Prognostics and Health Monitoring in Li-ion Batteries and Capacitors using Physics-based Modeling Approach

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http://prognostics.nasa.gov

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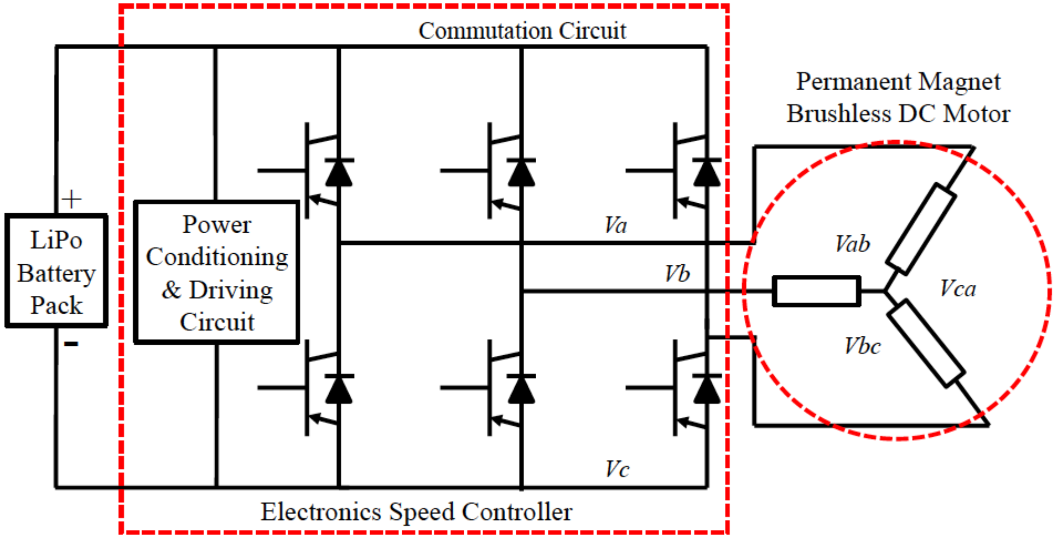
Motivation

- 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
  - Powertrain subsystems and components
  - Batteries are the sole energy storage
  - 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



- 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

Agenda

- Introduction to Prognostics
- Introduction to Model-based Prognostics
- Research Approach
  - Architecture
  - Accelerated Aging as a Prognostics Research Tool
- Case Study I: Electrolytic Capacitors
- Case Study II: Li-Ion Batteries
- Closing Remarks

INTRODUCTION TO PROGNOSTICS

Definitions

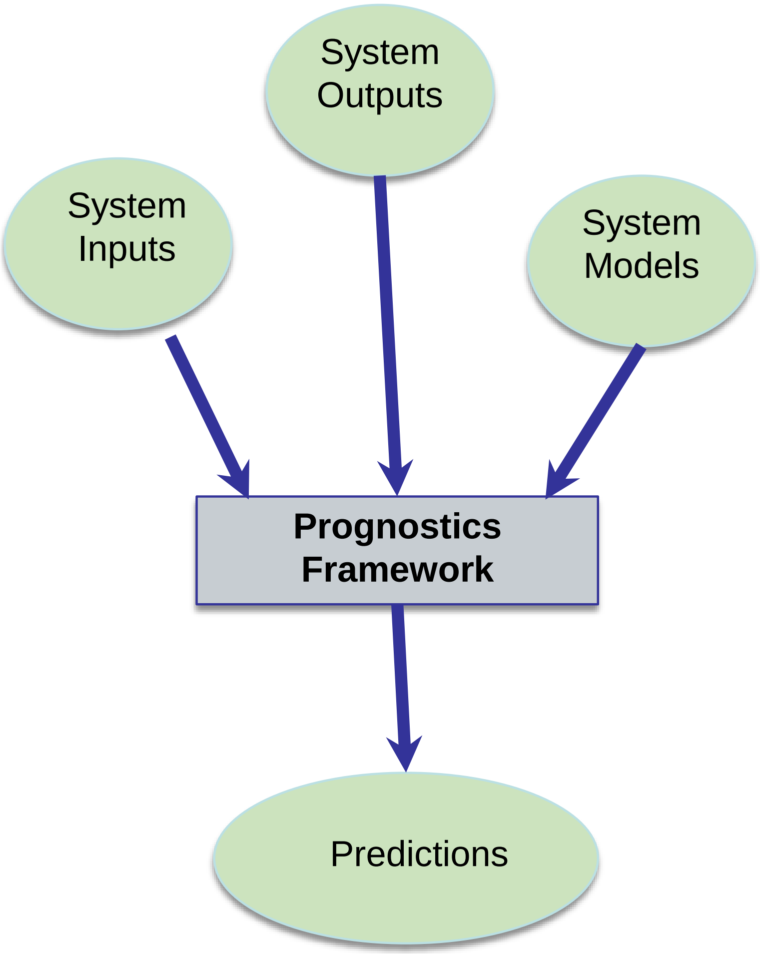
So what is "Prognostics" anyway?

- 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

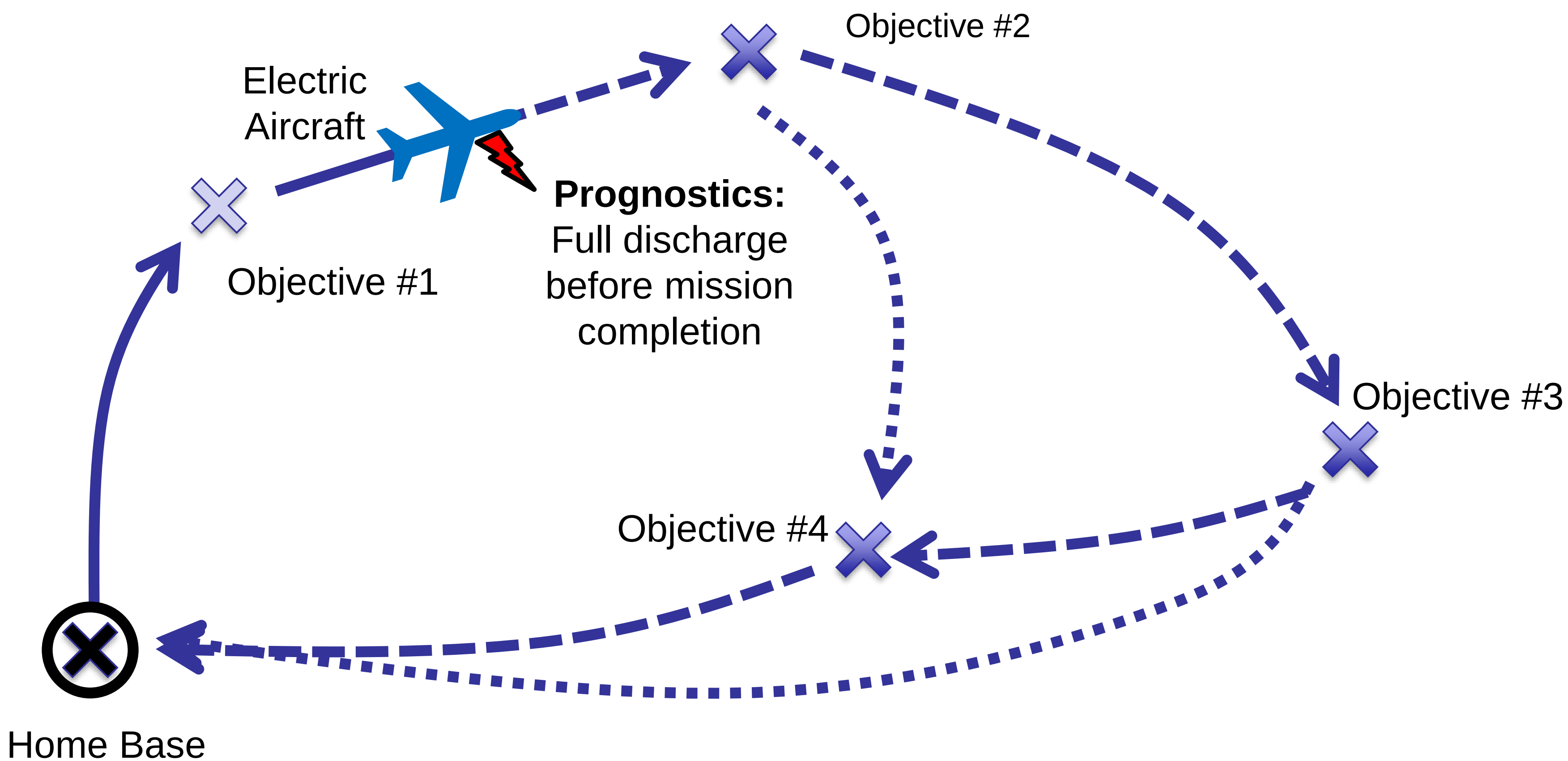
Why Model-Based Prognostics?

- With model-based algorithms, models are inputs
  - 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



Why Prognostics?

