Systems Health Management and Decision Making

Chetan S. Kulkarni
Diagnostics and Prognostics Group
KBR Inc, NASA Ames Research Center

The technical slides represent work done by PCoE members past and present, who have contributed to this presentation. All details presented here are in the public domain and used for information purposes only.

Acknowledgments

- Collaborators
  - Members of Diagnostics and Prognostics Group, NASA Ames
  - Members of Safety Critical Avionics Systems Branch, NASA Langley

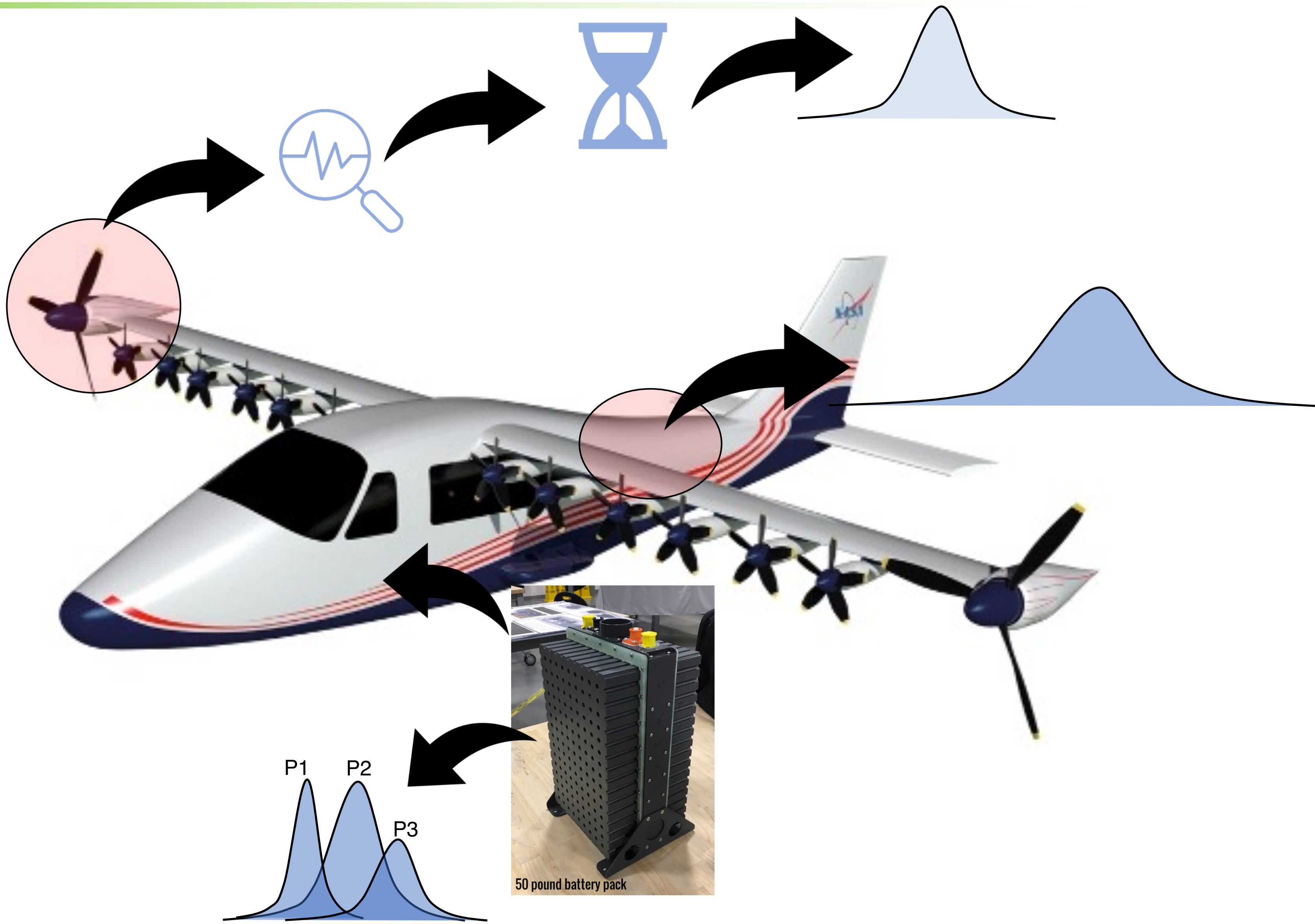
- Funding Projects
  - NASA System-wide Safety and Assurance Technologies Project
  - NASA Aviation Safety Program – IVHM Project
  - NASA SMART –NAS Project
  - NASA System Wide Safety (SWS) Project

