Health Management and Prognostics for Electric Aircraft Powertrain

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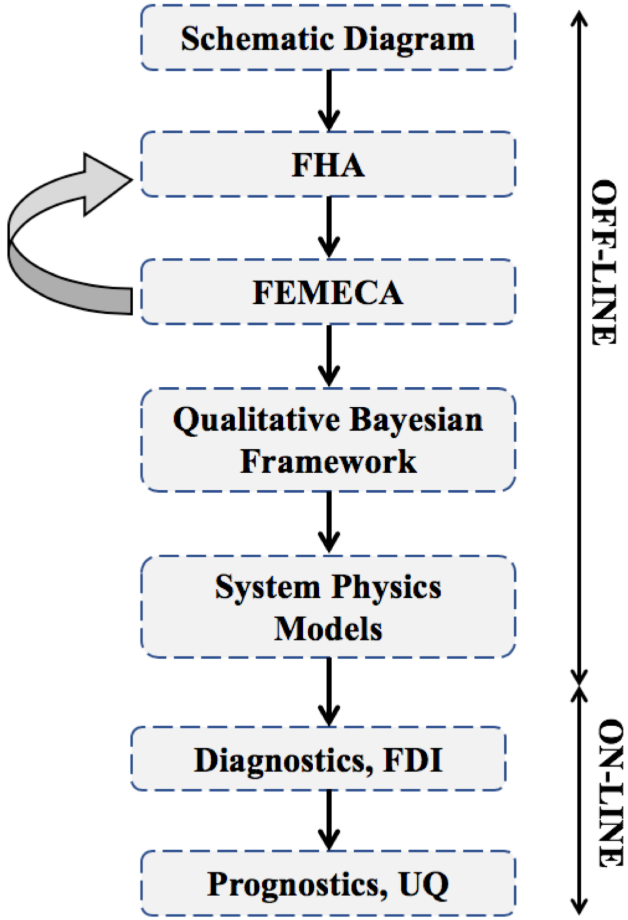
Motivation

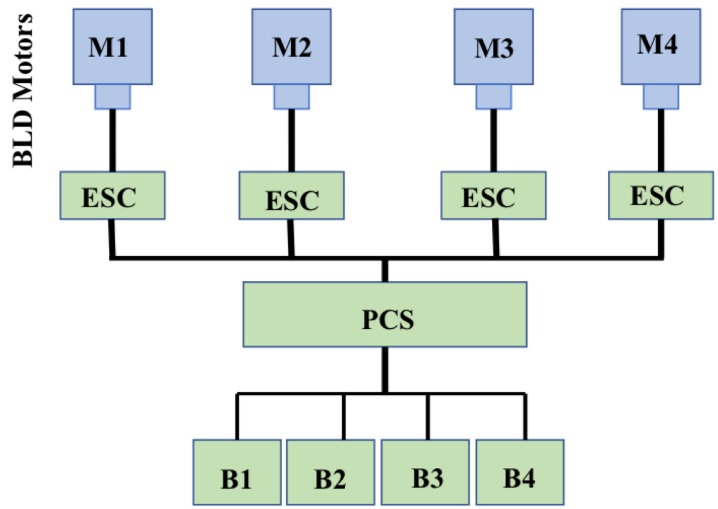
- Electrically-powered autonomous vehicles are being increasingly considered to develop vehicles to transport packages critical material, inter/intra-city operation
- Management of faults and component degradation is key
- Incorporating safety as key parameter of measure
- Inclusion of autonomy raises the critical need for safety under autonomous operations
- Safe Flight under failure operating conditions.

Background



- Earlier research work presented focused on individual systems and components to implement prognostics methodologies.
- Later approaches effects of component-level degradation on the system as a whole were studied
- The development of new models and integration with previous models enables to study and identify cascaded effects of degradation on connected

