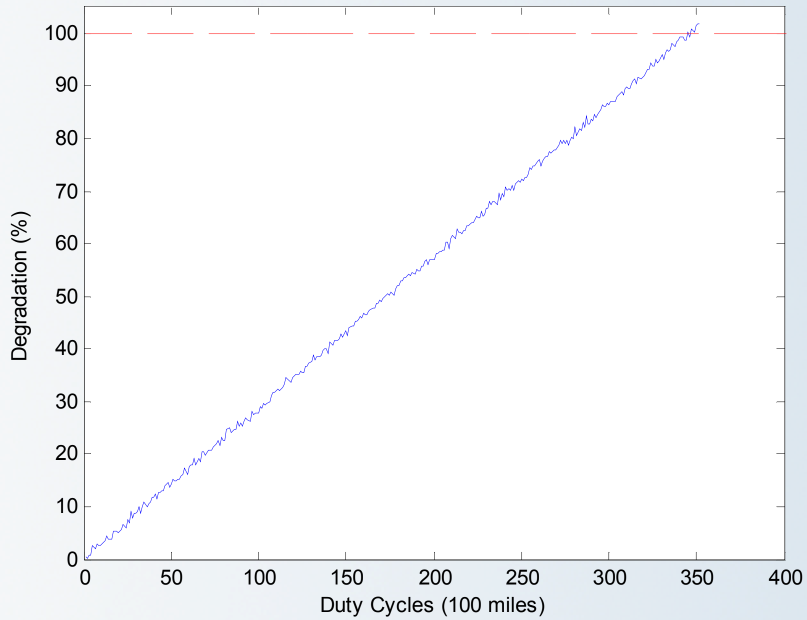
- **Use the new posterior estimates and prior information for the next observation.**

New degradation paths are used to test the GPM/Bayes algorithm

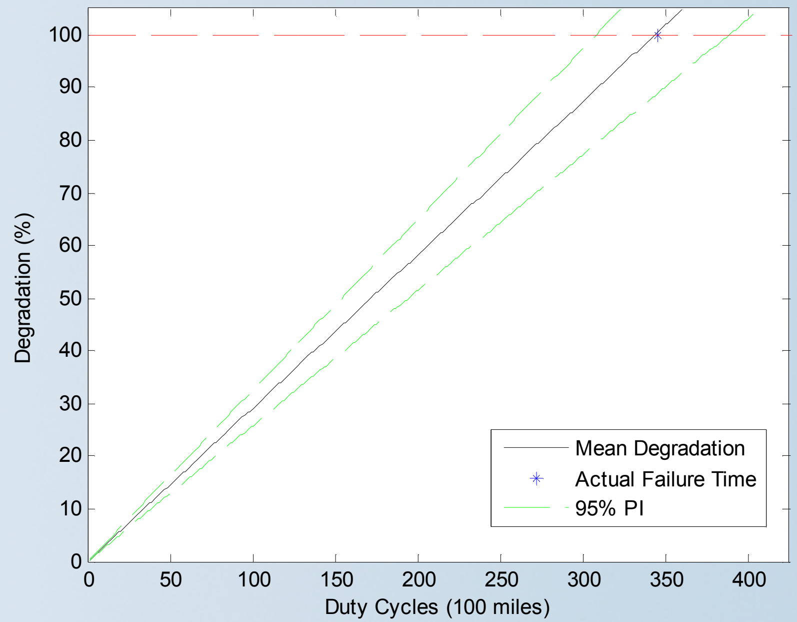
- Three degradation paths are tested
  - Test 1: Degradation similar to the population mean degradation path
    - This degradation path is tested with two different sampling rates
  - Test 2: “Extreme” degradation path which lies in the range of the training data set
  - Test 3: Degradation path which is well outside the range of the training data set

Test 1: Near-Mean Degradation Path

Test Case



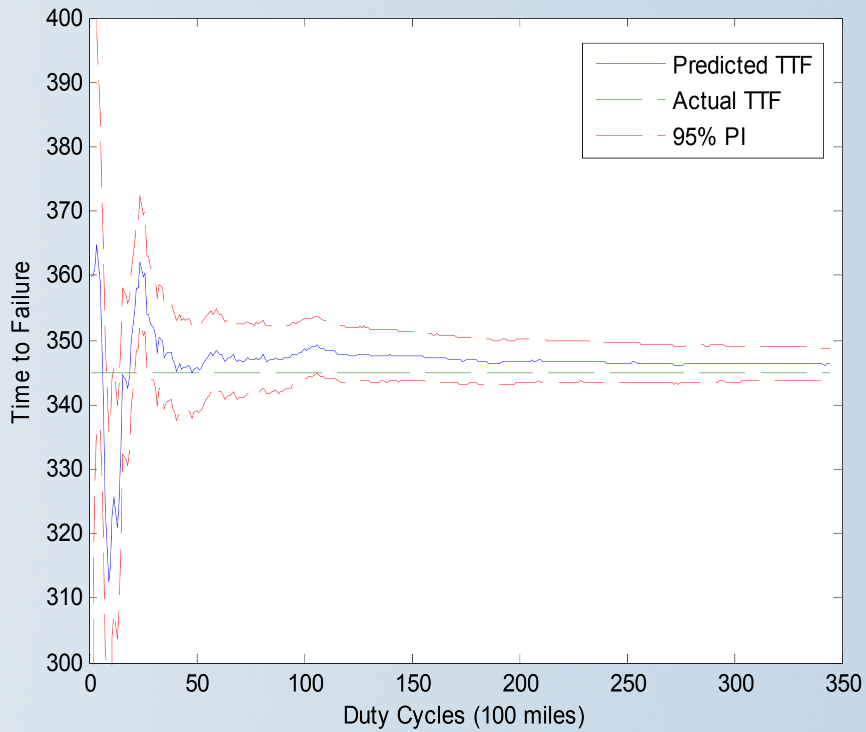
Original Prediction



- **The traditional reliability based estimated TTF is approximately 17 DC (~1,700 miles) greater than the actual TTF.**
- **However, the PI limits are quite large, the 95% PI for the population prognostics is 80 DC (8000 miles) wide.**

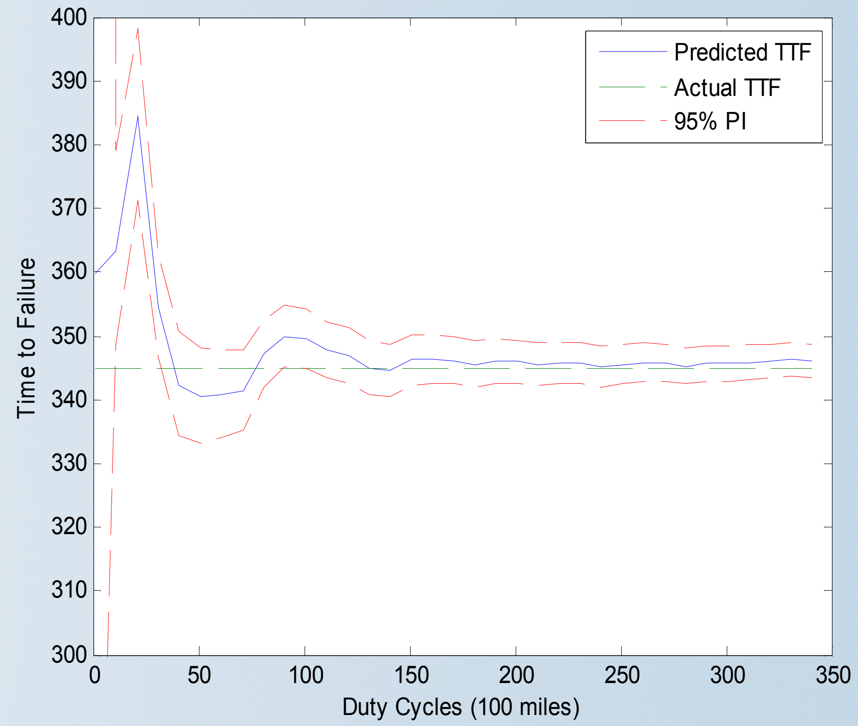
Test 1: TTF estimates

- **TTF estimates are correct to within ~1.5 DC (~150 miles)**
- **95% PI width for TTF estimate is ~5 DC (500 miles)**
- **This accuracy level is obtained after ~40 observations (4,000 miles)**