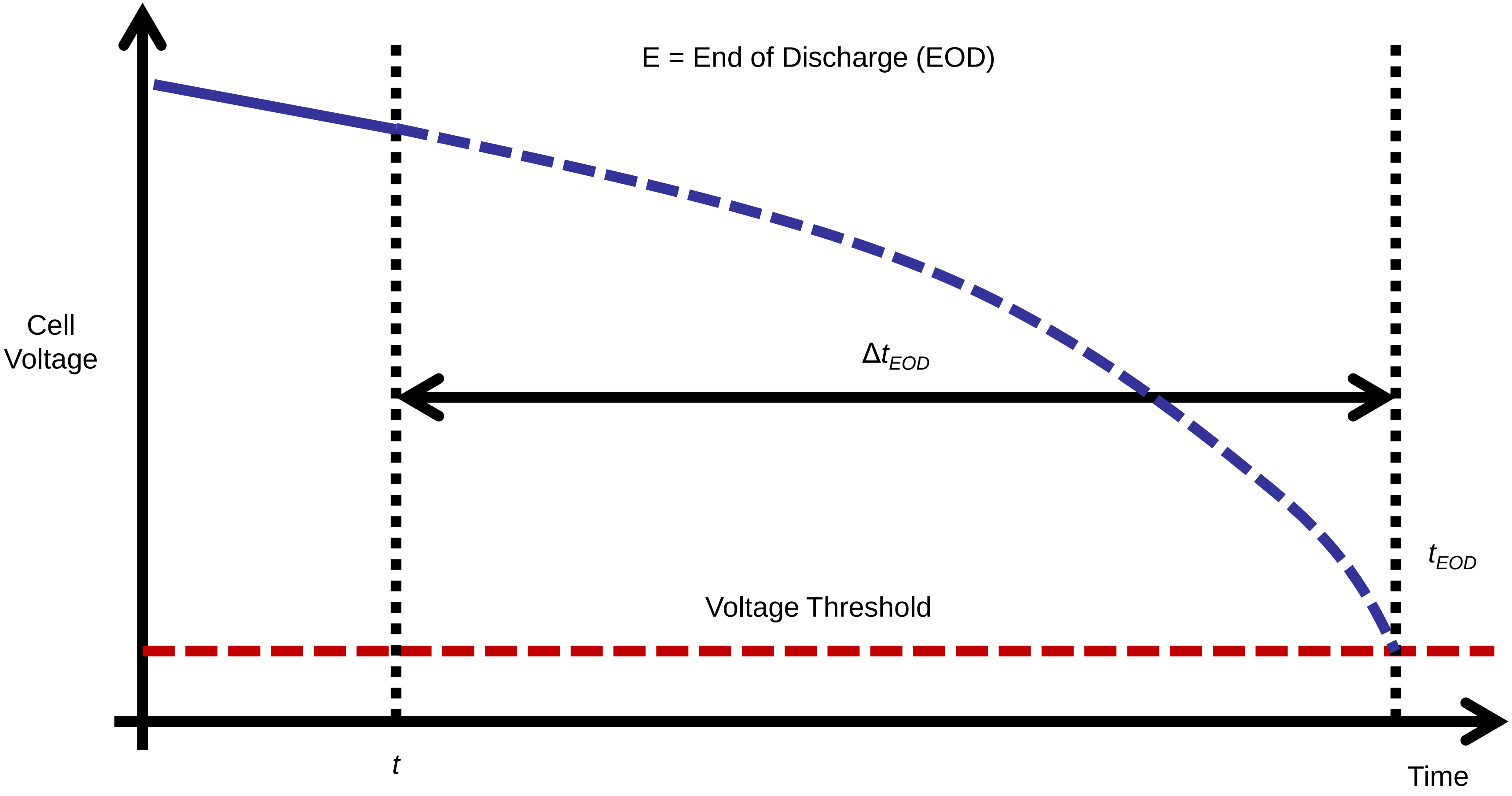
Example: UAV Mission
Visit waypoints to accomplish science objectives. Predict aircraft battery end of discharge to determine which objectives can be met. Based on prediction, plan optimal route. Replan if prediction changes.



Why Prognostics?

- Prognostics enables:
  - 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 : Batteries Example



PROGNOSTIC MEHTODS

Sources of Knowledge

- FMEA / FMECA
  - Failure modes
  - Effects (and Criticality) – which failure modes to go after
- Fault Tree Analysis
  - Propagation Models
- Designers / Reliability Engineers
  - System knowledge and insight
  - Expected / nominal behavior of the system
- Seeded Failure Testing / Accelerated Life Testing
  - Data
  - Failure signatures
  - Effects of environmental conditions
- Fielded Systems
  - Sensors measurements
  - Maintenance logs
  - Fleet Statistics
  - Performance Validation