Background



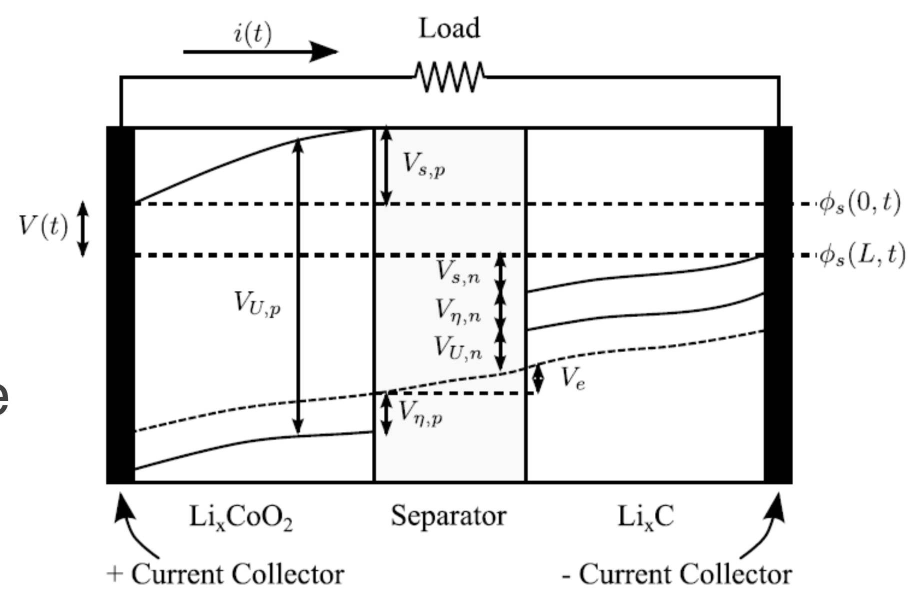
- Functional Hazard analysis (FHA) of a given system is the first step in a process to assess any associated risk of failure in the system
- FMECA is a bottom-up, inferred analytical method which includes criticality analysis, used to map the probability of failure modes with the severity of their consequences
- Bayesian theorem approach implemented using quantitative as well as qualitative methods

Component	Faults	Root Cause	Effect on UAV	Effect on Airspace	Severity	Probability of Occurrence	Safety Critical
Battert Pack	SOC	Operational Conditions	Directly affects operation of the power train system	In case the SOC goes below set low threshold and UAV is not able to do a safe landing may violate safety with crash landing/ may interfere in path of other UAV	High	High	High
Battery Pack	SOH	Operational conditions, loading profiles	Aging in the batteries may not directly affect other systems	The UAV may not able to do certain maneuvers within required time period	High	High	High

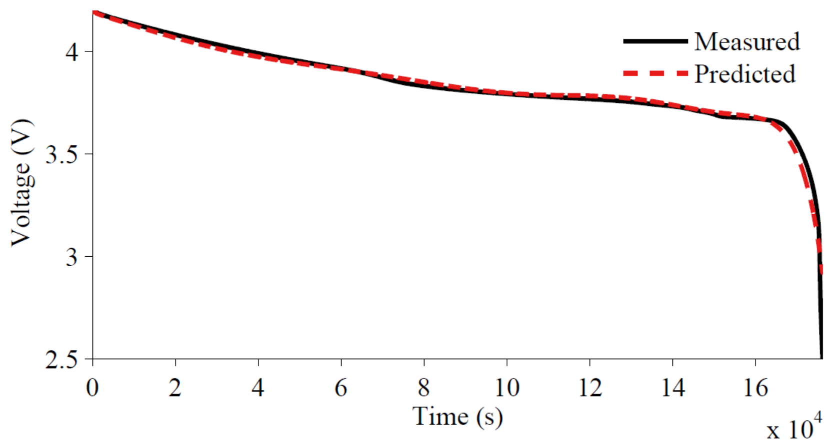
ELECTRICAL PROPULSION SYSTEM MODELING

Battery Modeling

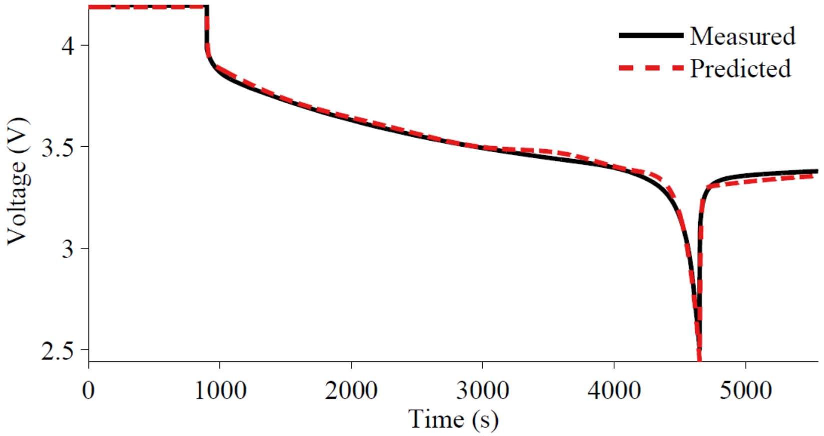
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential and bulk control volumes
  - Surface overpotential → Butler-Volmer equation applied at surface layers
  - Ohmic overpotential → Constant lumped resistance accounting for current collector resistances, electrolyte resistance, solid-phase ohmic resistances



