An Introduction to Data-Driven Prognostics of Engineering Systems

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Evolution of Maintenance Practices
From Reactive to Preemptive

- **Key Enabler:** Prognostics!
- **Condition Based Maintenance:** Predicting the future health of a component so that maintenance is done based on the actual condition of the component.
- **Enhanced Diagnostics:** Process of determining why a component has failed.
- **Reliability Centered Maintenance:** Systematic maintenance approach to ensure that assets continue to do what their users require in present operating context.
- **Repair / Replace When Broken**

Benefits (Availability, Cost Savings, Maintenance Scheduling, ...)

Complexity (Cost, Implementation, Infrastructure, ...)

- Reliability Centered Maintenance
- Enhanced Diagnostics
- Condition Based Maintenance
- Key Enabler: Prognostics!
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.

Data
- Is there an anomaly or fault?

Monitor and Detect
- What is the fault?

Diagnose
- What is the RUL?

Prognose

Mitigate
- How can the lifetime be extended?
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 meet 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
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)

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 ($\beta$) and
  • a characteristic life ($\theta$)

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

• Increasing failure rate ($\beta>1$), a constant failure rate ($\beta=1$), and a decreasing failure rate ($\beta<1$)

• 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 \( \alpha \), we can calculate the value of \( t \) such that \( R(t|T) = \alpha \)

\[
R(t|T) = \frac{R(t, t > T)}{R(T)} = \alpha
\]

\[
R(t, t > T) = \alpha \cdot R(T)
\]

\[
\text{note } R(t) = 1 - F(t)
\]

\[
\Rightarrow 1 - F(t, t > T) = \alpha \cdot R(T)
\]

\[
F(t, t > T) = 1 - \alpha \cdot R(T)
\]

\[
t = F^{-1}(1 - \alpha \cdot R(T)), t > T
\]

\[
RUL_\alpha = t - T
\]
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 RUL Estimation Error: MAPE = 114.5574
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 into 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

\[ \lambda(t, z) = \lambda_o(t) \psi(z; \beta) \]

- \( z \) is a row vector of covariates
- \( \beta \) is a column vector of regression parameters
  - Defines the effects of the covariates
- Different functional forms of \( \psi \) may be used
  - Typically exponential: \( \psi(z; \beta) = \exp(z\beta) \)
- Use maximum likelihood method to estimate the values of \( \beta \) 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

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

\[
R(t,Z) = \exp(-H(t,z))
\]

- 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 $Q$

\[
Q = \begin{bmatrix}
0.7 & 0.2 & 0.1 \\
0.2 & 0.7 & 0.1 \\
0.1 & 0.1 & 0.8 \\
\end{bmatrix}
\]
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.

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

$$= P( X_t = j \mid X_{t-1} = i_{t-1}) = P_{ij}(t-1)$$
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
  \[ D(t = n) = f(x_0, x_1, \ldots, x_n) \]

• 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, $t = 0$
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

<table>
<thead>
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<th>From</th>
<th>To 1</th>
<th>To 2</th>
<th>To 3</th>
<th>To 4</th>
<th>To 5</th>
<th>To 6</th>
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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)

<table>
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<td>-0.046</td>
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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.
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.

• Degradation paths were extrapolated to find estimated failure times
• The distribution was estimated from measured and estimated failure times
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 \( \varphi \) is the vector of fixed effects (population) parameters and \( \Theta_i \) is the vector of random (individual) effects for unit \( i \).

- The function, \( \eta \), 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.

\[ \text{Model for DATA } M(\Theta) \]

\[ \text{Likelihood } L(\text{DATA } | \Theta) \]

\[ \text{New Prior } \mathcal{f}(\Theta) \]

\[ \text{NEW DATA} \]

\[ \text{New Posterior } \mathcal{f}(\Theta | \text{DATA}) \]
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: \( \beta_j \sim N(\beta_{jo}, \sigma_{\beta j}^2) \)
- The prior information on \( \beta_j \) is treated as another observation in the regression

\[
Y^* = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \\ \beta_{jo} \end{bmatrix} \quad X^* = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \\ 0 & \cdots & 1 & 0 \end{bmatrix} \quad \Sigma_y^* = \begin{bmatrix} \sigma_y^2 & 0 & \cdots & 0 & 0 \\ 0 & \sigma_y^2 & \ddots & \vdots & 0 \\ \vdots & \ddots & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \sigma_y^2 & 0 \\ 0 & 0 & \cdots & 0 & \sigma_{\beta j}^2 \end{bmatrix}
\]

- New parameter estimates become the prior information for the next data observation
Prior Information About All Regression Coefficients

\[ \beta \sim N(\beta_0, \Sigma_\beta) \]

\[
Y^* = \begin{bmatrix} Y \\ \beta_0 \end{bmatrix} \quad X^* = \begin{bmatrix} X \\ I_k \end{bmatrix} \quad \Sigma^* = \begin{bmatrix} \Sigma_y & 0 \\ 0 & \Sigma_\beta \end{bmatrix}
\]

\[
\hat{\beta} = (X^{*T} \Sigma^*^{-1} X^*)^{-1} X^{*T} \Sigma^*^{-1} Y^*
\]
Comparison of GPM and GPM/Bayes RUL Predictions

![Graph showing mean absolute percent error for training cases with and without Bayes](image)
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

Type I

Type II

Type III

Operating Time
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?

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