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

RESEARCH APPROACH

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

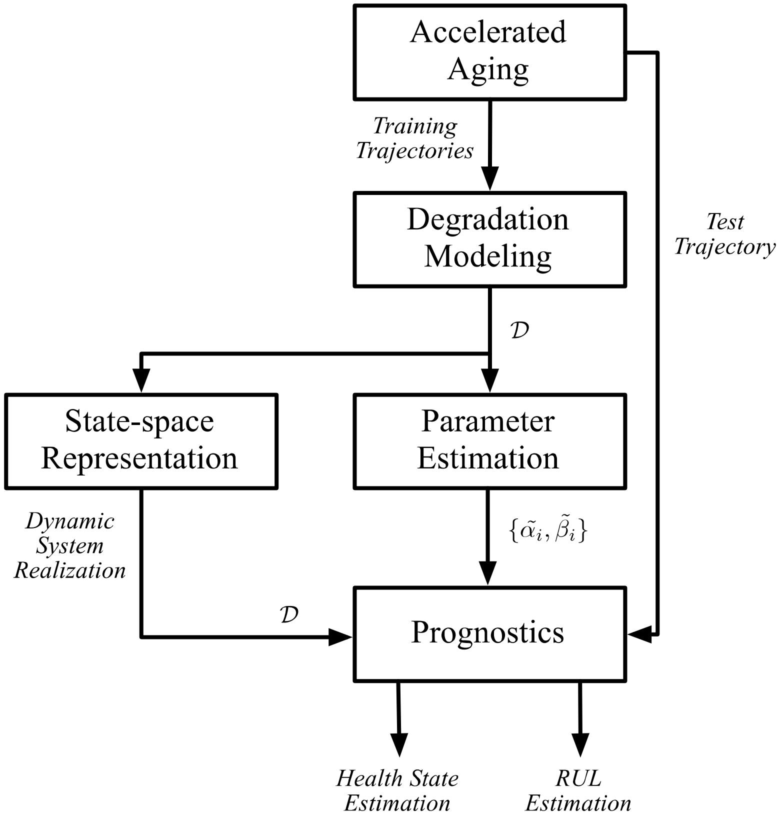
↓

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

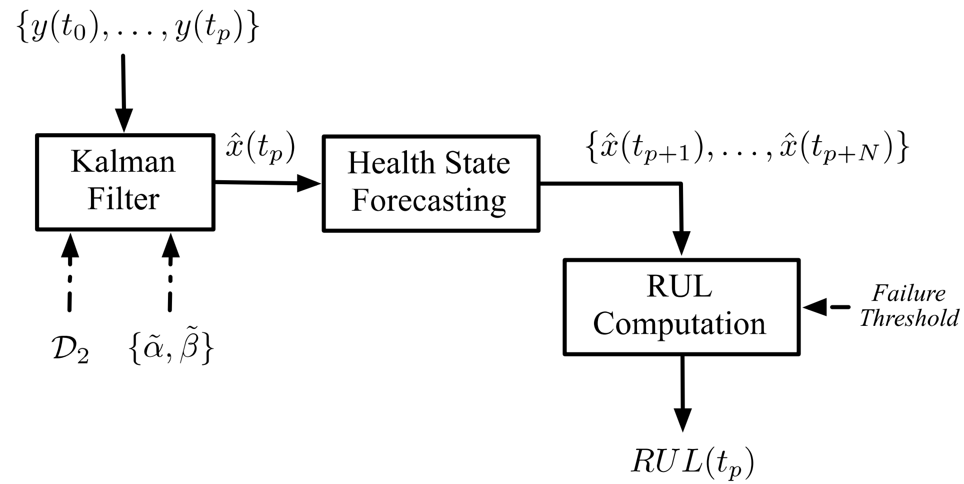
Methodology



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

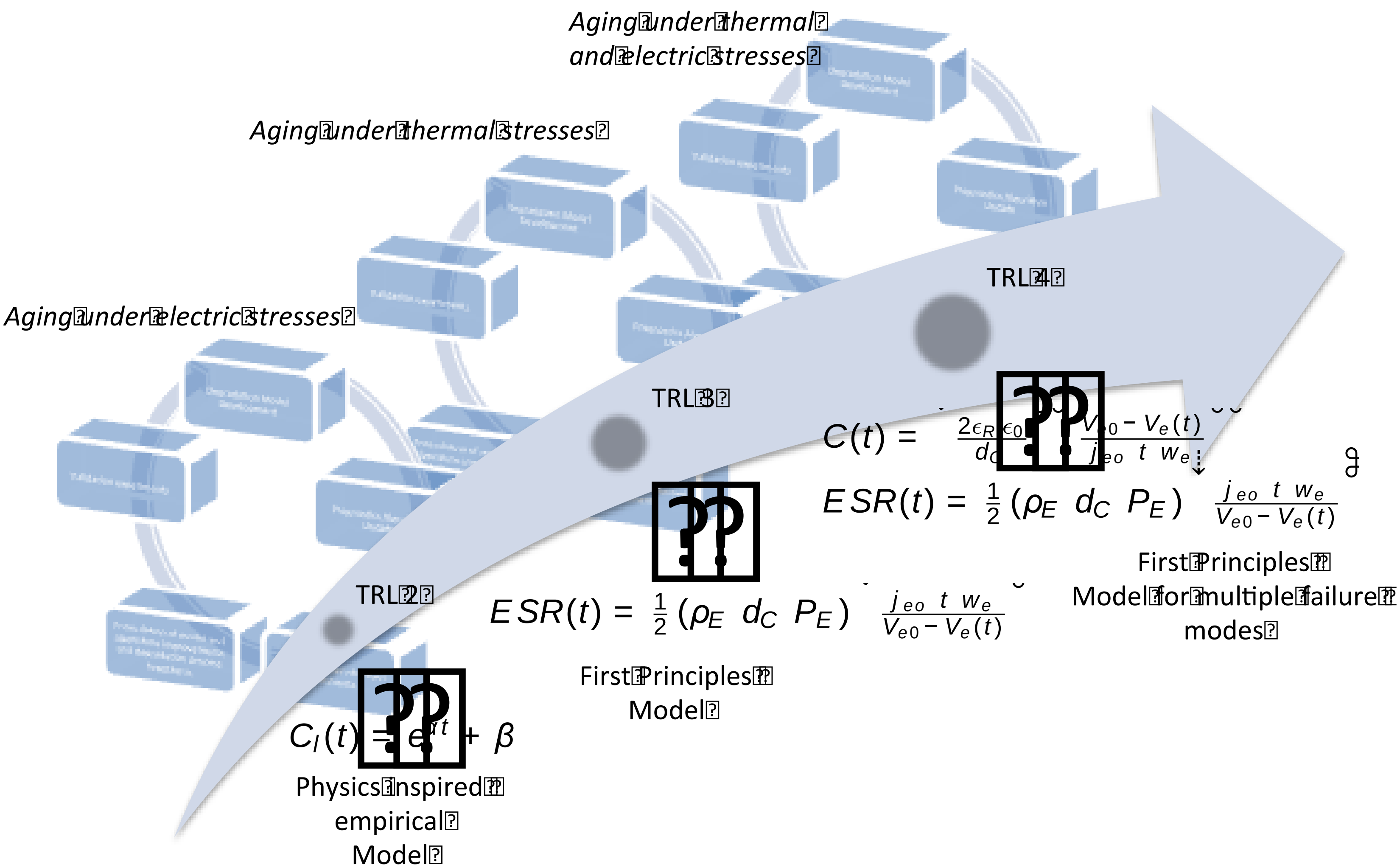
$$y_k = Hx_k + v_k$$

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



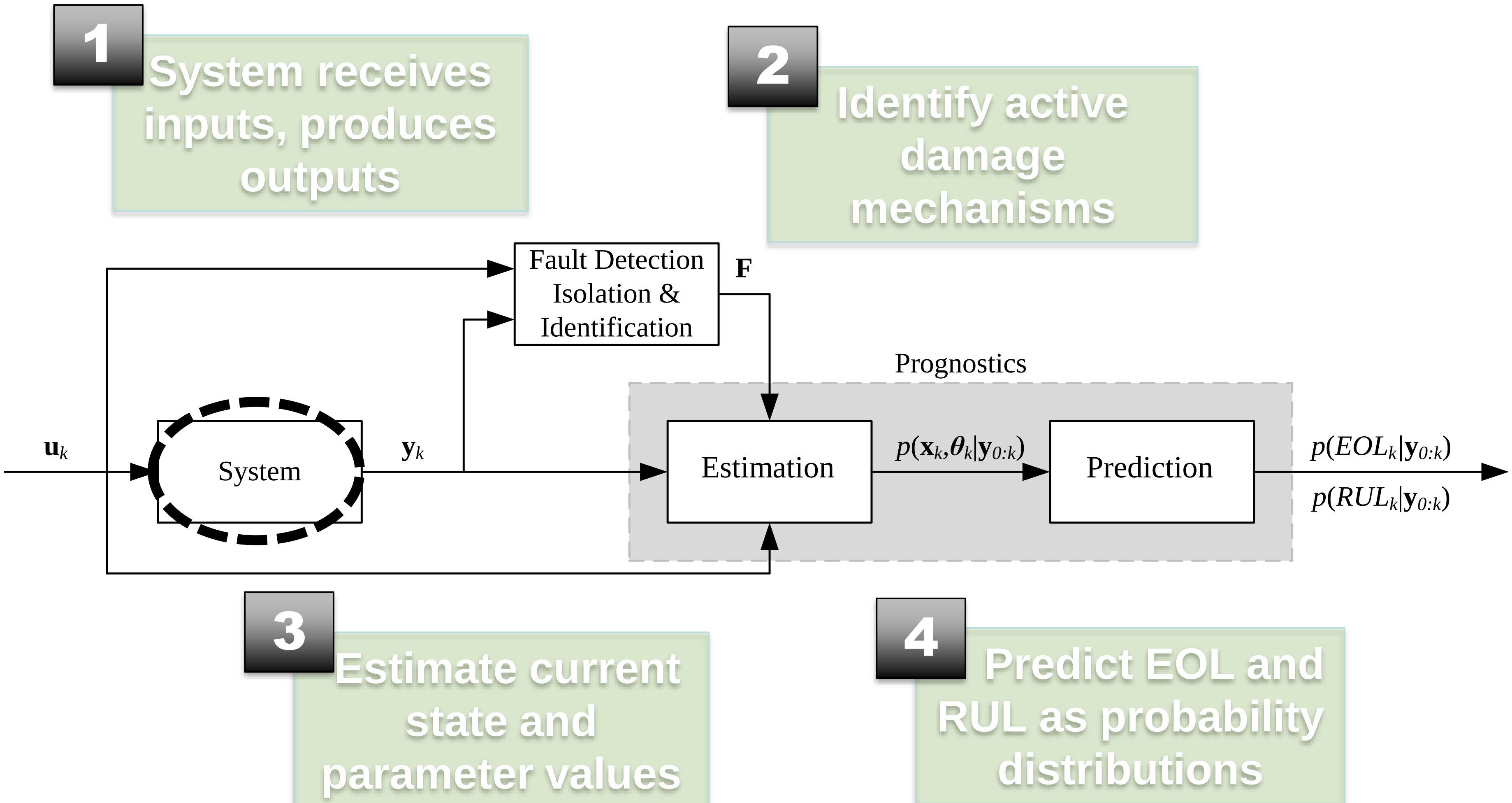
- State vector includes dynamics of operation/degradation process
- EOL defined at time in which performance variable cross failure threshold
- Failure threshold could be crisp or also a random variable

Algorithm Maturation through Validation Experiments



ARCHITECTURE

Model-Based Architecture



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

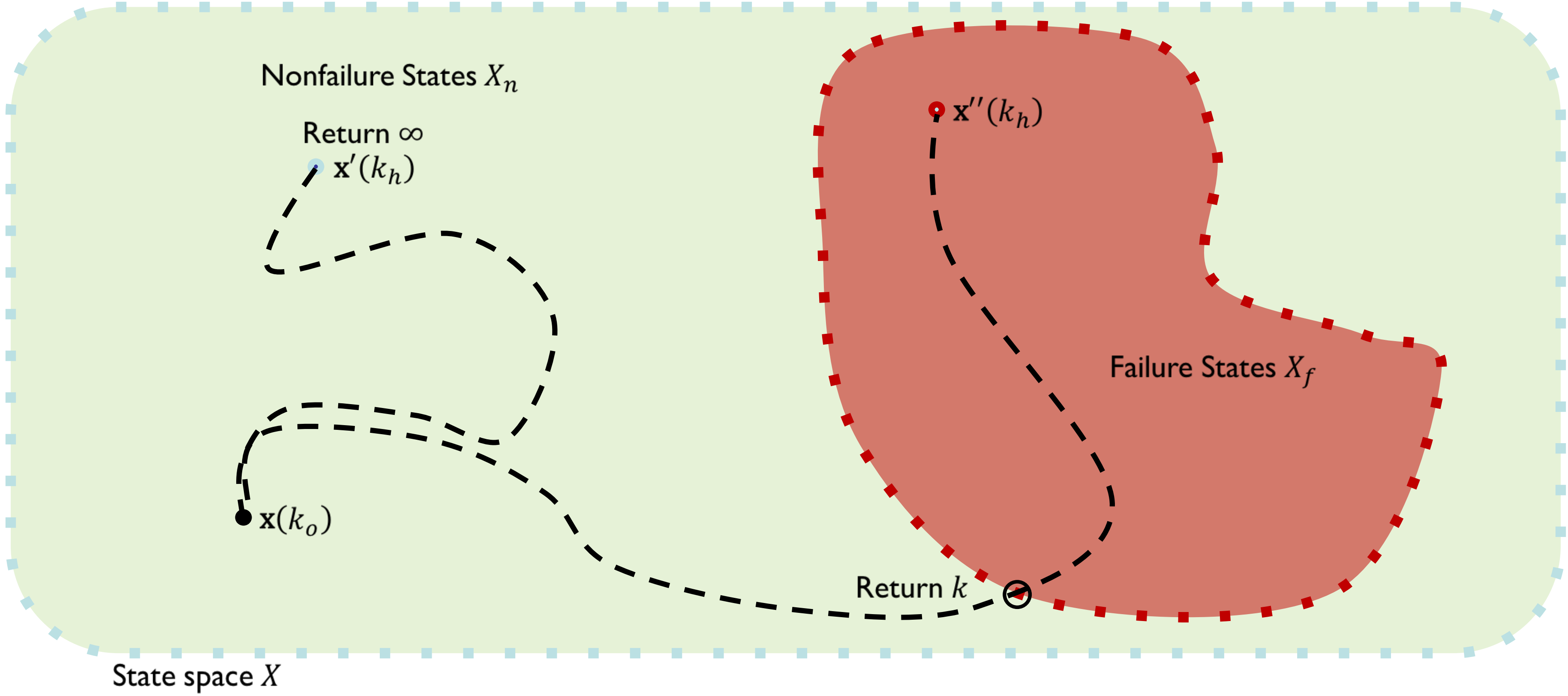
System Model

- 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
  - $T_f : \mathbb{R}^{n_x} \rightarrow \{true, false\}$
  - 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, $\mathbf{U}_{k_o,k_h} = [\mathrm{u}(k_o), \mathrm{u}(k_o + 1), \ldots, \mathrm{u}(k_h)]$
  - Process noise trajectory, $\mathbf{V}_{k_o,k_h} = [\mathrm{v}(k_o), \mathrm{v}(k_o + 1), \ldots, \mathrm{v}(k_h)]$
- 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*