Battery Model Validation

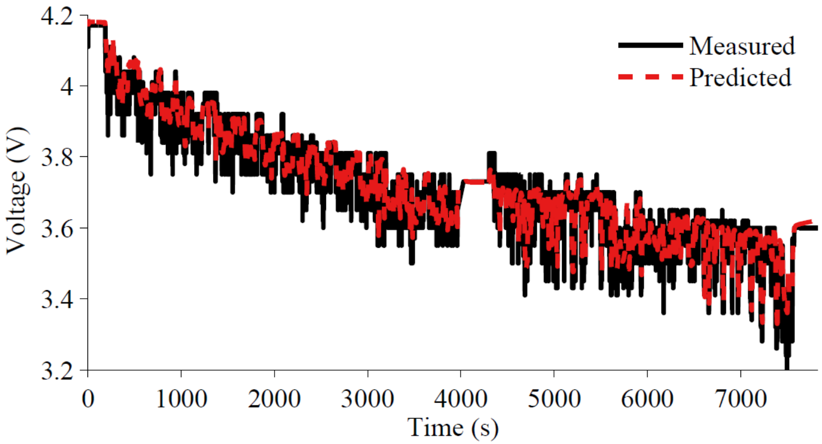


"Open-Circuit" Discharge Curve



Nominal 2A Discharge Curve

Model matches well for open-circuit, nominal discharge, and variable-load discharges on the rover.



Rover Battery Discharge Curve

Electronic Speed Control System

- ESC is modeled as an ideal power inverter employing
  - sinusoidal pulse width modulation (SPWM)
  - half bridge drivers for each of three phases within a control block

$$\begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix} V \begin{bmatrix} F1 \\ F2 \\ F3 \end{bmatrix} = \begin{bmatrix} v_{ab} \\ v_{bc} \\ v_{ca} \end{bmatrix}$$

- F_1, F_2 and F_3 are the outputs from the controlled block while v_{ab}, v_{bc}, v_{ca} are the winding voltages between respective phases.

Motor System

- The dynamic model of the motor describes a three-phase brushless DC motor, with wye-connected stator windings and a permanent magnet as the rotor.

$$\frac{d\omega_m}{dt} = \frac{1}{J}(-B\omega_m + (T_e(e,i) - T_l)).$$

J is the inertia, B is the frictional coefficient, and T_l is the load torque on the rotor

$$\frac{d\theta_m}{dt} = \frac{p}{2}\omega_m$$

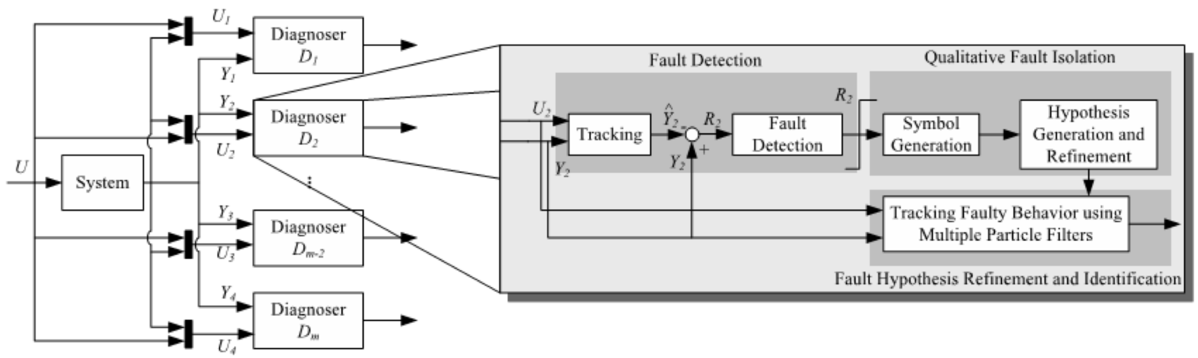
rotor position, θ_m, p (poles)

