Systems Health Monitoring and Prognostics using Model based Approach

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http://prognostics.nasa.gov

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Agenda

- Introduction to Prognostics
- Introduction to Model-based Prognostics
- Research Approach
- Architecture
- Accelerated Aging as a Prognostics Research Tool
- Case Study I: Prognostics of Electrolytic Capacitors
  - Model-based approach example
- Case Study II: Prognostics of Power Transistors
  - Precursors of Failure example
- Case Study III: Physics-based Prognostics of Capacitors
  - Degradation modeling example
- Case Study IV: Prognostics of Li-Ion Batteries
  - Degradation/Aging example
- Closing Remarks

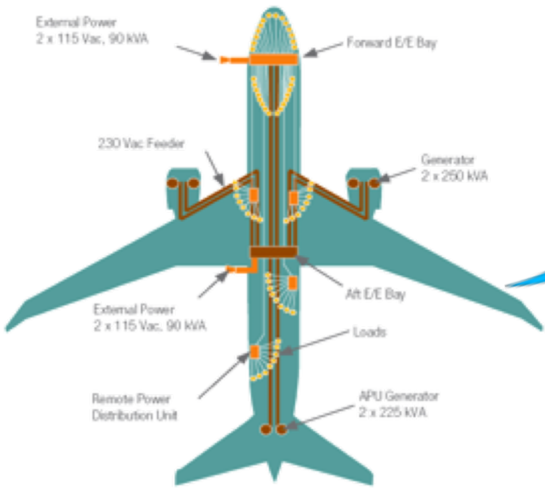
INTRODUCTION TO PROGNOSTICS

Motivation (1/2)

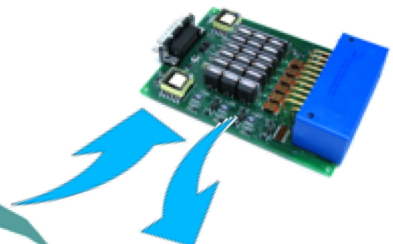
- Future aircraft systems will rely more on electrical and electronic components
- UAV's with all electric powertrain are increasingly being used for long missions
- Electrical and Electronic components have increasingly critical role in on-board, autonomous functions for
  - Vehicle controls, communications, navigation, radar systems
  - Power electronic devices such as power MOSFETs and IGBTs are frequently used in high-power switching circuits
  - Batteries are the sole energy storage
  - The integrated navigation (INAV) module combines output of the GPS model and inertial measurement unit.
- Assumption of new functionality increases number of faults with perhaps unanticipated fault modes
- We need understanding of behavior of deteriorated components to develop capability to anticipate failures/predict remaining RUL

Motivation (2/2)

Images courtesy : Boeing



Line Replaceable Unit:
Power Controller



Component:
Power Transistor

Definitions

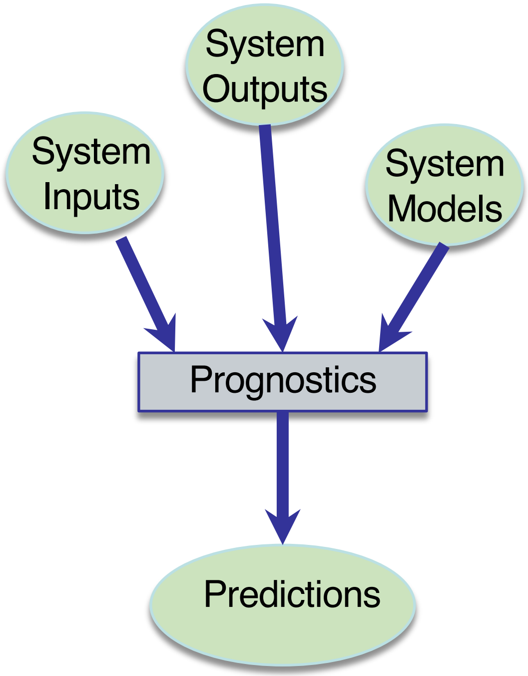
So what is “Prognostics” anyway?

- prog-nos-tic
  - M-W.com – “Something that foretells”
  - PHM Community – “Estimation of the *Remaining Useful Life* of a component”

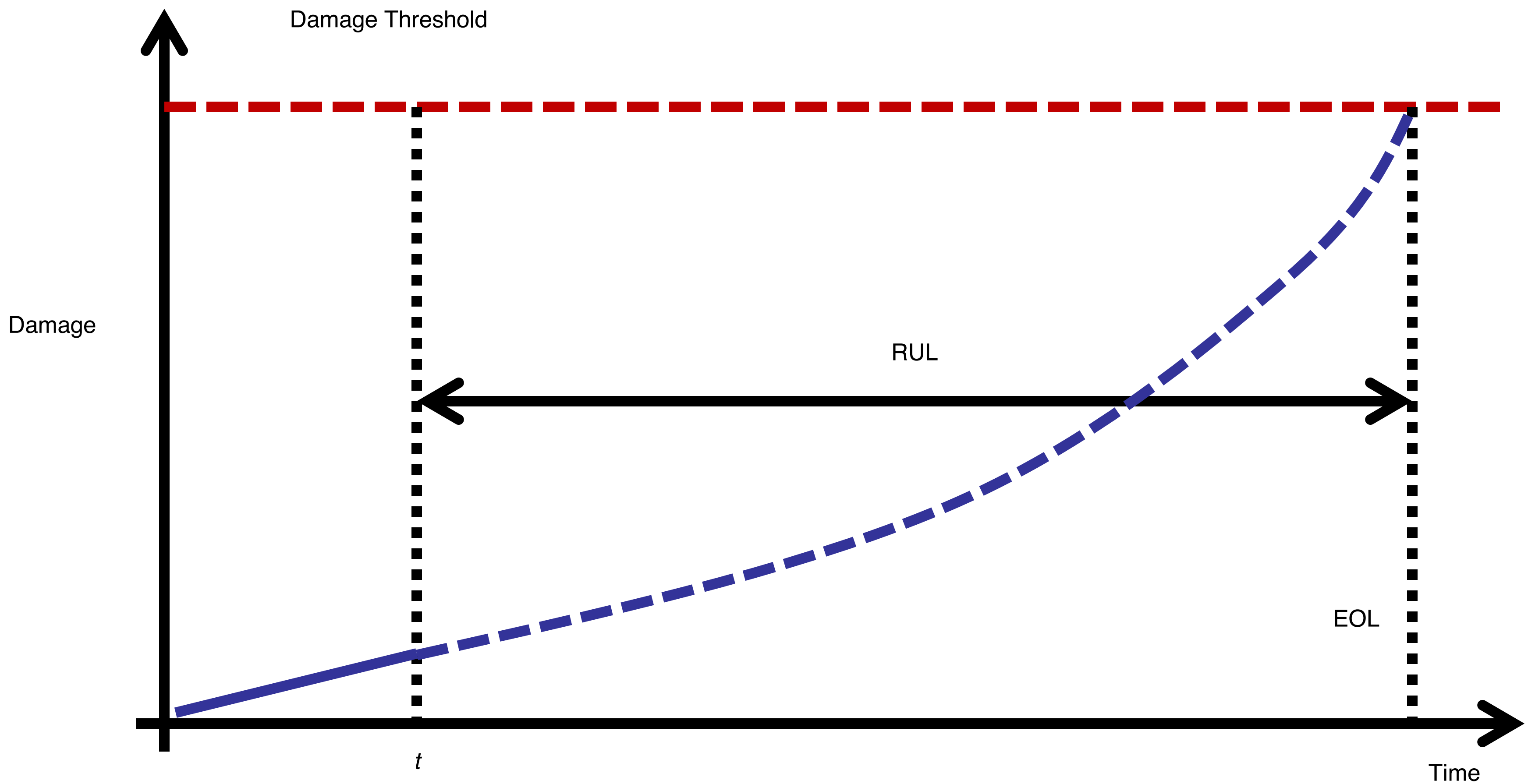
- Remaining Useful Life (RUL) – The amount of time a component can be expected to continue operating within its stated specifications.
  - Dependent on future operating conditions
    - Input commands
    - Environment
    - Loads

Why Model-Based Prognostics?

- With model-based algorithms, models are inputs
  - This means that, given a new problem, we use the same general algorithms
  - Only the models should change
- Model-based prognostics approaches are applicable to a large class of systems, given a model
- Approach can be formulated mathematically, clearly and precisely

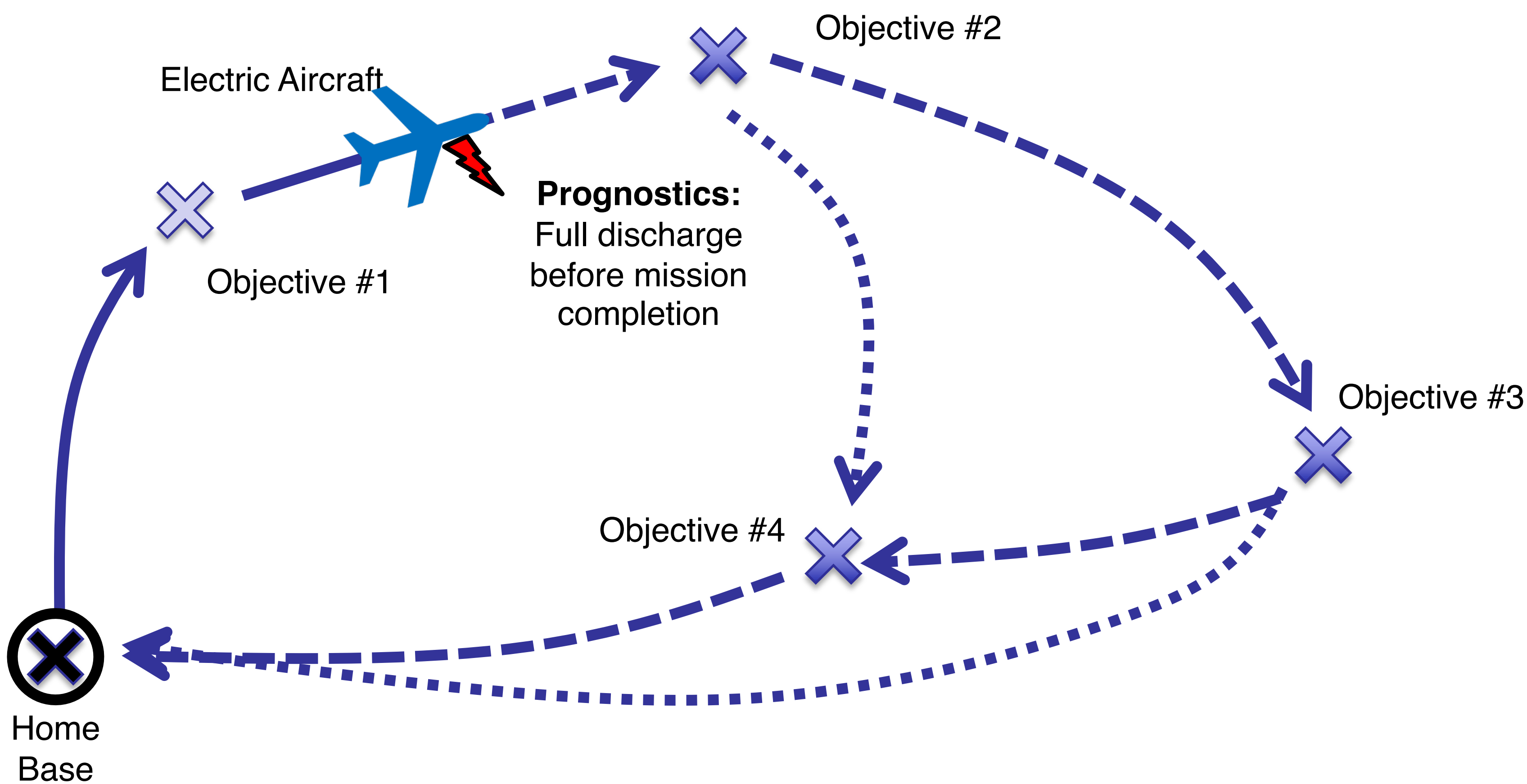


The Basic Idea



Why Prognostics?

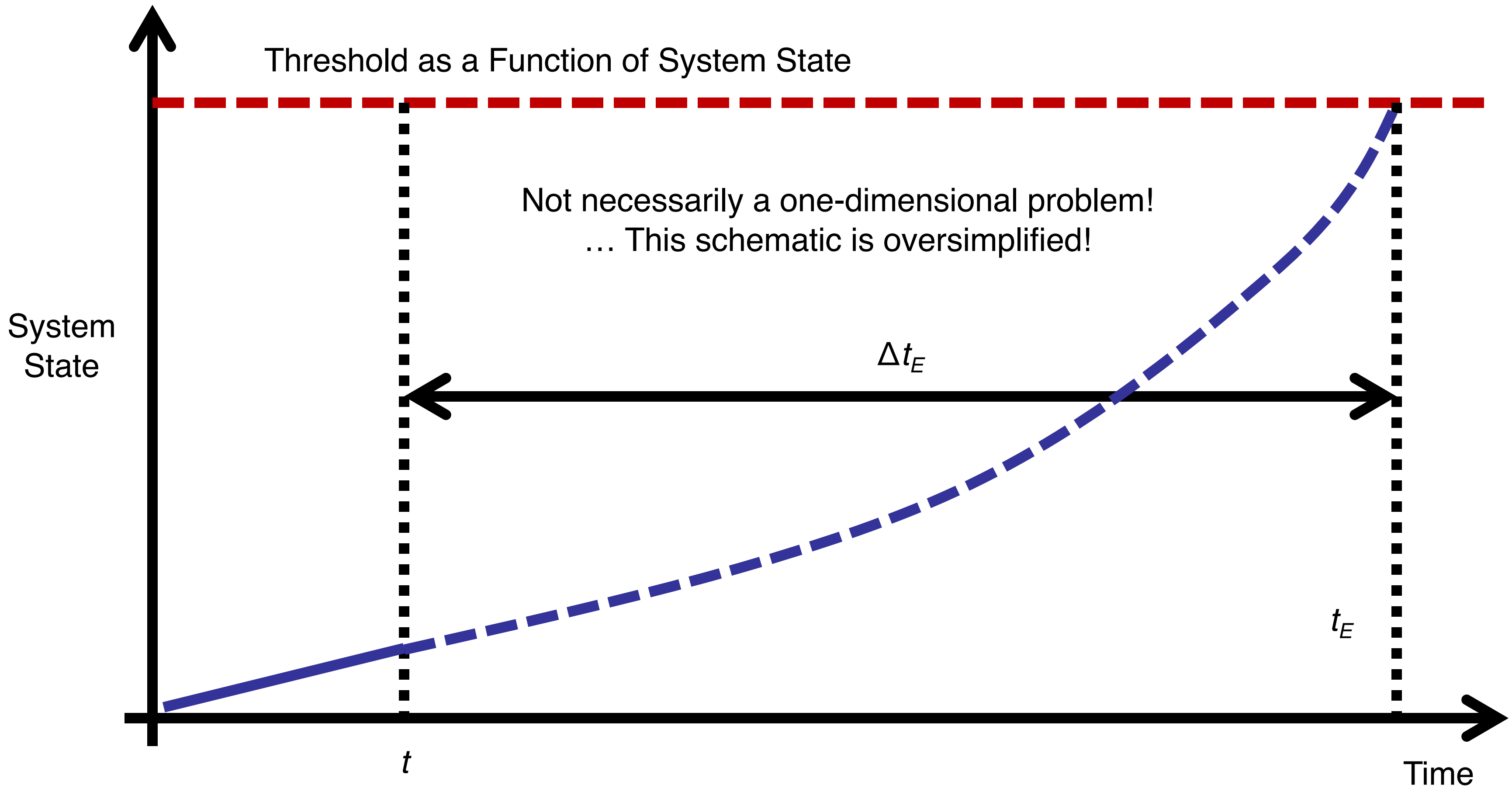
Example: UAV Mission
Visit waypoints to accomplish science objectives. Predict aircraft battery end of discharge to determine which objectives can be met. Based on prediction, plan optimal route. Replan if prediction changes.



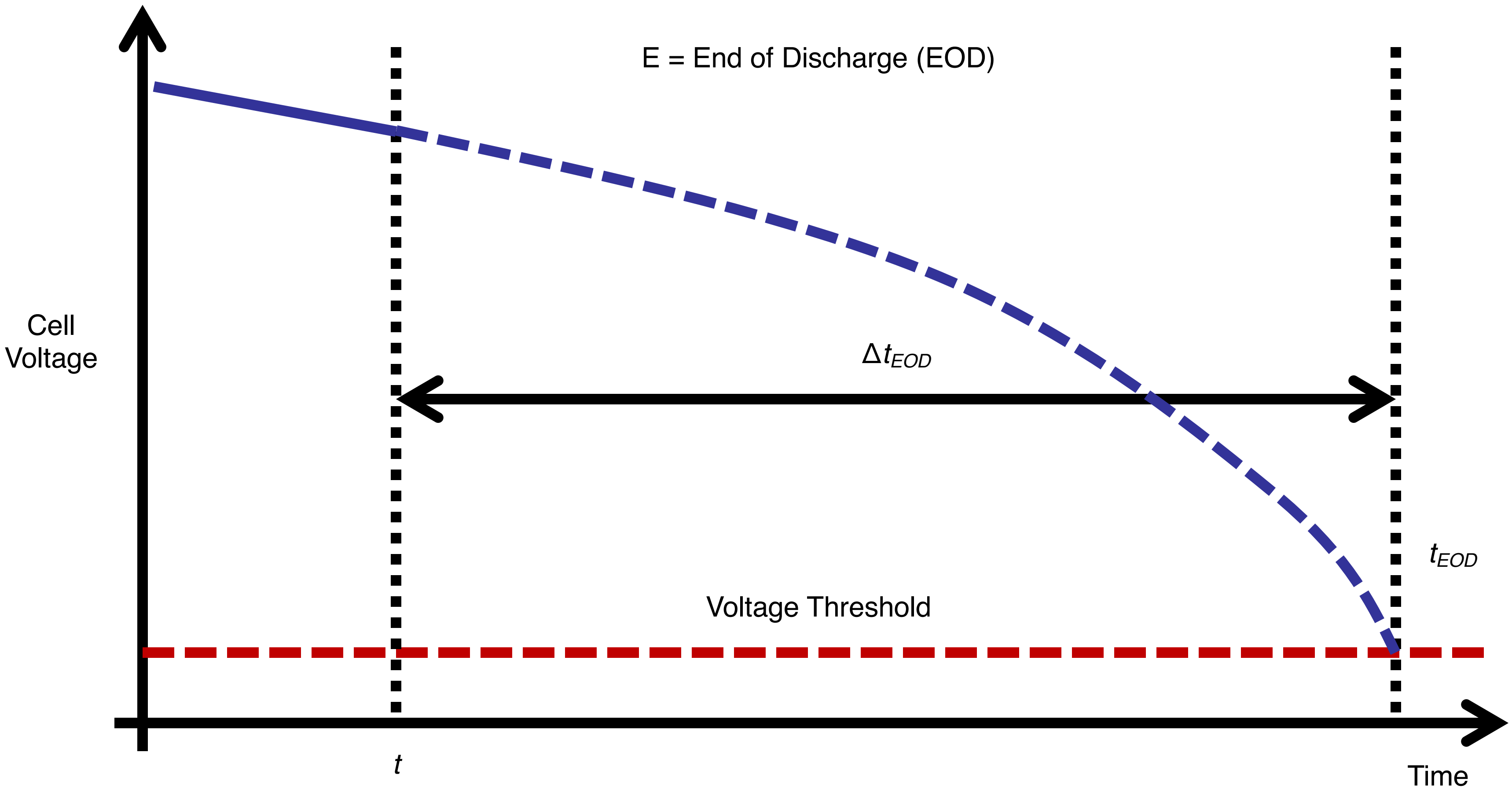
Why Prognostics?

- Prognostics can enable:
  - Adopting condition-based maintenance strategies, instead of time-based maintenance
  - Optimally scheduling maintenance
  - Optimally planning for spare components
  - Reconfiguring the system to avoid using the component before it fails
  - Prolonging component life by modifying how the component is used (e.g., load shedding)
  - Optimally plan or replan a mission
- System operations can be optimized in a variety of ways

The Basic Idea Revisited



The Basic Idea : Batteries Example



Prognostic Algorithm 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.
  - Ex: Weibull Analysis

- Type II: Stress-based
  - Use population based fault growth model – learned 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.
  - Ex: 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.
  - Ex: Cumulative Damage Model, Filtering and State Estimation

Data-Driven Methods

- Model is based solely on data collected from the system
- Some system knowledge may still be handy:
  - What the system 'is'
  - What the failure modes are
  - What sensor information is available
  - Which sensors may contain indicators of fault progression (and how those signals may 'grow')
- *General* steps:
  - Gather what information you can (if any)
  - Determine which sensors give good trends
  - Process the data to "clean it up" – try to get nice, monotonic trends
  - Determine threshold(s) either from experience (data) or requirements
  - Use the model to predict RUL
    - Regression / trending
    - Mapping (e.g., using a neural network)
    - Statistics

Data-Driven Methods

- Pros
  - Easy and Fast to implement
    - Several off-the-shelf packages are available for data mining
  - May identify relationships that were not previously considered
    - Can consider all relationships without prejudice
- Cons
  - Requires lots of data and a "balanced" approach
    - Most of the time, lots of run-to-failure data are not available
    - High risk of "over-learning" the data
    - Conversely, there's also a risk of "over-generalizing"
  - Results may be counter- (or even un-)intuitive
    - Correlation does not always imply causality!
  - Can be computationally intensive, both for analysis and implementation
- Example techniques
  - Regression analysis
  - Neural Networks (NN)
  - Bayesian updates
  - Relevance vector machines (RVM)

Physics-Based Methods

- Description of a system’s underlying physics using suitable representation
- Some examples:
  - Model derived from “First Principles”
    - Encapsulate fundamental laws of physics
      - PDEs
      - Euler-Lagrange Equations
  - Empirical model chosen based on an understanding of the dynamics of a system
    - Lumped Parameter Model
    - Classical 1st (or higher) order response curves
  - Mappings of stressors onto damage accumulation
    - Finite Element Model
    - High-fidelity Simulation Model

- Something in the model correlates to the failure mode(s) of interest

Physics-Based Models

- Pros
  - Results tend to be intuitive
    - Based on modeled phenomenon
    - And when they're not, they're still instructive (e.g., identifying needs for more fidelity or unmodeled effects)
  - Models can be reused
    - Tuning of parameters can be used to account for differences in design
  - If incorporated early enough in the design process, can drive sensor requirements (adding or removing)
  - Computationally efficient to implement

- Cons
  - Model development requires a thorough understanding of the system
  - High-fidelity models can be computationally intensive

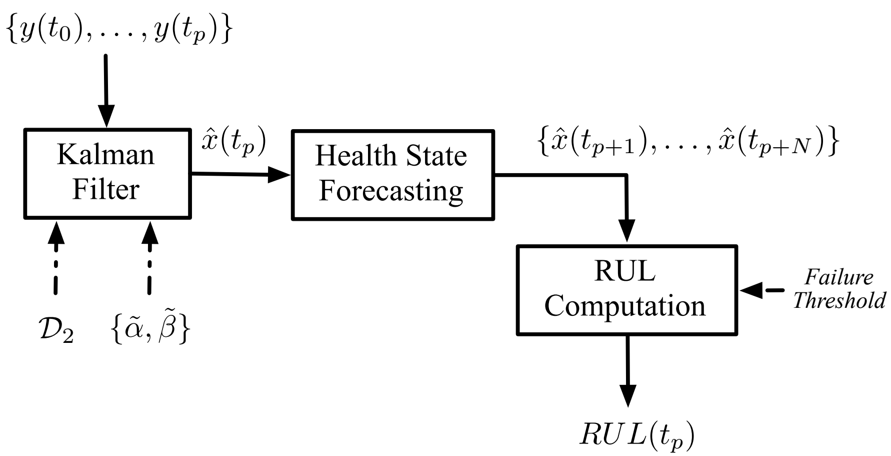
- Examples
  - Paris-Erdogan Crack Growth Model
  - Taylor tool wear model
  - Corrosion model
  - Abrasion model

INTRODUCTION TO MODEL-BASED PROGNOSTICS

Model-based prognostics (1/2)

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), u(t)) + w(t)$$
$$y(t) = h(\mathbf{x}(t)), u(t)) + v(k)$$