Outline

- Prognostics Overview
- Research Approach
- System Failure Approach
- Architecture
- Case Studies
- Closing Remarks

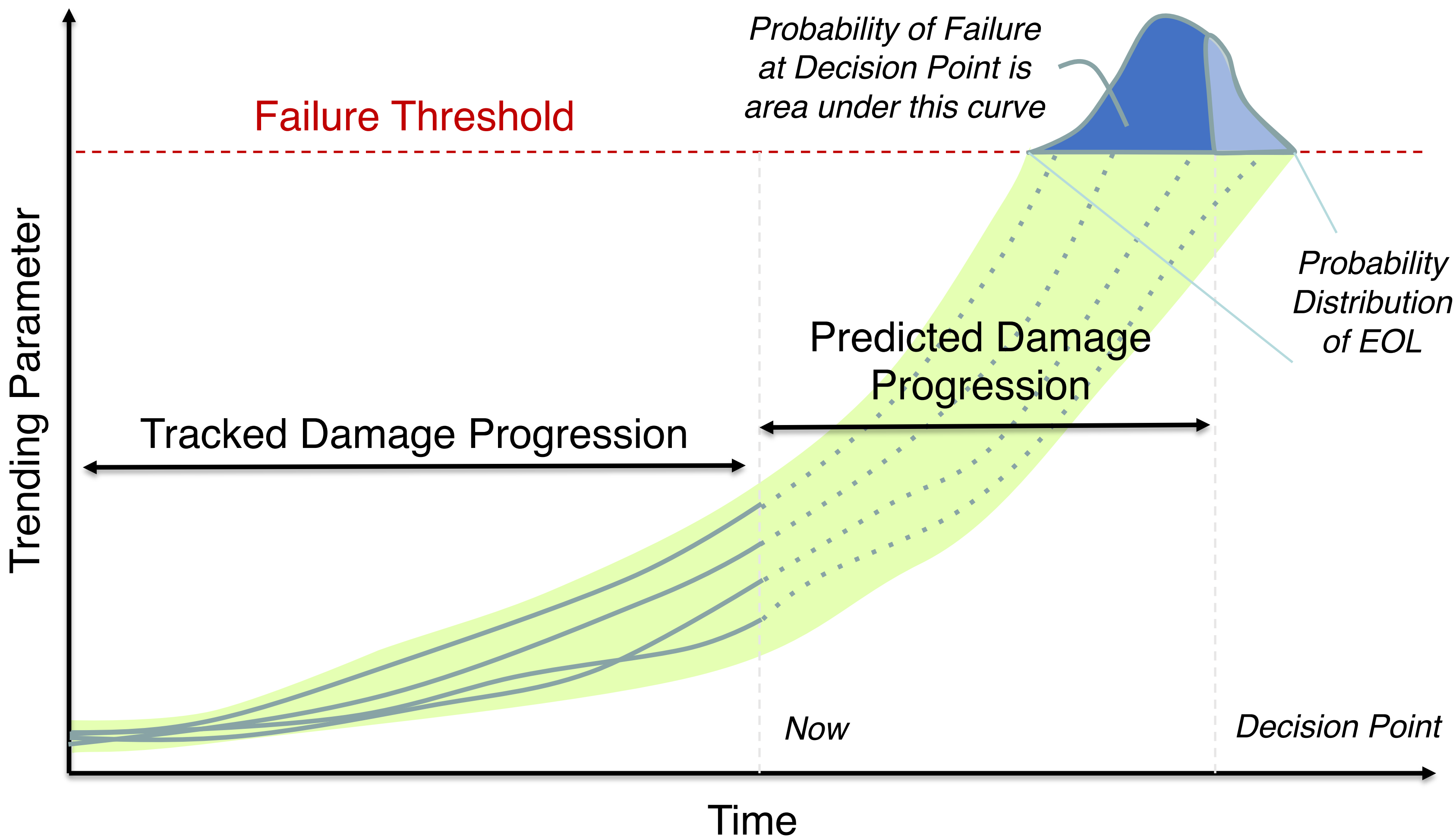
