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# Health Management and Prognostics for Electric Aircraft Powertrain

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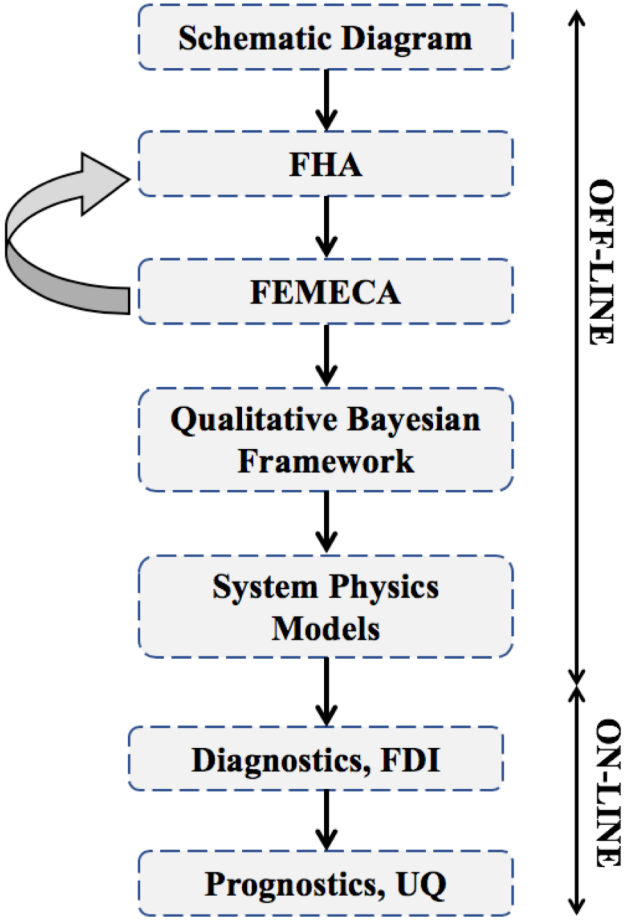
# Motivation

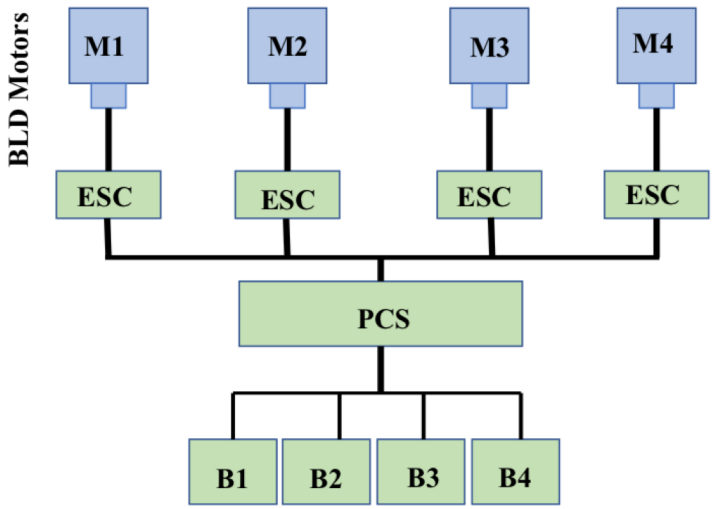
- Electrically-powered autonomous vehicles are being increasingly considered to develop vehicles to transport packages critical material, inter/intra-city operation
- Management of faults and component degradation is key
- Incorporating safety as key parameter of measure
- Inclusion of autonomy raises 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