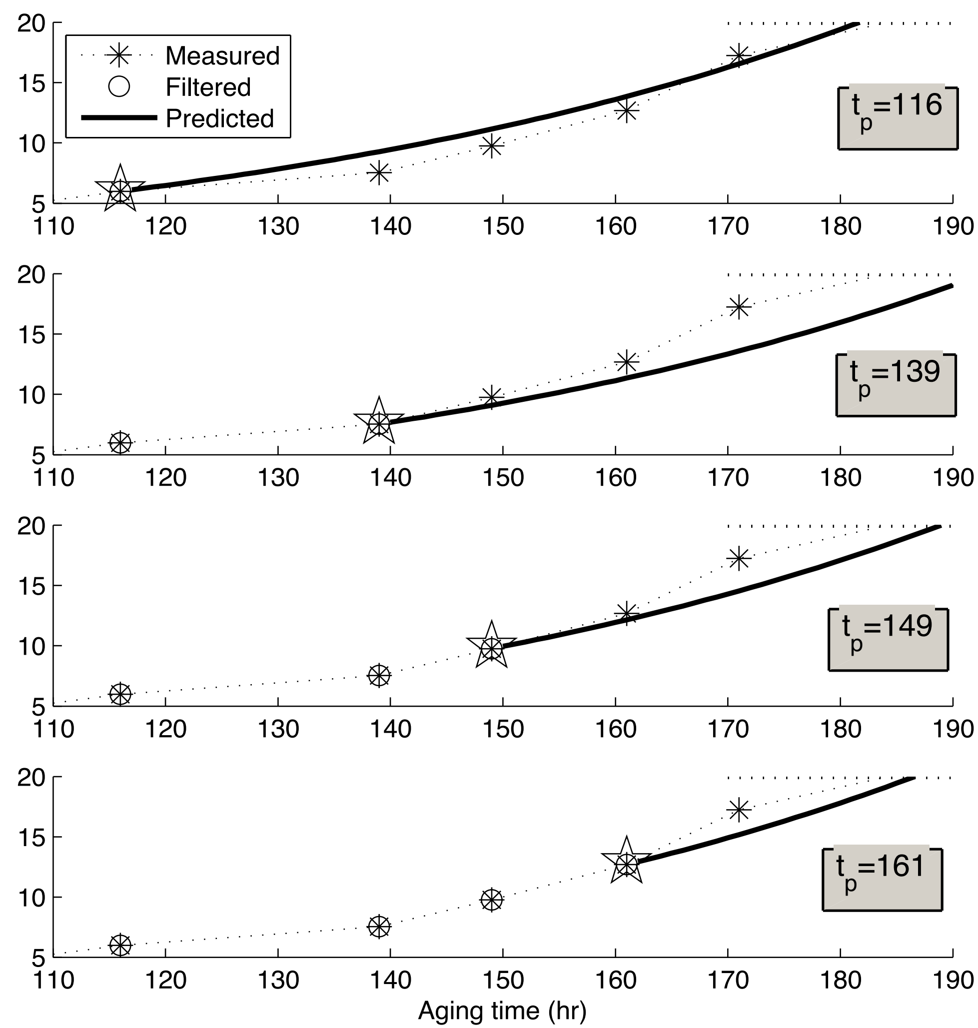
$$R(t_p) = t_{EOL} - t_p$$



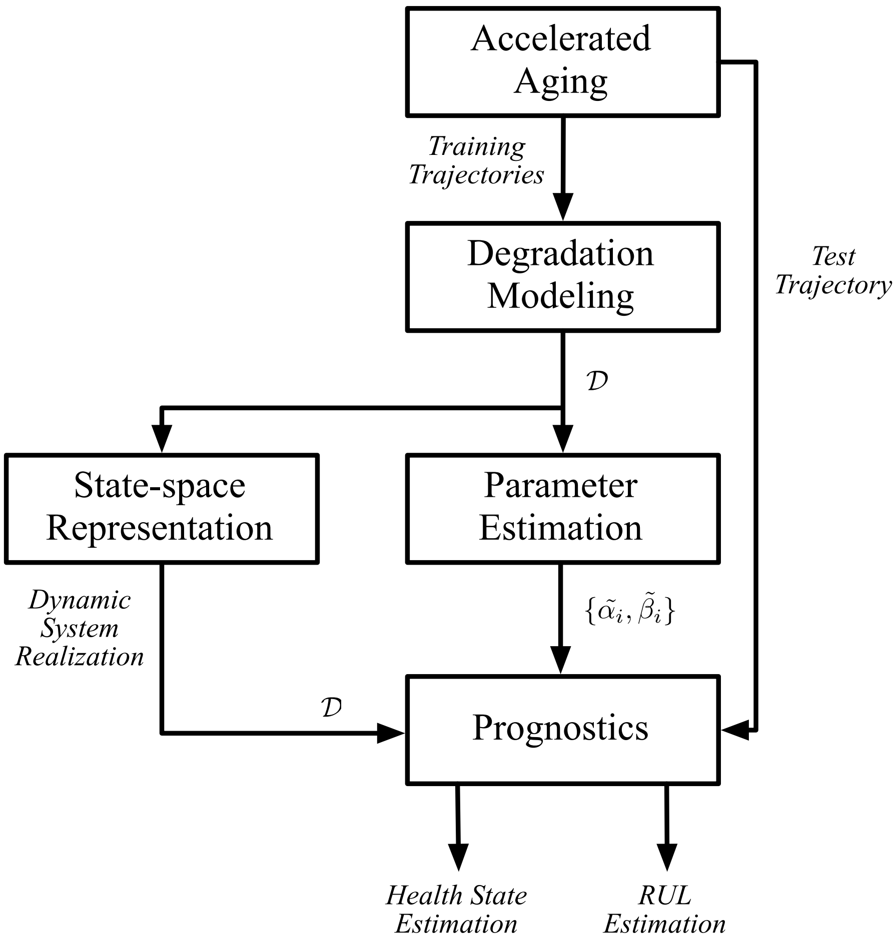
- State vector includes dynamics of the degradation process
- It might include nominal operation dynamics
- EOL defined at time in which performance variable cross failure threshold
- Failure threshold could be crisp or also a random variable

Model-based prognostics (2/2)

- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed

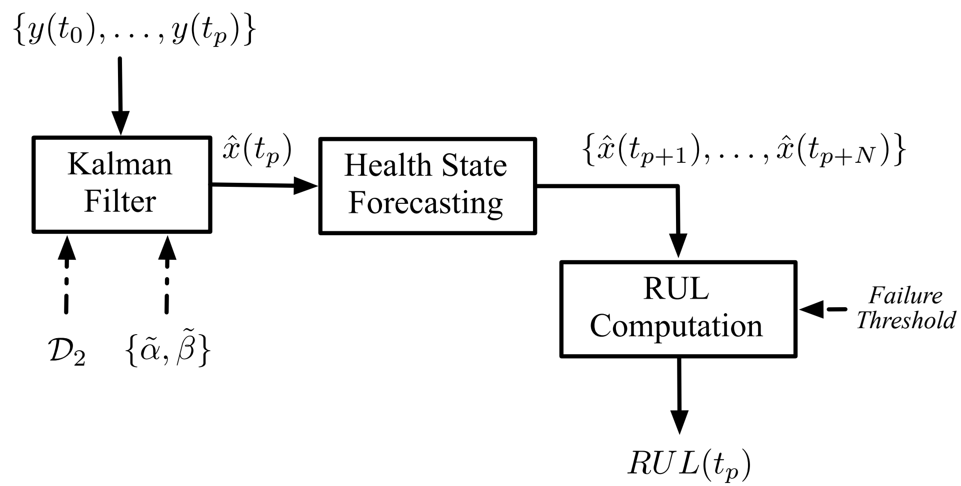


Methodology



$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$

$$y_k = Hx_k + v_k$$



RESEARCH APPROACH

High level research efforts

- Prognostics models and algorithms
  - Identification of precursors of failure for MOSFETs under different failure mechanism conditions
  - Identification of precursors of failure for different IGBT technologies
  - Modeling of degradation process MOSFETs
  - Development of prognostics algorithms
- Prognostics for output capacitor in power supplies (ARC)
  - Electrical overstress and thermal overstress
  - Development of prognostics algorithms
- Accelerated Life Testing
  - Thermal overstress aging of MOSFETs and IGBTs
  - Electrical overstress aging testbed MOSFETs
  - Electrical overstress aging testbed for Capacitors
- Effects of lightning events of MOSFETS (LaRC)
- Battery Degradation and ageing (ARC – LaRC)
- Ageing Effecting on ESC’s (ARC – LaRC)

Research Approach

Identification of failure modes and their relationship to their particular failure mechanisms

↓

Identification of precursors of failure which play an essential role in the prediction of remaining life

↓

Development of accelerated aging testbeds that facilitate the exploration of different failure mechanisms and aid the understanding of damage progression

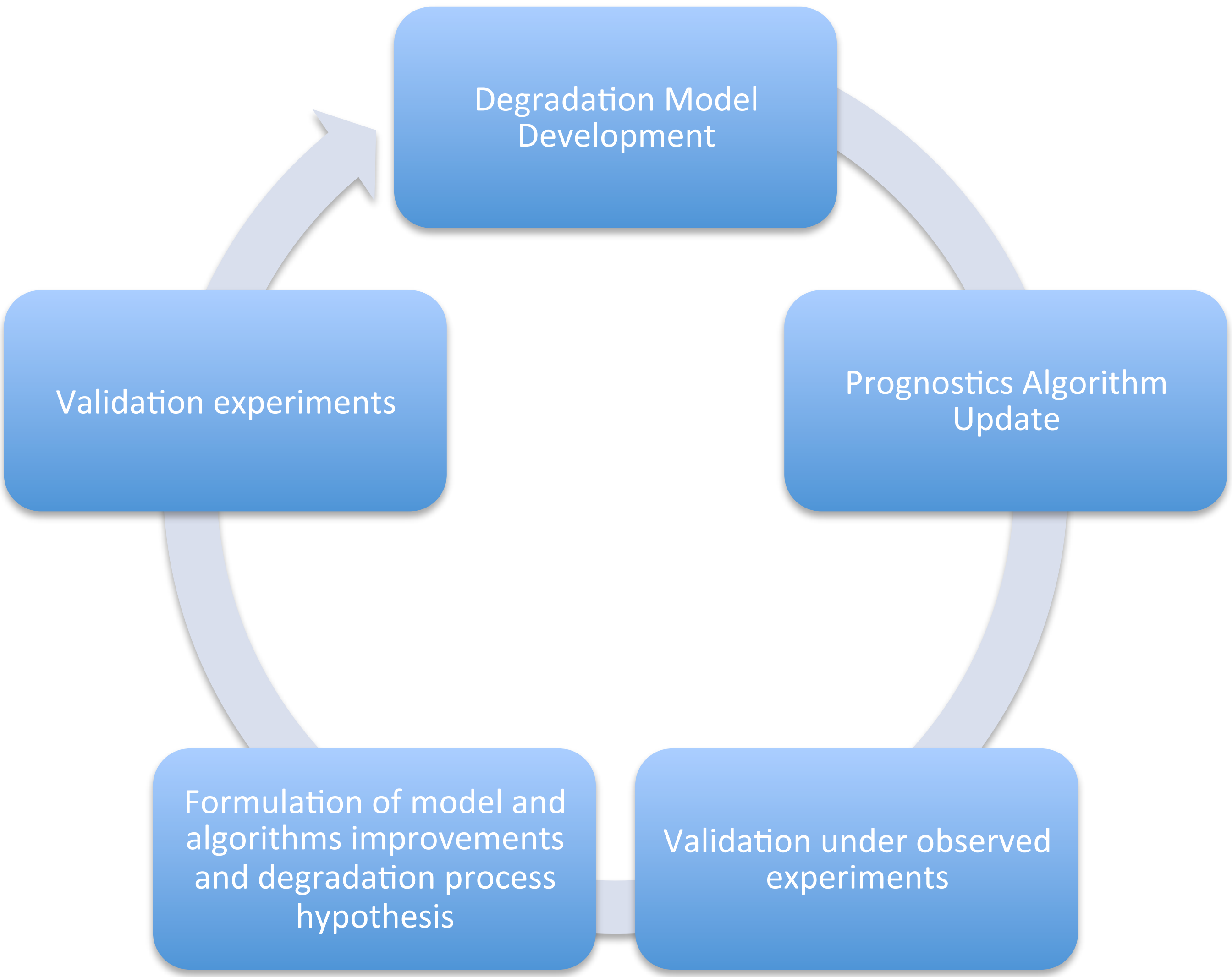
↓

Development of degradation models based on the physics of the device and the failure mechanisms

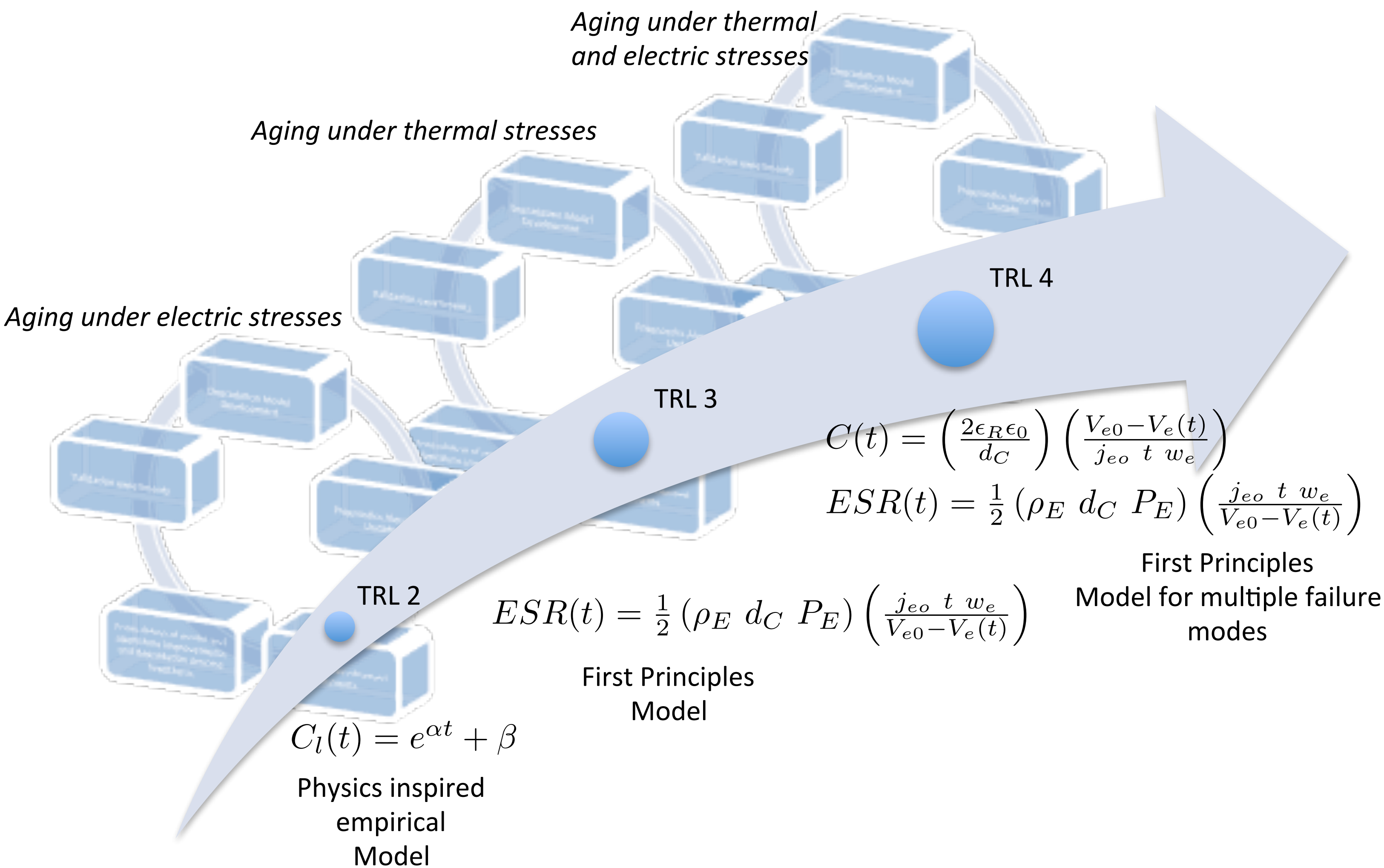
↓

Development of remaining life prediction algorithms that take into account the different sources of uncertainty while leveraging physics-based degradation models that considers future operational and environmental conditions

Prognostics Algorithm Maturation through Validation Experiments



Prognostics Algorithm Maturation through Validation Experiments

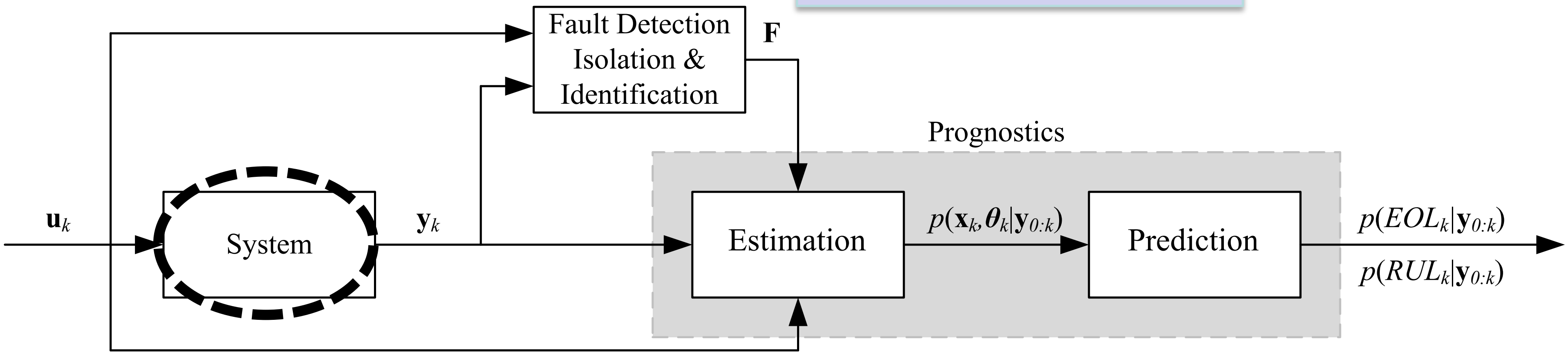


ARCHITECTURE

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

Problem Requirements

- System model
  - System state space
  - Partition into nonfailure and failure states
  - System inputs
  - State update equation
- Prediction inputs
  - Initial time k_o
  - Prediction horizon k_h
  - System inputs from k_o to k_h

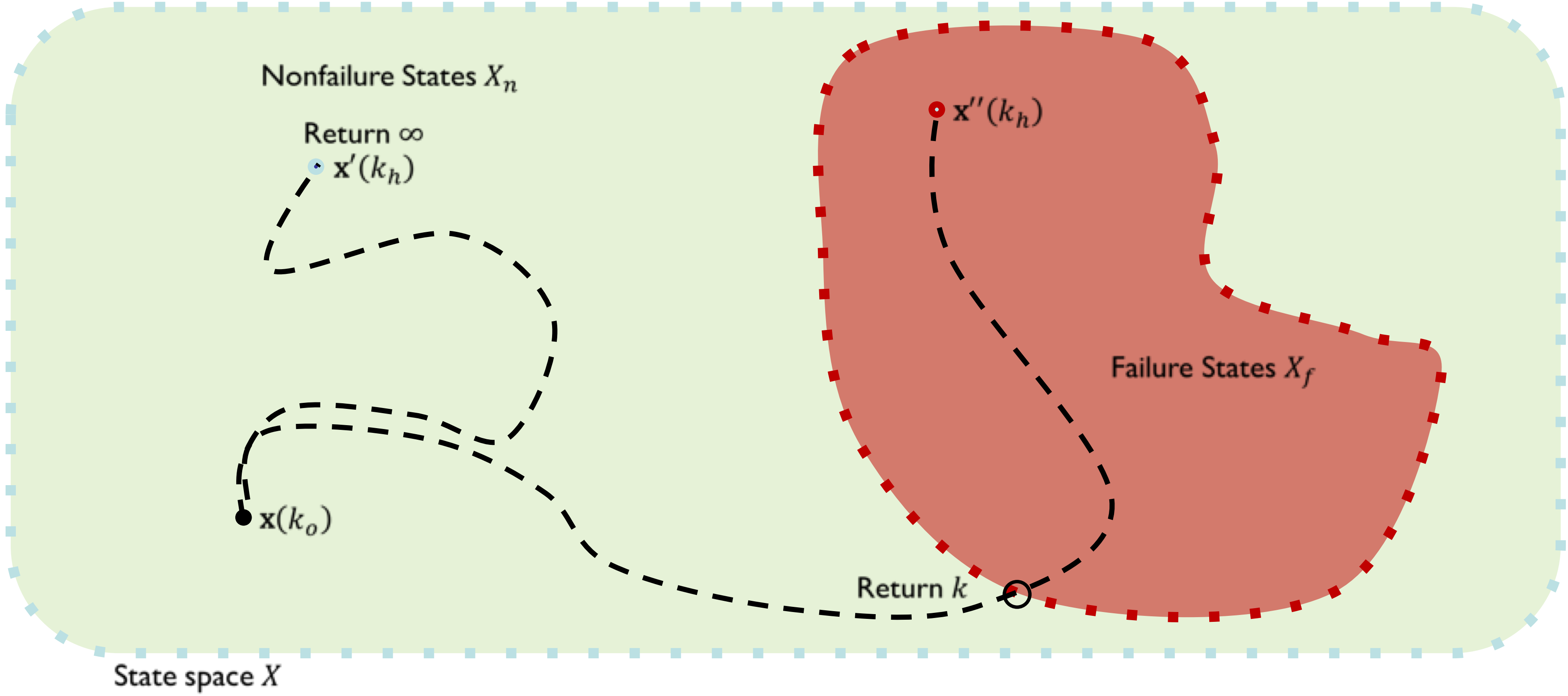
System Model

- Assume system can be modeled using
  - $\mathrm{x}(k+1) = \mathrm{f}\big(\mathrm{x}(k), \mathrm{u}(k), \mathrm{v}(k)\big)$
  - k is the discrete time variable
  - x is the state vector
  - u is the input vector
  - v is the process noise vector
  - f is the state update equation
- Define a function that partitions state-space into nonfailure and failure states
  - $T_f\colon \mathbb{R}^{n_x} \rightarrow \{true, false\}$
  - That is, $T_f\big(\mathrm{x}(k)\big)$ returns true when it is a failure state, false otherwise

Initial Problem Formulation

- Assume we know
  - Initial state, $\mathrm{x}(k_o)$
  - Future input trajectory, $\mathbf{U}_{k_o,k_h} = [\mathrm{u}(k_o), \mathrm{u}(k_o + 1), \dots, \mathrm{u}(k_h)]$
  - Process noise trajectory, $\mathbf{V}_{k_o,k_h} = [\mathrm{v}(k_o), \mathrm{v}(k_o + 1), \dots, \mathrm{v}(k_h)]$
- Problem definition
  - Given $k_o, k_h, \mathrm{x}(k_o), \mathrm{U}_{k_o,k_h}, \mathrm{V}_{k_o,k_h}$
  - Compute EOL
    - $\mathrm{EOL}(k) = \inf\{k' : k' \geq k$ and $T_f(\mathbf{x}(k))\}$

Concept: ComputeEOL



Computational Algorithm

ComputeEOL$\left(k_o, k_h, \mathbf{x}(k_o), \mathbf{U}_{k_o,k_h}, \mathbf{V}_{k_o,k_h}\right)$

$\mathbf{X}_{k_o,k_h}(k_o) \leftarrow \mathbf{x}(k_o)$ *// Set initial state*

for $k = k_o$ **to** $k_h - 1$ **do**

  if $T_f\left(\mathbf{X}_{k_o,k_h}\right)(k)$ *// Check if failure state*

    return k *// Return current time as EOL*

  end if

  $\mathrm{X}_{k_o,k_h}(k+1) \leftarrow \mathrm{f}\left(\mathrm{X}_{k_o,k_h}(k), \mathrm{U}_{k_o,k_h}(k), \mathrm{V}_{k_o,k_h}(k)\right)$ *// Update state*

end for

if $T_f\left(\mathbf{X}_{k_o,k_h}\right)(k)$ *// Check if failure state*

  return k *// Return current time (k_h) as EOL*

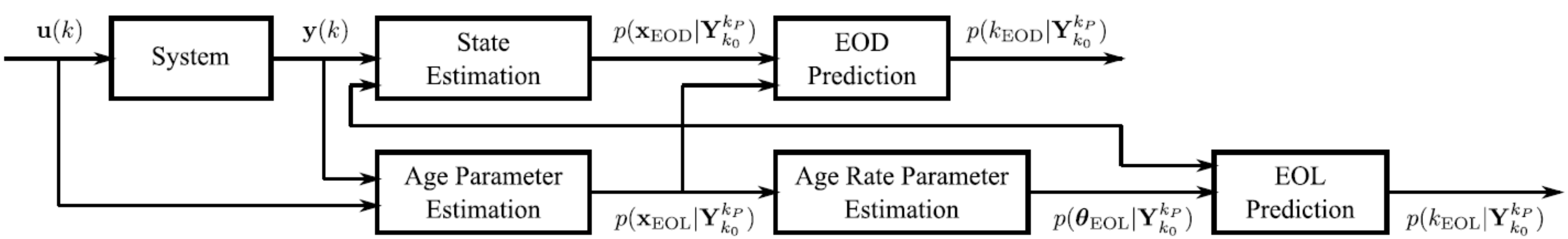
else

  return ∞ *// Return infinity*

end if

Integrated Prognostics Architecture

- System (battery) gets inputs (current) and produces outputs (voltage)
- State estimation computes estimate of state given estimates of age parameters
- EOD prediction computes prediction of time of EOD, given state and age parameter estimates
- Age parameter estimation computes estimates of age parameters
- Age rate parameter estimation computes parameters defining aging rate progression
- EOL prediction computes prediction of time of EOL, given age parameter and age rate parameter estimates