OVERVIEW

Prognostics Overview



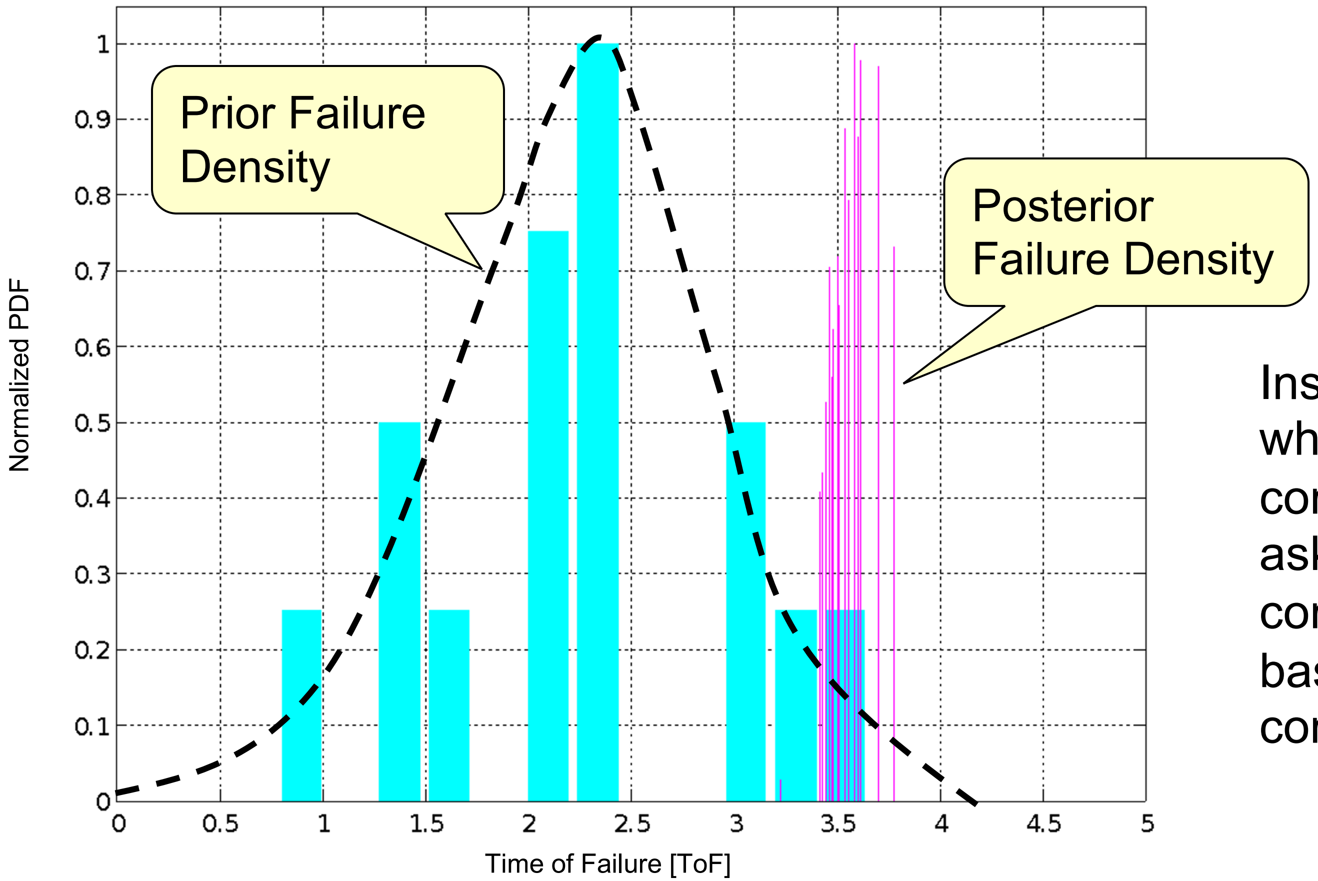
Prognostics Overview

How to track/predict the evolution of a system state to failure?