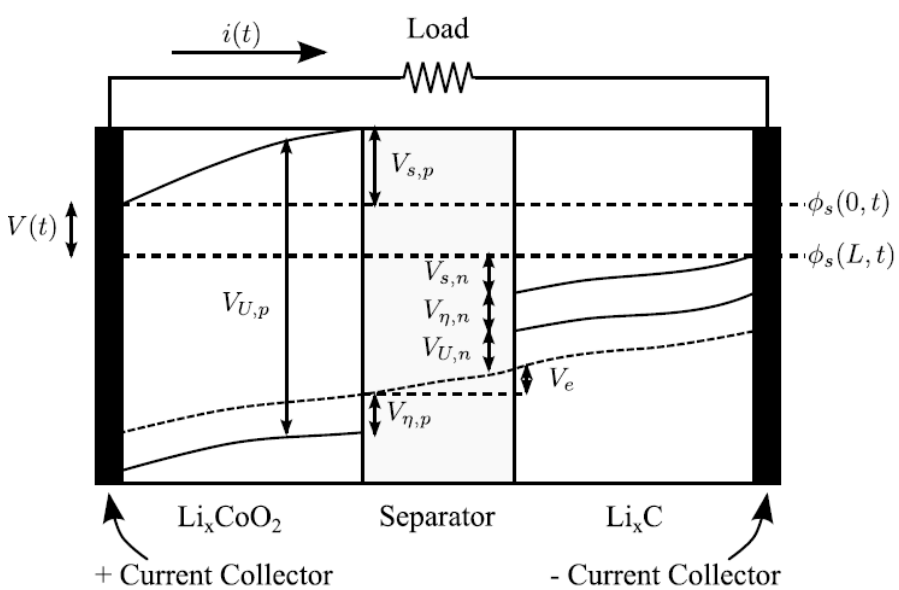

- Functional Hazard analysis (FHA) of a given system is the first step in a process to assess any associated risk of failure in the system
- FMECA is a bottom-up, inferred analytical method which includes criticality analysis, used to map the probability of failure modes with the severity of their consequences
- 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 |

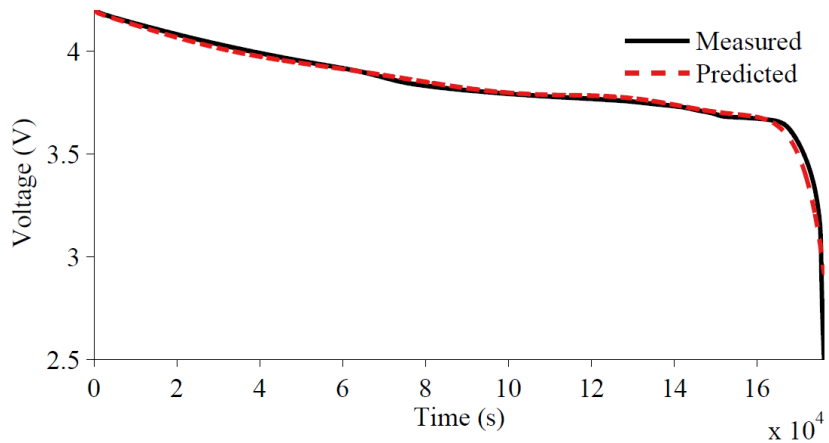
# ELECTRICAL PROPULSION SYSTEM MODELING

# Battery Modeling

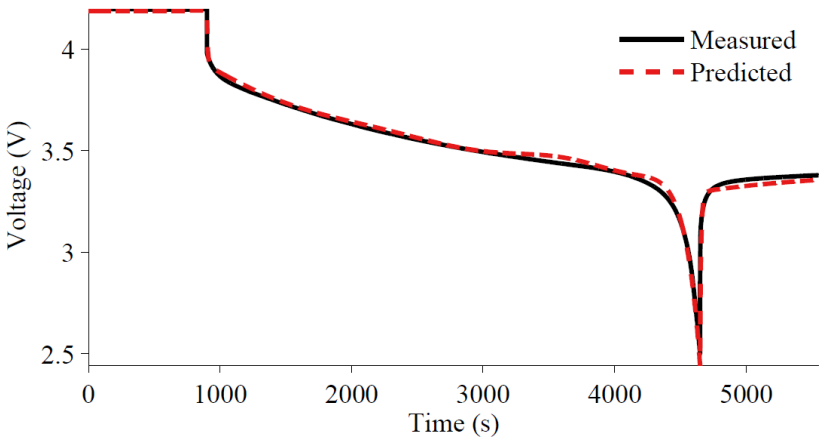
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential and bulk control volumes
  - Surface overpotential → Butler-Volmer equation applied at surface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