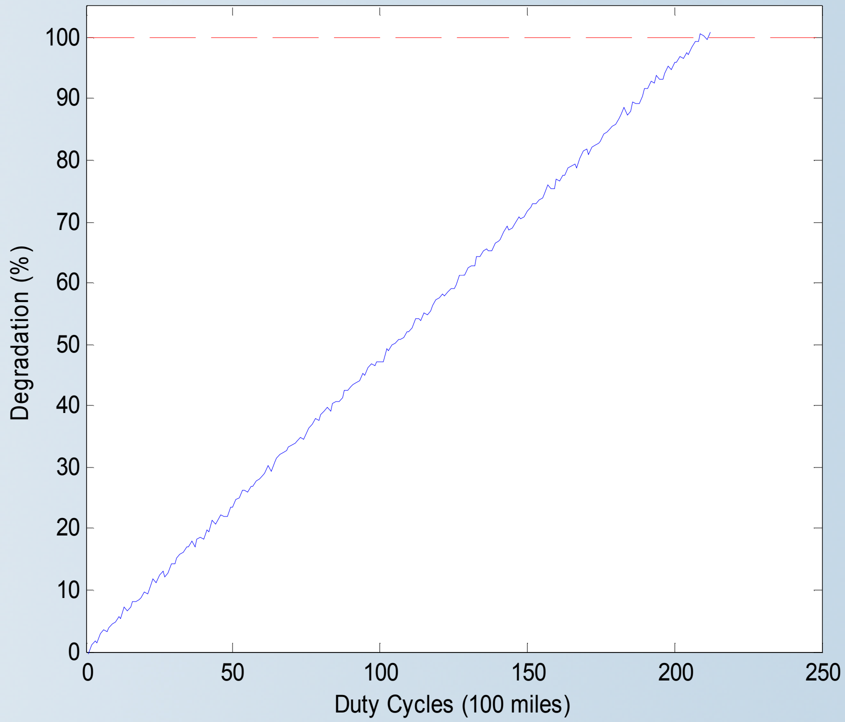
Test 1: Less frequent sampling rate

- One observation per DC may be unrealistically frequent
- The algorithm was applied with 1 obs per 10 DC (1,000 miles)
- Estimates are accurate to ~1 DC with 95% PI width ~5 DC
- Accuracy obtained after 14 obs (14,000 miles)



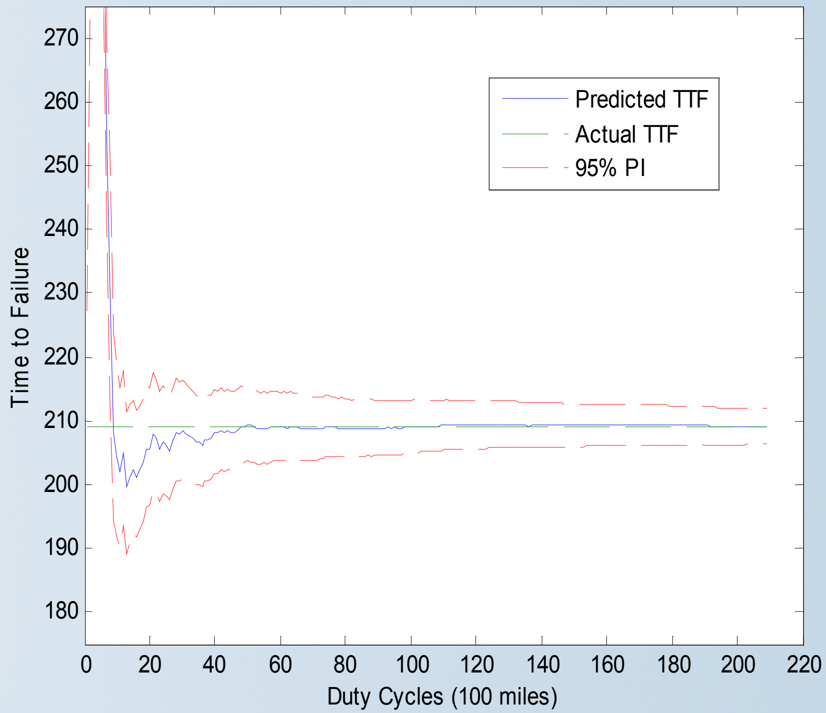
Test 2: "Extreme" Degradation Rate within Training

- Test 2 degradation path is for a tire in the *high slip* condition
  - Test path has high degradation rate (fails sooner)
- Degradation path lies within the range of the historical paths used to establish prior information



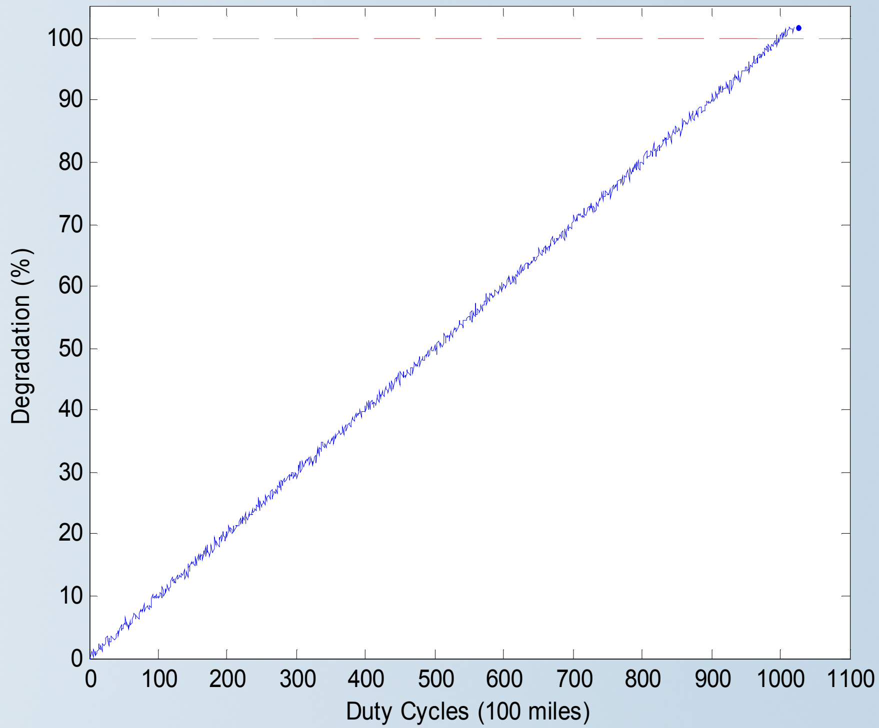
Test 2: TTF estimates

- **Initial TTF estimates are highly biased by the prior information, but result is similar to Test 1 case**
- **The TTF estimate is accurate to less than 1 DC after ~40 observations (4,000 miles)**
- **95% PI is ~5 DC (500 miles)**



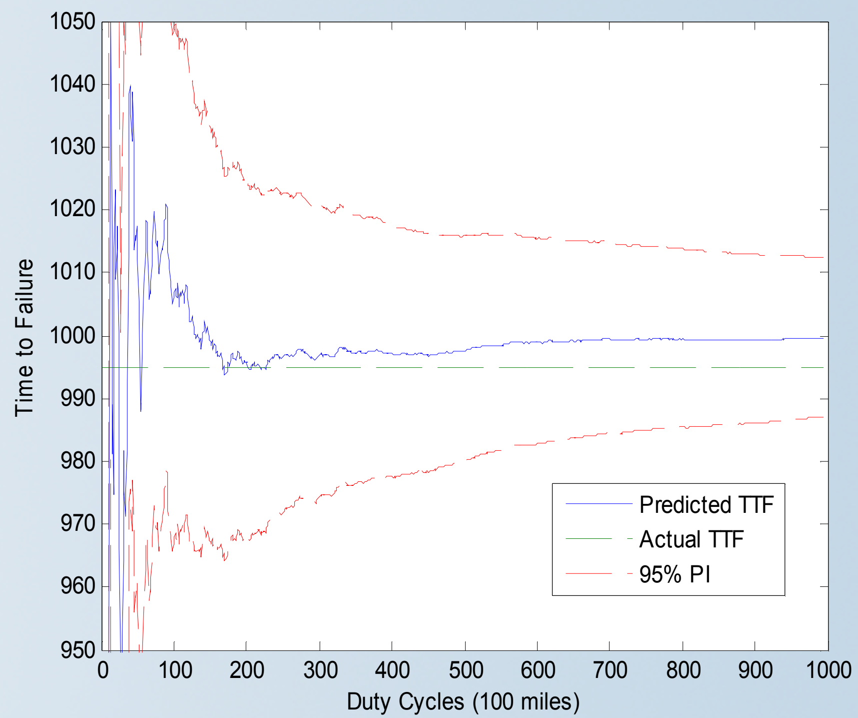
Test 3: "Extreme" Degradation Rate outside Training