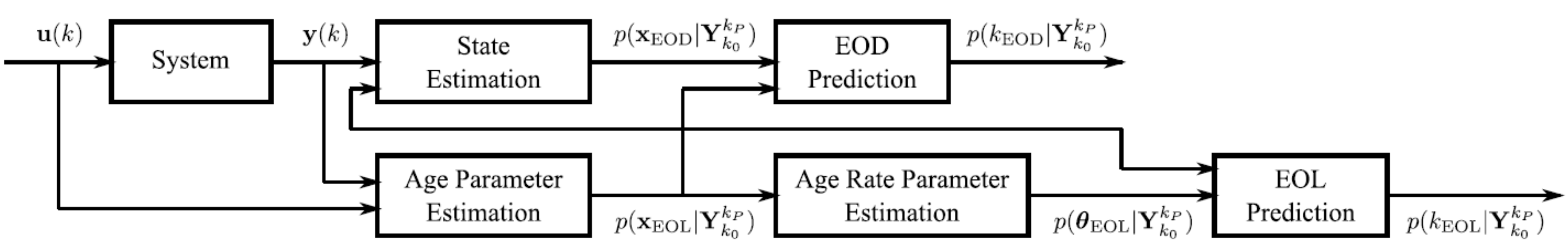
else

  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

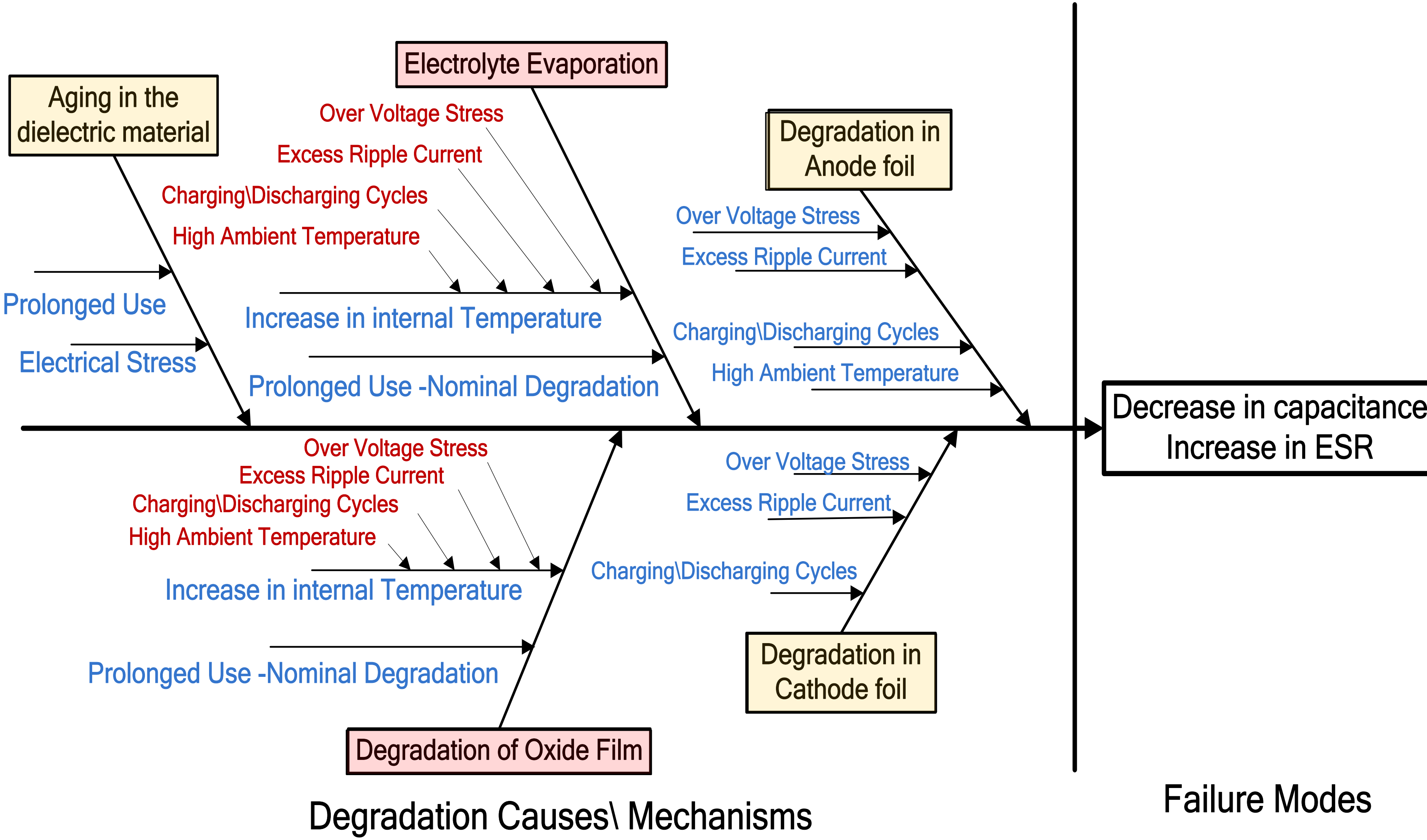
- Most algorithms operate by simulating samples forward in time until E
- Algorithms must account for several sources of uncertainty besides that in the initial state
  - A representation of that uncertainty is required for the selected prediction algorithm
  - A specific description of that uncertainty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

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

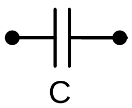
CASE STUDY I: CAPACITORS

Degradation Mechanisms



Capacitor Degradation Model

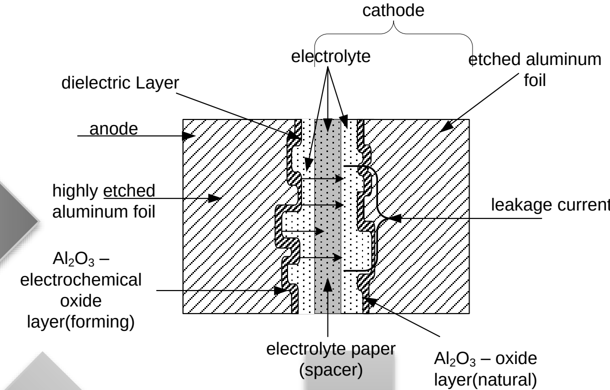
Pristine Capacitor



Ideal

Non- Ideal

Degradation



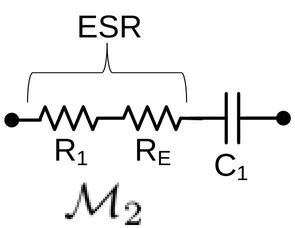
Electrolyte volume V_e maximum
Capacitance Value maximum

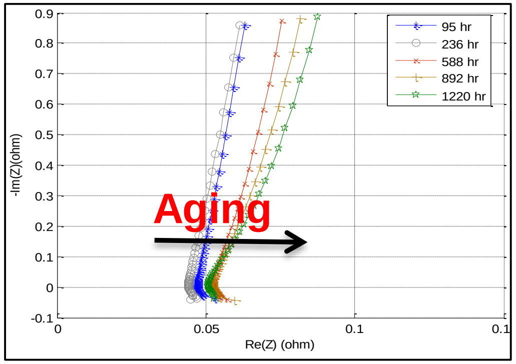
Thermal Stress

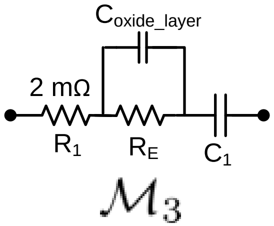
Electrical Stress

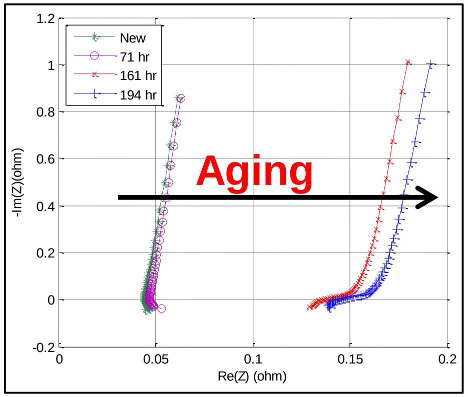
Avg. surface area decreases (A_s) + oxide layer breakdown

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









Capacitance Degradation Model

- Decrease in electrolyte volume :

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

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:

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

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

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

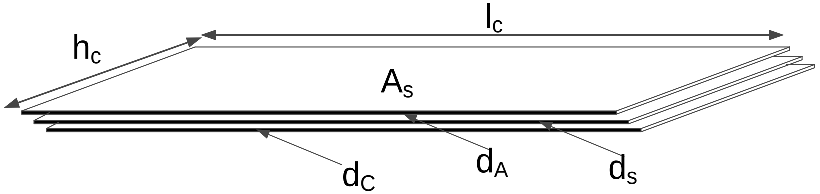
where:
C : capacitance of the capacitor,
ϵ_R : relative dielectric constant,
ϵ_O : permittivity of free space,
d_C : oxide thickness.