State Estimation

- What is the current system state and its associated uncertainty?
  - Input: system outputs y from k_0 to k, $y(k_0{:}k)$
  - Output: $p(x(k),\theta(k)|y(k_0{:}k))$
- Battery models are nonlinear, so require nonlinear state estimator (e.g., extended Kalman filter, particle filter, unscented Kalman filter)
- Use unscented Kalman filter (UKF)
  - Straight forward to implement and tune performance
  - Computationally efficient (number of samples linear in size of state space)

Prediction

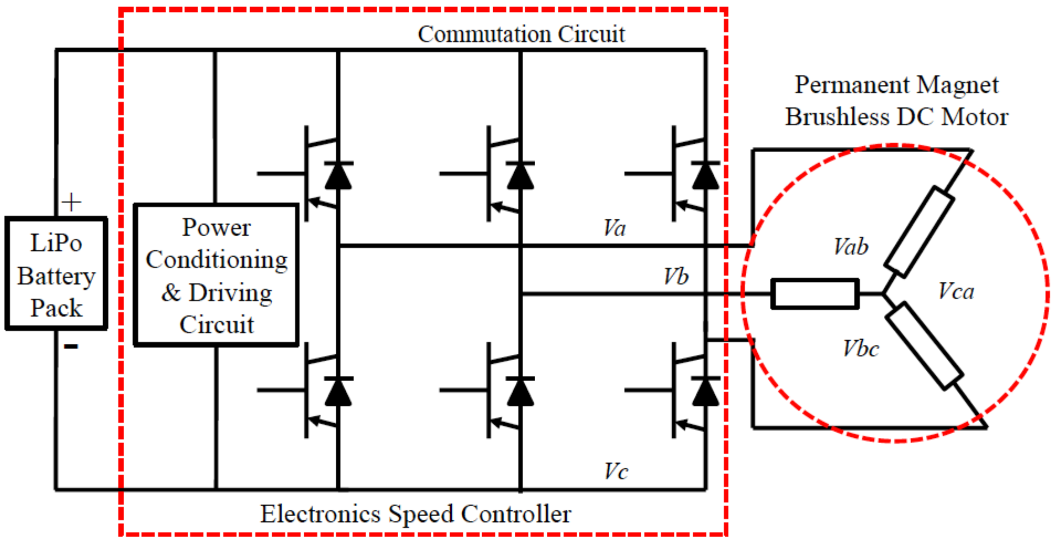
- Most algorithms operate by simulating samples forward in time until E
- Algorithms must account for several sources of uncertainty besides that in the initial state
  - A representation of that uncertainty is required for the selected prediction algorithm
  - A specific description of that uncertainty is required (e.g., mean, variance)

End of Introduction Section

DISCUSSION AND QUESTIONS?

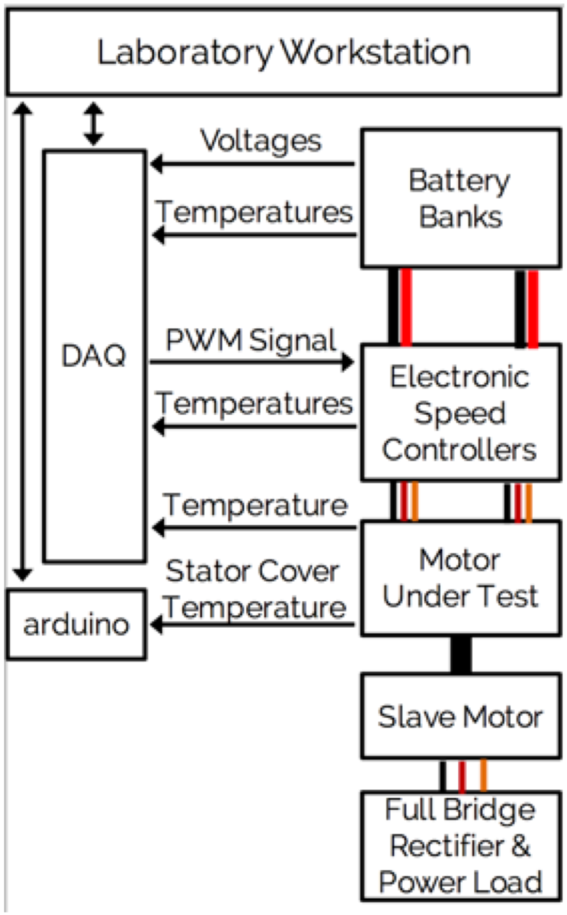
ELECTRIC VEHICLE POWERTRAIN

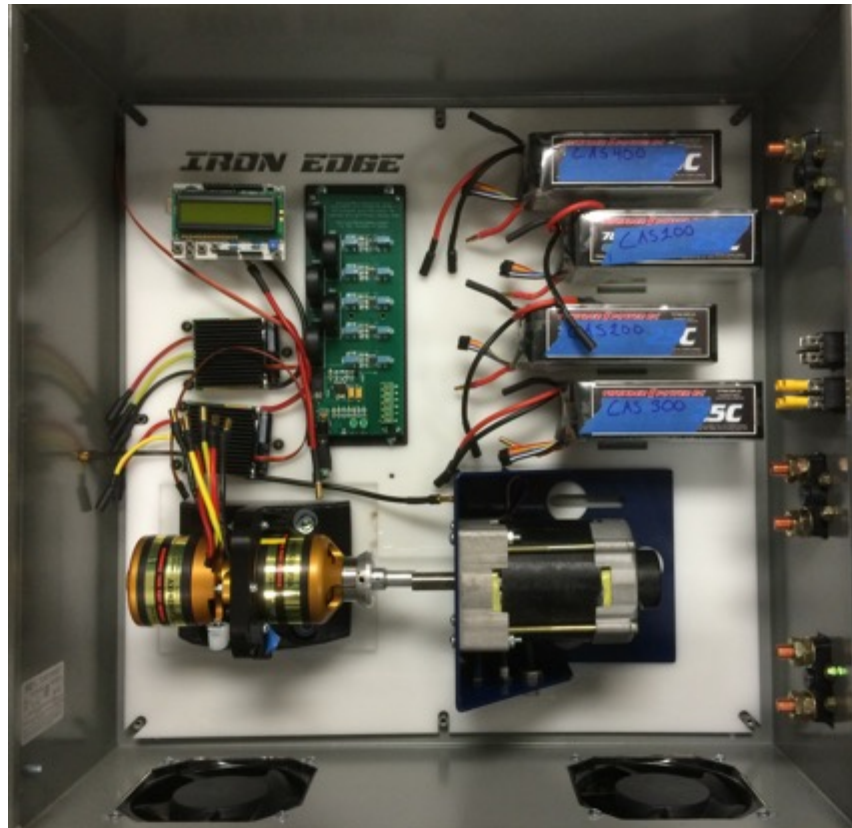
Electric Propulsion System



- LiPo Batteries
  - Lithium corrosion, plating, electrolyte layer formation, and contact losses
- Permanent Magnet Brushless DC Motors
  - Bearing wear, and electrical faults in the form of poor contacts and insulation deterioration
- Electronics Speed Controllers
  - MOSFETs are not synchronized while operating, or when the switching circuit is malfunctioning
- Study Cascading faults
- Effects of component level aging/degradation on system performance

Hardware in Test Loop





ACCELERATED AGING TOOL FOR PROGNOSTICS RESEARCH

Accelerated Aging

- Traditionally used to assess the reliability of products with expected lifetimes in the order of thousands of hours
  - in a considerably shorter amount of time
- Provides opportunities for the development and validation of prognostic algorithms
- Such experiments are invaluable since run-to-failure data for prognostics is rarely or never available
- Unlike reliability studies, prognostics is concerned not only with time to failure of devices but with the degradation process leading to an irreversible failure
  - This requires in-situ measurements of key output variables and observable parameters in the accelerated aging process with the associated time information
- Thermal, electrical and mechanical overstresses are commonly used for accelerated aging tests of electronics

Example: Electrical overstress aging of Power Transistors

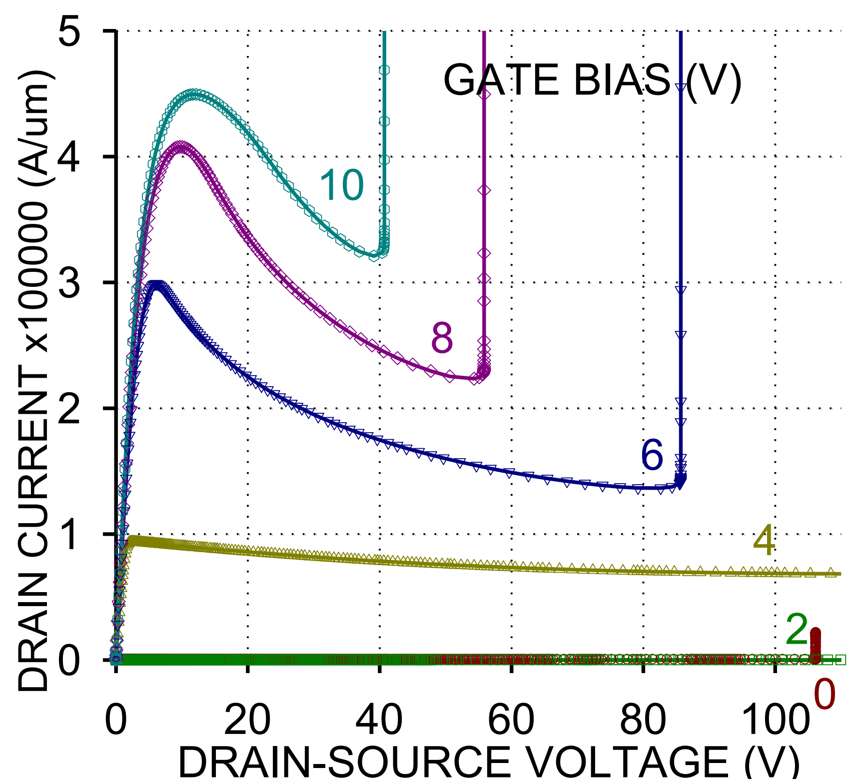
Accelerate aging strategy (1/2)

- Main strategy
  - application of electrical overstress
  - fixed junction temperature in order to avoid thermal cycles
  - avoid package related failures
- Accelerated test conditions are achieved by electrical operation regime of the devices at temperatures within the range below maximum ratings and above the room temperatures.

Accelerate aging strategy (2/2)

- The highest acceleration factor for aging can be achieved in the proximity of the Safe Operation Area (SOA) boundary
- Instability points represent the critical voltages and currents limiting the SOA
- An electrical regime close to the SOA boundary serves as the accelerator factor (stressor) and it is expected to reduce the life of the device
- The SOA boundary shifts closer to the origin as the temperature increases

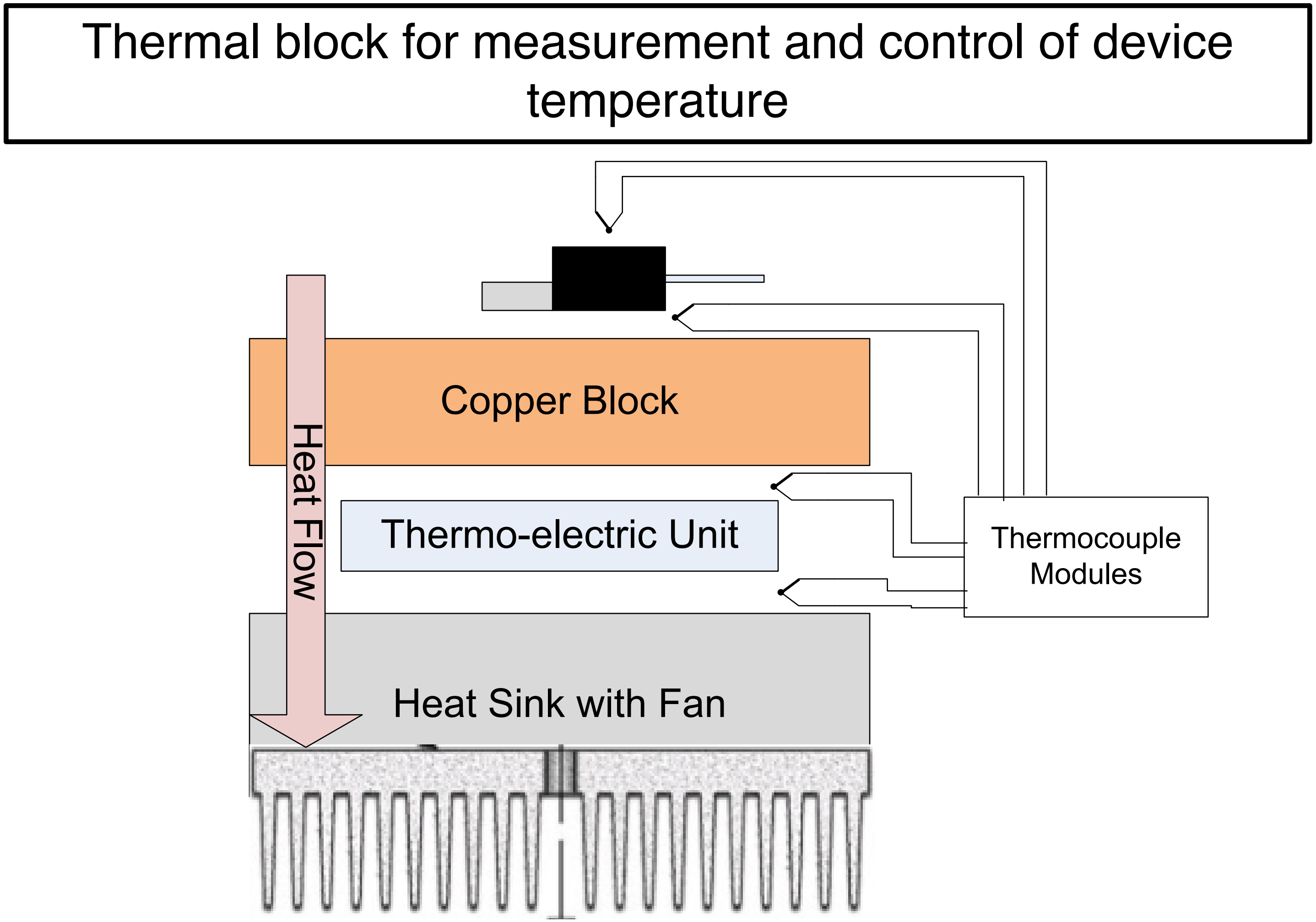
Simulated I-V characteristics and instability boundary at 300° K for power MOSFET.



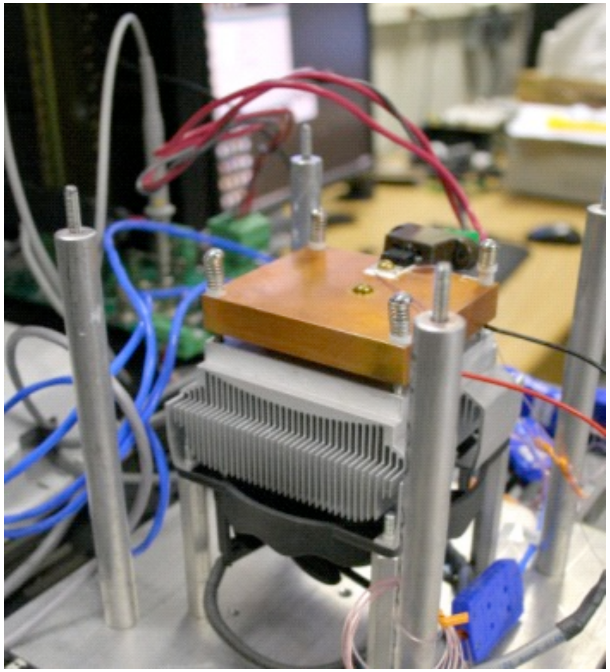
Aging system description (1/3)

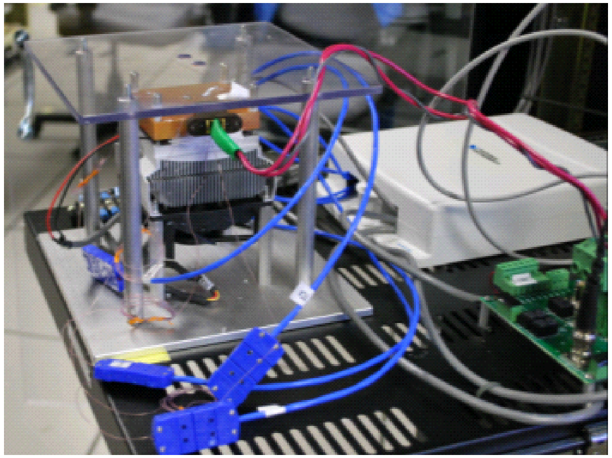
- Three main components in terms of hardware
  - Electrical operation unit of the device
    - custom made printed circuit boards for the instrumentation circuitry and gate drivers
    - commercially available power supplies and function generator to control the operation of the DUT
  - An in-situ measurement unit of key electrical and thermal parameters
    - commercially available measurement and data acquisition for slow and high speed measurements
  - Thermal block section for monitoring and control of the temperature

Aging system description (2/3)



Aging system description (3/3)



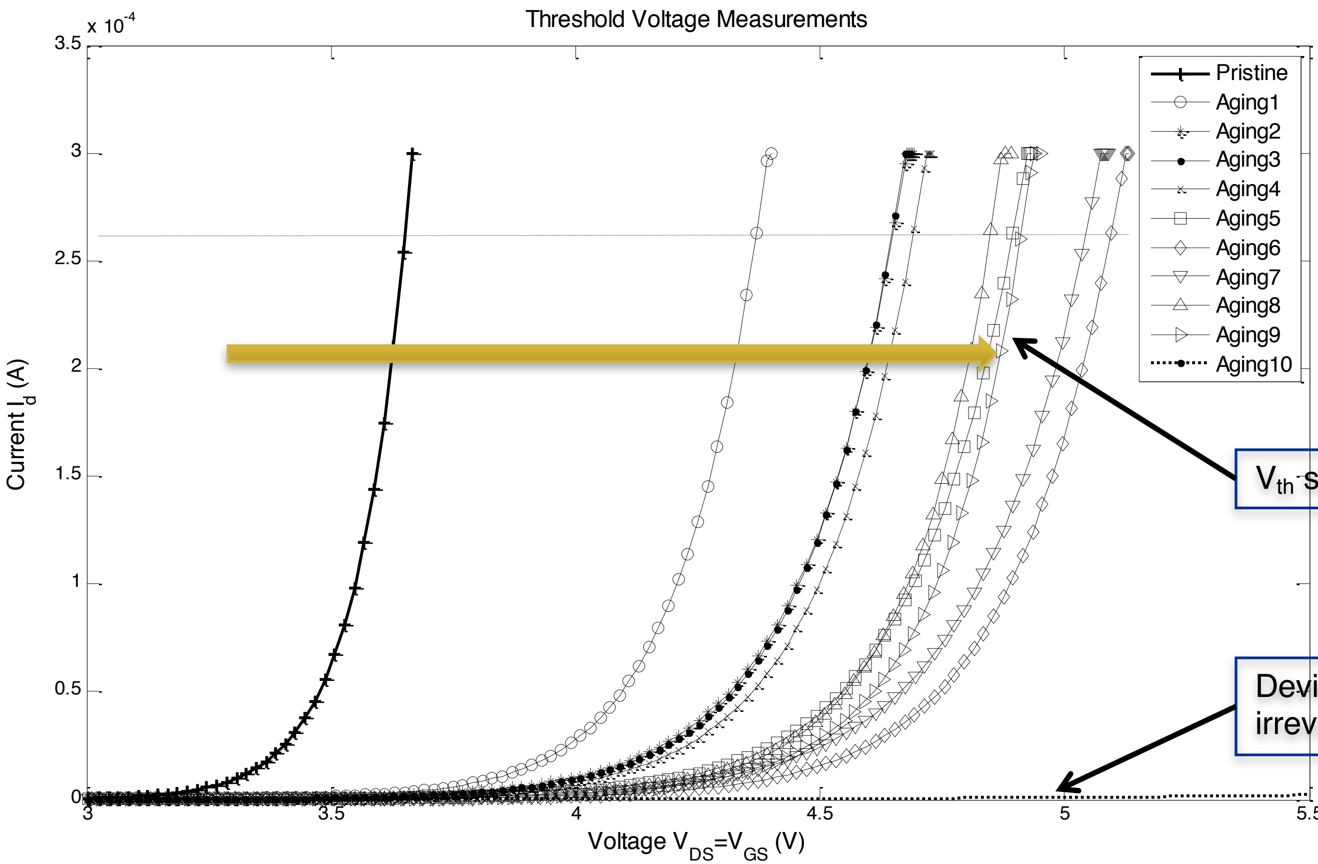


Experiment on power MOSFET (1/2)

- IRF520Npbf power MOSFET
  - TO220 package,100V/9A.
- Electrical overstress used as acceleration factor. High potential at the gate
  - Vgs= 50V, Vgs rating is 20V max.
  - Vds= 2.4V with a 0.2 ohm load.
- Temperatures kept below maximum rating $T_j$max=175° C
- Objective is to induce failure mechanism on the gate structure

Experiment on power MOSFET (2/2)

- Degradation process as observed on threshold voltage (V_{th})



V_{th} shifts right as a result of degradation

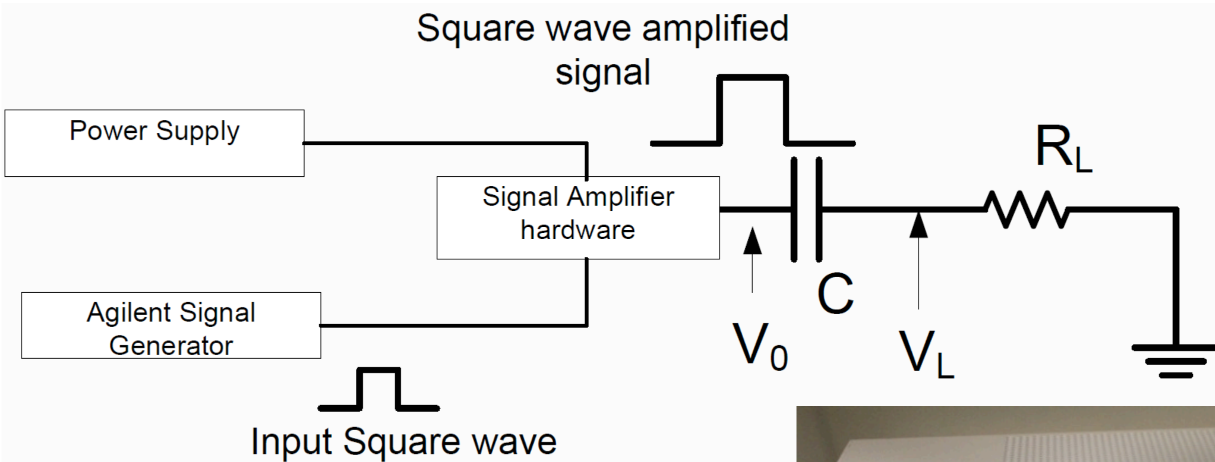
Devices lost gate control and failure is irreversible

