Prognostics for Microgrid Components

Batteries, Capacitors, and Power Semiconductor Devices

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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

Contingency Management View

- More efficient maintenance planning
- Reduced spares
- Service only specific aircraft which need servicing
- Service only when it is needed

Maintenance Management View

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

Contingency Management View

- Condition Based Mission Planning
- System Reconfiguration
- Control Reconfiguration
- Condition Monitoring Safety and Risk Analyses

Maintenance Management View

- Planning + Scheduling
- Training
- Knowledgebase e.g. IETMs
- Portable Maintenance Aids
- Feedback to Production Control
- Predictive Maintenance
- Condition Monitoring Reliability Analysis

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

PROGNOSTICS CENTER OF EXCELLENCE
Fundamentals of Predicting Remaining Useful Life

Understanding the Prognostic Process

PROGNOSTICS CENTER OF EXCELLENCE
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.
Prognostics Framework

Fault Dimension (\(a\))

Failure Threshold (\(a_{FT}\))

VERTICLE SLICE

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

![Diagram of Particle Filter Process]

1. **Initialize PF Parameters**
2. **Propose Initial Population**, \( \{x_0, w_0\} \)
3. **Propagate Particles using State Model**, \( X_{k-1} \rightarrow X_k \)
4. **Update Weights**, \( W_{k-1} \rightarrow W_k \)
5. **Weights degenerated?**
   - Yes: **Resample**
   - No: Return to Step 3
Particle Filter-Based Prognostics

Model Parameters are part of the State Vector

\[ x \equiv [x_k, \theta_k] \]

System Sensors

Raw Data

Feature Extraction/ Direct Measurement

Parameter Identification

System Model

Prior

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

Particle Filter

Posterior

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

Failure Threshold

Tuned System Model

Prediction Loop

Measurement

\( z_k \)

State Tracking Loop

Identified Model
Examples

Prognostics Applications
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

![Graph showing battery voltage over time]

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

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

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

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*Data Source: NASA PCoE Data Repository [http://it.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]*

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

![Graph showing voltage over time and EOD threshold with predictions and actual EOD.]
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

\[
\begin{align*}
\text{State transition model} &= \beta_{j,k} = \beta_{j,k} + \varphi_{j,k}, j = 1, 2, \\
C_{k+1} &= \eta_c C_k + \beta_{1,k} \exp(-\beta_{2,k}/\Delta t_k) + \varphi_k, \\
\text{Measurement model} &= \tilde{C}_k = C_k + \psi_k,
\end{align*}
\]

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

* Data Source: NASA PCoE Data Repository [http://tl.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]
* B. Soha, K. Goebel, 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

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

![Graphs and diagrams related to capacitor failure analysis.](image)
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?