Prognostics and Reliability Analysis

Prior versus Posterior Knowledge

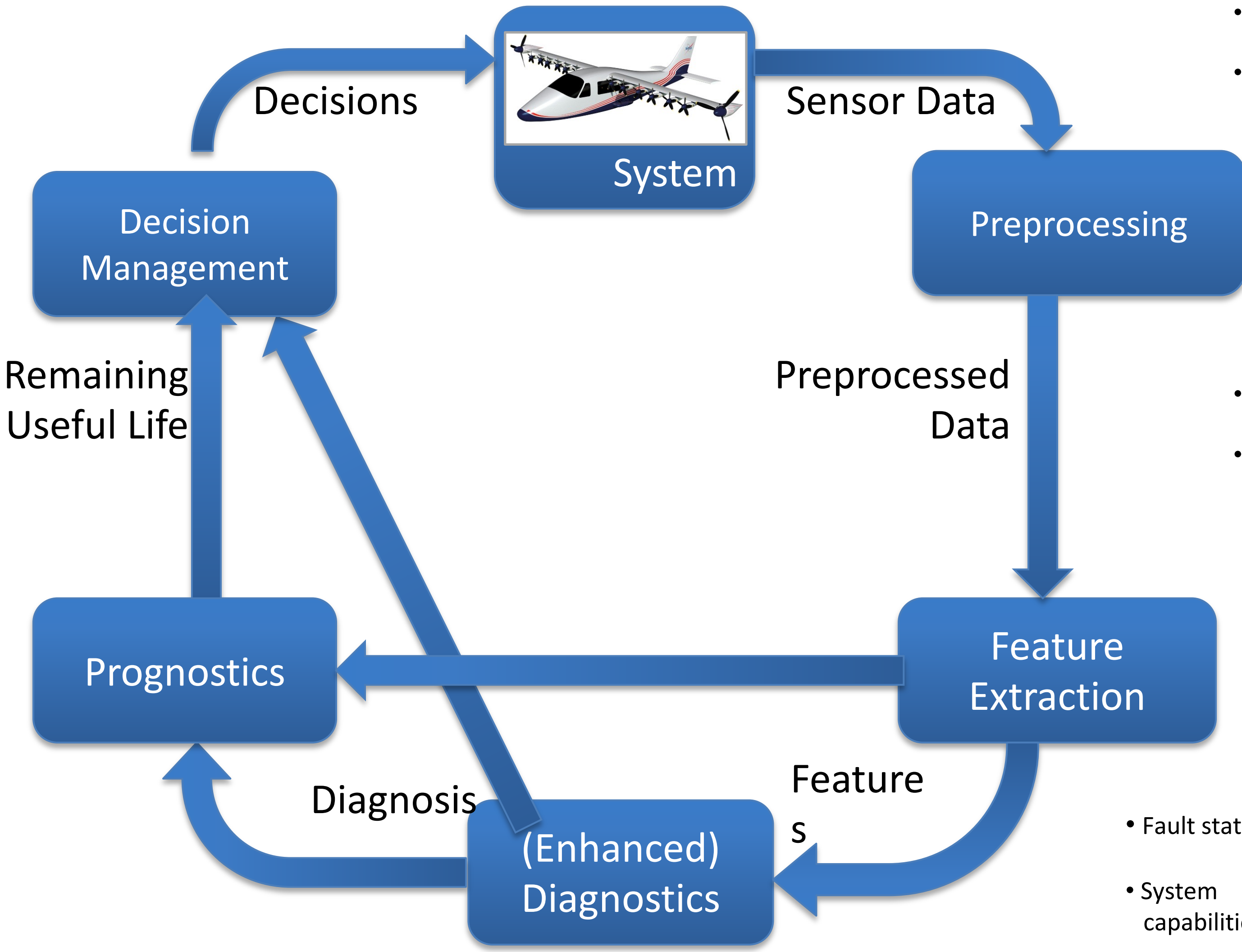


Instead of asking what a population of components will do, ask what this specific component will do – based on its condition (state)

Prognostics and Decision Making Framework

- Maintenance planning
- Mission planning

- De-noising
- Filtering



- Signal statistical processing
- Parameter estimation

- Future capabilities
-
- Component RUL

- Fault status
- System capabilities

* A. Saxena (Ph.D.); European PHM Conference 2010

Prognosis: Systematic Approach

Constituent Problems

In order to compute EOL, we need to know

- What is the system state at time of prediction?
- What potential inputs will the system have from time of prediction to EOL?
- What model describes the system evolution?
- What is the process noise distribution?
- What is the future input trajectory distribution?