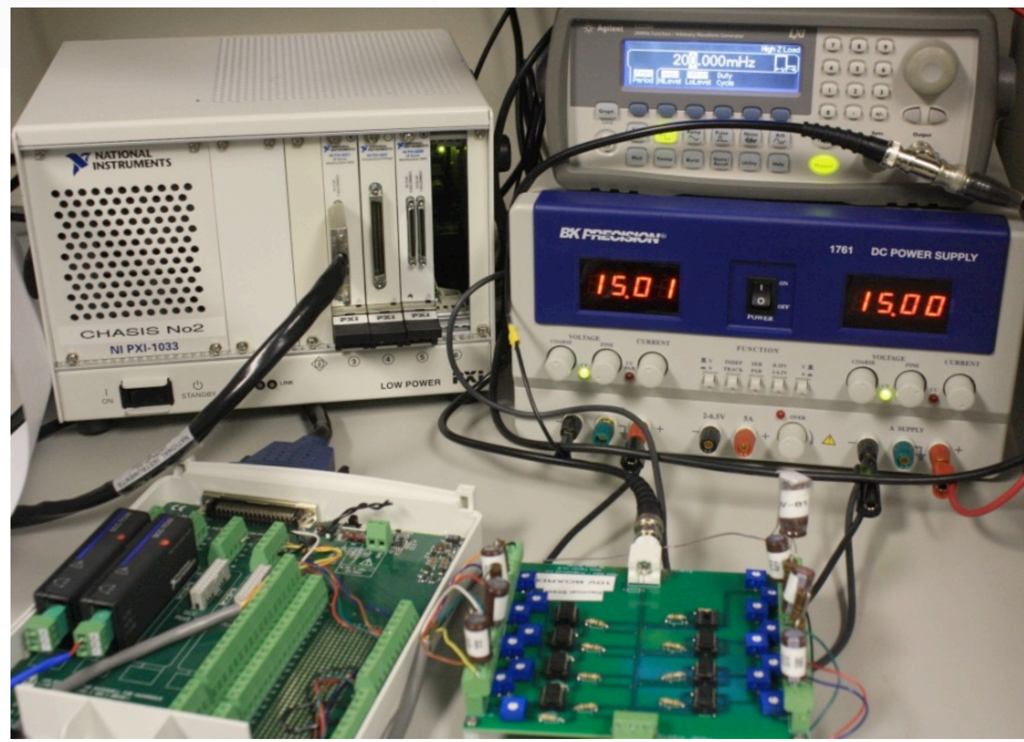
Example: Electrical overstress aging of Electrolytic Capacitors

Accelerated aging system

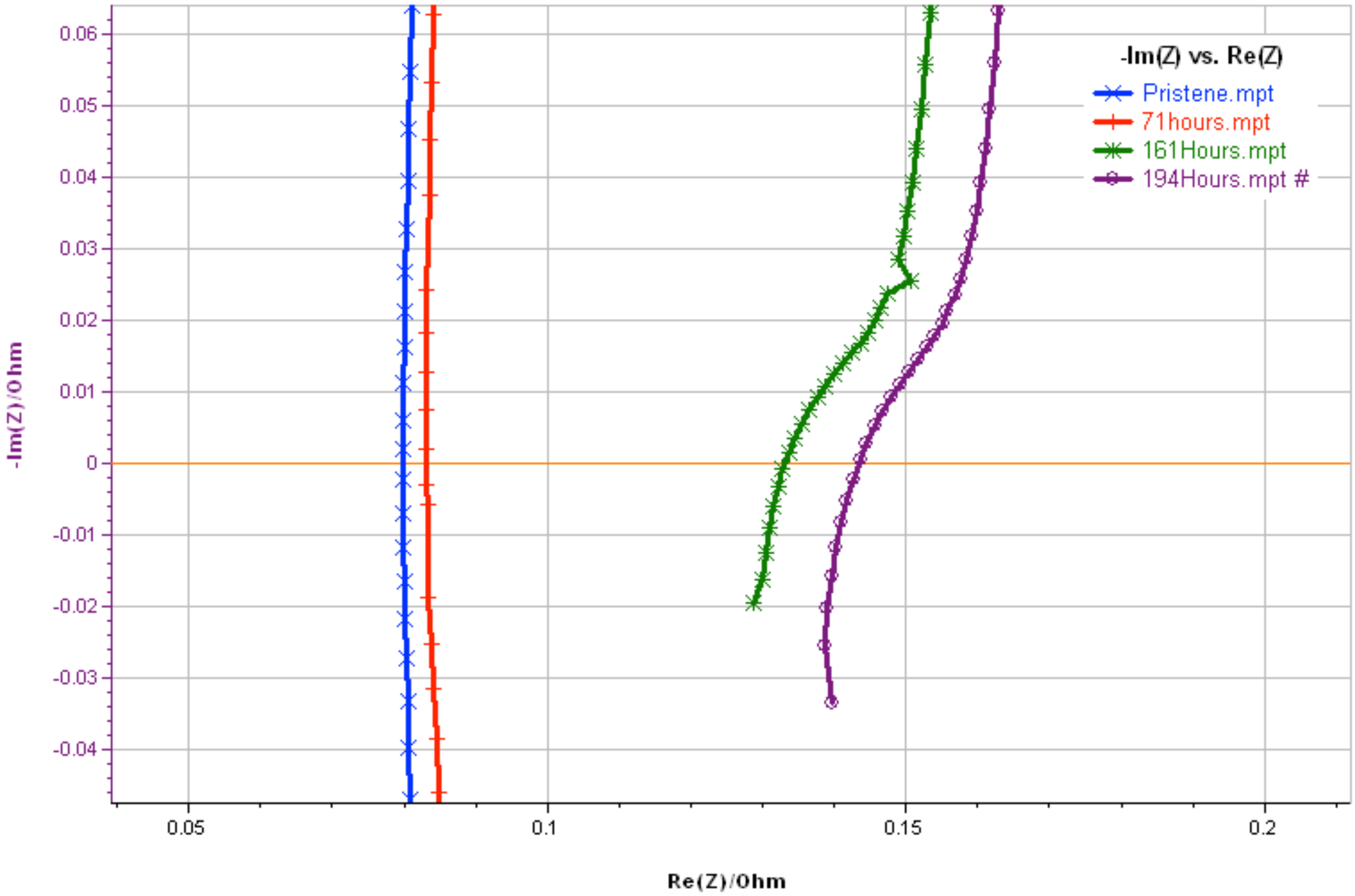
- Allows for the understanding of the effects of failure mechanisms, and the identification of leading indicators of failure essential for the development of physics-based degradation models and RUL prediction
- Electrolytic capacitor 2200uF, 10V and 1A
- Electrical overstress >200 hrs
  - Square signal at 200 mHz with 12V amplitude and 100 ohm load

Electrical Overstress Aging System





Degradation observed on EIS measurements

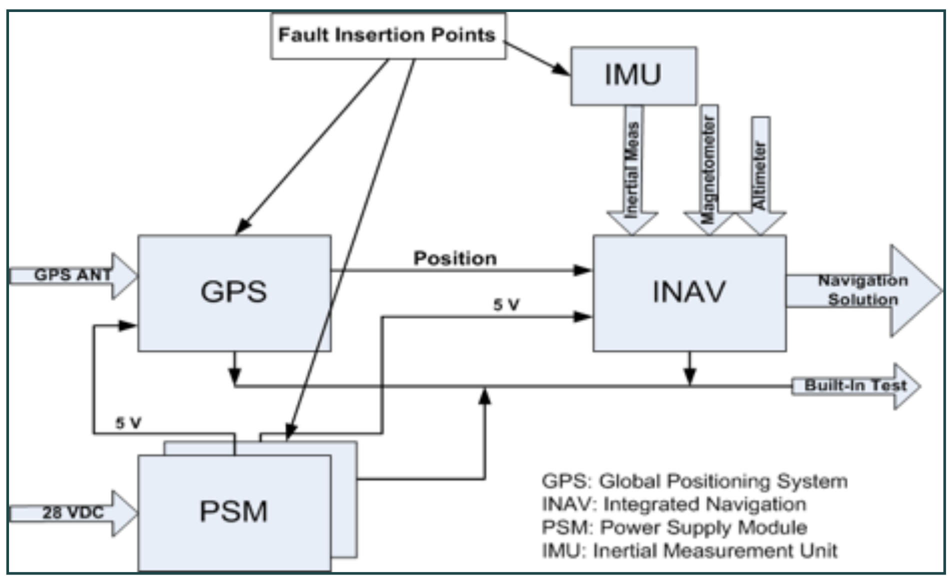


CASE STUDY I: PROGNOSTICS OF ELECTROLYTIC CAPACITORS

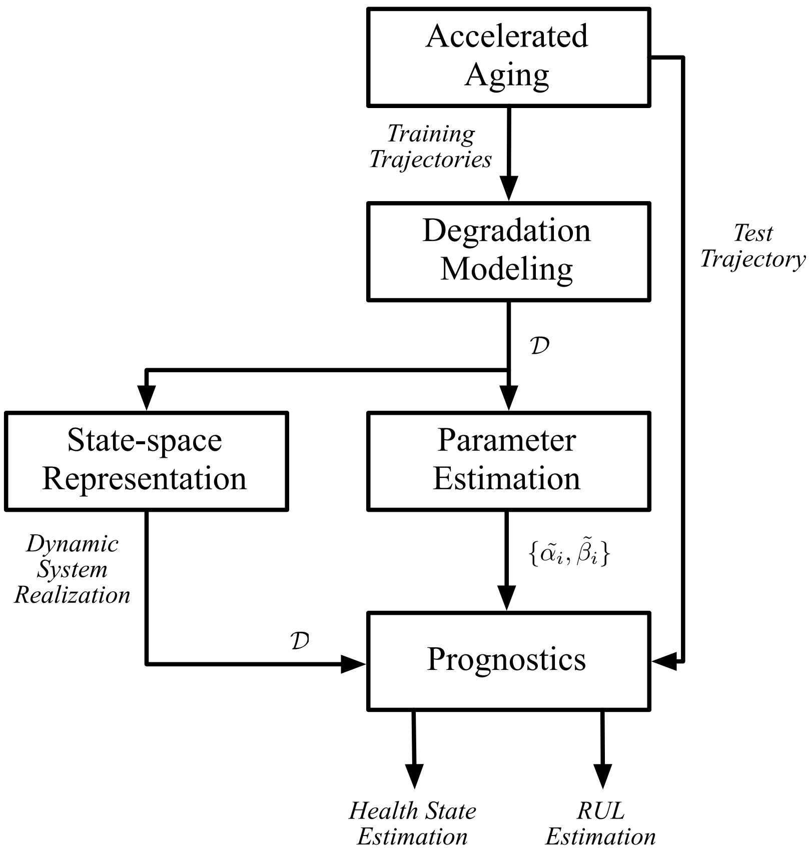
MODEL-BASED APPROACH EXAMPLE

Case Study: Avionics System

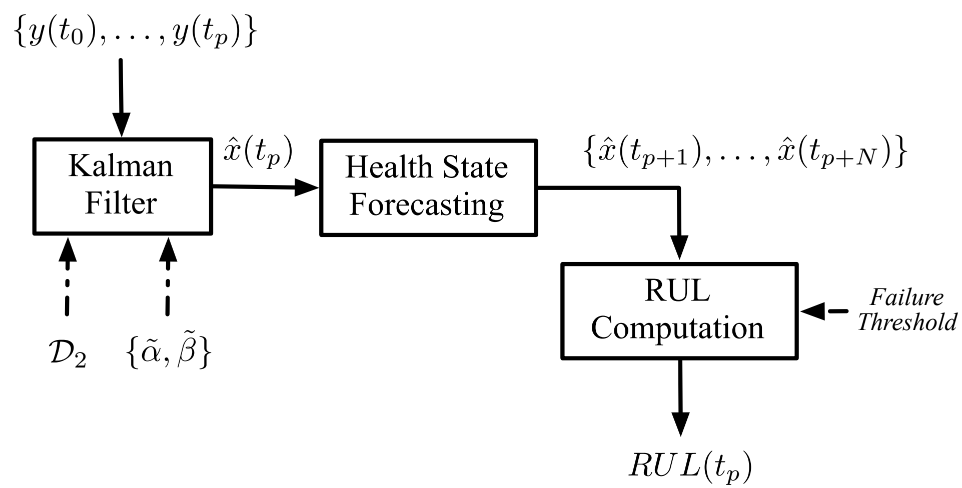
- Integrated Avionics systems consists of:
  - Global Positioning System (GPS) module
  - Integrated navigation (INAV) module combines output of the GPS model and Inertial measurement unit
  - Power Supply module



Methodology

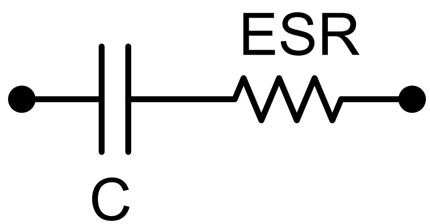


$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$y_k = Hx_k + v_k$$

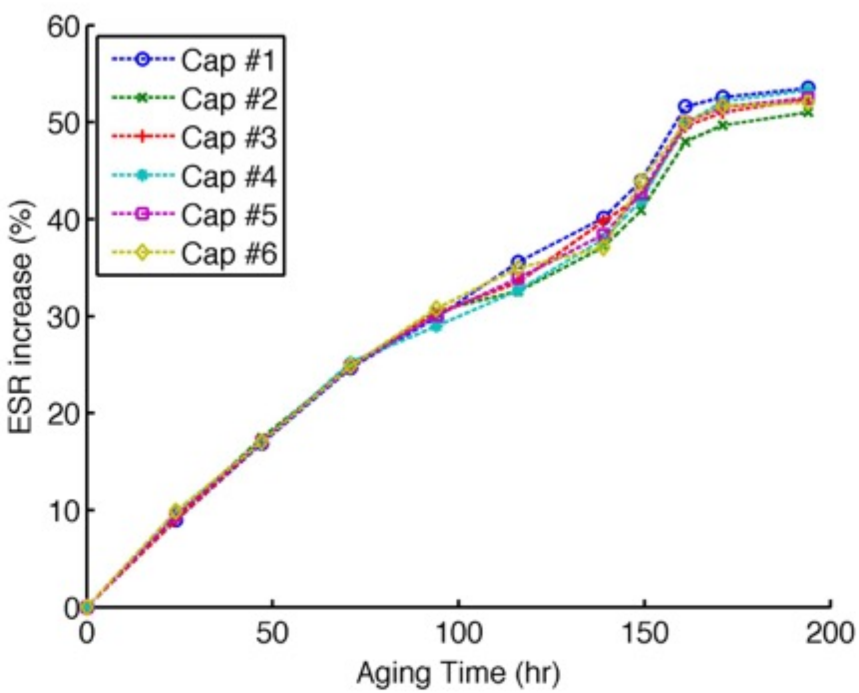


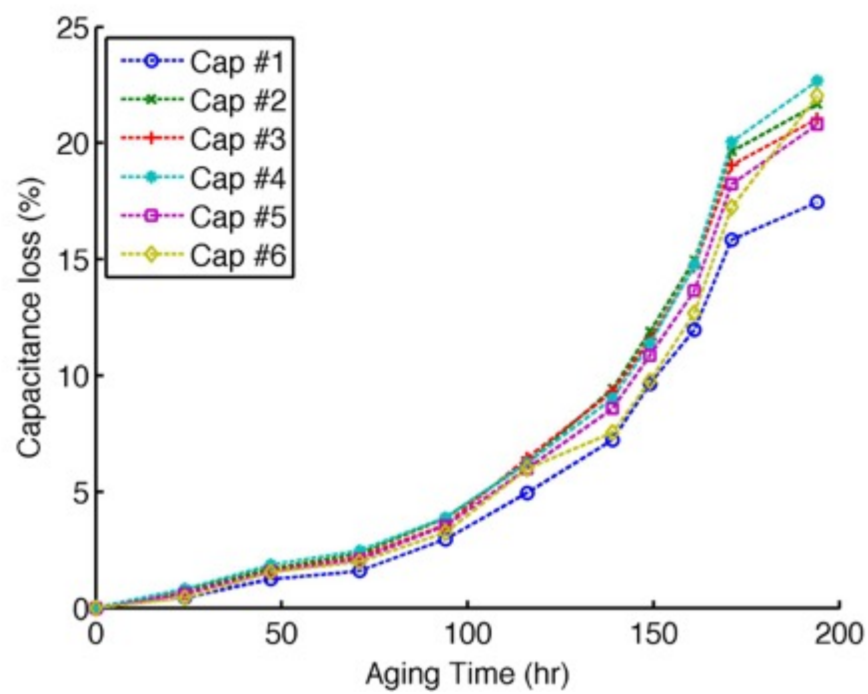
Accelerated Aging and Precursors of Failure Features

Degradation on lumped parameter model



C and ESR are estimated from EIS measurements

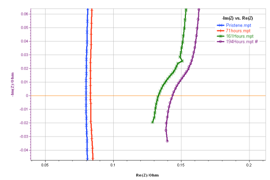




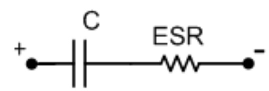
Methodology

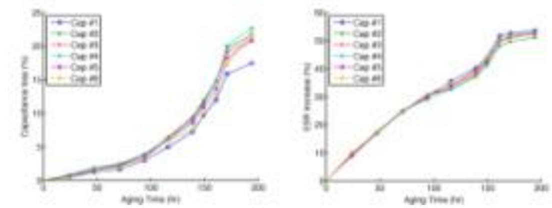
Real Capacitor

EIS



Reduced order model

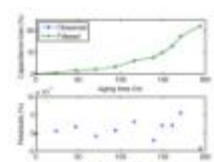




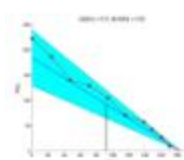
Degradation model (time)

$$C_k = e^{\alpha t_k} + \beta$$

Health state estimation



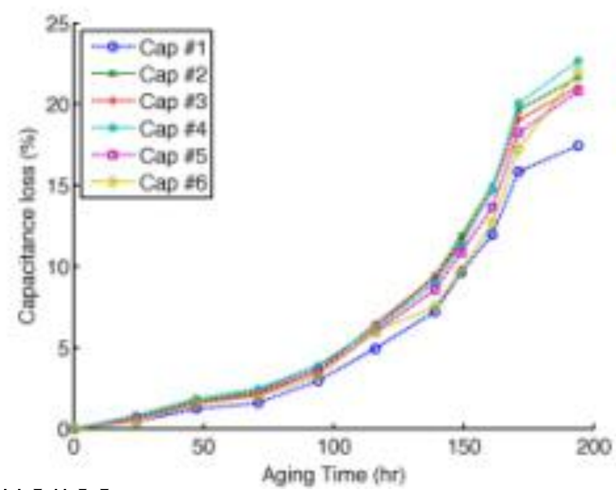
RUL prediction



Empirical degradation model

- Based on observed degradation from capacitance parameter
- Using training capacitor data to estimate degradation model parameters
- Assumed exponential model based on capacitance loss
- Parameter estimation with least-squared regression

$$C_k = e^{\alpha t_k} + \beta$$



Degradation model results

Validation test	Test capacitor	Training capacitor	α (95% CI)	β (95% CI)	σ_v^2
T_2	#2	#1, #3–#6	**0.0162** (0.0160, 0.0164)	**-0.8398** (-1.1373, -0.5423)	1.8778
T_3	#3	#1, #2, #4–#6	**0.0162** (0.0160, 0.0164)	**-0.8287** (-1.1211, -0.5363)	1.9654
T_4	#4	#1–#3, #5, #6	**0.0161** (0.0159, 0.0162)	**-0.8217** (-1.1125, -0.5308)	1.8860
T_5	#5	#1–#4, #6	**0.0162** (0.0161, 0.0164)	**-0.7847** (-1.1134, -0.4560)	2.1041
T_6	#6	#1–#5	**0.0169** (0.0167, 0.0170)	**-1.0049** (-1.2646, -0.7453)	2.9812

- The optimal parameter presented along the 95% confidence interval.
- The residuals are modelled as a normally distributed random variable with zero mean and variance

Prognostics algorithm

- Implementation of prognostics algorithm with Kalman filter
- Capacitance loss considered as state variable
- EIS measurements and lumped parameter model used to obtained measured capacitance loss values
- Empirical degradation model used to generate the state transition equation
- Use one Capacitor for testing and the rest for model parameter estimation (leave on out test)
- Failure threshold of 20% drop on capacitance based on MIL-C-62F

Kalman filter implementation

- State transition equation derived from degradation model

$$C_k = e^{\alpha t_k} + \beta$$

$$\frac{\partial C}{\partial t} = \alpha C - \alpha\beta$$

$$\frac{C_t - C_{t-\Delta t}}{\Delta t} = \alpha C_{t-\Delta t} - \alpha\beta$$

$$C_t = (1 + \alpha\Delta_t)C_{t-\Delta t} - \alpha\beta\Delta_t$$

$$C_k = (1 + \alpha\Delta_k)C_{k-1} - \alpha\beta\Delta_k$$

- State-space model for filter implementation

$$C_k = A_k C_{k-1} + B_k u + v$$

$$y_k = hC_k + w, \text{where}$$

$$A_k = (1 + \Delta_t),$$

$$B_k = -\alpha\beta\Delta_k,$$

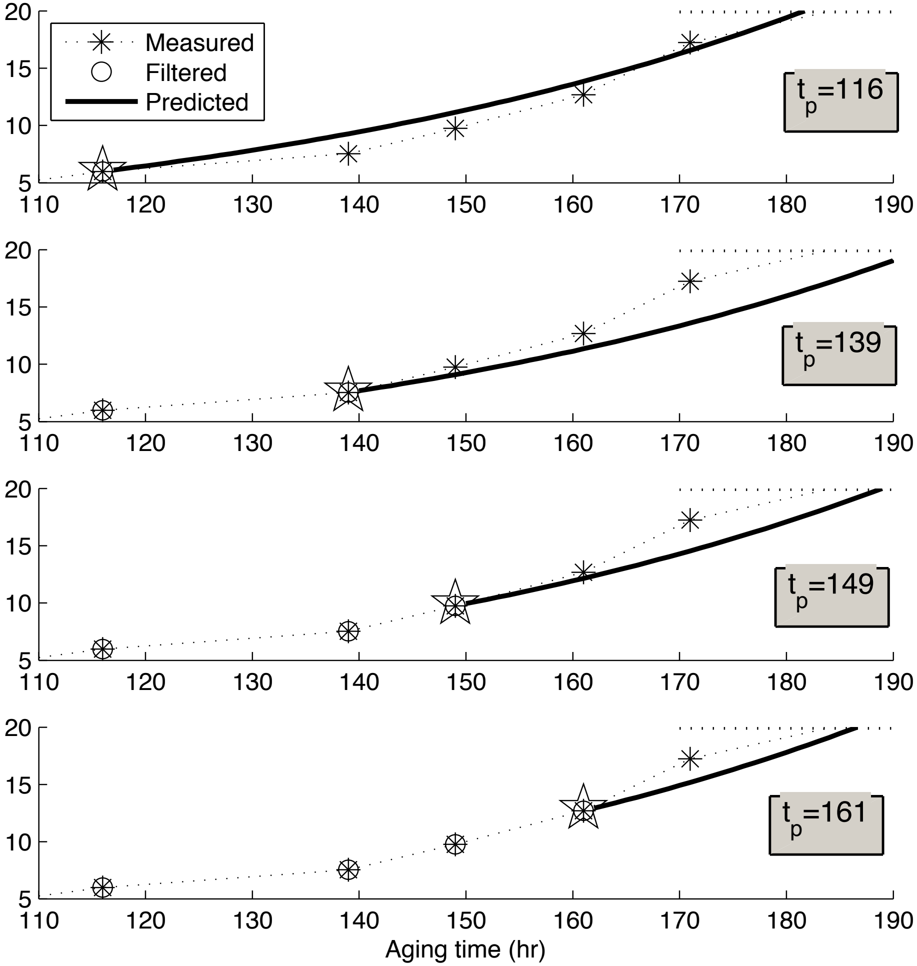
$$h = 1,\ u = 1.$$

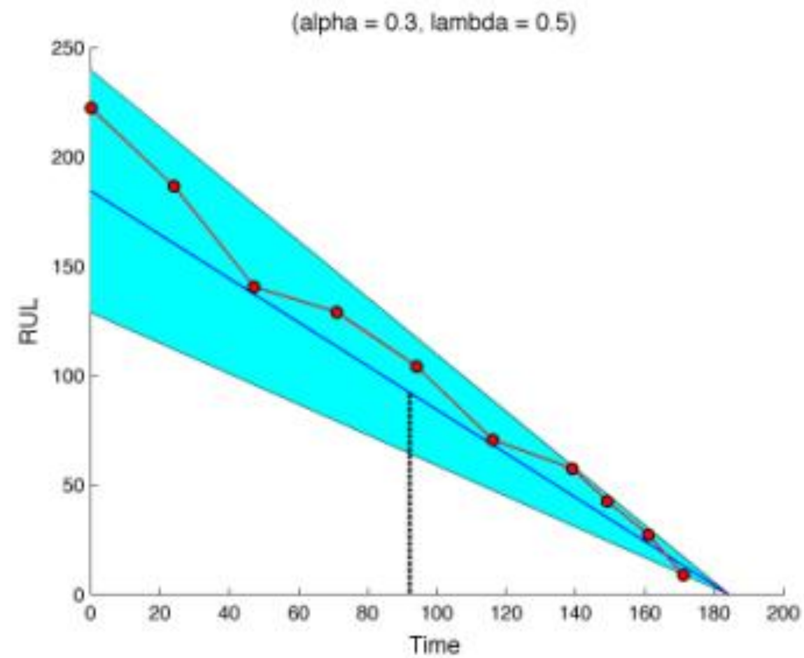
Prediction mode

- Assumed measurements are not available at some point in time
- Filter used in forecasting mode to predict future states
- Predictions done at 1 hr. intervals
- State transition equation used to propagate state (n: number of prediction steps, *l*: last measurement at t_l)

$$\hat{C}_{l+n} = A^n C_l + \sum_{i=0}^{n-1} A^i B$$

Tracking and forecasting (Cap. #6)

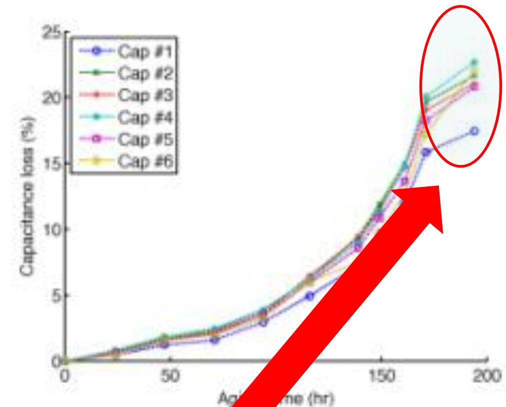




Relative Accuracy

$$RA = 100\left(1 - \frac{RUL^{*} - RUL^{'}}{RUL^{*}}\right)$$

t_p	RA_{T2}	RA_{T3}	RA_{T4}	RA_{T5}	RA_{T6}	$\widetilde{RA}$
24	94.8	95.5	91.9	96.9	99.7	**95.5**
47	97.4	99.3	96.4	96.7	91.7	**96.7**
71	87.5	91.9	84.5	94.1	97.1	**91.9**
94	85.6	90	78.9	94.8	94.2	**90**
116	86	99.1	76.5	98	96.2	**96.2**
139	77.8	95.8	53.1	96.7	81.1	**81.1**
149	82.1	98.4	46.9	94.8	86.6	**86.6**
161	77.2	87.3	16.6	87.5	89.8	**87.3**
171	26.6	26.4	N/A	34.8	63.7	**30.7**



End of Case Study I:

DISCUSSION AND QUESTIONS?