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 :

$$V_e = A_s.d_C,$$

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



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

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

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

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

Dynamic Model of Capacitance

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

Similarly Capacitace can be expressed as :

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

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)

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

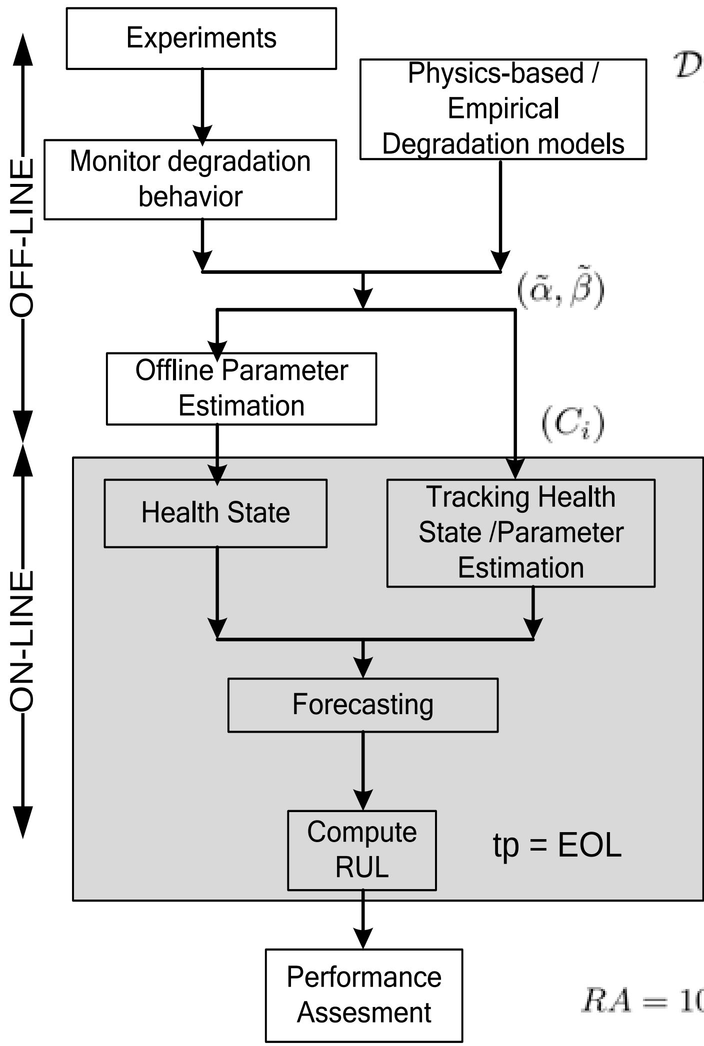
$$\mathcal{D}_2 : ESR(t) = \frac{1}{2}(\rho_E \; d_C \; P_E)\left(\frac{j_{eo} \; t \; w_e e_{bk(t)}}{V_e(t)}\right)$$

Dynamic ESR degradation Model :

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

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

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

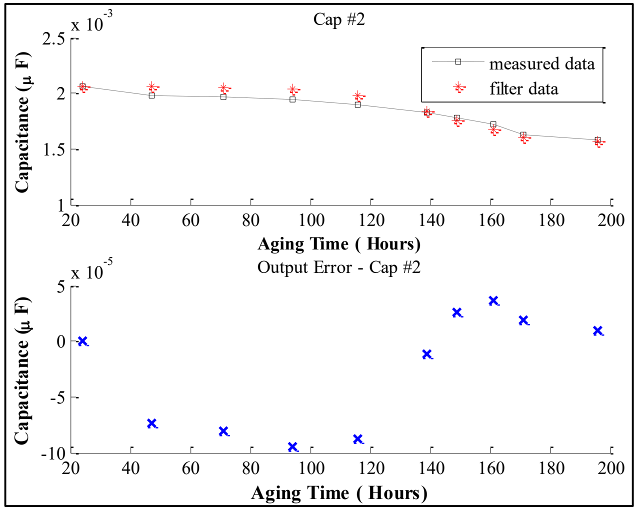
$$A = 1,$$
$$B = -\frac{(2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk})}{d_C^2} \Delta t,$$
$$H = 1,$$
$$u = j_{eo}, c_{bk}.$$

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

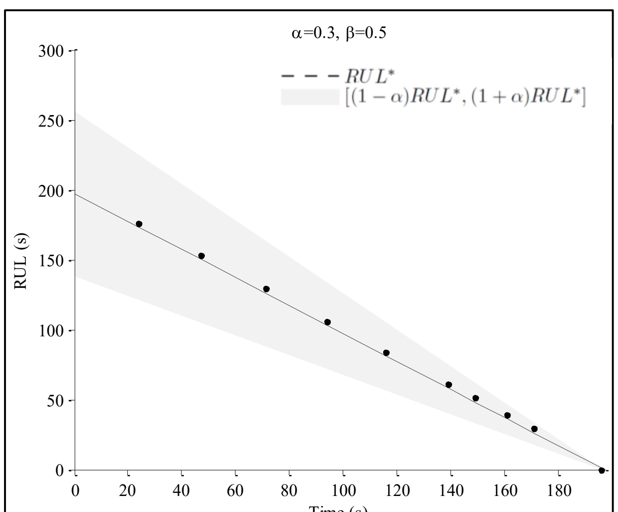
Process noise was estimated from the model regression for the empirical model
Measurement noise was estimated from the EIS measurements