- **Test 3 degradation path has a very low degradation rate**
  - **Test path has extremely long lifetime (100,000 miles)**
- **Degradation path lies well outside the range of the historical paths used to establish prior information**



Test 3: TTF estimates

- Test 3 results are very poor
- TTF estimates are accurate to ~ 5 DC (500 miles)
- 95% PI width is ~25 DC (2,500 miles)
- This indicates that the current prognostic model is not suitable for use outside its training data range



GPM Conclusions

- The General Path Model methodology can easily be applied to problems of estimating RUL
- A Bayesian Regression method for including prior information in parameter estimation was presented
- Application of the GPM/Bayes method to a simple tire degradation problem was described
  - Method performed well for degradation paths contained within the range of training paths, even with infrequent data collection
    - RUL estimates were both accurate (within 1 DC) and precise (PI width of ~5 DC)
  - Method did not perform well on a degradation path well outside the training data, giving an estimate which was neither accurate nor precise

More Practical GPM Situations

- More complicated degradation models
  - Models with multiple degradation signals
  - Linear-regression for non-linear models (transformation)
  - Nonlinear-regression models
- Reduced measurement accuracy.
- Use of degradation paths with variable sampling rate for both training and application
- Variable or uncertain failure levels.
- Model misspecification
- Environmental conditions change
- Application for control.

Markov Chain Tire Case Study

- **The Markov chain model will be applied for Type II and III.**

***E(Road Conditions)* = { 1 = *Normal,* 2 = *Off Road,* 3 = *High Slip* }**

- **A tire only operates in one condition for one duty cycle, but conditions can change from duty cycle to duty cycle.**
- **Each environmental condition imposes a certain tire degradation rate, which can be deterministic or stochastic.**
  - **Deterministic Relationship: Certain degradation rate = R_i,**
  - **Stochastic Relationship: Probability distribution FR(r) = P(Ri > r)**

MC Simulated Data

- transition matrix is taken to be of the following form

$$M = \begin{bmatrix} .8 & .15 & .05 \\ .5 & .4 & .1 \\ .5 & .2 & .3 \end{bmatrix}$$

- The initial environmental condition is always normal.

$$\pi(E_0) = [\ 1\ \ 0\ \ 0\ ]$$

Effects Based (Type III)

- **The tire degradation is expressed in terms of tread depth.**
  - **The value of 9mm is taken to be the initial degradation level.**
  - **The value of 1.6 mm is taken to be the critical threshold.**

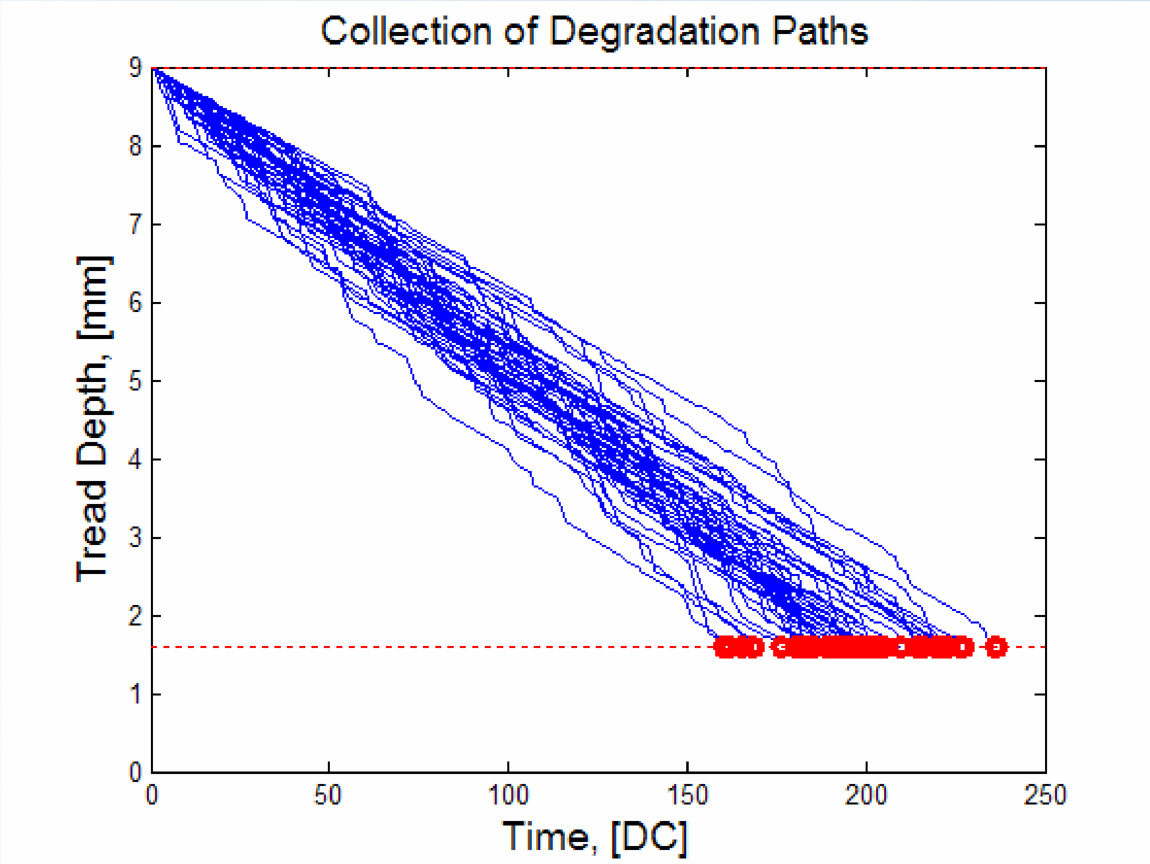
- **Degradation rates are chosen to be**

  R = [-0.0247 -0.0370 -0.1480] mm / duty cycle

  where a duty cycle (dc) is taken to be 100 miles.

- **The choice of the degradation rate values means that the tire mean lifetime is about 300 duty cycles for the normal condition, 200 dc for the "off-road" condition, and 50 dc for the "high-slip" condition.**

Simulated Degradation Paths



Example Degradation Data

Duty Cycle #	Degradation, mm	Env. Condition
1	8.975	1
2	8.950	2
3	8.926	1
…	…	…
163	1.883	2
164	1.859	1
165	1.711	3
166	>1.6 (failure)	

- **50 degradation paths are generated.**
- **The degradation measurements are assumed to be taken once a duty cycle.**
- **Each simulated tire's lifespan has about 200 measurements.**
- **The measurements are assumed to be noiseless.**

Estimation of the Markov chain model

- **Observe the states, collect data.**
- **Compute the residence times in each state**
- **Estimate the transition probabilities q_{ij}**