# Battery Model Validation

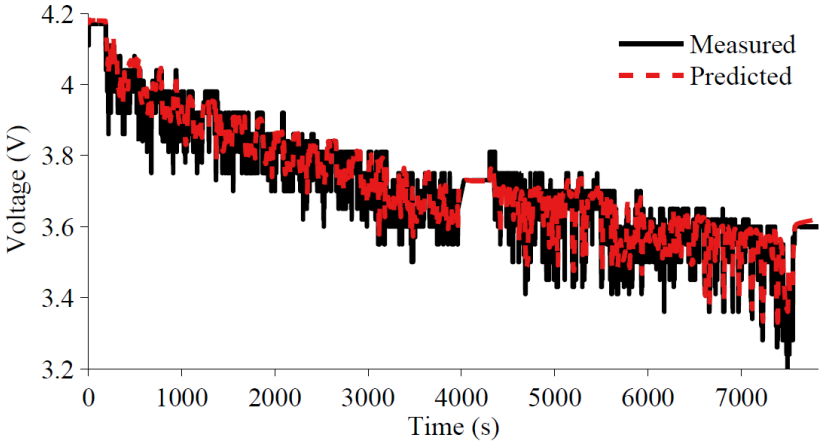



**"Open-Circuit" Discharge Curve**




**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*

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

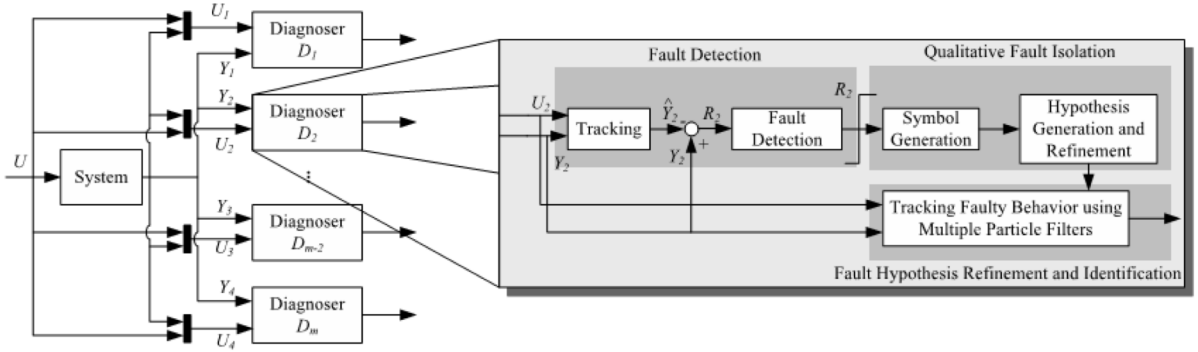
*rotor position, $\theta_m$, p (poles)*

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

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

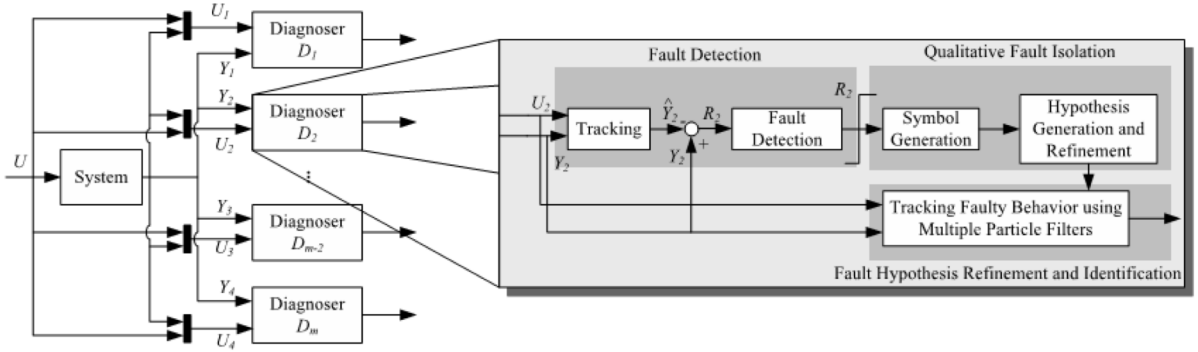
# Model Based Diagnostics

- 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

$$\dot{\mathbf{x}}(t) = \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t))$$

Output

$$\mathbf{y}(t) = \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t))$$

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

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

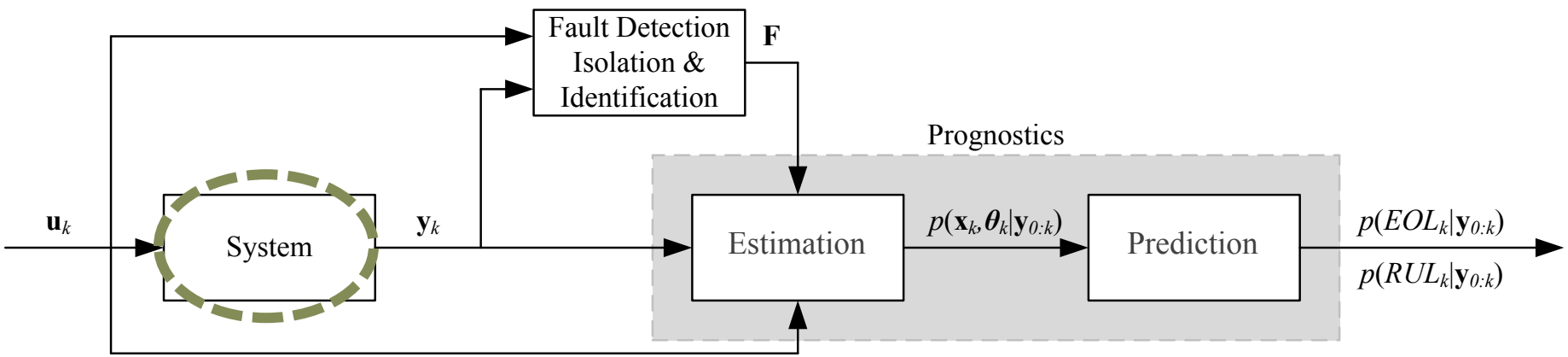
$$RUL(t_P) \triangleq EOL(t_P) - t_P$$

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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