- The model only describes the mechanical device
  - Assumes that the electronic speed controller provides a given input to the three-phase terminals

$$\frac{d}{dt}\begin{bmatrix} i_a \\ i_b \end{bmatrix} = -\frac{R_s}{L_M}\begin{bmatrix} i_a \\ i_b \end{bmatrix} + \frac{1}{L_M}\begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} v_{ab} \\ v_{bc} \end{bmatrix} - \frac{1}{L_M}\begin{bmatrix} 2 & -1 & -1 \\ 1 & 0 & -1 \end{bmatrix}\begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix}$$

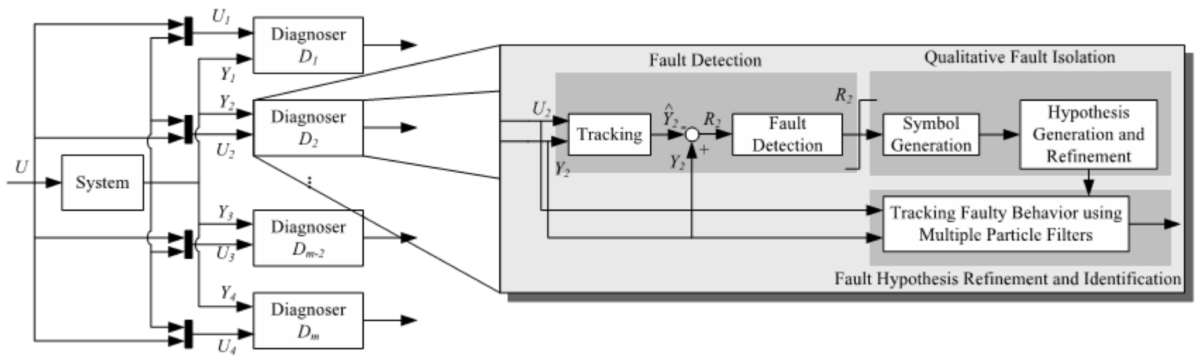
Model Based Diagnostics

- Distributed diagnosis scheme does not use a centralized coordinator,
- Each local diagnoser generates globally correct diagnosis results through local analysis, by only communicating a minimal number of measurements with other local diagnosers
- The diagnoser design creates a partition structure and local diagnosers simultaneously.



Model Based Diagnostics

- For each local diagnoser, separate particle filter (PF) based inference algorithms for fault detection, isolation, and identification are implemented
- The quantitative diagnosis scheme is employed in combination with a qualitative fault isolation scheme to improve diagnosis efficiency



Prognostics Problem Formulation

- Prognostics goal
  - Compute EOL = time point at which component no longer meets specified performance criteria
  - Compute RUL = time remaining until EOL
- System model

State Parameters Input Process Noise

$$
\begin{aligned}
\dot{\mathbf{x}}(t) &= \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t)) \\
\mathbf{y}(t) &= \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t))
\end{aligned}
$$

Output Sensor Noise

- Define threshold $T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t))$ from performance specs that is 1 when system is considered failed, 0 otherwise
- EOL and RUL defined as

$$EOL(t_P) \triangleq \inf\{t \in \mathbb{R} : t \geq t_P \wedge T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 1\}$$