$$\hat{q}_{ij} = \frac{n_{ij}}{N_i}$$

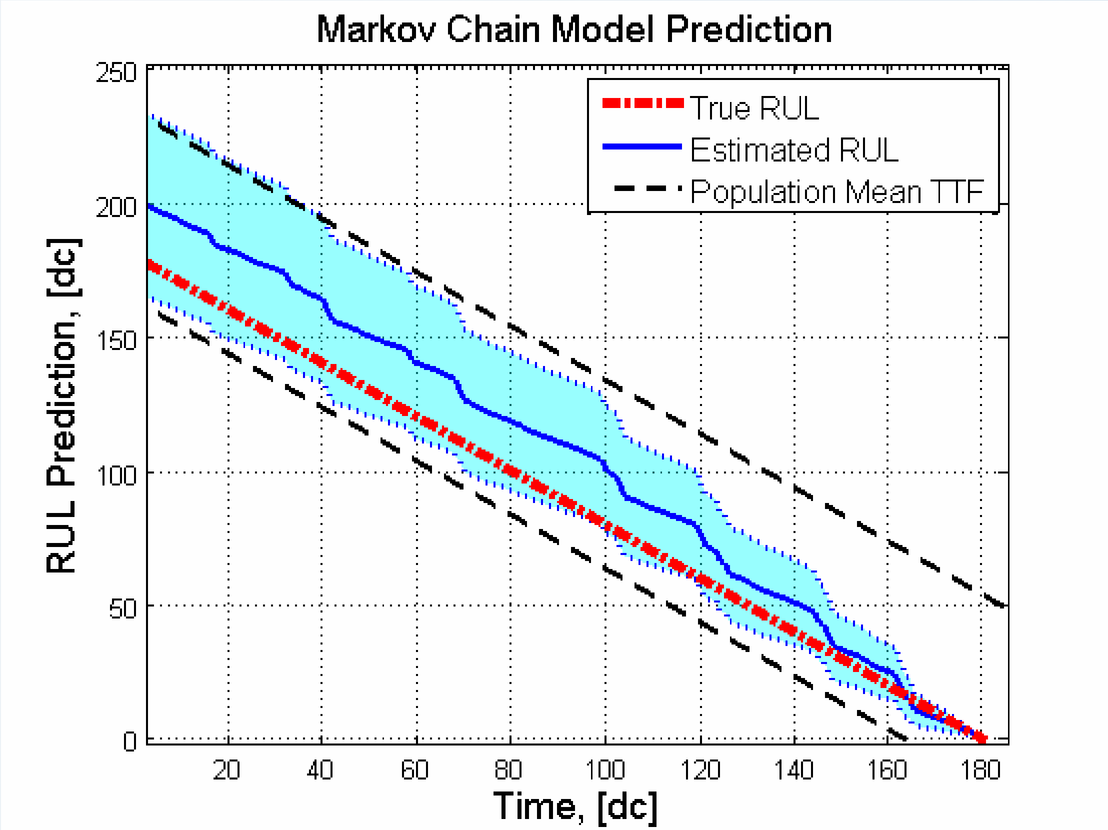
- **where n_{ij} is the number of transitions from State i to State j, N_i is the number of duty cycles where the condition has not changed.**
- **The estimated transition matrix is close to the true values of the transition probabilities**

$$\hat{M} = \begin{bmatrix} .803 & .148 & .049 \\ .497 & .404 & .099 \\ .475 & .208 & .316 \end{bmatrix}$$

$$M = \begin{bmatrix} .8 & .15 & .05 \\ .5 & .4 & .1 \\ .5 & .2 & .3 \end{bmatrix}$$

Time to Failure Prediction w/95% CI

- **At the initial prediction phase the RUL prediction is identical with the population-based mean time-to-failure and variance. However, the 95% prediction intervals associated with the predicted remaining useful life tend to converge to the true time-to-failure.**

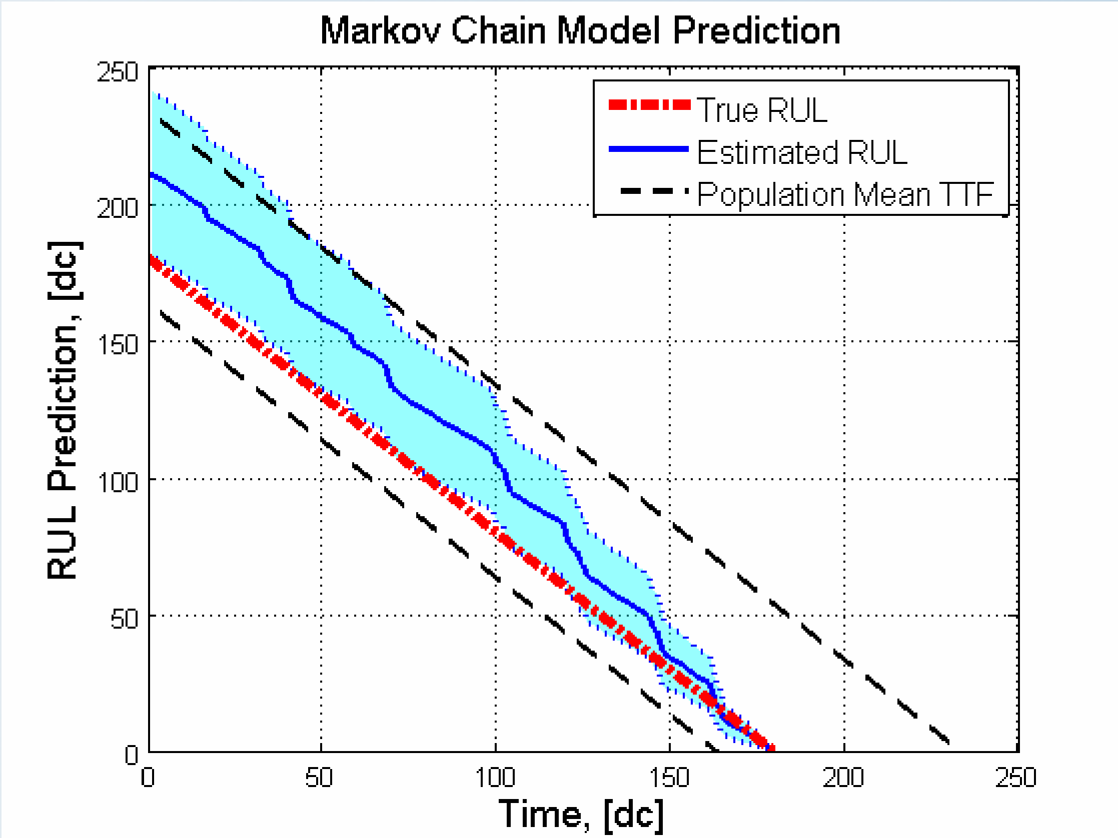


MC Continued

- **If we assume that only 5 observations are available for each tire, the estimation is expected to be less certain.**

$$\hat{M} = \begin{bmatrix} .811 & .142 & .047 \\ .526 & .395 & .079 \\ .539 & .231 & .231 \end{bmatrix}$$

$$M = \begin{bmatrix} .8 & .15 & .05 \\ .5 & .4 & .1 \\ .5 & .2 & .3 \end{bmatrix}$$



Transition Matrix Estimation

- If one has *apriori* knowledge of how many environmental conditions can be encountered during the usage of the tire, a good technique to apply is a clustering method,
- This approach allows for a relatively good estimation of the degradation rates:

$$R_{est} = [.0247\ .0370\ .1480]$$

- However, the uncertainty in the degradation rates still affects the estimated transition matrix.

$$\hat{M} = \begin{bmatrix} .763 & .187 & .050 \\ .549 & .359 & .092 \\ .471 & .217 & .312 \end{bmatrix}$$

$$M = \begin{bmatrix} .8 & .15 & .05 \\ .5 & .4 & .1 \\ .5 & .2 & .3 \end{bmatrix}$$

MC Stress-based Prognostics: Type II

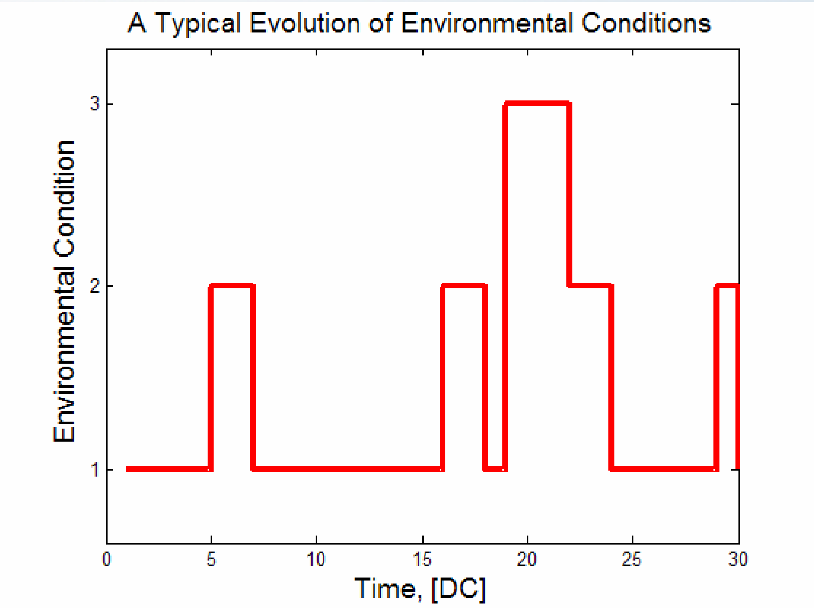
- If environmental stress condition is the only available information in the degradation analysis, one needs to deduce two models
  1. A stochastic model for the random behavior of the environmental conditions (Environment Model),
  2. A stochastic relationship between the environmental model and the failure mechanism under investigation (Prognostic Parameter Model).
- The prognostic parameter is represented as a cumulative function of observable environmental conditions.