CASE STUDY II: PROGNOSTICS OF POWER TRANSISTORS

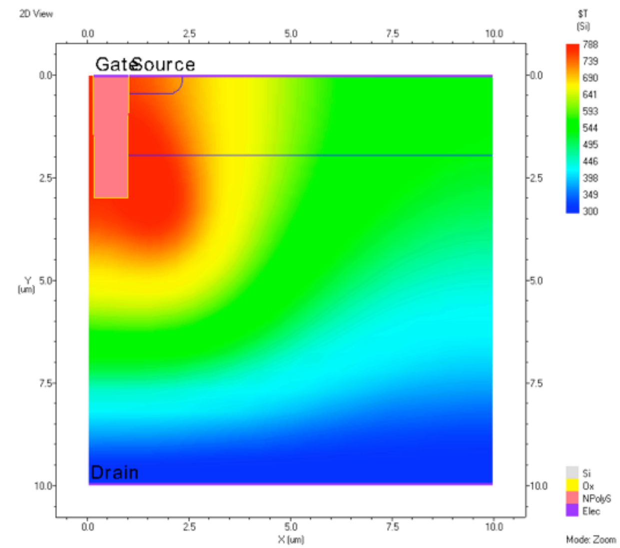
PRECURSORS OF FAILURE EXAMPLE

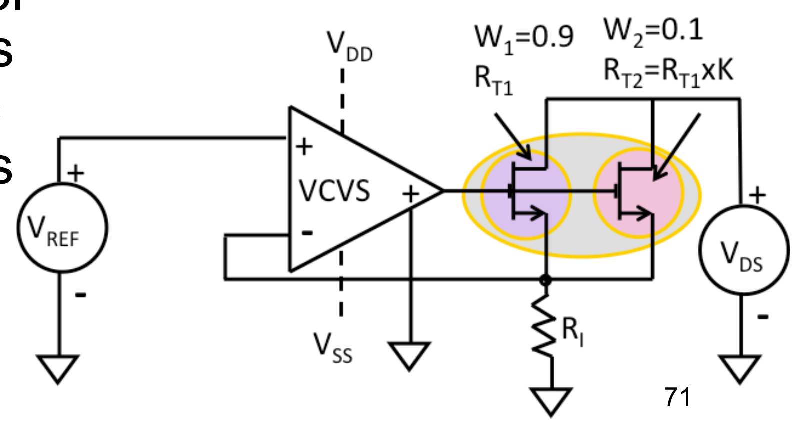
Modeling for Power MOSFET under electrical overstress

- Two-transistor model is shown to be a good candidate for a degradation model for model-based prognostics

- The model parameters K and W1 could be varied as the device degrades as a function of usage time, loading and environmental conditions

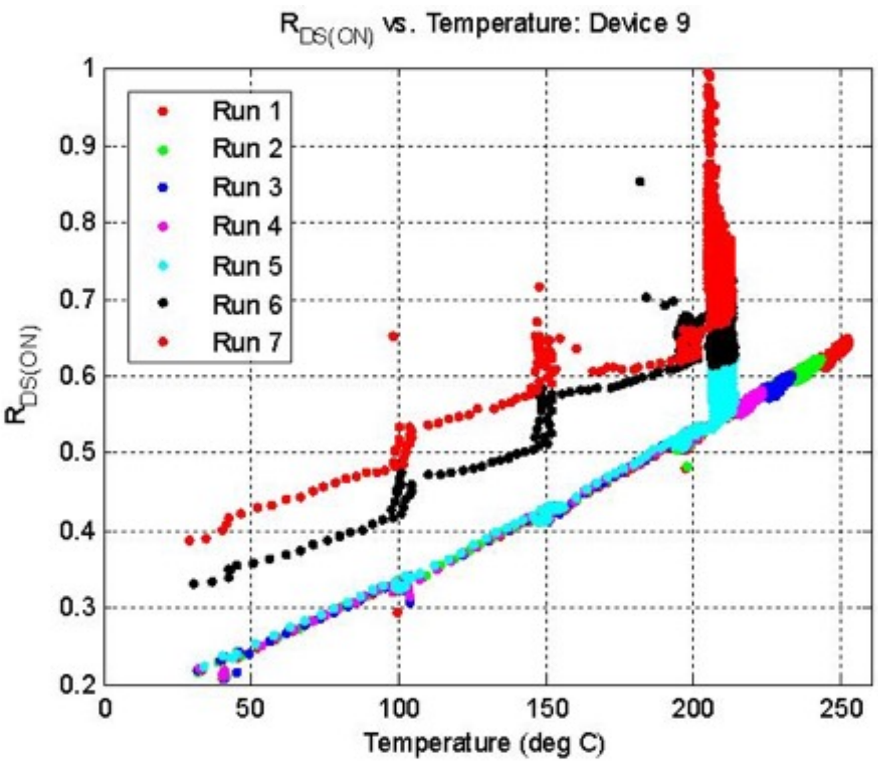
- Parameter W1 defines the area of the healthy transistors, the lower this area, the larger the degradation in the two-transistor model. In addition, parameter K serves as a scaling factor for the thermal resistance of the degraded transistors, the larger this factor, the larger the degradation in the model.





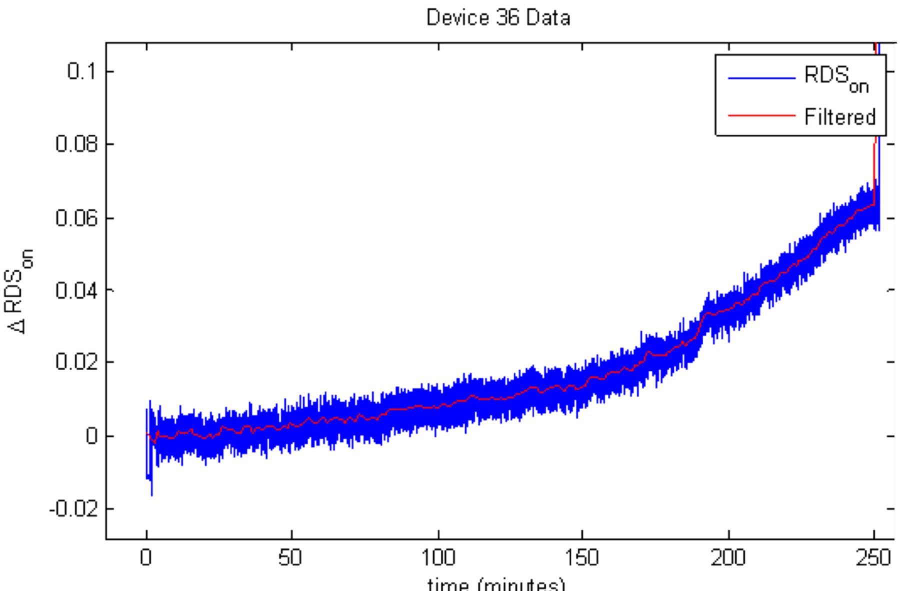
Precursor of Failure

- As case temperature increases, ON-resistance increases
- This relationship shifts as the degradation of the device increases
- For a degraded state, ON-resistance will be higher at any given case temperature
- This is consistent with the die-attach damage since it results on increased junction temperature operation
- This plot can be used directly for fault detection and diagnostics of the die-attach failure mechanism



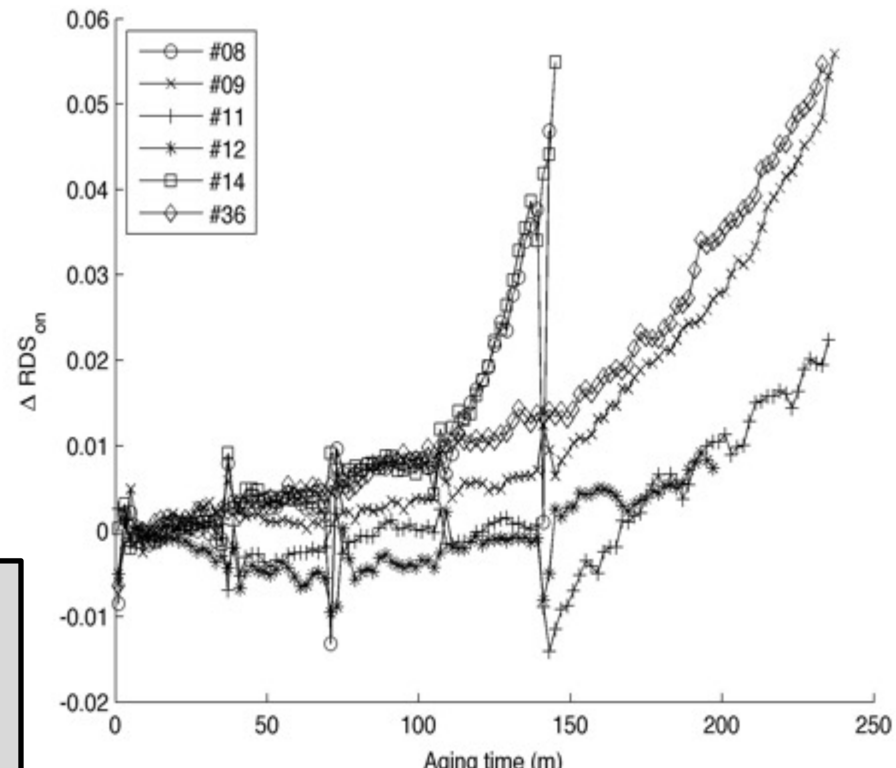
Degradation process data

Normalized ON-state resistance ($\Delta R_{DS(ON)}$) and filtered trajectory for device #36



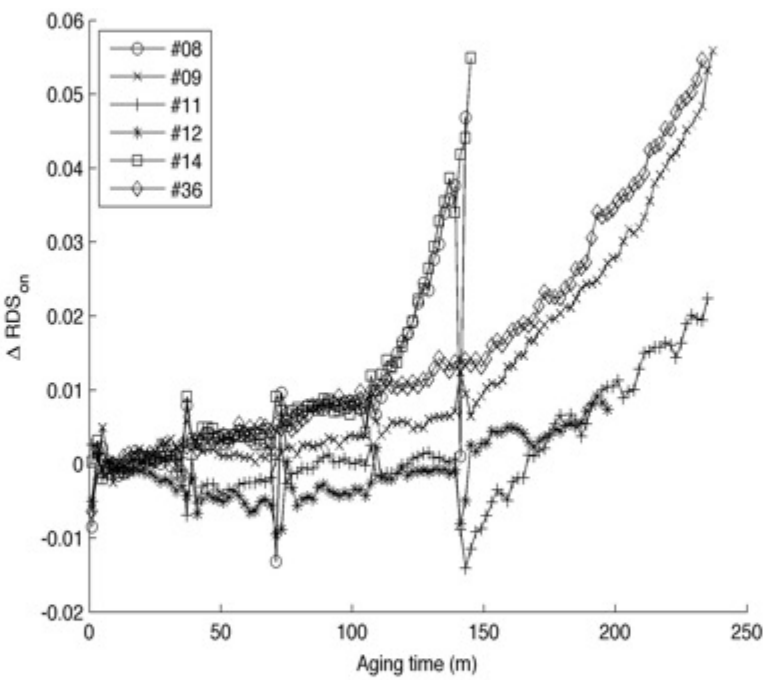
- Cases #08, #09, #11, #12 and #14 are used for algorithm development purposes.
- Case #36 is used to test the algorithms.

Normalized ON-state resistance ($\Delta R_{DS(ON)}$) and filtered trajectory for device #36



Empirical Degradation Model

- An empirical degradation model was selected for the model-based algorithms
- Exponential based function to capture degradation process
- Two parameters in the model which will be estimated on-line



$$\Delta R_{DS(ON)} = \alpha(e^{\beta t} - 1)$$

Prediction of Remaining Life

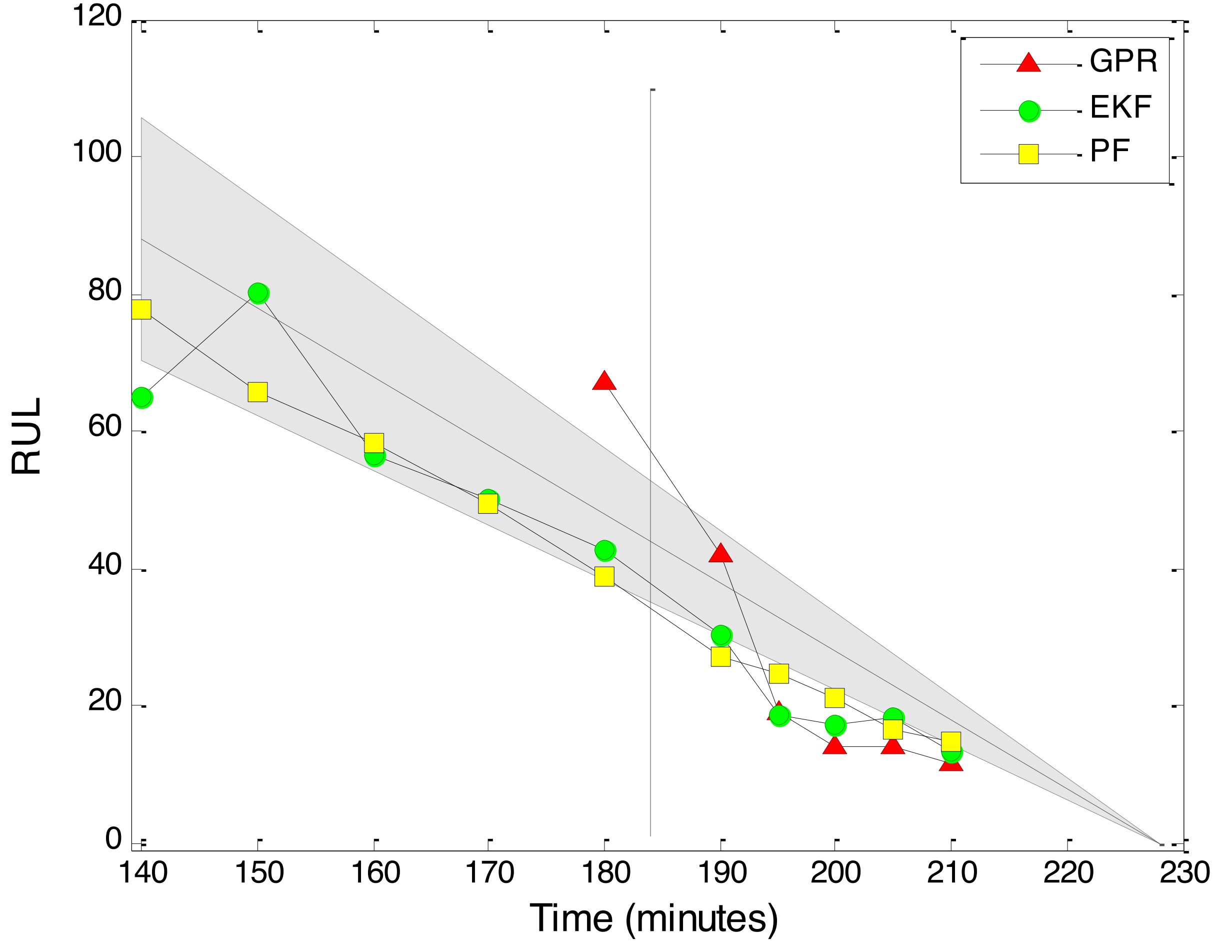
RUL Prediction Methodology Considerations

- A single feature is used to assess the health state of the device ($\Delta R_{DS(ON)}$)
- It is assumed that the die-attached failure mechanism is the only active degradation during the accelerated aging experiment
- Furthermore, $\Delta R_{DS(ON)}$ accounts for the degradation progression from nominal condition through failure
- Periodic measurements with fixed sampling rate are available for $\Delta R_{DS(ON)}$
- A crisp failure threshold of 0.05 increase in $\Delta R_{DS(ON)}$ is used
- The prognostics algorithm will make a prediction of the remaining useful life at time t_p, using all the measurements up to this point either to estimate the health state at time t_p in a regression framework or in a Bayesian state tracking framework
- It is also assumed that the future load conditions do not vary significantly from past load conditions

RUL Prediction Algorithms

- Gaussian Process Regression
  - Algorithm development cases used to select covariance matrix structure and values
- Extended Kalman filter
  - Empirical degradation model
  - State variable: Normalized ON-resistance and degradation model parameters
  - Arbitrary values for measurement and process noise variance
- Particle filter
  - Empirical degradation model
  - State variable: Normalized ON-resistance, degradation model parameters
  - Exponential growth model used for degradation model parameters
  - Arbitrary values for measurement and process noise variance

RUL estimation results



End of Case Study II:

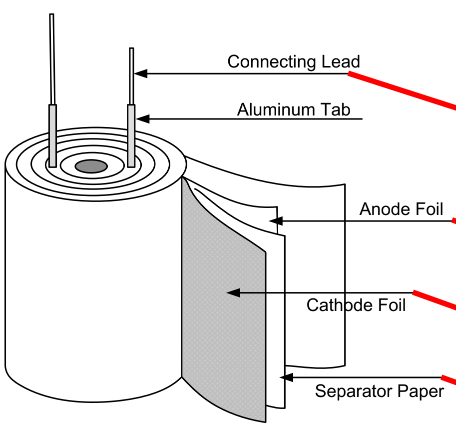
DISCUSSION AND QUESTIONS?

CASE STUDY III: PHYSICS-BASED PROGNOSTICS OF CAPACITORS

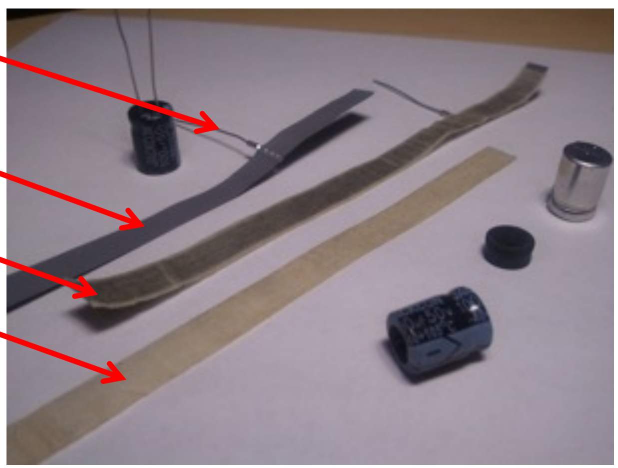
DEGRADATION MODELING EXAMPLE

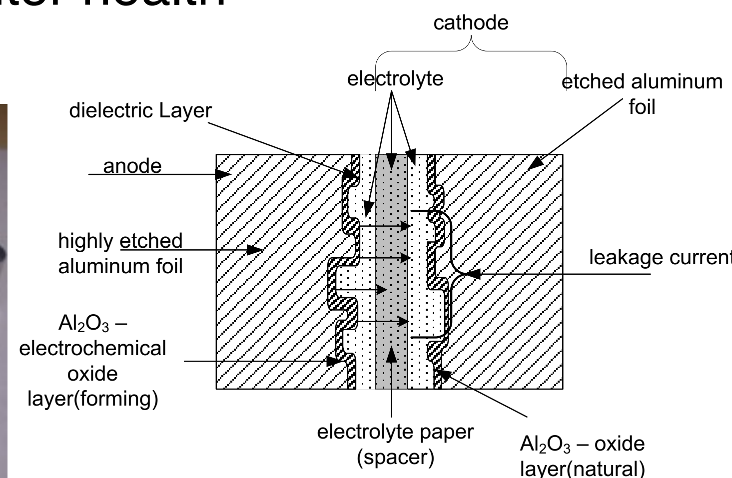
Capacitor Structure

- An aluminum electrolytic capacitor, consists of
  - Cathode aluminum foil,
  - Electrolytic paper, electrolyte
  - Aluminum oxide layer on the anode foil surface, which acts as the dielectric.
  - Equivalent series resistance (ESR) and capacitance(C) are electrical parameters that define capacitor health