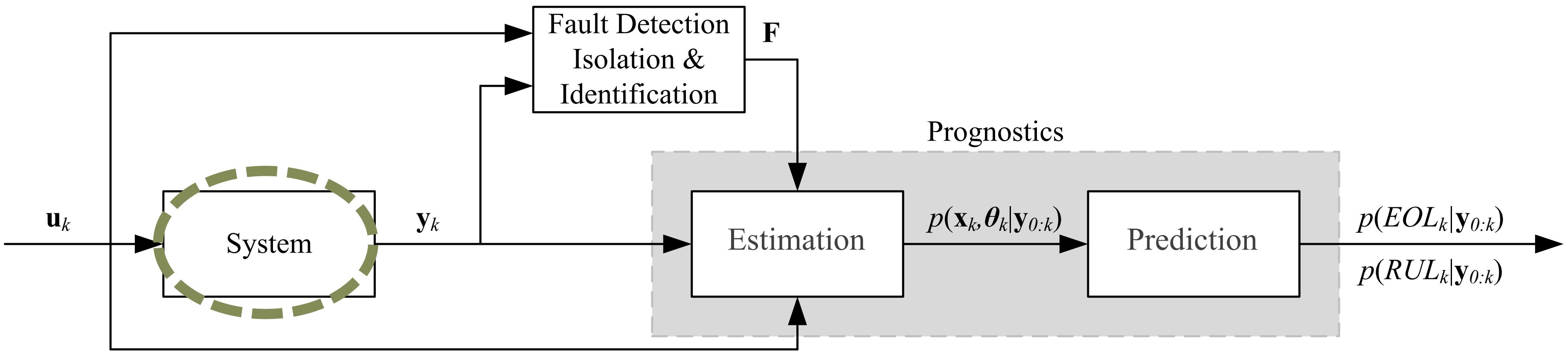
$$RUL(t_P) \triangleq EOL(t_P) - t_P$$

Compute $p(EOL(t_P)|\mathbf{y}_{0:t_P})$ and/or $p(RUL(t_P)|\mathbf{y}_{0:t_P})$

Model-Based Architecture

1 System receives inputs, produces outputs

2 Identify active damage mechanisms



3 Estimate current state and parameter values

4 Predict EOL and RUL as probability distributions

Uncertainty Representation

- Un-modeled physical phenomena and states of the system ignored by the model contribute to uncertainty in the monitored state variables and model parameters
- The state variables
  - un-observable,
  - therefore estimators from available sensor data of such hidden states are necessary to characterize the current condition of the system
- Tools and sensors utilized to measure the observable quantities are themselves affected by limited accuracy and precision, which may also depend on environmental conditions, aleatory in nature

Uncertainty in the Battery model

- Two independent variables
  - amount of Li-ions on the positive side of the surface $q_{s,p}$ and bulk $q_{b,p}$ of the cell, respectively.
  - derived quantities - random variables because of their relationship to $q_{s,p}$ and $q_{b,p}$.

$$q_{s,p,k} = q_{s,p,k-1} + \dot{q}_{s,p,k-1}\Delta t_{k-1} + \sigma_{q_{s,p}} \sqrt{\Delta t_{k-1}}\, r_1$$
$$q_{b,p,k} = q_{b,p,k-1} + \dot{q}_{b,p,k-1}\Delta t_{k-1} + \sigma_{q_{b,p}} \sqrt{\Delta t_{k-1}}\, r_2$$

  - The perturbations are represented by $\sigma_{qs,p}\, r_1$, $\sigma_{qb,p}\, r_2$, where r_i, $i = \{1, 2\}$ are random realizations from a standard normal distribution

Uncertainty in the ESC model

- PWM signals may slowly decrease as time passes by because of MOSFET degradation
- Uncertainty represented by a monotonic behavior of the PWM carrier frequency
- Modeled using a negative, log-Normally distributed rate of change

$$f_k = f_{k-1} - \left.\frac{\mathrm{d}f}{\mathrm{d}t}\right|_{k-1} \exp \eta$$

$$\eta \sim \mathcal{N}\left(-\sigma_\eta^2/2, \sigma_\eta^2\right)$$

- Degradation is expected to be slow, and its effect likely to be negligible in a single flight.
- Switch matrix failures represented using typical reliability analysis,
- Using time- dependent failure rates λ(t), mean time between-failures

Discussion

- FMECA based Qualitative Bayesian approach with Diagnostics and Prognostics framework
- Identify essential sub-systems components which have a high probability failure rate
- Diagnoser tool to identify and isolate systems in case of any failure or degradation
- Prognoser is instantiated to estimate remaining useful life and further take decisions based on operational requirements
- Minimum Computational power requirement on-board
  - systematically identified sub-system and components are monitored instead of the whole set

Future Work

- A combined qualitative and quantitative approach for e-UAV
- Evaluate the developed FEMCA to quantitative failure rates and probabilities
  - Bayesian Approach

THANK YOU

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