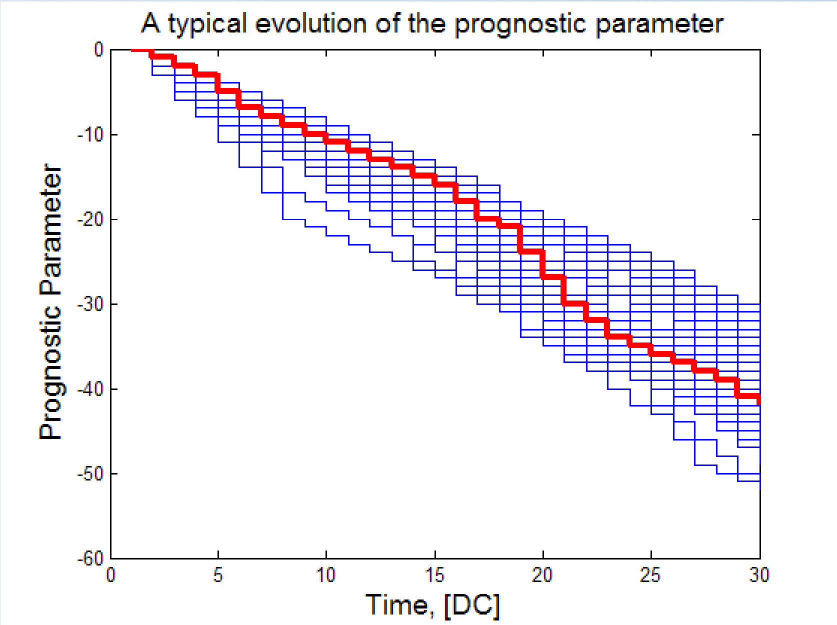
$$Y(t_k) = \sum_{i=1}^{k} g\left(E(t_i, t_i + \Delta t_i)\right)\Delta t_i$$

where $Y(t_k)$ is the prognostic parameter value at time t_k,
$E(t_i, t_i+\Delta t)$ is the environmental condition observed at the time interval $[t_i , t_i+\Delta t]$,
g(.) is a function of environmental conditions.

Environmental Changes

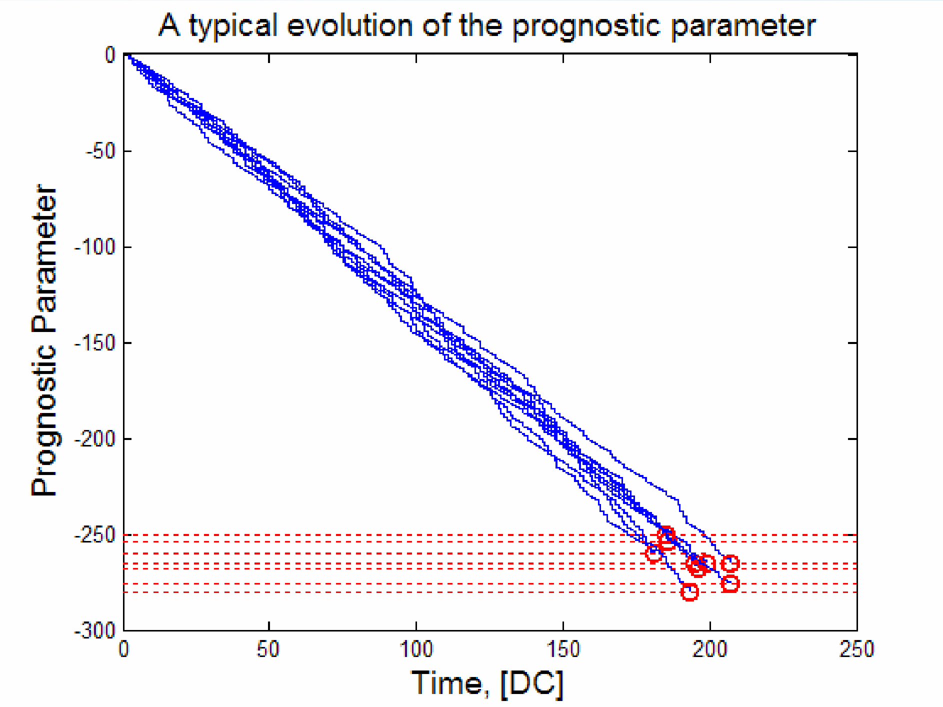
- The typical evolution on the left was simulated with the prior transition matrix
- On the right is a collection of paths with a typical one in red.
- Since we cannot measure the prognostic parameter, there is another source of uncertainty which is discussed next.





Failure Evaluation

- The stochastic relationship between the prognostic parameter and failure can be established via statistical analysis of available failure data.
- Failure data will allow for expressing the failure times in terms of prognostic parameter values. P[failure | y] = F(y)



- With 10 degradation paths to failure, one is able to estimate the critical prognostic parameter value as a certain distribution function with the following mean and variance.
- Mean = –264.3; Var = 82.9

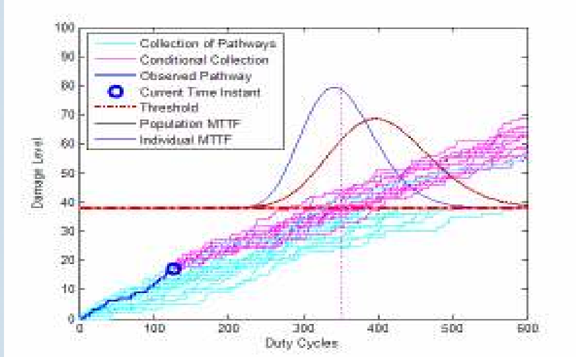
Tire Example Conclusions

- A simple tire simulation is provided to show the relative benefits of the different types of prognostic models.

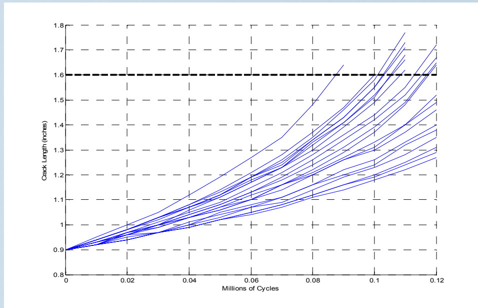
1. If failure time data is available but no measurements related to the operating condition or degradation state can be obtained, then a reliability based distributional model (Type I) can be used.
2. If the operating condition is known, but does not change during the life of the component, then Type II models such as the proportional hazards model can be used.
3. If the degradation state can be measured, a general path model (Type III) can be used.
4. Lastly, if the operating condition changes during the life of the component, then a Markov chain model may be the best selection and implemented as either Type II or III depending on the observational data.

Prognostic Models

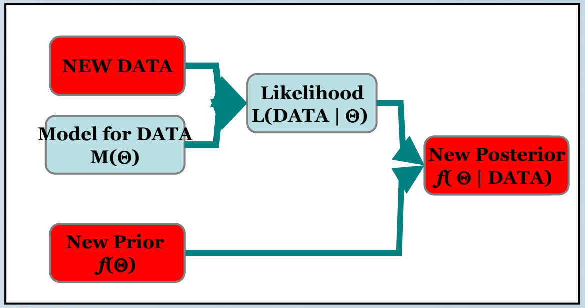
- Markov Chain Models
  - The transition probability matrix is used to generate possible operating condition evolutions (Model I)
  - These potential operating histories are then mapped to a degradation measure (Model II)



- General Path Models
  - The GPM assumes that the degradation is a function of time, duty cycles, or some other measure
  - Extrapolation of this degradation function can be used to predict remaining useful life