RUL and Validation – Capacitance Degradation Model

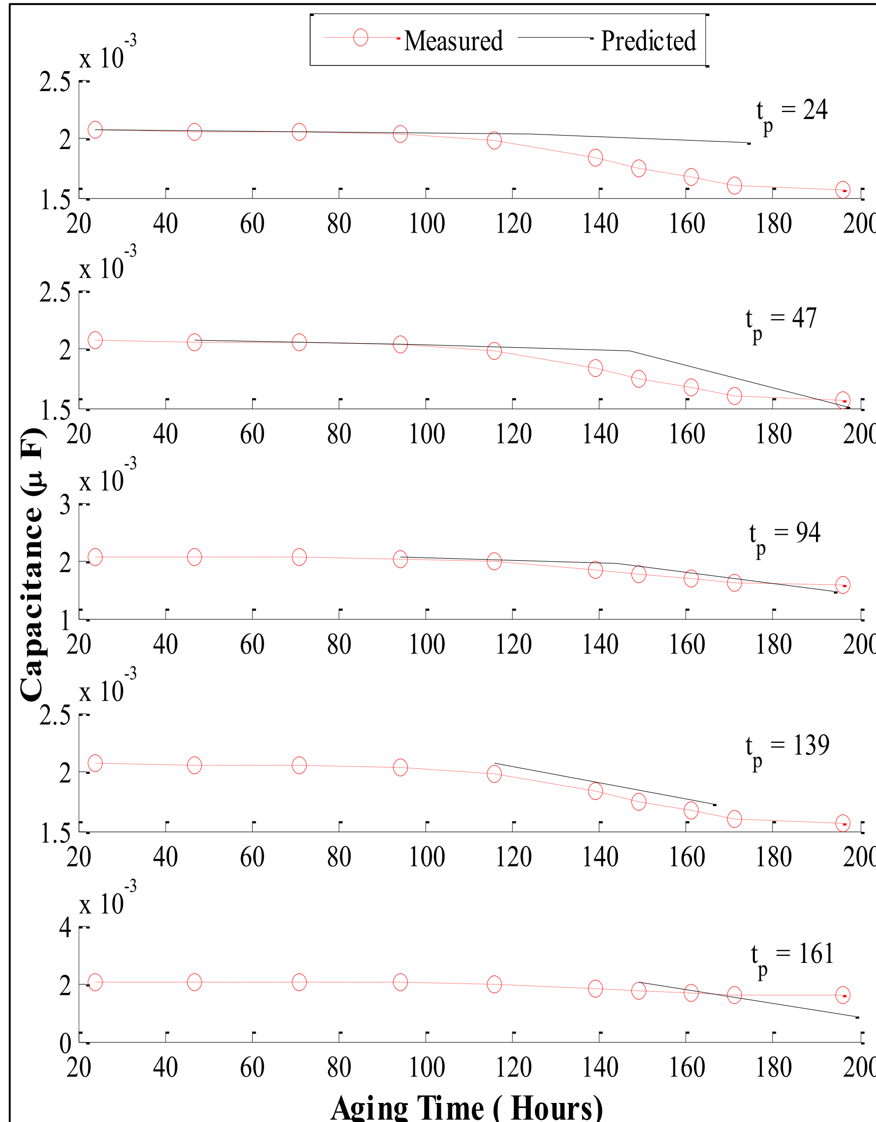
Tracking



Alpha Lambda

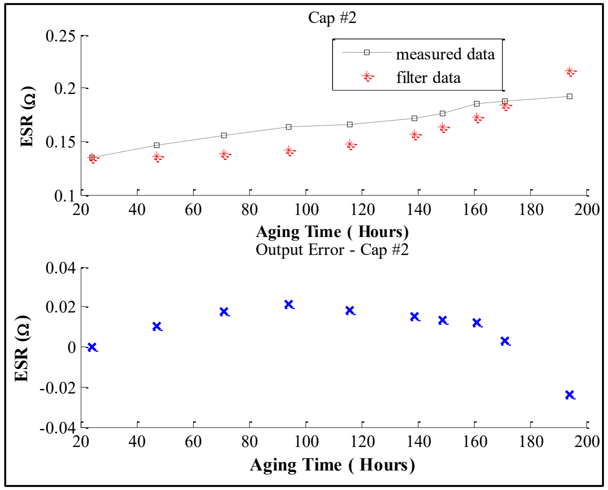


Predictions at different aging time

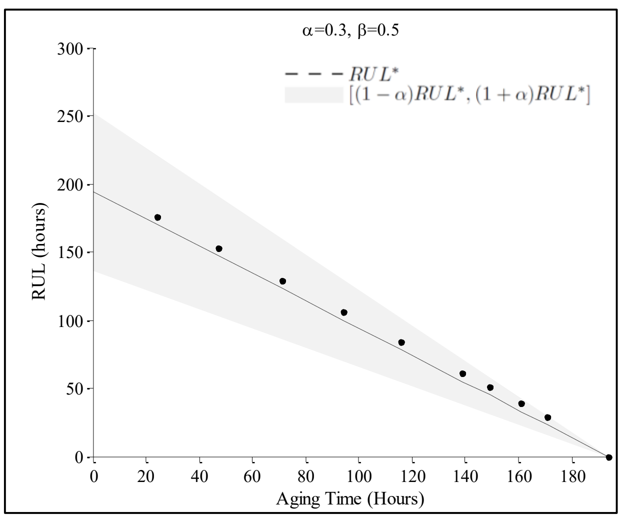


RUL and Validation –ESR Degradation Model

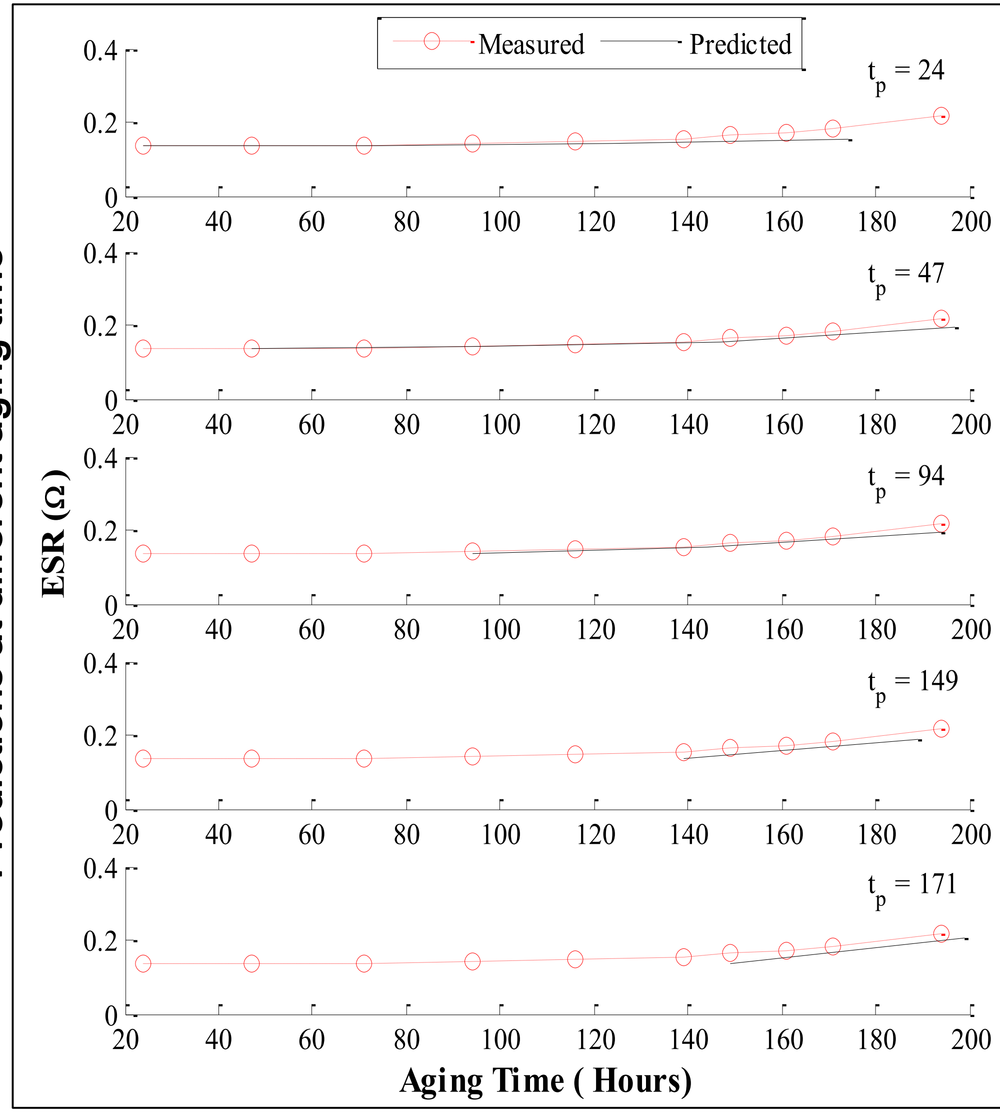
Tracking



Alpha Lambda



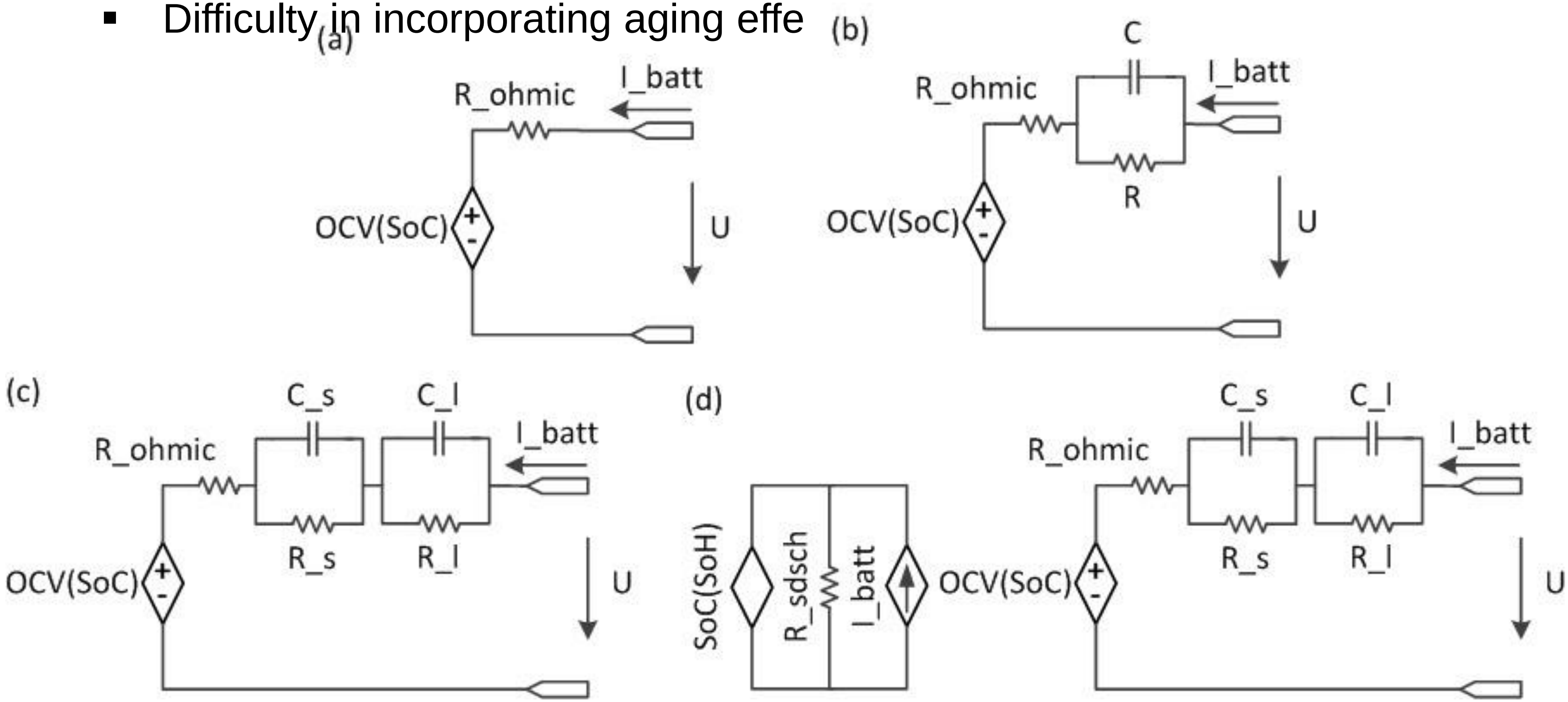
Predictions at different aging time



CASE STUDY II: LI-ION BATTERIES

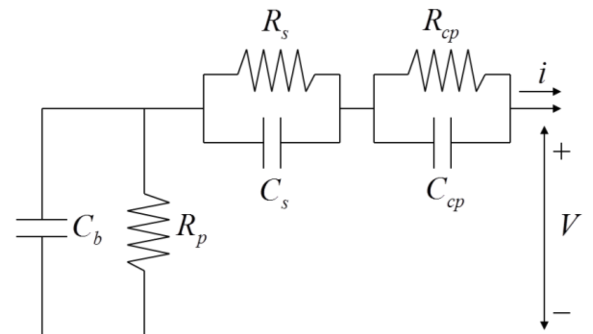
Battery Modeling

– <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



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

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

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

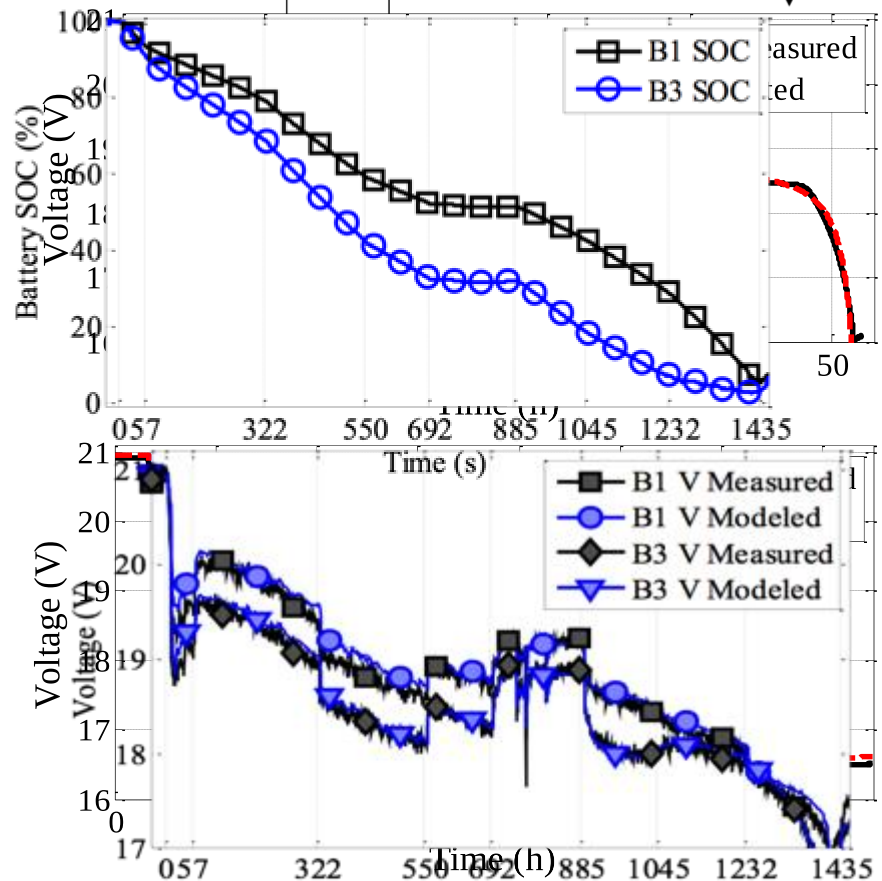
- Two laboratory loading experiments are used to fit the following parameterization coefficien

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

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

