Prognostics for Microgrid Components

Batteries, Capacitors, and Power Semiconductor Devices

Abhinav Saxena
Stinger Ghaffarian Technologies, Inc.
NASA Ames Research Center, Moffett Field CA 94035

Presented at
Advanced Microgrid Concepts and Technologies Workshop
Beltsville, MD
June 7 - 8, 2012
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

• 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
Data Comm
- Sensors
- Reporting
- Scheduled Inspections
Troubleshooting and Repair
Knowledgebase e.g. IETMs
Portable Maintenance Aids
Condition Based Maintenance
Feedback to Production Control
Predictive Maintenance
Condition Monitoring Reliability Analysis

Maintenance Management View

Wholesale Logistics
Planning + Scheduling
Tech Support
Anticipatory Material
Training


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

RUL Prediction

Grid Map

Take Corrective Action

Maintenance Dispatch
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.
Fault Dimension (a)

Prognostics Framework

Failure Threshold (a_{FT})

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 Filters]

- $x$: actual state value
- $\hat{x}$: measured state value
- $x_{\text{particle}}$: state particle value
- $P(x)$: state pdf (belief)
- $z_k$: measurement

Flowchart:
1. Initialize PF
2. Parameters
3. Propose Initial Population, $\langle x_0, w_0 \rangle$
4. Propagate Particles using State Model, $x_{k-1} \rightarrow x_k$
5. Update Weights, $w_{k-1} \rightarrow w_k$
6. Weights degenerated? (No)
7. Resample
Particle Filter-Based Prognostics

System Sensors

Raw Data

Feature Extraction/ Direct Measurement

Model Parameters are part of the State Vector
\( X = [x_k, \theta_k] \)

System Model

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

Parameter Identification

Particle Filter

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

Measurement
\( z_k \)

Measurement

State Tracking Loop

 Identified Model

Prediction Loop

Tuned System Model

Failure Threshold

Prediction

PROGNOSTICS CENTER OF EXCELLENCE
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

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

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

---

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

\[
\begin{align*}
\text{State transition model} & = \beta_{j,k}^f = \beta_{j,k}^f + \varphi_{j,k}, \quad f = 1, 2, \\
C_{k+1} & = \eta C_k + \beta_{1,k} C_k \exp(-\beta_{2,k}/\Delta t_k) + \varphi_k,
\end{align*}
\]

\[
\text{Measurement model} = \tilde{C}_k = C_k + \nu_k,
\]

![Graph showing discharge and self-recharge](image)

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

- Data Source: NASA PCoE Data Repository [http://n1.arc.nasa.gov/tech/dash/pcde/prognostic-data-repository/]
- B. Soha, K. Goobie, 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

- Increase in $R_{D\text{s(on)}}$ due to Device Degradation

- $R_{D\text{s(on)}}$ Prediction

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

PROGNOSTICS CENTER OF EXCELLENCE
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?