Prognostics for Microgrid Components

Batteries, Capacitors, and Power Semiconductor Devices

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Prognostics and Health Management

In Perspective
Goals for Prognostics

What does prognostics aim to achieve?

- Improved mission planning
- Ability to reassess mission feasibility
- Avoid cascading effects onto healthy subsystems
- Maintain consumer confidence, product reputation
- More efficient maintenance planning
- Reduced spares
- Service only specific aircraft which need servicing
- Service only when it is needed

Contingency Management View

Maintenance Management View

- Prognostics goals should be defined from users’ perspectives
- Different solutions and approaches apply for different users
**Health Management**

[Diagram showing integrated logistics information and health management systems]

- **Contingency Management View**
  - Condition Based Mission Planning
  - System Reconfiguration
  - Control Reconfiguration
  - Prognostic Control
  - Condition Monitoring
  - Safety and Risk Analyses

- **Maintenance Management View**
  - Planning + Scheduling
  - Tech Support
  - Anticipatory Material
  - Training
  - Feedback to Production Control
  - Predictive Maintenance
  - Condition Monitoring
  - Reliability Analysis

- **Condition Based Monitoring**
  - Data Comm
  - Sensors
  - Reporting
  - Scheduled Inspections
  - Troubleshooting and Repair
  - Knowledgebase e.g. IETMs
  - Portable Maintenance Aids

- **Wholesale Logistics**

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Prognostics for Microgrids

• Key components
  – Power storage
    • Batteries
    • Capacitors and SuperCapacitors
  – Power components and devices
    • Power switches (semiconductor switches and packaging)
    • Passive components (inductors, capacitors, high frequency transformers)
    • Controllers and Gate drivers

• Microgrids PHM – Potential benefits*
  – Advanced inverter controls for microgrids
  – Robust operation during fault conditions
  – More informed decision support

* Key R&D Areas for micro grid reliability as identified in 2011 DoE Microgrid Workshop, San Diego CA
Grid PHM Framework

- Classification Algorithms
- Prognostic Framework
- Grid Map
- Take Corrective Action
- Maintenance Dispatch

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Fundamentals of Predicting Remaining Useful Life

Understanding the Prognostic Process
Prognostics Categories

- **Type I: Reliability Data-based**
  - Use population based statistical model
  - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of a typical component under nominal usage conditions
  - Example: Weibull Analysis

- **Type II: Stress-based**
  - Use population based fault growth model – learnt from accumulated knowledge
  - These methods also consider the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions
  - Example: Proportional Hazards Model

- **Type III: Condition-based**
  - Individual component based data-driven model
  - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions
  - Example: Cumulative Damage Model, Filtering and State Estimation

*For more details please refer to last year’s PHM09 tutorial on Prognostics by Dr. J. W. Hines: [http://www.phmsociety.org/events/conference/phm/09/tutorials]*
Prognostics Framework

Risk is now a compound function of chosen failure threshold and the decision point.

\[
\pi_{a_{FT}} = P_{H}(a = a_{FT}) \cdot \int_{t_{Decision}}^{t} P_{EoL}(t | a = a_{FT}) dt
\]

\( \pi \) is adjusted with probability of failure at the given damage size.
Fault Dimension ($a$)

Prognostics Framework

Probability of damage size being greater than the critical value at time $t_3$

$$\pi_{t_3} = \int_{a_{FT}}^{\infty} p_a(a|t = t_3) da$$

$$= 1 - \int_{0}^{a_{FT}} p_a(a|t = t_3) da$$

$$= 1 - P_a(a_{FT}|t = t_3)$$

Damage size pdf at a given time can be useful when planning a mission (usage) profile. Answers how risky it is to go on a mission of known duration?

We can figure out if the system would withstand by the time mission is completed.
Particle Filters

- Allows model adaptation
- State estimation, tracking and prediction
- Nice tradeoff between MC and KF
- Useful in both diagnostics and prognostics
- Represents uncertainty
- Manages uncertainty

\[ \begin{align*}
  \text{actual state value} & \quad \text{measured state value} \\
  x & \quad \text{state particle value} \\
  \text{x} & \quad \text{state pdf (belief)}
\end{align*} \]

\[\begin{align*}
  t_k & \quad t_{k+1} & \quad t
\end{align*}\]

\[ P(x) \]

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Particle Filter-Based Prognostics

System Sensors

Raw Data

Feature Extraction/ Direct Measurement

Model Parameters are part of the State Vector

\[ X \equiv [x_k, \theta_k] \]

Parameter Identification

System Model

Prior

\[ p(x_k|x_{k-1}) \]

Particle Filter

Posterior

\[ p(x_k|x_{k-1}, z_k) \]

Tuned System Model

Failure Threshold

Prediction

Measurement

\[ z_k \]