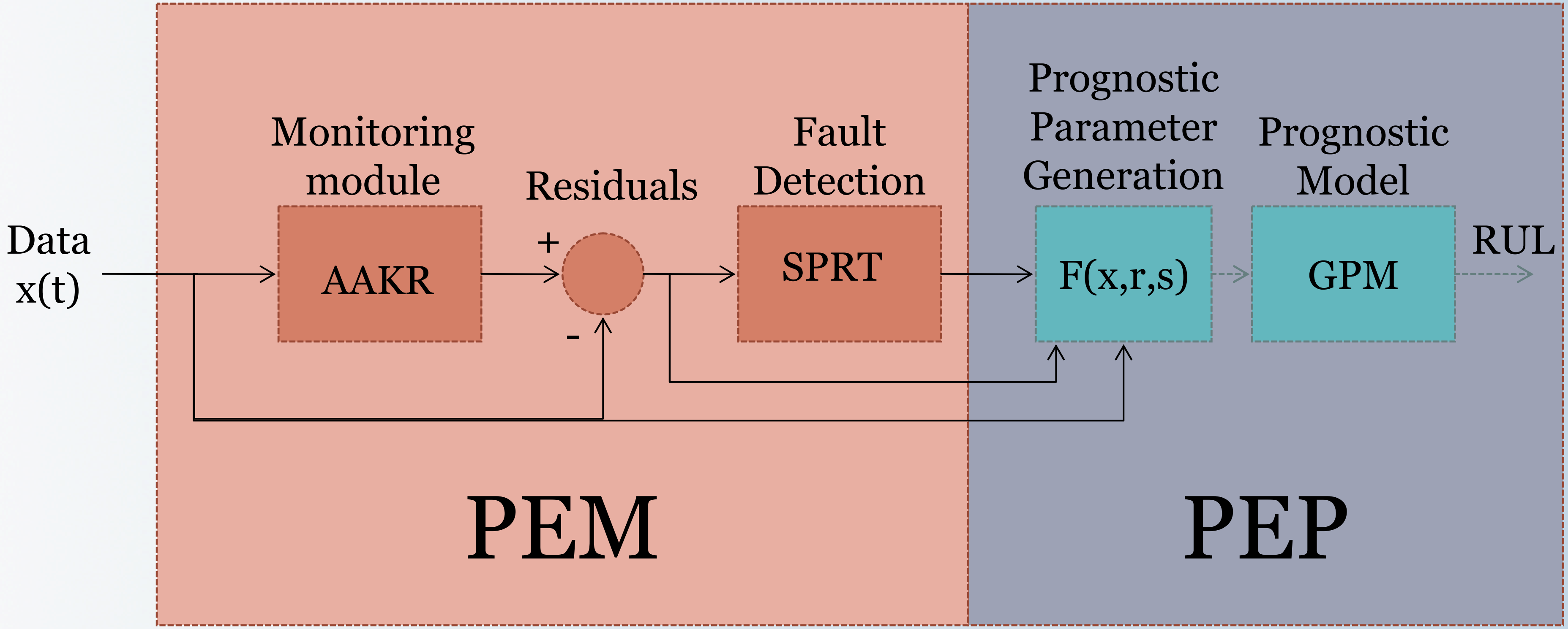


- Bayesian methods
  - Can be used to incorporate prior knowledge in GPM models



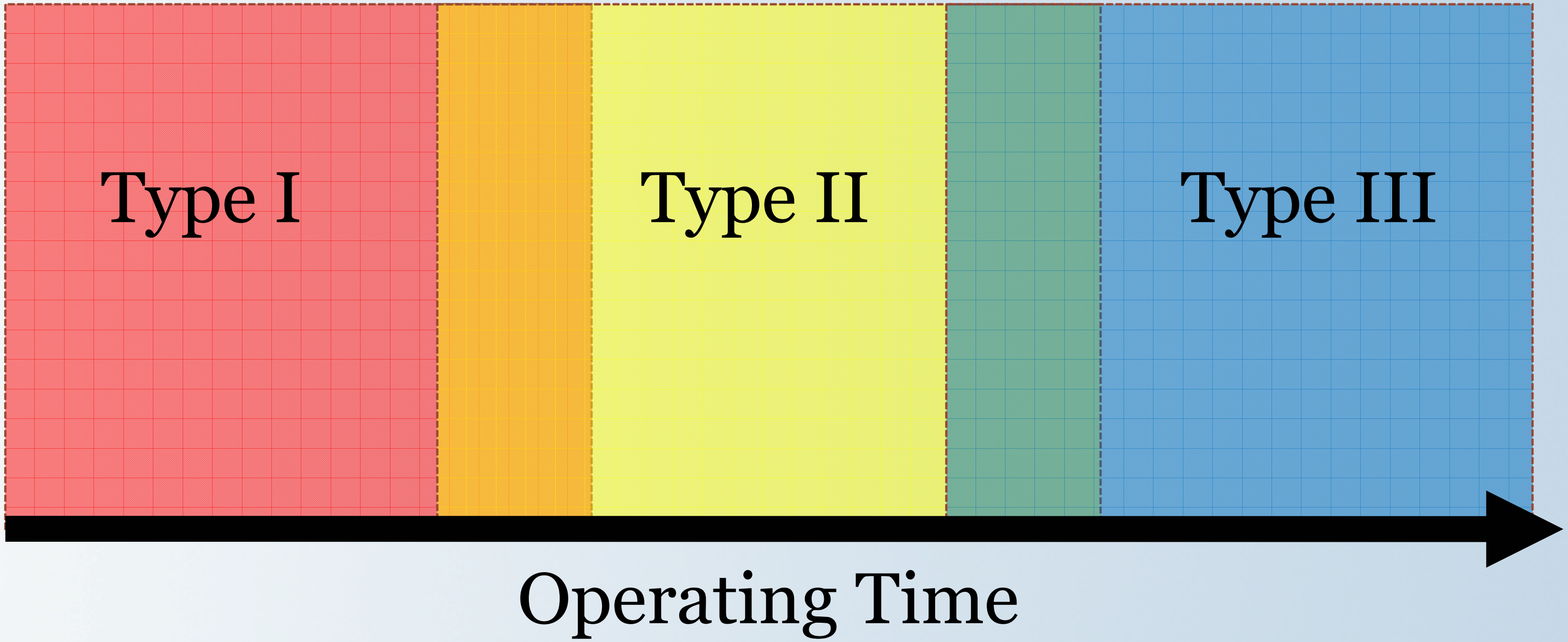
- Hybrid Mixed Models
  - Weibull, Stressor, Performance

The PEM and PEP toolboxes can be used in conjunction for a total monitoring, detection, and prognostics system.



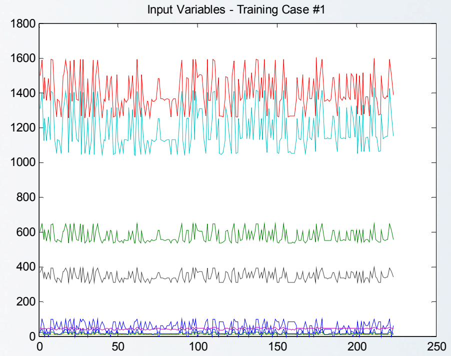
Hybrid Model: Progressing through Prognostic Types

- Architecture Combines Type I, II and III Prognostics
  - I. Historical failure data will be used to estimate the population POF.
  - II. Covariates (e.g. speeds, currents, pressures, vibration, etc.)
  - III. Empirical model residuals will be used to develop a degradation parameter and used to augment population POF to provide individual POF.
  - A Bayesian framework has been developed to update RUL or POF predictions based on new data.