Physical Structure



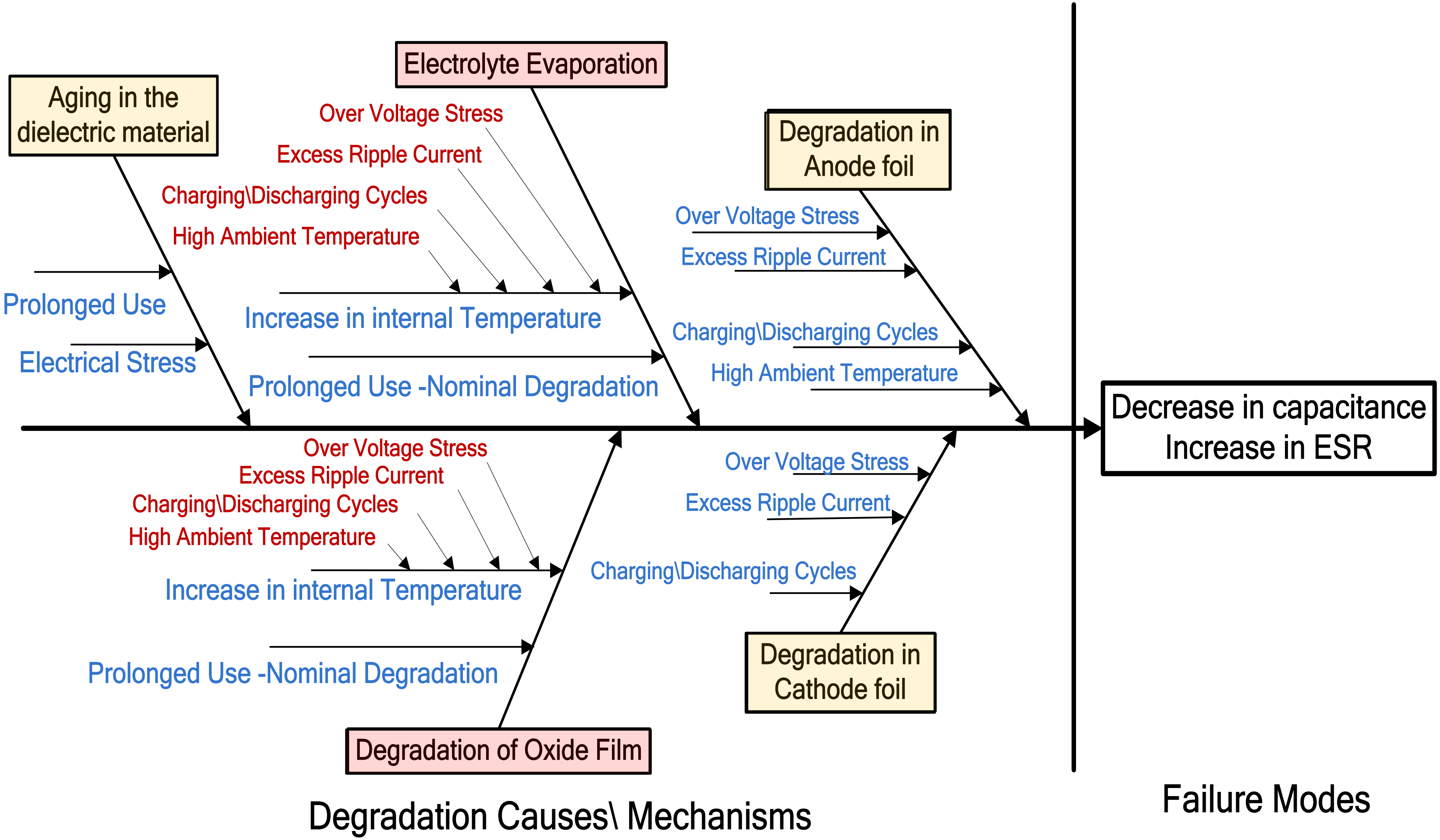


Internal Structure

Ref :http://en.wikipedia.org/wiki/File:ElectrolyticCapacitorDisassembled.jpg

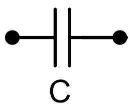
Open Structure

Degradation Mechanisms

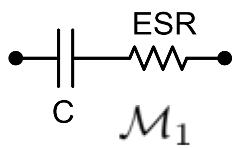


Capacitor Degradation Model

Pristine Capacitor

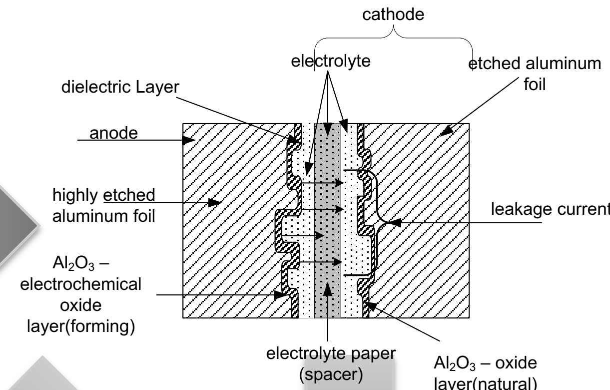


Ideal



Non- Ideal

Degradation



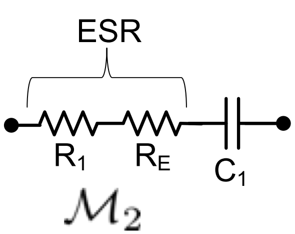
Electrolyte volume V_e maximum
Capacitance Value maximum

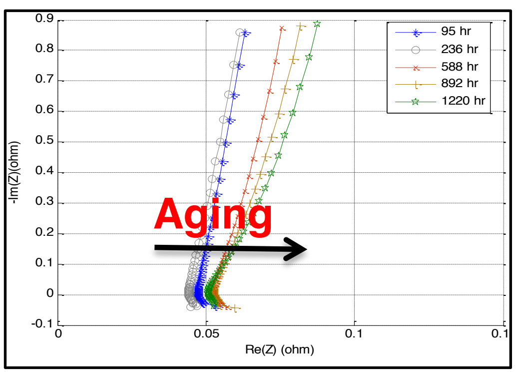
Thermal Stress

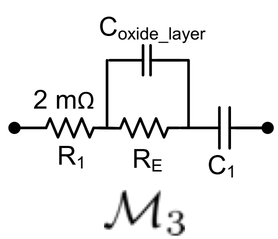
Electrical Stress

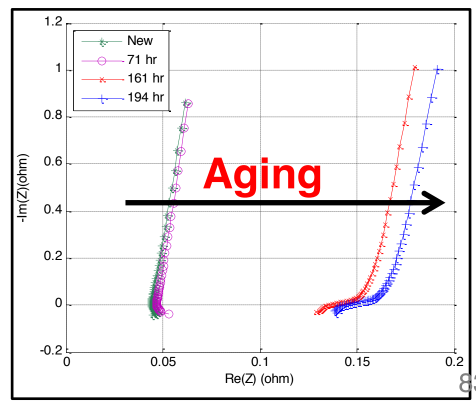
Avg. surface area decreases (A_s) + oxide layer breakdown

Electrolyte degradation + Decrease in (A_s) + crystallization +oxide layer breakdown









Empirical Model with static parameters

- This empirical model represents an approximation of lumped parameter model $\mathcal{M}_1$

$$\mathcal{E}_1 : C_l(t) = e^{\alpha t} + \beta,$$

  - α and β are degradation model parameters estimated from the experimental data.

- The following system structure is used in the implementation of the filtering and the prediction using the Kalman filter.

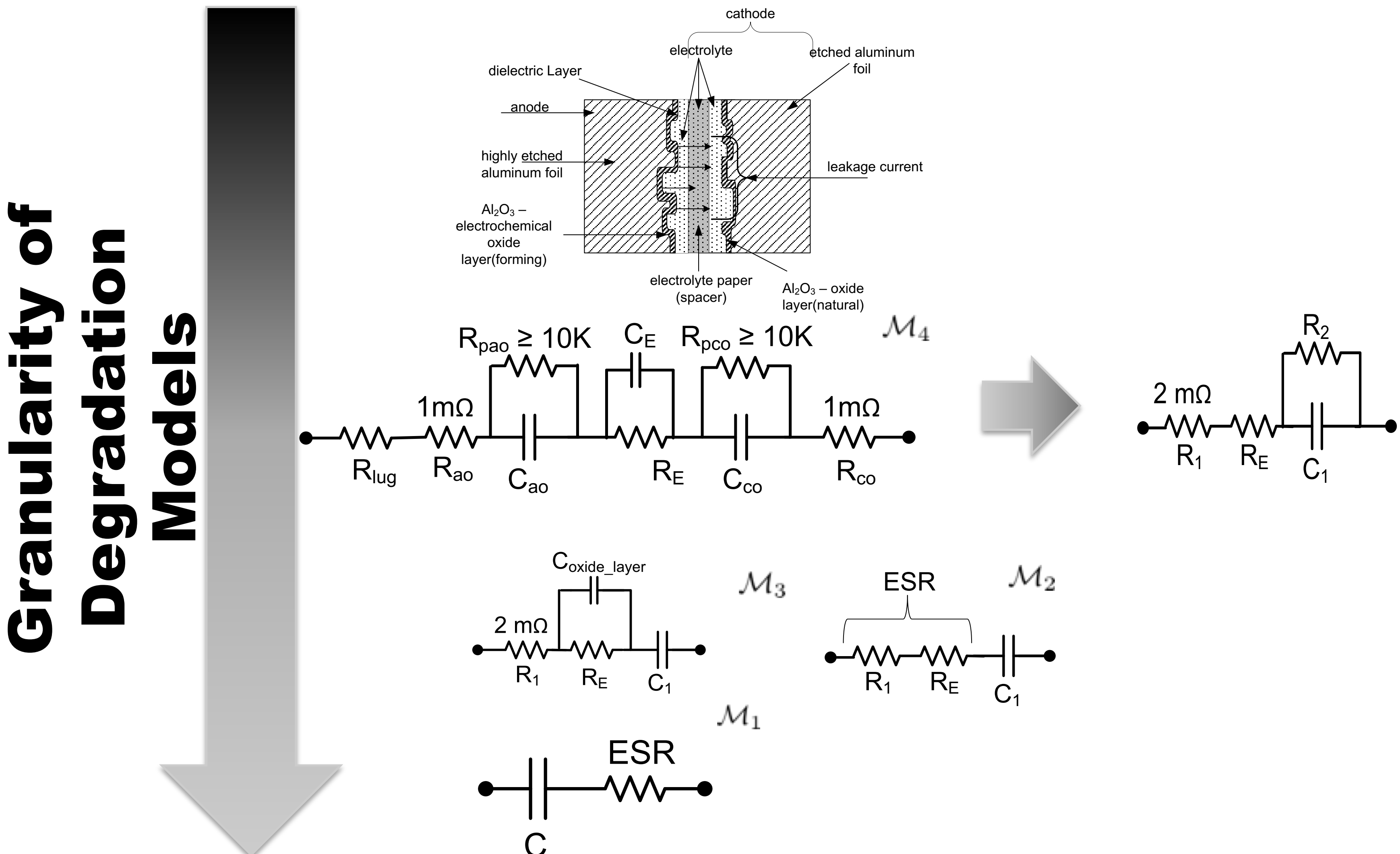
$$x_k = A_k x_{k-1} + B_k u + v,$$
$$y_k = h x_k + w,$$

$$A_k = (1 + \Delta_k),$$
$$B_k = -\alpha\beta\Delta_k,$$
$$h = 1,$$
$$u = 1.$$

- The state variable (x_k) at aging time (t_p) is the percentage loss in Capacitance.

- Process noise was estimated from the model regression for the empirical model
- Measurement noise was estimated from the EIS measurements

Degradation Model: Electrical Circuit Equivalent



Capacitance Degradation Model

- Decrease in electrolyte volume :

$$\boxed{Ve(t) = V_{e0} - (w_e A_s j_{eo} t)} \tag{1}$$

where:
V: dispersed volume at time t, V_e: initial electrolyte volume
A_s: surface area of evaporation, j_{eo} : evaporation rate
t : time in minutes, w_e = volume of ethyl glycol molecule

- Capacitance (C)): Physics-Based Model:

$$C = (2\epsilon_R \epsilon_O A_s)/d_C \tag{2}$$

- Electrolyte evaporation dominant degradation phenomenon
  - First principles: Capacitance degradation as a function of electrolyte loss

$$\mathcal{D}_1 : C(t) = \left(\frac{2\epsilon_R \epsilon_0}{d_C}\right)\left(\frac{V_{e0} - V_e(t)}{j_{eo}\ t\ w_e}\right), \tag{3}$$

where:
C : capacitance of the capacitor,
ϵ_R : relative dielectric constant,
ϵ_O : permittivity of free space,
d_C : oxide thickness.

Capacitance Degradation Model

- Oxide breakdown observed - experimental data
- The breakdown factor is exp. function of electrolyte evaporation

$$C_{bk(t)} = \exp f(V_{eo} - V_{e(t)})$$

- Updated in capacitance degradation model :

$$C = (2\epsilon_R \epsilon_0 A_s c_{bk})/d_C,$$

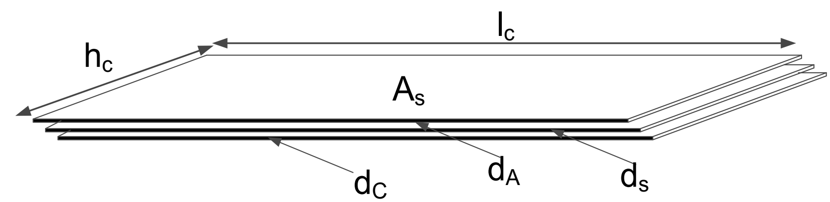
$$\mathcal{D}_{11} : C(t) = c_{bk(t)} \left(\frac{2\epsilon_R \epsilon_0}{d_C} \right) \left(\frac{V_{e0} - V_e(t)}{j_{eo}\ t\ w_e} \right)$$

Dynamic Model of Capacitance

From the structure of capacitor we have the electrolyte volume(V_e) expressed in the form of oxide surface area (A_s) as :

$$V_e = A_s.d_C, \qquad (4)$$

$$A_s = \frac{V_e}{d_C}.$$



The first order discrete approximation for change in electrolyte volume can be expressed as:

$$\frac{dV_e}{dt} = -(w_e A_s j_{eo}), \qquad (5)$$

$$V_{e(k+1)} = V_{e(k)} + \frac{dV_e}{dt}\Delta t,$$

$$V_{e(k+1)} = V_{e(k)} - (w_e A_s j_{eo})\Delta t.$$

Dynamic Model of Capacitance

$$V_{e(k)} = \frac{C_k}{2\epsilon_R \epsilon_0 c_{bk}} d_C^2,$$
$$V_{e(k)} = (C_k)\alpha \tag{6}$$

Similarly Capacitace can be expressed as :

$$C_{k+1}\alpha = C_k\alpha + \frac{dV_e}{dt}\Delta t,$$
$$C_{k+1}\alpha = C_k\alpha - (w_e A_s j_{eo})\Delta t, \text{ hence}$$
$$C_{k+1} = C_k - \frac{(w_e A_s j_{eo})}{\alpha}\Delta t. \tag{7}$$

The complete discrete time dynamic model for capacitance degradation can be summarized as :

$$\boxed{\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2}\right)\Delta t}$$

Dynamic Model of ESR

- Decrease in electrolyte volume :

$$Ve(t) = V_{e0} - (w_e A_s j_{eo} t)$$

- ESR
  - Based on mechanical structure and electrochemistry.
  - With changes in R_E (electrolyte resistance)

$$ESR = \frac{1}{2}\left(\frac{\rho_E d_C P_E e_{bk(t)}}{A_s}\right)$$

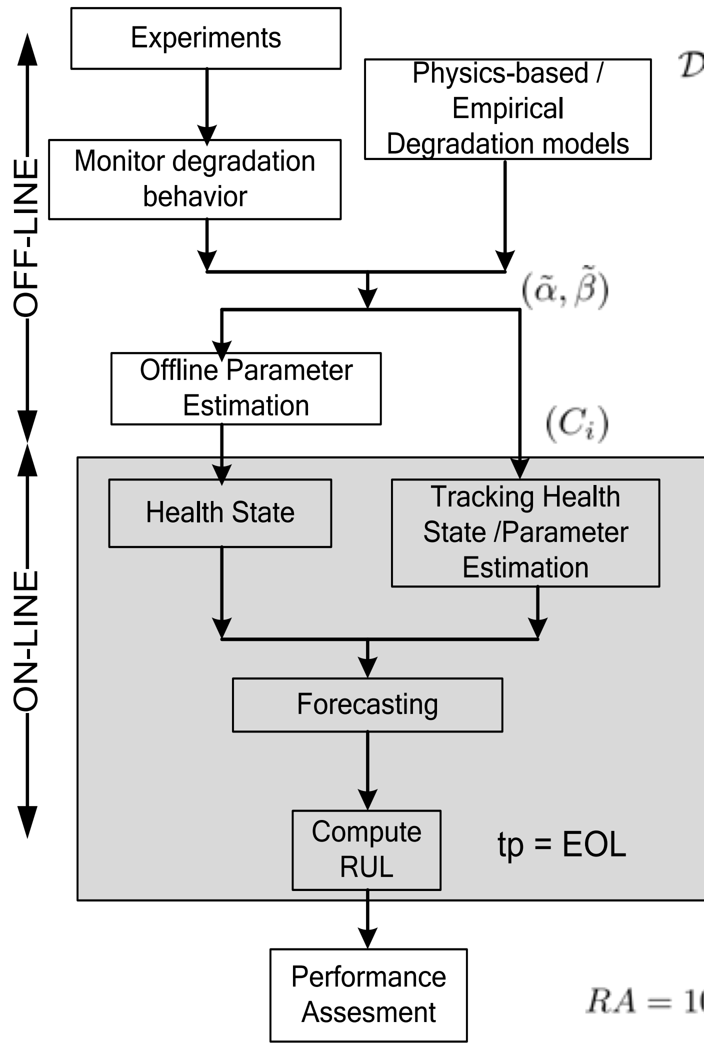
$$\mathcal{D}_2 : ESR(t) = \frac{1}{2}\left(\rho_E \ d_C \ P_E\right)\left(\frac{j_{eo} \ t \ w_e e_{bk(t)}}{V_e(t)}\right) \quad (8)$$

Dynamic ESR degradation Model :

$$\mathcal{D}_5 : \frac{1}{ESR_{k+1}} = \frac{1}{ESR_k} - \left(\frac{2w_e A_s j_{eo}}{\rho_E \ P_E \ d_C^2 \ e_{bk(t)}}\right)\Delta t$$

where:
ρ_E : electrolyte resistivity,
P_E : correlation factor related to electrolyte spacer porosity and average liquid pathway,
$e_{bk(t)}$: resistance dependence oxide breakdown factor

Process Flow



$$\mathcal{D}_1 : C(t) = \left(\frac{2\epsilon_R \epsilon_0 c_{bk}}{d_C}\right)\left(\frac{V_0 - V_e(t)}{j_{eo}\ t\ w_e}\right)$$

$$\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2}\right)\Delta t,$$

$$(C_i, j_{eo(i)}, c_{bk(i)})$$

$$(C)$$

$$RA = 100\left(1 - \frac{RUL^* - RUL}{RUL^*}\right)$$

Unscented Kalman Filter for State Estimation

$$\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2} \right) \Delta t$$

- Derived physics-based degradation model

- The following system structure is implemented for state estimation

$$\mathbf{x}_k = A_k \mathbf{x}_{k-1} + B_k u + \mathbf{v},$$
$$\mathbf{y}_k = H_k \mathbf{x}_k + \mathbf{w}.$$

$$A = 1,$$
$$B = -\frac{(2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk})}{d_C^2} \Delta t,$$
$$H = 1,$$
$$u = j_{eo}, c_{bk}.$$

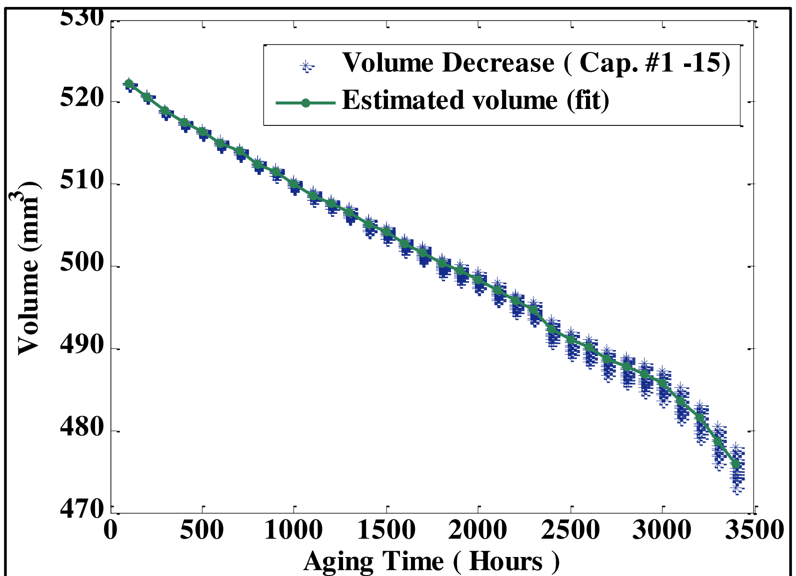
- The state variable (x_k) is the current health state at aging time (t_p)

Process noise was estimated from the model regression for the empirical model
Measurement noise was estimated from the EIS measurements

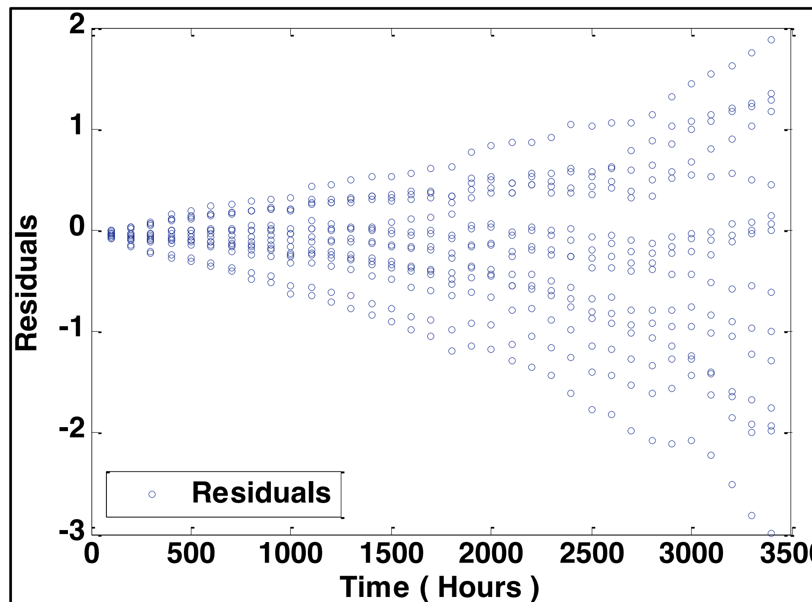
Electrolyte Volume Estimation for TOS Experiment

Parameter	$\bar{X}$	$\tilde{X}$	S.D	C.I
$\hat{\theta}_1(mm^3)$	523.6112	523.6113	0.0026	[523.6098, 523.6127]
$\hat{\theta}_2(mm^2/t)$	0.0161	0.0161	1.8748×10^{-5}	[0.01614, 0.01611]
$\hat{\theta}_3(mm/t^2)$	3.8077×10^{-7}	3.8072×10^{-7}	6.9373×10^{-9}	$[0.3769 \times 10^{-6}, 0.3846 \times 10^{-6}]$
RMSE	26.2232	26.2277	0.0483	[26.1965, 26.2500]
RMSPE	0.8589	0.8591	0.0016	[0.8580, 0.8598]

Summary for Linear Regression Electrolyte Degradation Model



Volume estimation for all capacitors



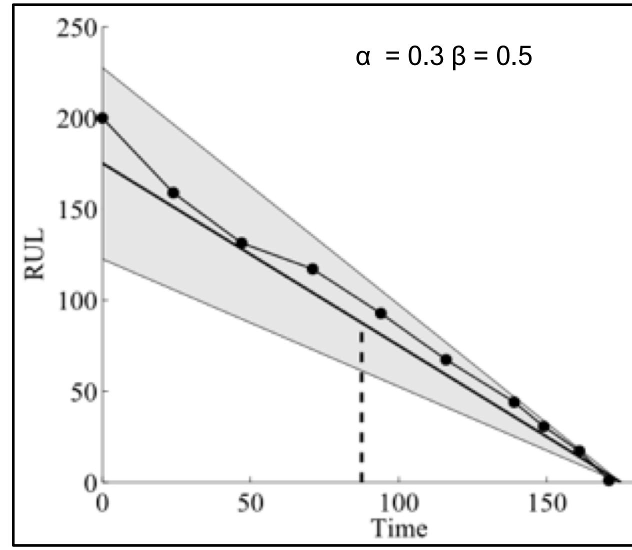
Volume estimation Error

EOS Experiment RA Results – Discussion

Capacitance - Over RA summary for model $\mathcal{E}_1$

Aging Time	$\overline{RA_a}$
24	95.5
47	96.7
71	91.9
94	90
116	96.2
139	81.1
149	86.6
161	87.3
171	30.7

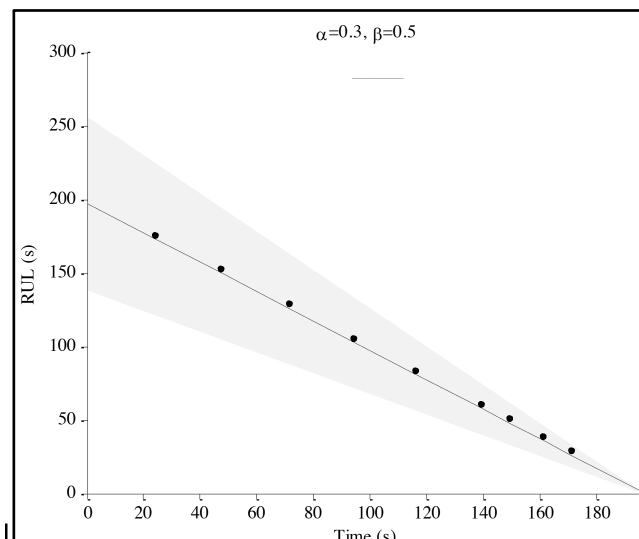
$$\mathcal{E}_1 : C_l(t) = e^{\alpha t} + \beta,$$