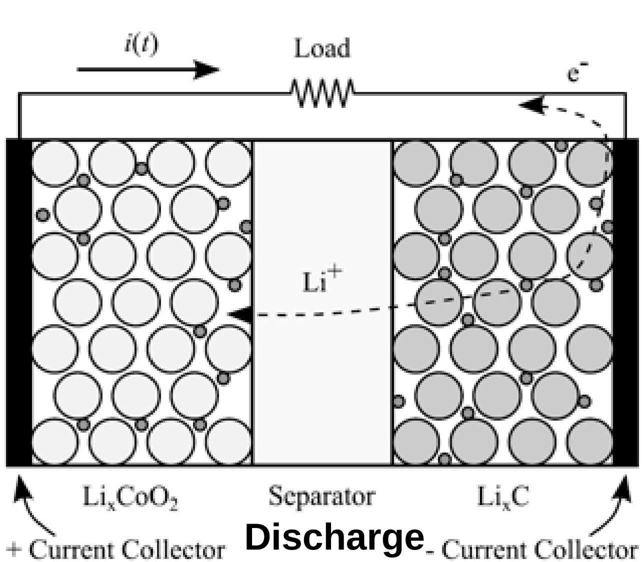
$$C_{cp} = C_{cp0} + C_{cp1} \cdot \exp\left(C_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

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



Battery Modeling

– <u>Electrochemical Models vs. Empirical Models</u>
  - 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:

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

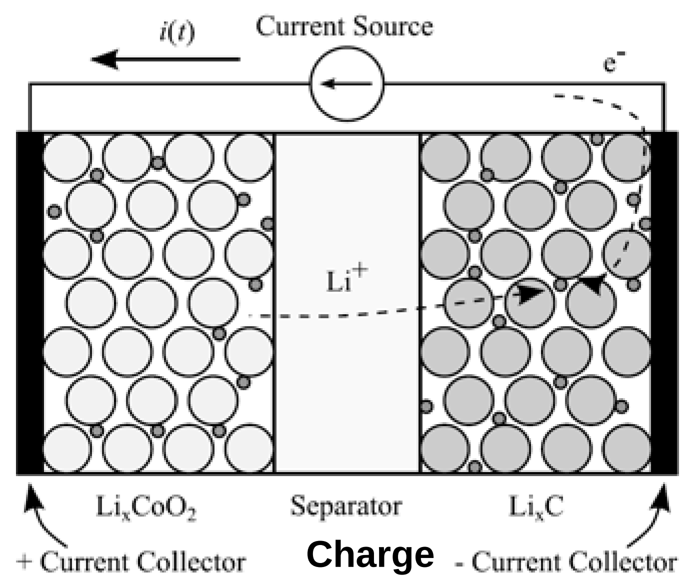
Oxidation at neg. electrode:

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

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:

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

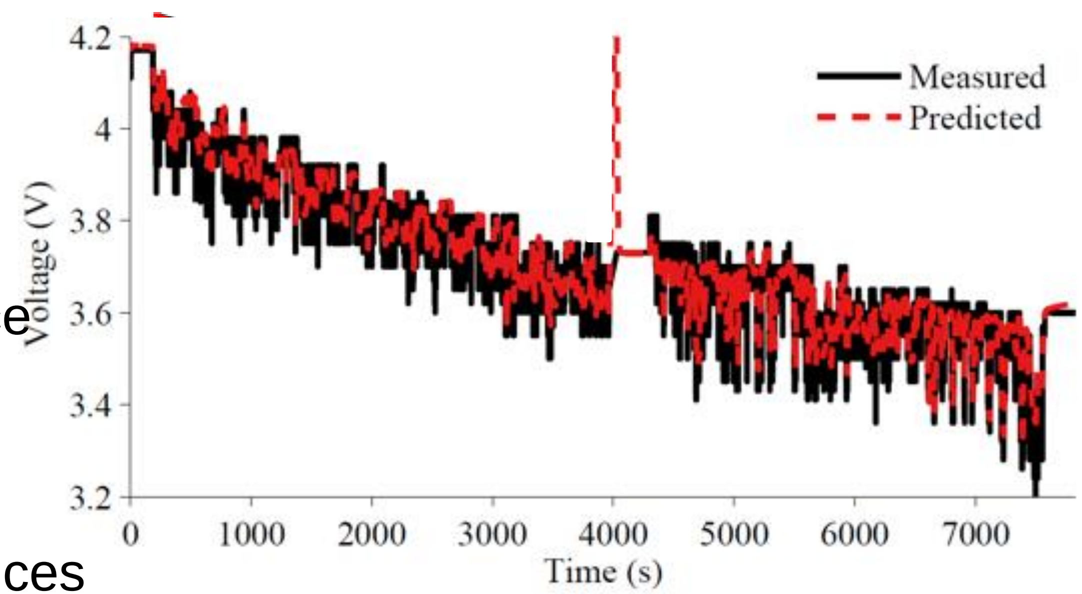
Current flows – to +

Electrons flow + to –

Lithium ions flow + to –

Electrochemical Li-ion Model

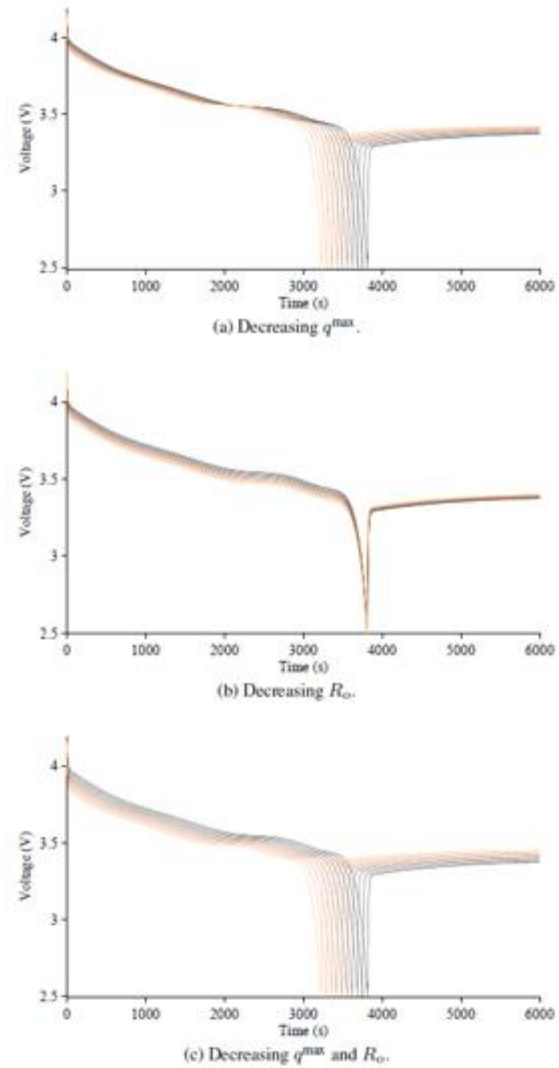
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control volumes
  - Surface overpotential → Butler-Volmer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