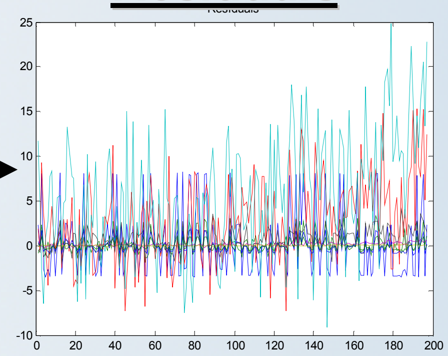
Degradation Parameter Development

Inputs

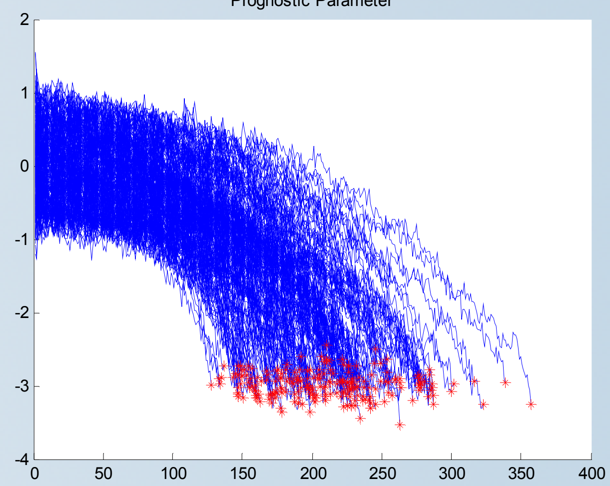


KR

Residuals

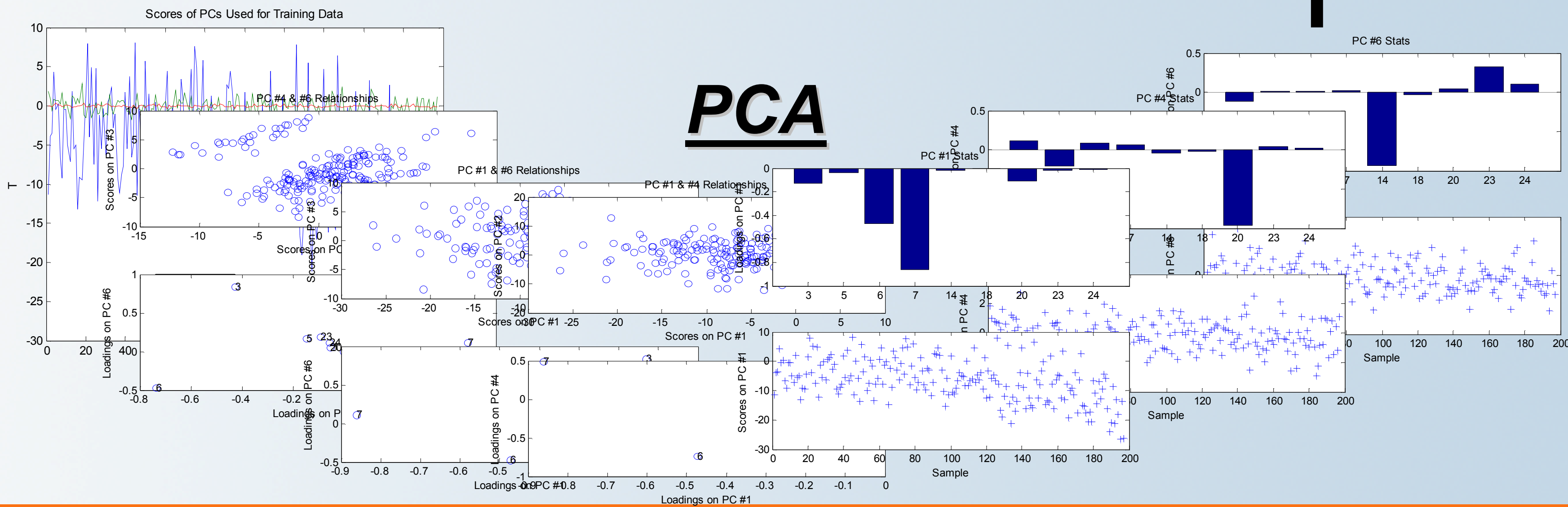


Degradation Paths

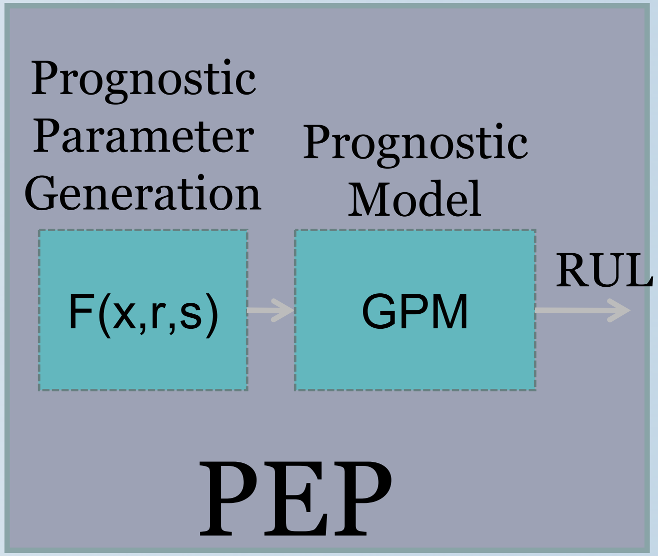


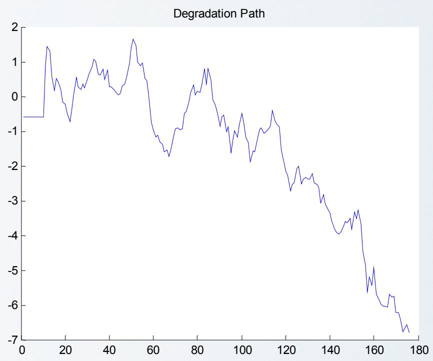
Combine

PCA

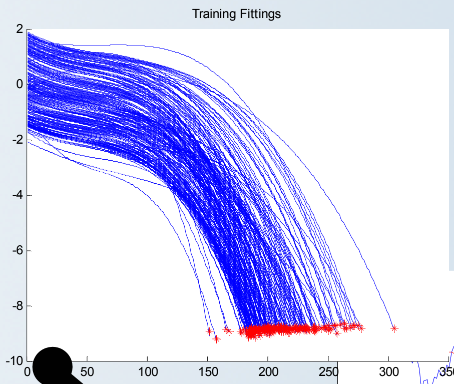


General Path Model

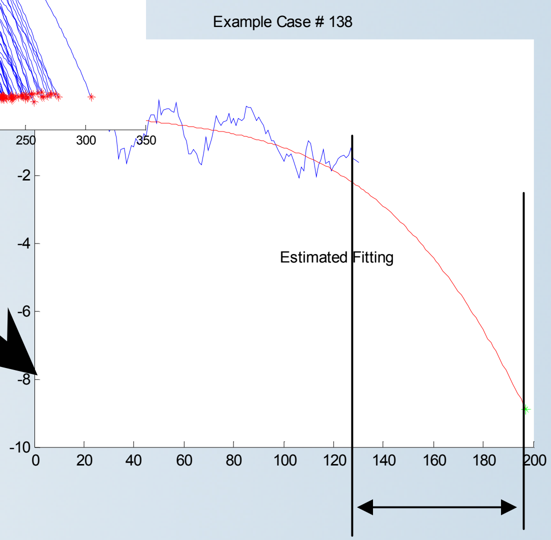




Find Current Degradation Path



Compare To Historical Fittings

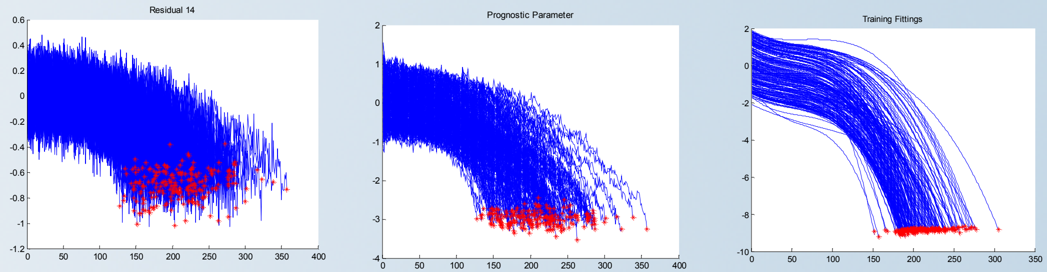


Fit Degradation Path

Estimated RUL

Methods are being developed to aid in and automate model development.

- **Black box approach to identify an appropriate prognostic parameter from data**
  - **Trendability**
  - **Monotonicity**
  - **Prognosability**

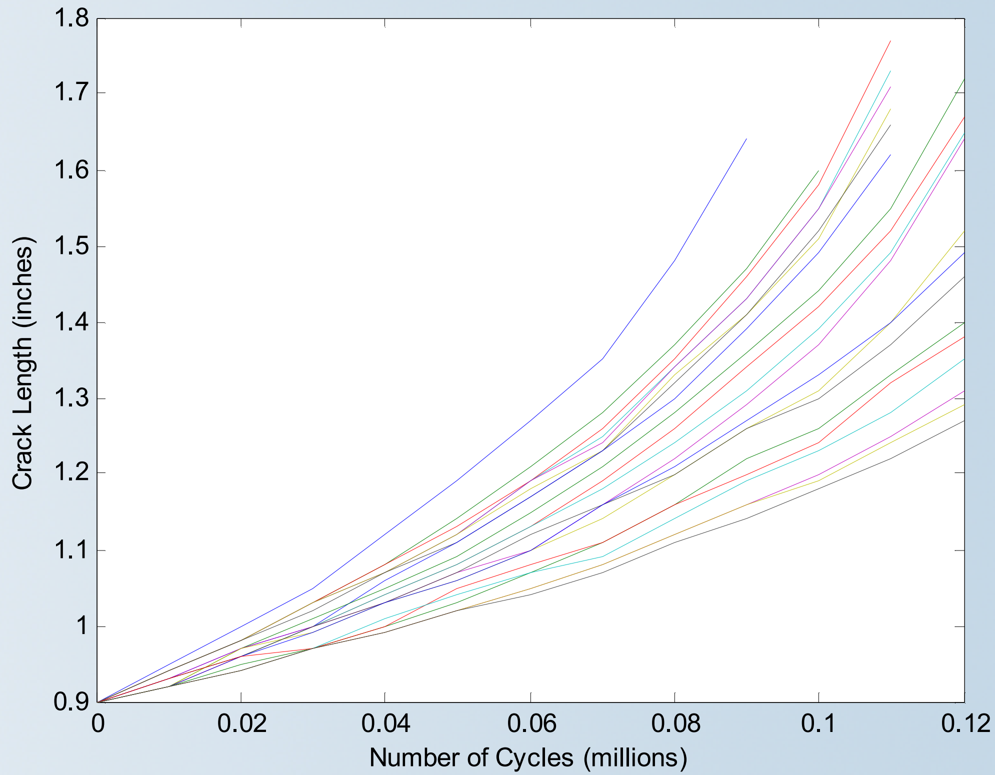


- **Method and metrics to determine which algorithm type and modeling method are best suited for a specific situation**