State Tracking Loop

Identified Model

Prediction Loop

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Power Storage Systems: Predicting Battery Discharge

- **Objective:** Predict when the battery voltage will dip below 2.7 volts
  - Example: when to recharge laptop or cell phone batteries
- **Approach**
  - Model SOC as a sum of 3 sub-processes
    - mass transfer, self discharge and reactant depletion
  - Use PF algorithm to predict RUL

\[
E(t_k) = E^0 - \Delta E_{IR}(t_k) - \Delta E_{AP}(t_k) - \Delta E_{CP}(t_k)
\]

where
\[
\Delta E_{IR}(t_k) = I_k R - \alpha_{1,k} t_k,
\]
\[
\Delta E_{AP}(t_k) = \alpha_{2,k} \exp(-\alpha_{3,k} / t_k),
\]
\[
\Delta E_{CP}(t_k) = \alpha_{4,k} \exp(\alpha_{5,k} t_k).
\]

- **Complexity:** Non-linear failure growth characteristics

*Data Source: NASA PCoE Data Repository [http://it.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]*
*B. Saha, K. Goebel, Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework. Proceedings of Annual Conference of the PHM Society 2009*
Model Validation in Realistic Environments

- Battery discharge algorithm was used in e-UAV BHM
- More than 3 dozen successful flights
  - Prediction update rates at 1Hz
  - Limited onboard computational power
Power Storage Systems - Predicting Battery Capacity

- **Objective:** Predict when Li-ion battery capacity will fade by 30% indicating life (EOL)
  - determine when to replace old batteries
- **Approach:**
  - Model self-recharge at rest and capacity loss due to Coulombic efficiency
  - Use PF algorithm to predict RUL

\[
\begin{align*}
\beta_{i,k+1} &= \beta_{i,k} + \phi_{j,k}, \quad f = 1,2, \\
C_{k+1} &= \eta_{C_i} C_k + \beta_{i,k} \exp(-\beta_{2,k} / \Delta t_k) + \phi_k, \\
\tilde{C}_k &= C_k + \psi_k.
\end{align*}
\]

- **Complexity:** Self-healing characteristics make them highly non-linear

*Data Source: NASA PCOE Data Repository [http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository]*
*B. Soha, K. Goobal, Modeling Li ion Battery Capacity Depletion in a Particle Filtering Framework, Proceedings of Annual Conference of the PHM Society 2009*
Power Electronics Failure - MOSFETs

- **Objective**: predict abnormal functioning of power electronics devices
  - Prediction approach validated in data from 100V power MOSFETs
  - The failure mechanism for the stress conditions is determined to be die-attachment degradation
  - Change in ON-state resistance is used as a precursor of failure due to its dependence on junction temperature

![Image of power electronics components]

Power Component Failure - Capacitors

- **Objective:** Predict remaining useful life for capacitors
  - The failure mechanism is electrical overstresses via repeated charge/discharge of capacitors at high voltages
  - Lumped-parameter model identified as a viable reduced-order model for prognostics-algorithm development
  - Equivalent series resistance (ESR) and capacitance (C) identified as precursor of failure feature parameters
  - Health state tracking and RUL prediction algorithm based on the Kalman filtering framework
  - Connect observations to physical models for a model based algorithm
Prognostic Performance Metrics

- New metrics were proposed specific to prognostics for PHM
- These metrics were applied to
  - a combination of different algorithms and different datasets
- Metrics were evaluated and refined

- Prognostics horizon
- $\alpha$-$\lambda$ performance
- Relative accuracy
- Cumulative relative accuracy
- Convergence

Prognostic Performance Metrics

- Metrics Hierarchy

I. Prognostic Horizon
   - Does the algorithm predict within desired accuracy around EoL and sufficiently in advance?

II. $\alpha$-$\lambda$ Performance
   - Further does the algorithm stay within desired performance levels relative to RUL at a given time?

III. Relative Accuracy
   - Quantify how well an algorithm does at a given time relative to RUL.

IV. Convergence Rate
   - If the performance converges (i.e., satisfies above metrics) quantify how fast does it converge.
Challenges in Prognostics

• Requirements Specification
  – How can a requirement be framed for prognostics considering uncertainty?
  – How to define and achieve desired prognostics fidelity

• Uncertainty in prognostics
  – Quantification, representation, propagation and management
  – To what extent the probability distribution of a prediction represent reality

• Validation and Verification
  – How can a system be tested to determine if it satisfies specified requirements?
  – If a prediction is acted upon and an operational component is removed from service, how can its failure prediction be validated since the failure didn’t happen?
  – Prognostics performance evaluation – offline and online?
  – Verifiability of prognostics algorithms
Thanks!

Questions?