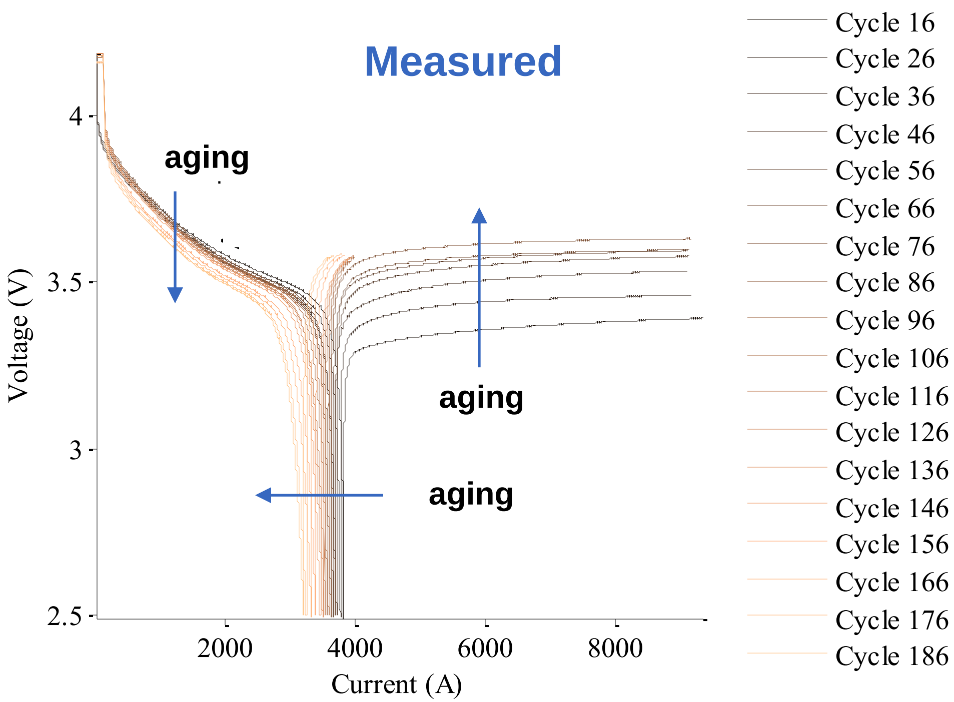
Battery Aging

- 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

Simulated

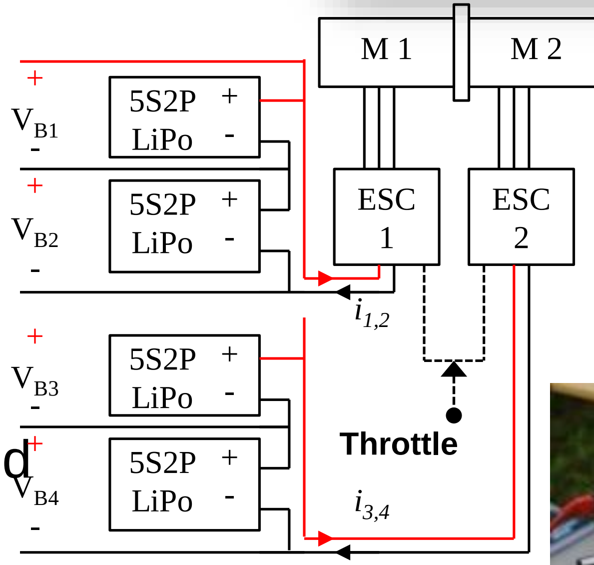


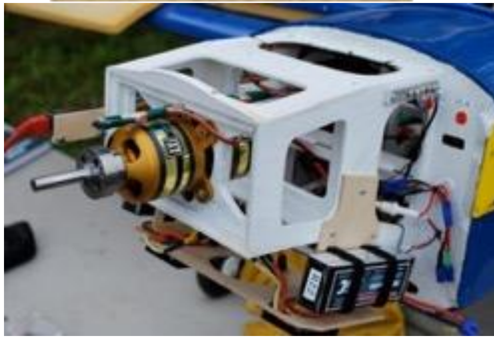
Measured



Edge UAV Use Case

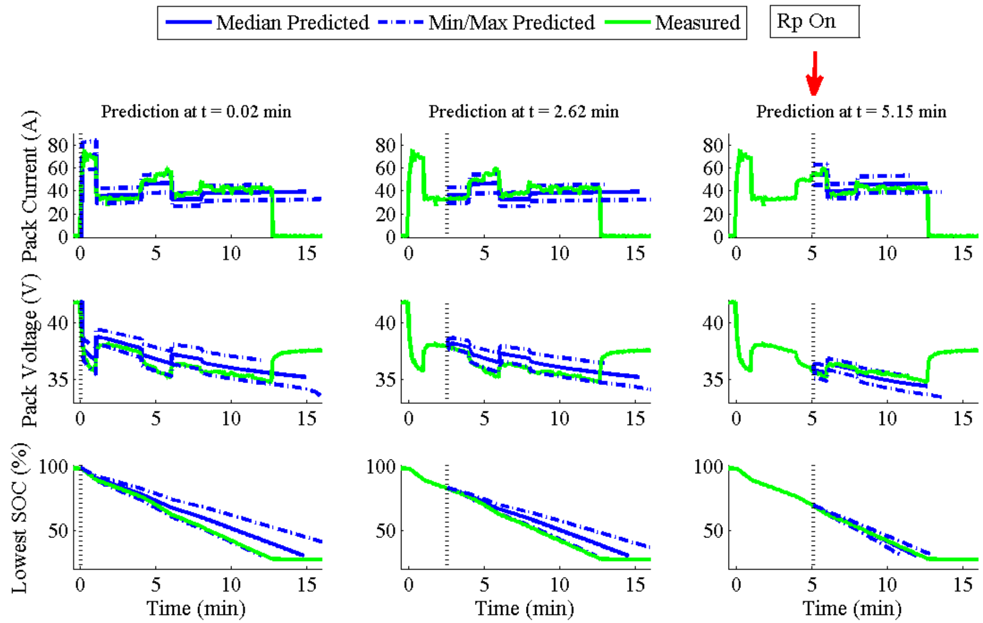
- Piloted and autonomous missions, visiting waypoints
- Require 2-minute warning for EOD so pilot/autopilot has sufficient time to land safely
  - Depends on battery age
  - Need to track both current level of charge and current battery age
  - Based on current battery state, current battery age, and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



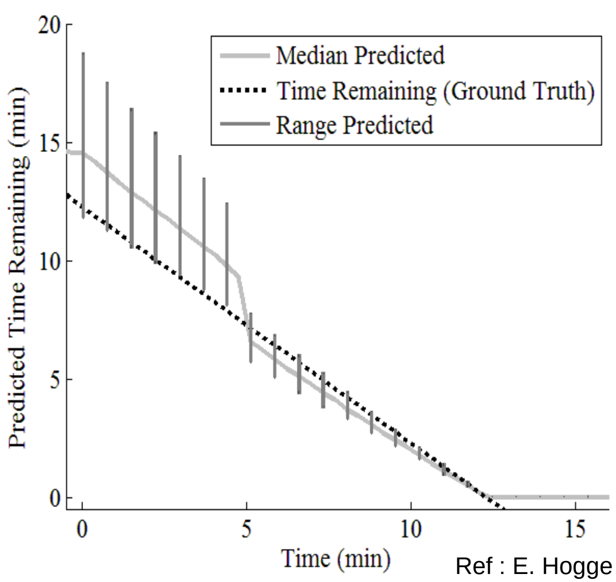


Predication over Flight Plan

- 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%



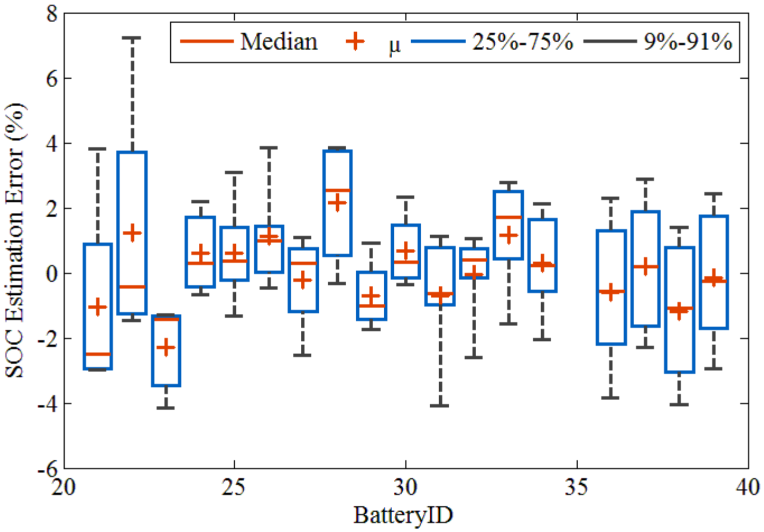
- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

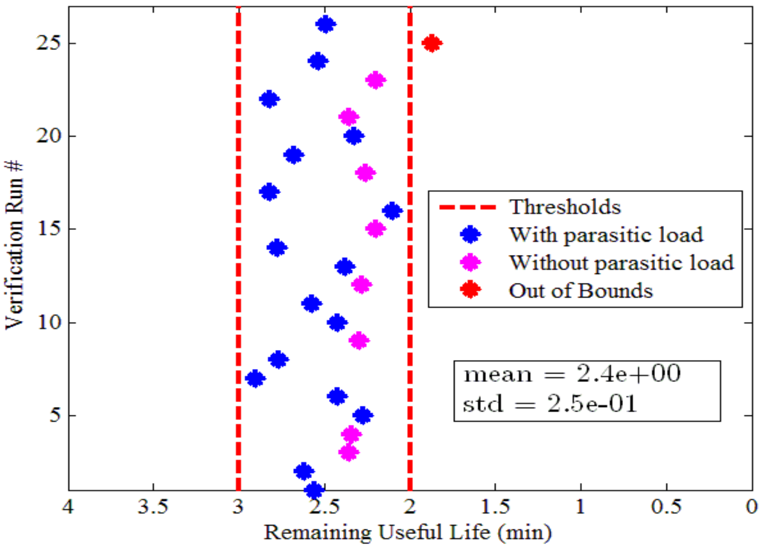


Ref : E. Hogge et al, "Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft", PHM 2015

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*





CLOSING REMARKS

Remarks (1/2)

- Electrical and Electronics PHM Maturity - scientific and engineering challenges
- Research approach challenges
  – 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
- Validate models and algorithms with data from experiments and fielded systems
- A success in developing PHM methodologies in an real usage application will require the right team

THANK YOU!