- **Bayesian methods to progress between prognostic model types as information becomes available**

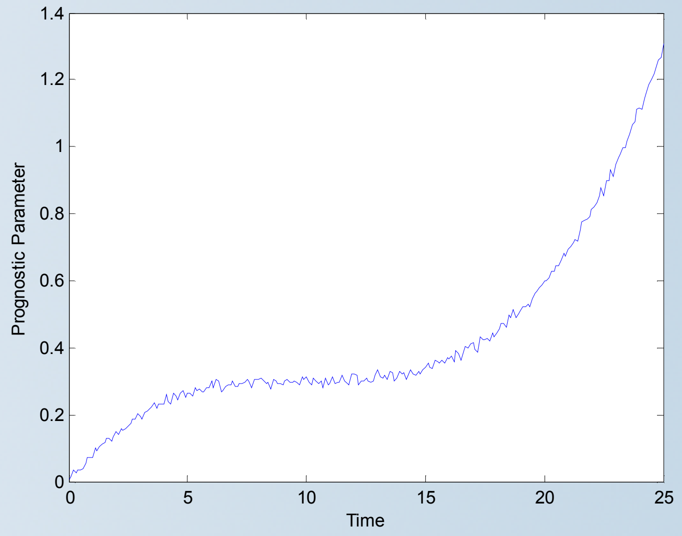
Trendability

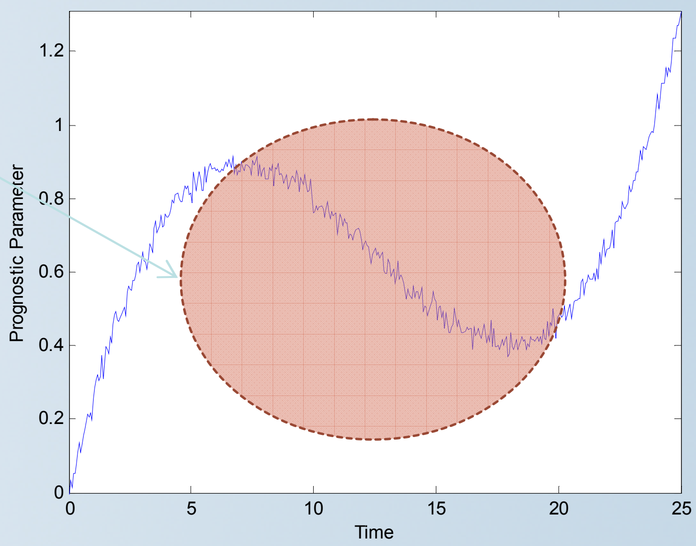
- The degree to which the parameters of a population of systems have the same underlying shape
- Each example appears to have a roughly exponential shape



Monotonicity

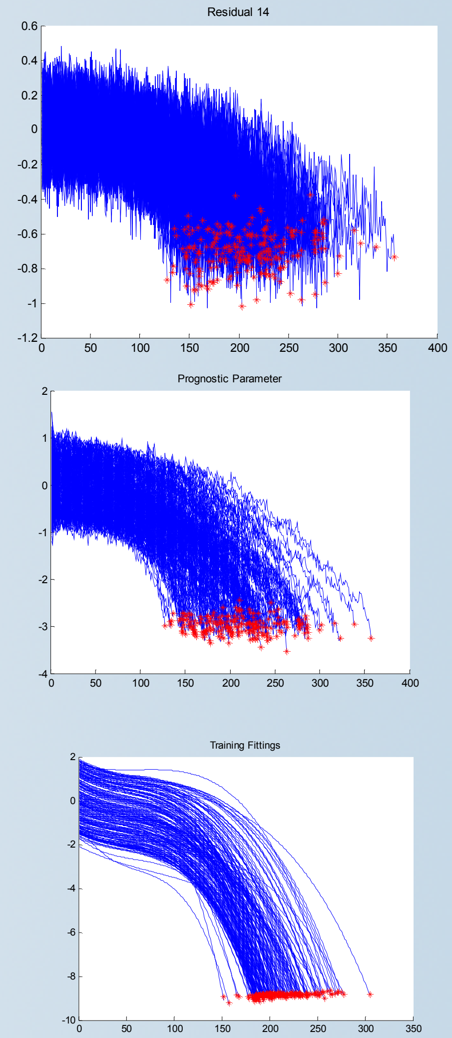
- The underlying positive or negative trend of the parameter
- Parameter should be monotonic because 'self-healing' is considered non-physical





Prognosability

- A measure of the variance in the critical failure value of a population of systems
- Failure should occur at approximately the same value for the entire population
- This may be improved by bagging multiple parameters or denoising the signals



Selecting an Appropriate Prognostic Architecture

- Selecting the correct prognostic type and architecture for a particular system can be complicated
- Usually based on engineering judgment and personal expertise
- The PEP toolbox will automate this based on
  - The type of data available
  - Assumptions which can be made about the system
  - Assumptions of each prognostic algorithm

Selected recent publications

- **Sharp, M. and J.W. Hines, "Analysis of Prognostic Opportunities in Power Industry with Demonstration" *Sixth American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Control, and Human-Machine Interface Technologies* NPIC&HMIT 2009, Knoxville, Tennessee, April 5-9, 2009.**
- **Humberstone, M., B. Wood, J. Henkel, and J.W. Hines, "An Adaptive Model for Expanded Process Monitoring", Sixth American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Control, and Human-Machine Interface Technologies NPIC&HMIT 2009, Knoxville, Tennessee, April 5-9, 2009.**
- **Coble, J., and J. Hines, "Fusing Data Sources for Optimal Prognostic Parameter Selection", Sixth American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Control, and Human-Machine Interface Technologies NPIC&HMIT 2009, Knoxville, Tennessee, April 5-9, 2009.**
- **Usynin, A. J.W. Hines, A. Urmanov, "Prognostics-Driven Optimal Control for Equipment Performing in Uncertain Environment", 2008 IEEE Aerospace Conference, 2008.**
- **Hines, J.W., J. Garvey, J. Preston, and A. Usynin, "Empirical Methods for Process and Equipment Prognostics", 53nd Annual Reliability and Maintainability Symposium (RAMS), Las Vegas, NV, Jan, 2008.**
- **Usynin, A., A. Urmanov, and J.W. Hines, "Uncertain Failure Thresholds in Cumulative Damage Models", 53nd Annual Reliability and Maintainability Symposium (RAMS), Las Vegas, NV, Jan, 2008.**
- **Garvey, J, and J.W., Hines, "Merging Data Sources for Predicting Remaining Useful Life", Maintenance and Reliability Conference, Knoxville, TN, May 2008.**
- **Garvey, D.R. and J.W. Hines , "An Integrated Fuzzy Inference Based Monitoring, Diagnostic, and Prognostic System for Intelligent Control and Maintenance", *Foundations of Generic Optimization, Volume 2*, Editors, R. Lowen, A. Verschoren, Springer, 2007.**
- **Dustin R. Garvey, J. Wesley Hines, and Kenny C. Gross, "Remaining Useful Life Estimation of Computer Server Power Supplies", *61th Meeting of the Society for Machinery Failure Prevention Technology*, Virginia Beach, Virginia, April, 2007.**

Conclusions

- **Sensed data contains degradation information and should be used to improve operational reliability through:**
  - **Optimizing maintenance scheduling (condition-based)**
  - **Improving operations (equipment state knowledge)**
- **The potential benefits of early warning are significant**
  - **Improved availability**
  - **Reduced equipment damage**
  - **Improved safety**
- **Several methods exist, the selection is based on**
  - **Data available: failure, causal, effects.**
  - **Knowledge of degradation mode (physical model)**