Capacitance - Over RA summary for model $\mathcal{D}_4$

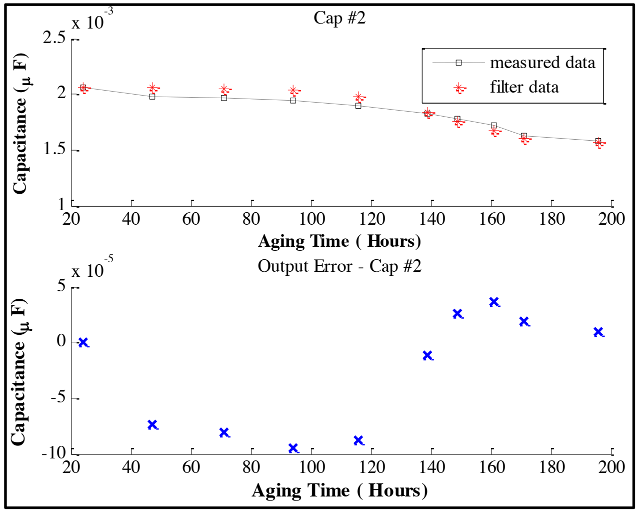
Aging Time	$\overline{RA_a}$
24	98.06
47	97.76
71	97.34
94	96.73
116	95.84
139	94.16
149	92.92
161	90.49
171	86.67

$$\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2} \right) \Delta t$$

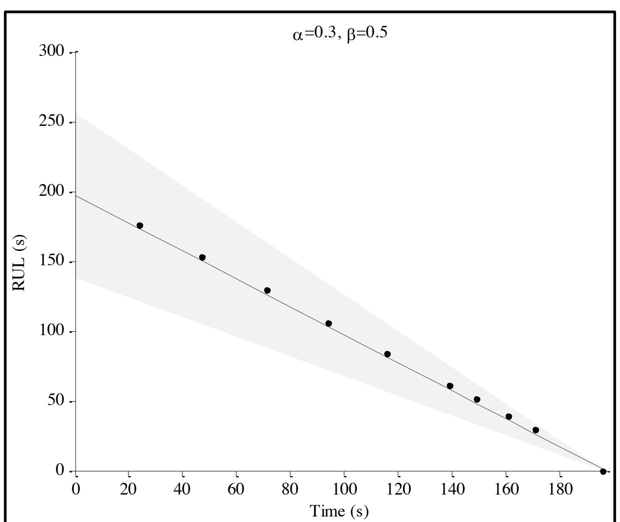


RUL and Validation – EOS -Experiment – Capacitance Degradation Model

Tracking

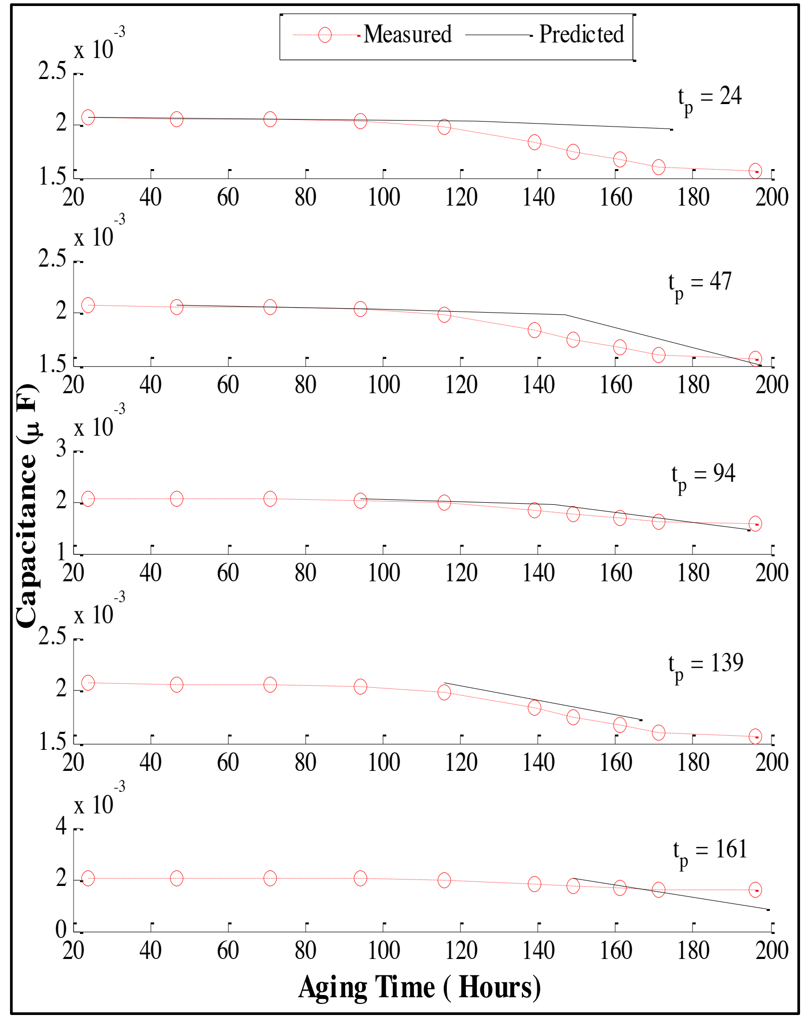


Alpha Lambda



Predictions at different aging time

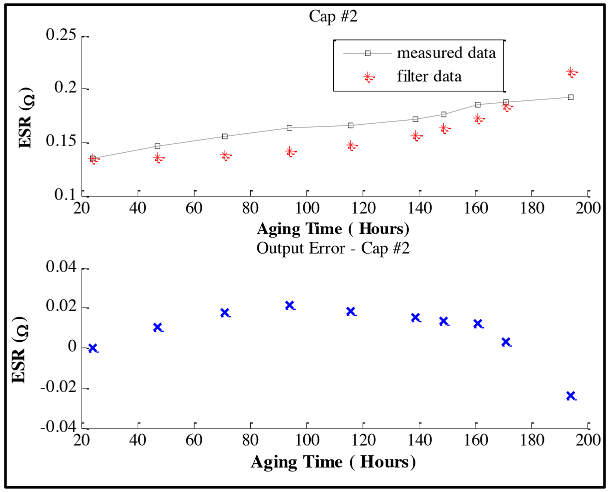
$\mathcal{D}_4$



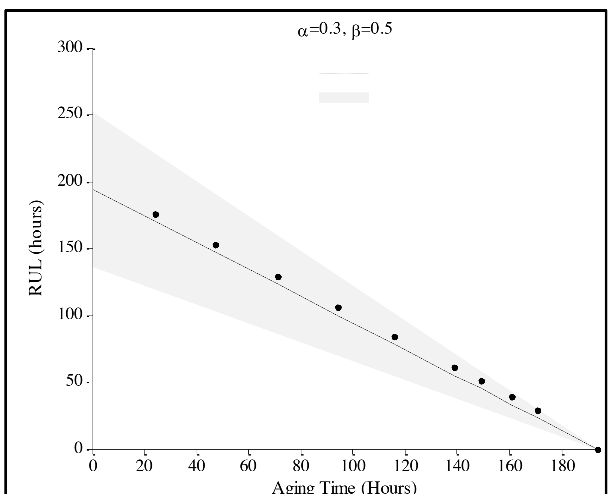
RUL and Validation – EOS -Experiment – ESR Degradation Model

$\mathcal{D}_5$

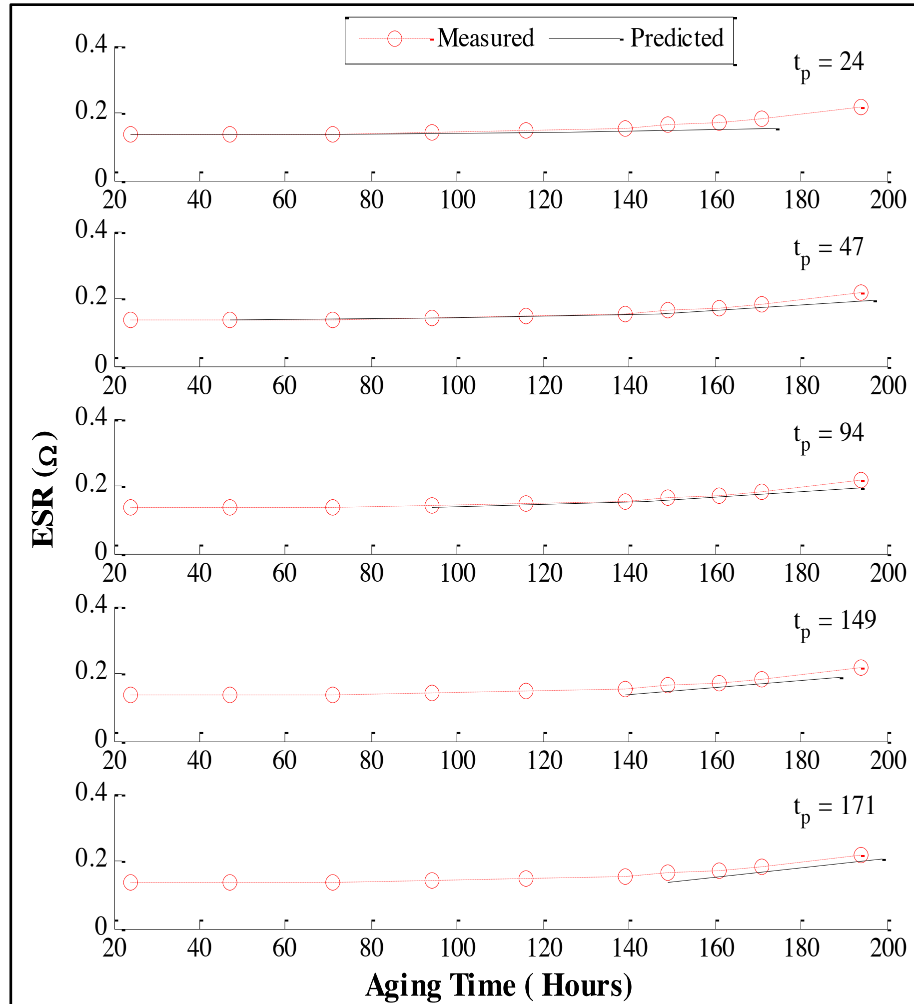
Tracking



Alpha Lambda

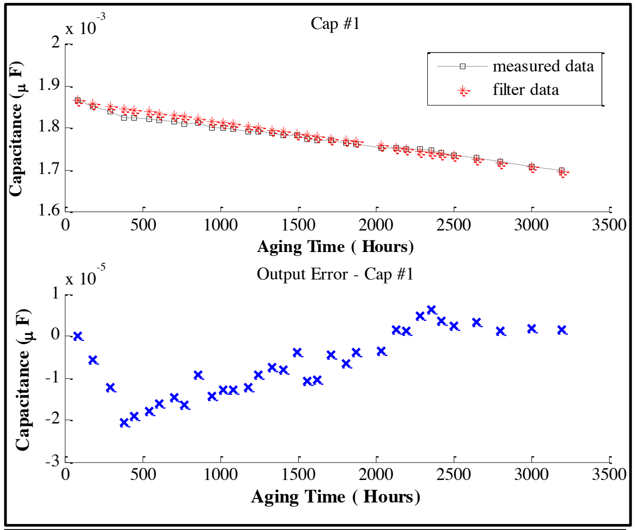


Predictions at different aging time

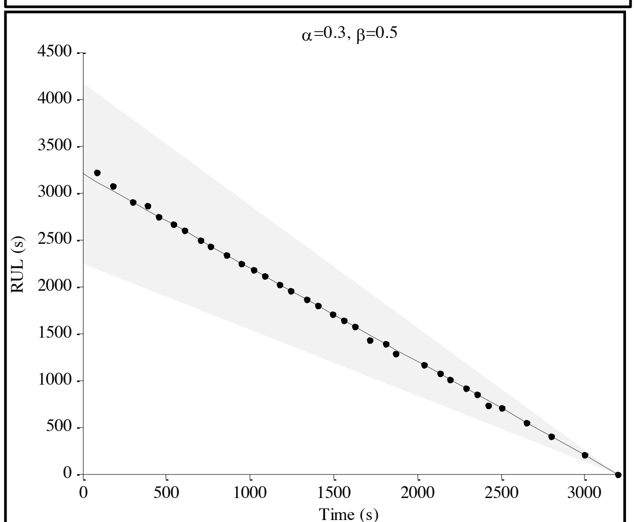


RUL and Validation – TOS -Experiment - Capacitance

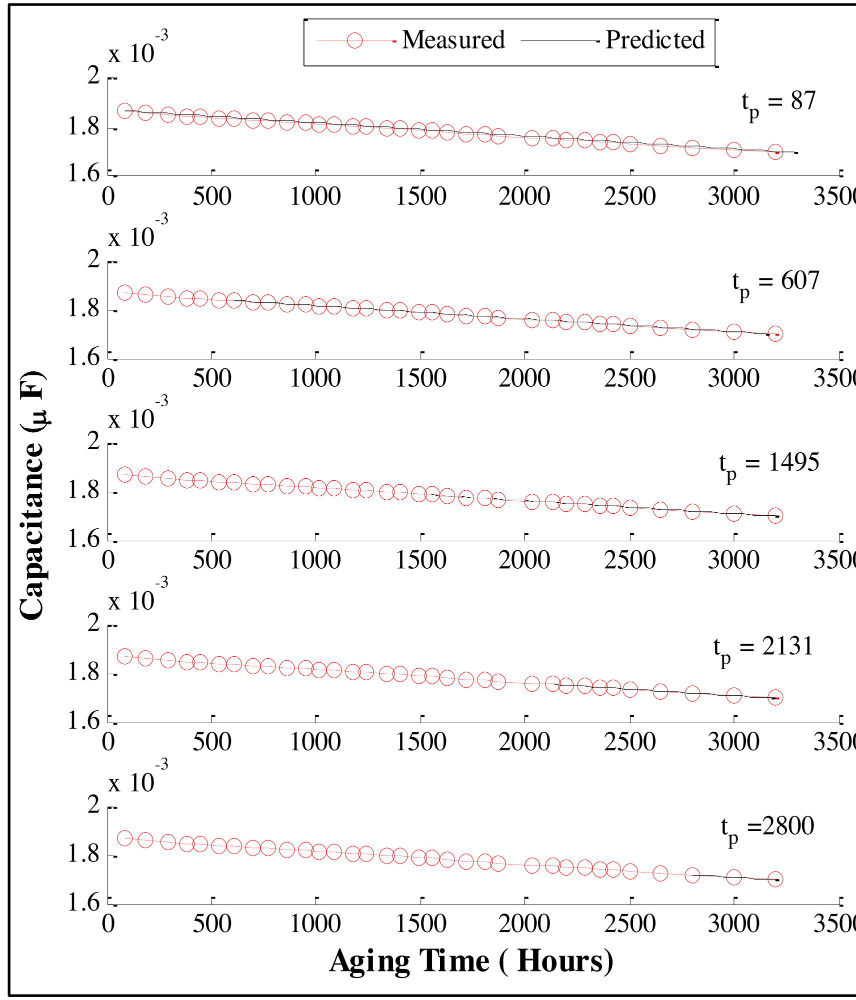
Tracking



Alpha Lambda



Predictions at different aging time



End of Case Study III:

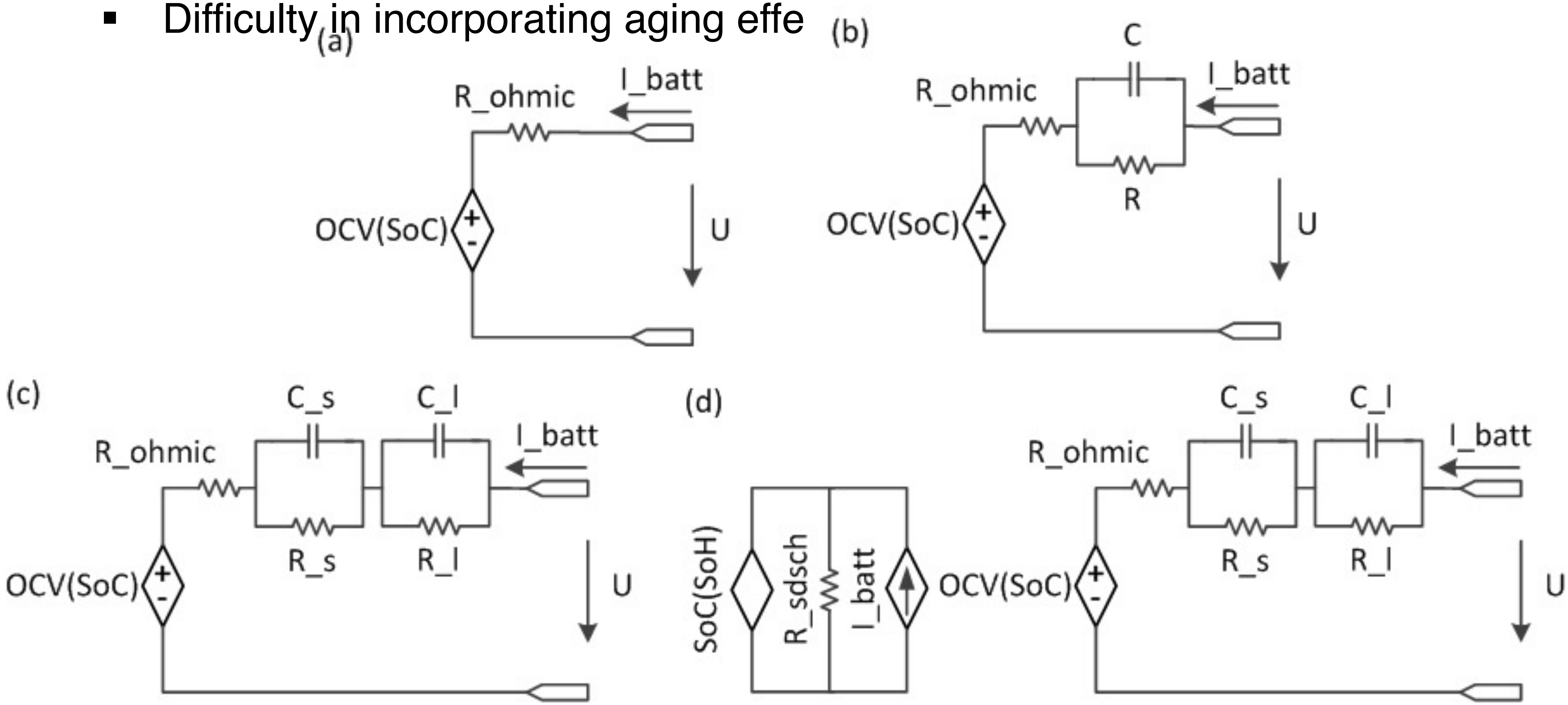
DISCUSSION AND QUESTIONS?

CASE STUDY IV: PROGNOSTICS OF LI-ION BATTERIES

DEGRADATION MODELING EXAMPLE

Battery Modeling

– <u>Equivalent Circuit Empirical Models</u>
  - Most common approach
  - Various model complexities used
  - Difficulty in incorporating aging effe



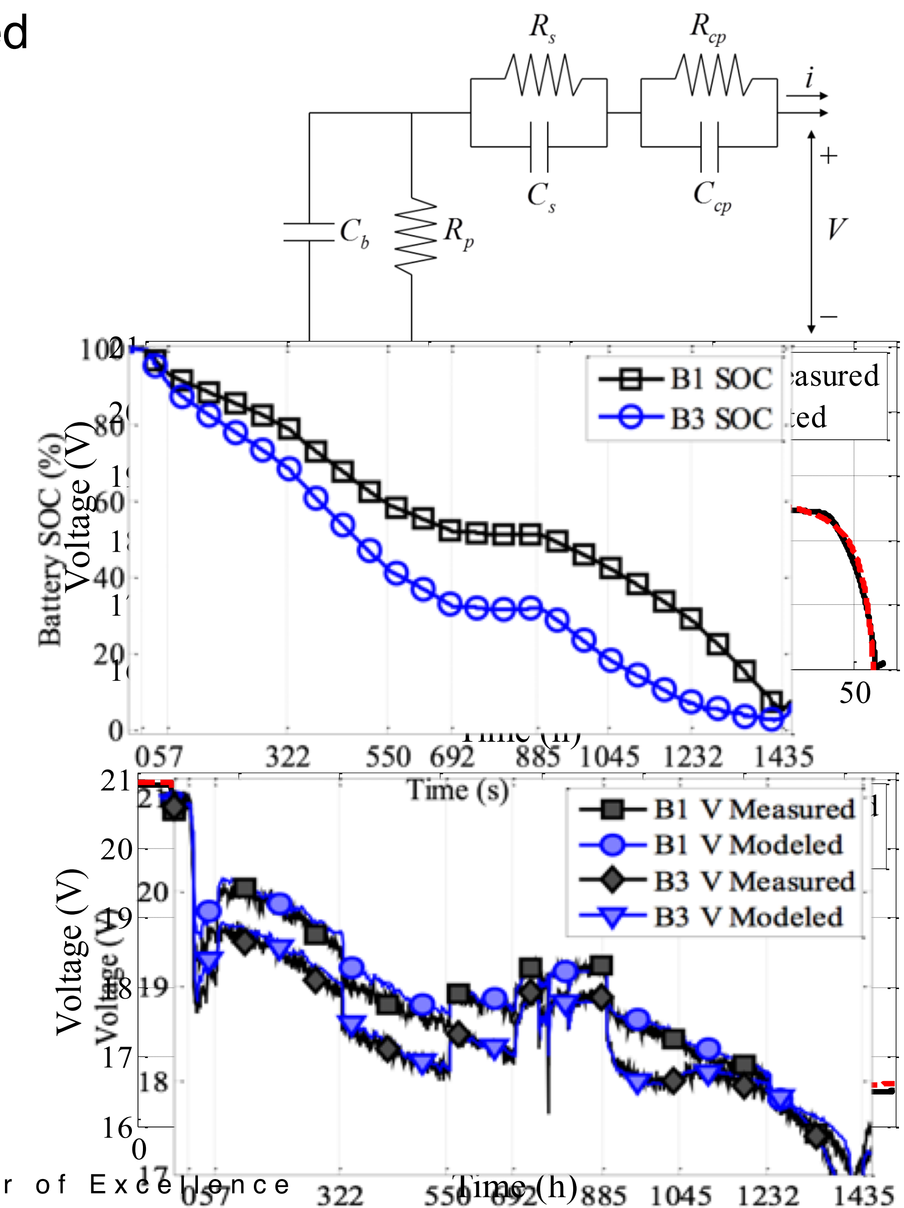
Battery Model – Tuned using Lab Data

- An equivalent circuit battery model is used to represent the battery terminal voltage as a function of current and the charge stored in 3 capacitive elements

$$x = [q_b \; q_{cp} \; q_{Cs}]^T$$

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{R_{cp}C_{cp}} & 0 \\ 0 & 0 & -\frac{1}{R_s C_s} \end{bmatrix} x + \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} i + \xi$$

$$y = V = \begin{bmatrix} \frac{1}{C_b} & -\frac{1}{C_{cp}} & -\frac{1}{C_s} \end{bmatrix} \cdot x$$



- Two laboratory loading experiments are used to fit the following parameterization coefficien'

$$\mathrm{SOC} = 1 - \frac{q_{max} - q_b}{C_{max}}$$

$$C_b = C_{Cb0} + C_{Cb1} \cdot \mathrm{SOC} + C_{Cb2} \cdot \mathrm{SOC}^2 + C_{Cb3} \cdot \mathrm{SOC}^3$$

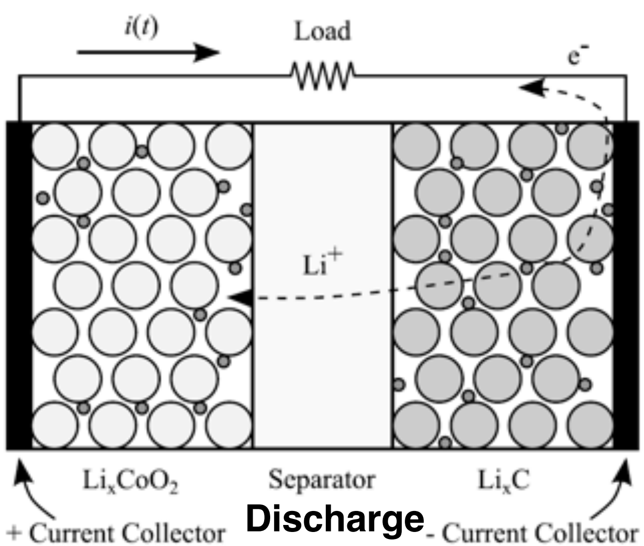
$$C_{cp} = C_{cp0} + C_{cp1} \cdot \exp\left(C_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

$$R_{cp} = R_{cp0} + R_{cp1} \cdot \exp\left(R_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

Battery Modeling

– Electrochemical Models vs. Empirical Models

- Battery physics models enable more direct representation of age-related changes in battery dynamics than empirical models
- Typically have a higher computational cost and more unknown parameters



Discharge

Reduction at pos. electrode:

$Li_{1-n}CoO_2 + nLi^+ + ne^- \rightarrow LiCoO_2$

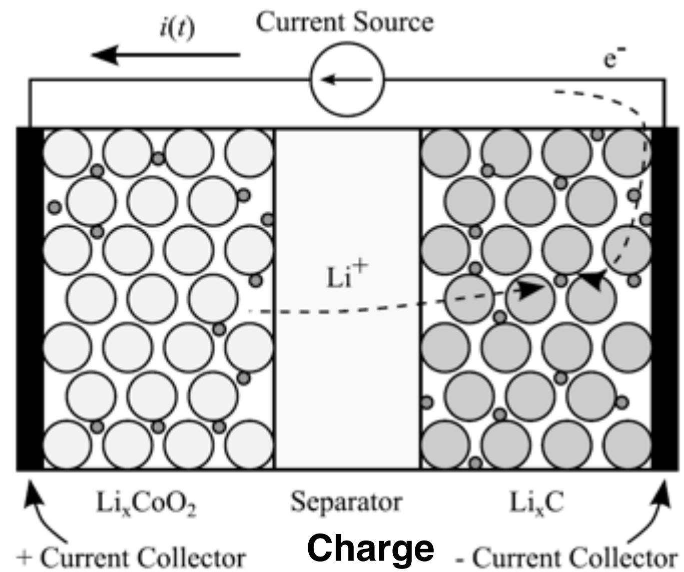
Oxidation at neg. electrode:

$Li_nC \rightarrow nLi^+ + ne^- + C$

Current flows + to –

Electrons flow – to +

Lithium ions flow – to +



Charge

Oxidation at pos. electrode:

$LiCoO_2 \rightarrow Li_{1-n}CoO_2 + nLi^+ + ne^-$

Reduction at neg. electrode:

$nLi^+ + ne^- + C \rightarrow Li_nC$

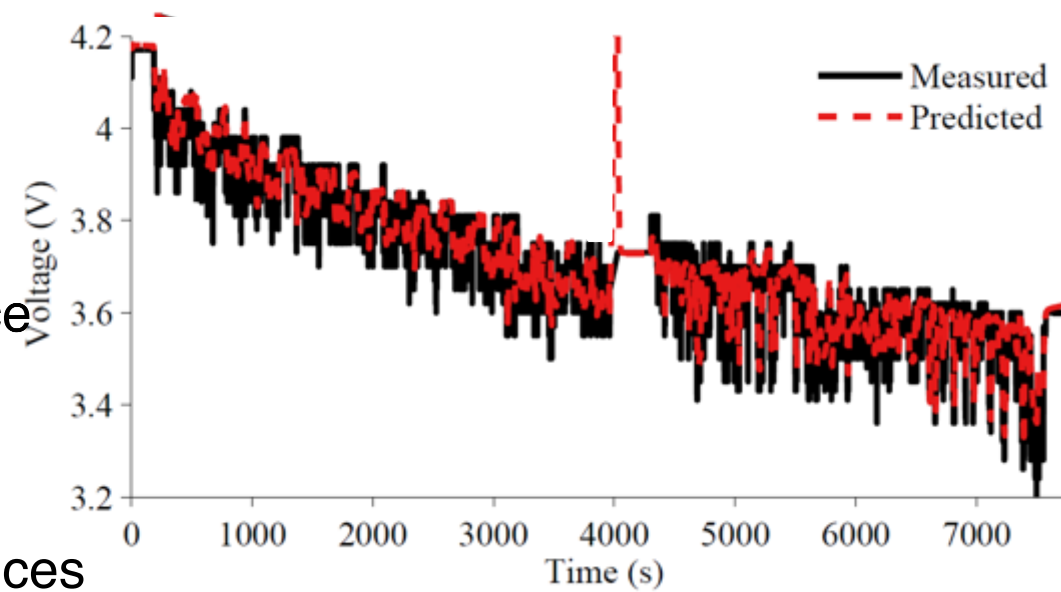
Current flows – to +

Electrons flow + to –

Lithium ions flow + to –

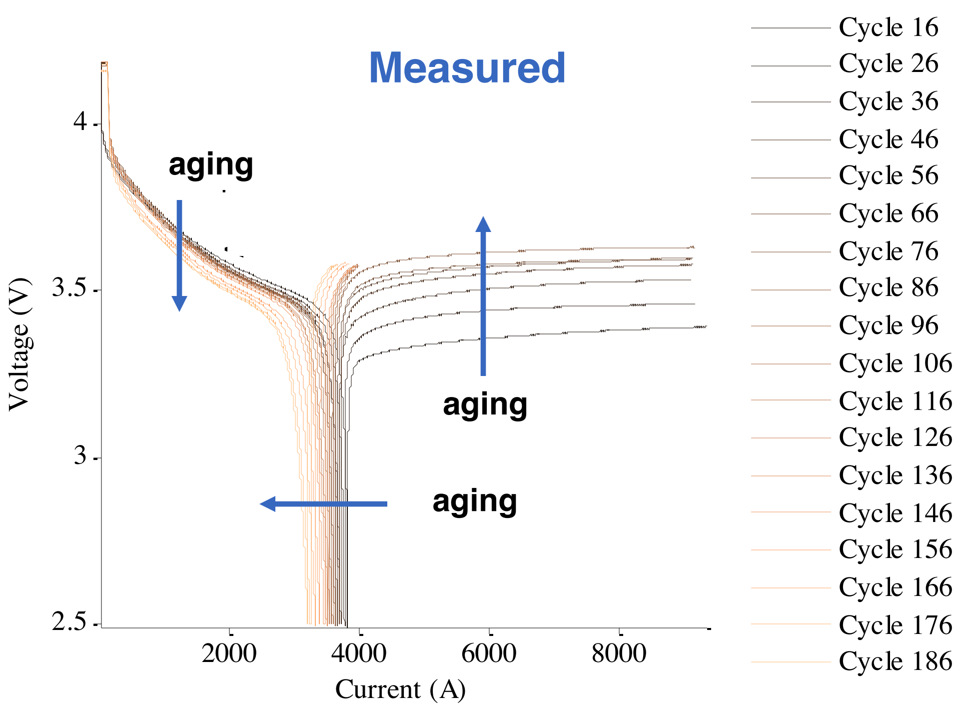
Electrochemical Li-ion Model

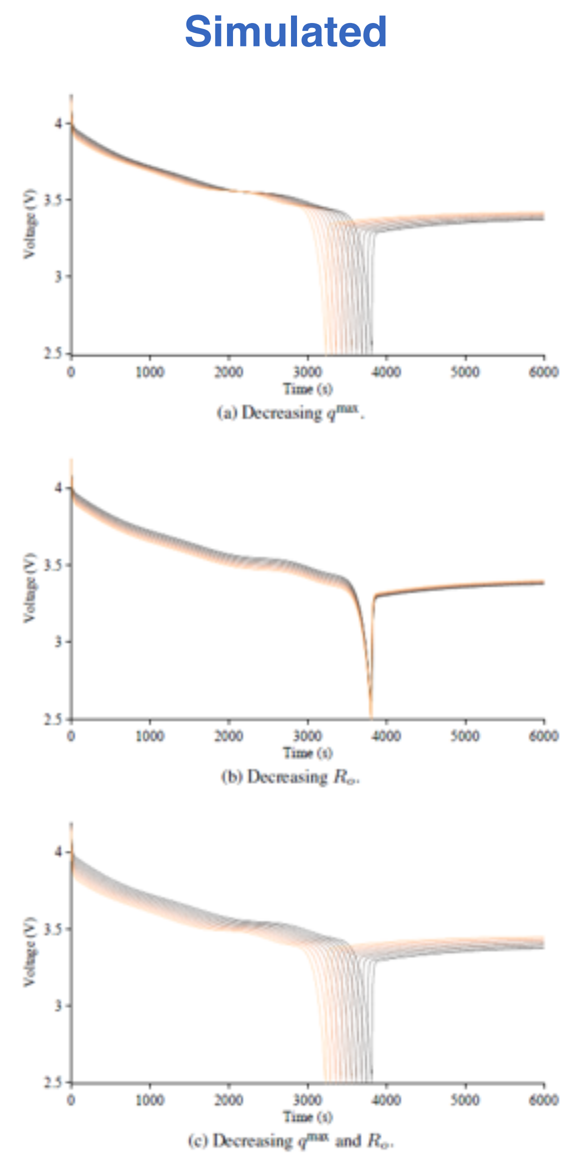
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control volumes
  - Surface overpotential → Butler-Volmer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



Battery Aging

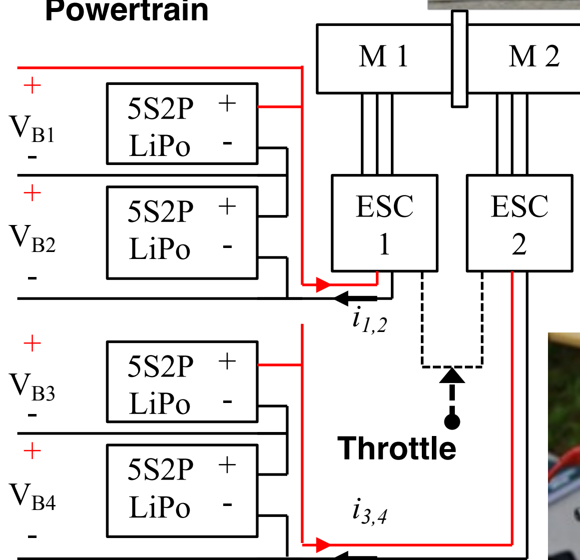
- Contributions from both decrease in mobile Li ions (lost due to side reactions related to aging) and increase in internal resistance
  - Modeled with decrease in “q^{max}” parameter, used to compute mole fraction
  - Modeled with increase in “R_o” parameter capturing lumped resistances





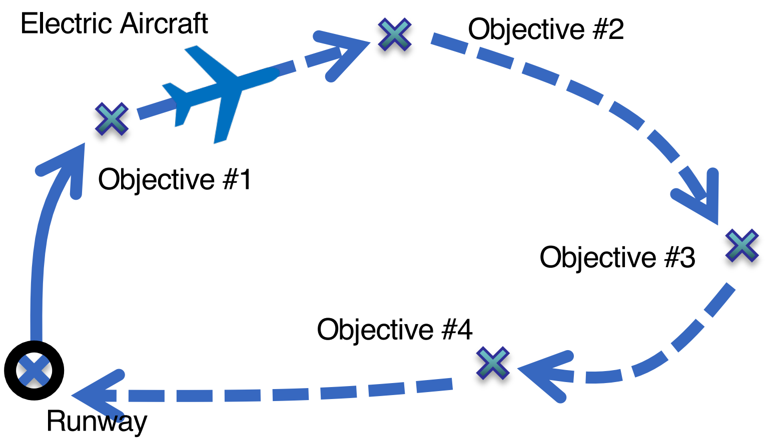
Edge 540-T

- Subscale electric aircraft operated at NASA Langley Research Center
- Powered by four sets of Li-polymer batteries
- Estimate SOC online and provide EOD and remaining flight time predictions for ground-based pilots



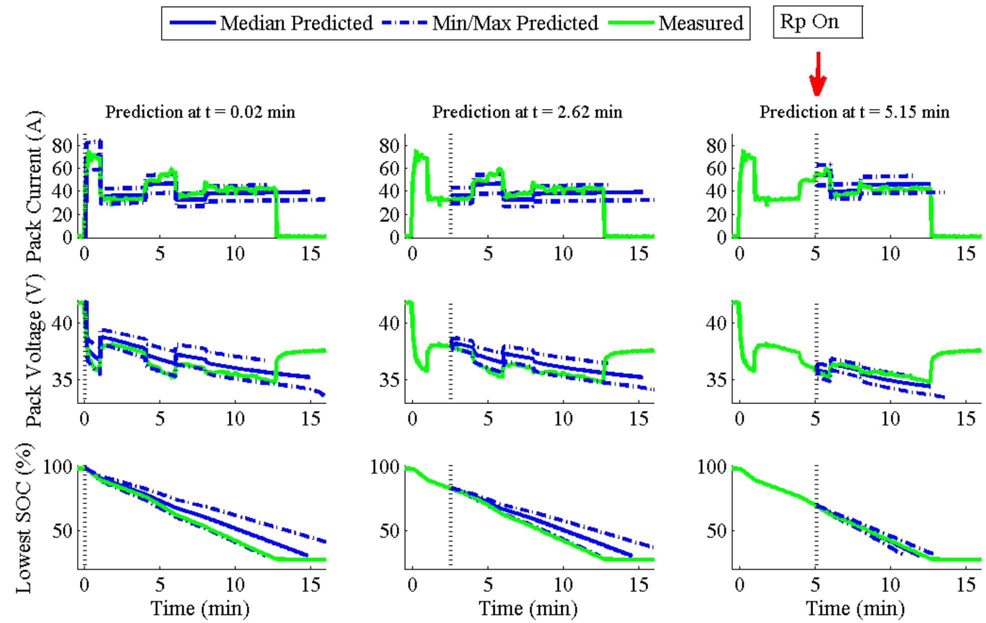
Edge UAV Use Case

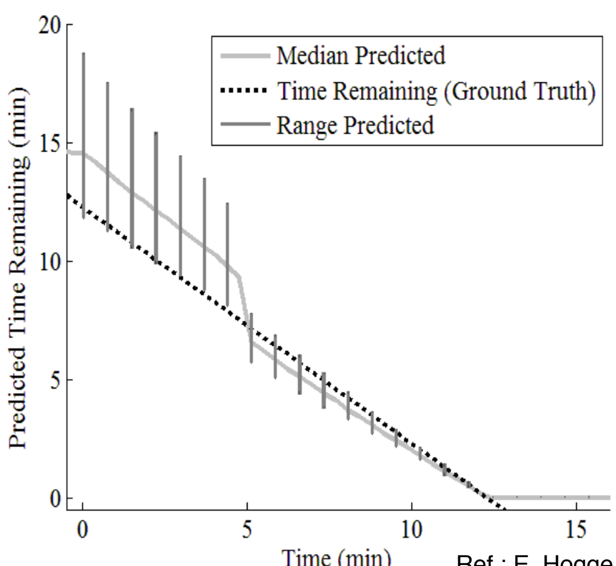
- Piloted and autonomous missions, visiting waypoints
- Require 2-minute warning for EOD so pilot/autopilot has sufficient time to land safely
  - This answer depends on battery age
  - Need to track both current level of charge and current battery age
  - Based on current battery state, current battery age, and expected future usage, can predict EOD and correctly issue 2-minute warning



Predication over Flight Plan

- Measured and predicted battery current, voltage and SOC different time steps
- The min, max and median predictions are plotted from each sample time until the predicated SOC reaches 30%



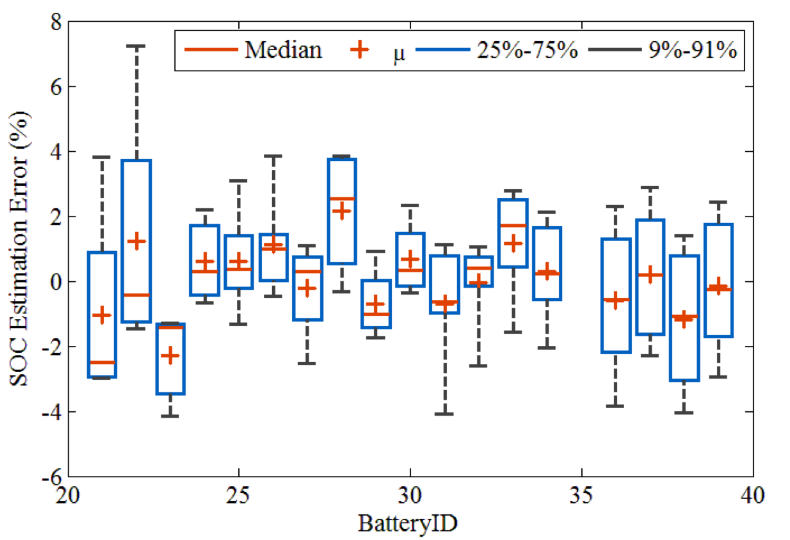


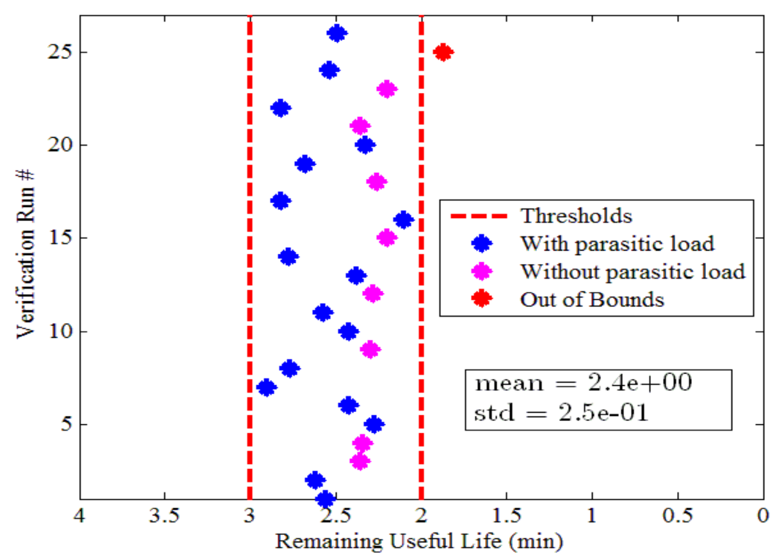
- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

Ref : E. Hogge et al, "Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft", PHM 2015

Performance Requirements

- Accuracy requirements for the two minute warning were specified as:
  – *The prognostic algorithm shall raise an alarm no later than two minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  – *The prognostic algorithm shall raise an alarm no earlier than three minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  – *Verification trial statistics must be computed using at least 20 experimental runs*





End of Case Study IV:

DISCUSSION AND QUESTIONS?

Data Sets Available for Download

- https://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/

Randomized Battery Usage Data Set
Publications using this data set

Description	Batteries are continuously cycled with randomly generated current profiles. Reference charging and discharging cycles are also performed after a fixed interval of randomized usage in order to provide reference benchmarks for battery state of health.
Format	
Datasets	+ Download Randomized Battery Usage Data Set 1 (1285 downloads) + Download Randomized Battery Usage Data Set 2 (936 downloads) + Download Randomized Battery Usage Data Set 3 (906 downloads) + Download Randomized Battery Usage Data Set 4 (4217 downloads) + Download Randomized Battery Usage Data Set 5 (825 downloads) + Download Randomized Battery Usage Data Set 6 (890 downloads) + Download Randomized Battery Usage Data Set 7 (857 downloads)
Dataset Citation	B. Bole, C. Kulkarni, and M. Daigle "Randomized Battery Usage Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	B. Bole, C. Kulkarni, and M. Daigle, 'Adaptation of an Electrochemistry-based Li-Ion Battery Model to Account for Deterioration Observed Under Randomized Use', Annual Conference of the Prognostics and Health Management Society, 2014

HIRF Battery Data Set
Publications using this data set

Description	Battery Data collected from the Experiments on the Edge 540 Aircraft in HIRF Chamber. Refernce document can be downloaded here
Format	The set is in .mat format and has been zipped.
Datasets	+ Download HIRF Battery Data Set 1 (184 downloads) + Download HIRF Battery Data Set 2 (127 downloads) + Download HIRF Battery Data Set 3 (131 downloads) + Download HIRF Battery Data Set 4 (125 downloads) + Download HIRF Battery Data Set 5 (149 downloads) + Download HIRF Battery Data Set 6 (135 downloads)
Dataset Citation	C. Kulkarni, E. Hogge, C. Quach and K. Goebel "HIRF Battery Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft. Edward F. Hogge, Brian M. Bole, Sixto L. Vazquez, Jose R., Annual Conference of the Prognostics and Health Management, PHM 2015

CLOSING REMARKS

Remarks (1/2)

- Electrical and Electronics PHM Maturity - scientific and engineering challenges
- Research approach challenges
  - How to balance lack of knowledge of the system vs own expertise on particular PHM tools
  - Data-driven or model-based?
    - Data is always needed but more important, information about degradation/aging processes is key
    - Experiments and field data

Remarks (2/2)

- Aging systems as a research tool
  - Value in terms of exploration of precursors of failure and their measurements is evident
  - Still an open question on how degradation models and algorithms are translated to the real usage timescale
- In the use of physics
  - It should be embraced
- Validate models and algorithms with data from lab experiments and fielded systems
- A success in developing PHM methodologies in an real usage application will require the right team

Publications (1/3)

[1] C. Kulkarni, G. Biswas, X. Koutsoukos, J. Celaya, and K. Goebel, "Integrated diagnostic/prognostic experimental setup for capacitor degradation and health monitoring," in *IEEE AUTOTESTCON, 2010*, (Big Sky, MT), pp. 1–7, 2010.

[2] C. Kulkarni, G. Biswas, X. Koutsoukos, J. Celaya, and K. Goebel, "Aging methodologies and prognostic health management for electrolytic capacitors," in *Annual Conference of the Prognostics and Health Management Society 2010*, (Portland, OR), 2010.

[3] C. Kulkarni, G. Biswas, X. Koutsoukos, J. Celaya, and K. Goebel, "Diagnostic/prognostic experiments for capacitor degradation and health monitoring in DC-DC converters," in *ASME 2010 Conference on Smart Materials, Adaptive Structures and Intelligent Systems*, (Philadelphia, PA), 2010.

[4] J. Celaya, C. Kulkarni, G. Biswas, S. Saha and K. Goebel, "A Model-based Prognostics Methodology for Electrolytic Capacitors Based on Electrical Overstress Accelerated Aging", Proceedings of Annual Conference of the Prognostics and Health Management Society, September 25-29, 2011, Montreal, Canada.

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[8] J. R. Celaya, S. Saha, P. Wyscoki, and K. F. Goebel, "Effects of lightning injection on power-MOSFETs," in *Annual Conference of the Prognostics and Health Management Society, 2009*, (San Diego, CA), 2009.

Publications (2/3)

[9] N. Patil, J. Celaya, D. Das, K. Goebel, and M. Pecht, "Precursor parameter identification for insulated gate bipolar transistor (IGBT) prognostics," *IEEE Transactions on Reliability*, vol. 58, no. 2, pp. 271–276, 2009.

[10] B. Saha, J. R. Celaya, P. F. Wysocki, and K. F. Goebel, "Towards prognostics for electronics components," in *IEEE Aerospace conference 2009*, (Big Sky, MT), pp. 1–7, 2009.

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[12] J. Celaya, A. Saxena, P. Wysocki, S. Saha, and K. Goebel, "Towards prognostics of power MOSFETs: Accelerated aging and precursors of failure," in *Annual Conference of the Prognostics and Health Management Society 2010*, (Portland, OR), 2010.

[13] J. J. Ely, T. X. Nguyen, G. N. Szatkowski, S. V. Koppen, J. J. Mielnik, R. K. Vaughan, P. F. Wysocki, J. R. Celaya, and S. Saha, "Lightning pin injection testing on MOSFETS," *NASA Technical Memorandum*, vol. TM-2009-215794, 2009

[14] J. R. Celaya, P. Wysocki, V. Vashchenko, S. Saha, and K. Goebel, "Accelerated aging system for prognostics of power semiconductor devices," in *IEEE AUTOTESTCON, 2010*, (Orlando, FL), pp. 1–6, 2010.

[15] A. E. Ginart, I. N. Ali, J. R. Celaya, P. W. Kalgren, D. P. S, and M. J. Roemer, "Modeling SiO2 ion impurities aging in insulated gate power devices under temperature and voltage stress," in *Annual Conference of the Prognostics and Health Management Society 2010*, (Portland, OR), 2010.

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Publications (3/3)

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[21] Raj Bharadwaj, K. Kim, C. Kulkarni, G. Biswas, “Model-Based Avionics Systems Fault Simulation and Detection ”, American Institute of Aeronautics and Astronautics, Infotech@Aerospace 2010, April 2010, Atlanta, GA.

[22] C. Kulkarni, G. Biswas, J. Celaya, and K. Goebel, “Prognostics techniques for capacitor degradation and health monitoring,” in *The Maintenance and Reliability Conference (MARCON)*, (Knoxville TN), 2011.

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[24] E. Hogge, , C. Kulkarni, S. Vazquez, K. Smalling, T. Strom, B. Hill, C. Quach “Flight Tests of a Remaining Flying Time Prediction System for Small Electric Aircraft’, Proceedings of the Annual Conference of the Prognostics and Health Management Society 2017 (to be published)

[25] G. Gorospe, C. Kulkarni, E. Hogge, A. Hsu, N. Ownby, “A Study of the Degradation of Electronic Speed Controllers for Brushless DC Motors”, Proceedings Asia Pacific Conference of the Prognostics and Health Management Society 2017, Jeju, South Korea (to be published)

THANK YOU!

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