Prognostics is often split into two sequential problems

- Estimation: determining the system state at a given time
- Prediction: determining EOL

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

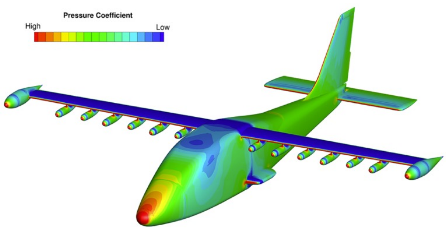
- Model is based solely on data collected from the system
- Some system knowledge may still be handy:
  - What the system 'is'
  - What the failure modes are
  - What sensor information is available
  - Which sensors may contain indicators of fault progression (and how those signals may 'grow')
- *General* 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

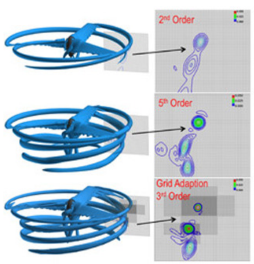
Physics-Based Methods

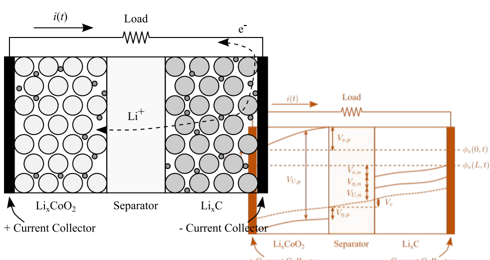
- Description of a system's underlying physics using suitable representation
- Some examples:
  - Model derived from "First Principles"
    - Encapsulate fundamental laws of physics
      - PDEs
      - Euler-Lagrange Equations
  - Empirical model chosen based on an understanding of the dynamics of a system
    - Lumped Parameter Model
    - Classical 1^{st} (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

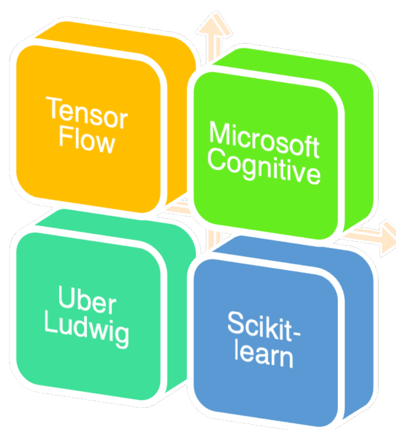
Hybrid Approach

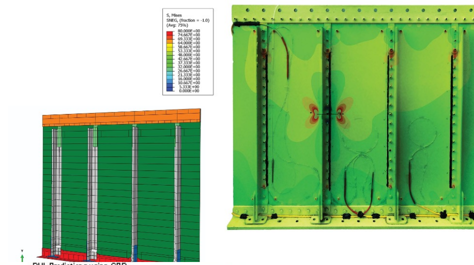


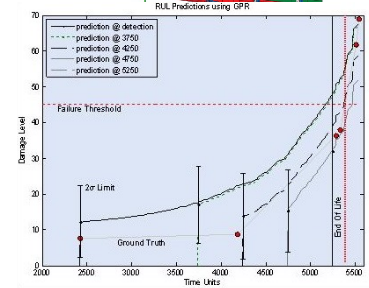


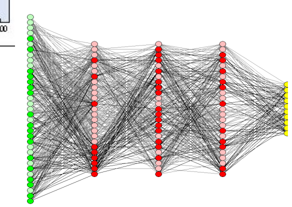


Machine-Learning underlying physics parameters



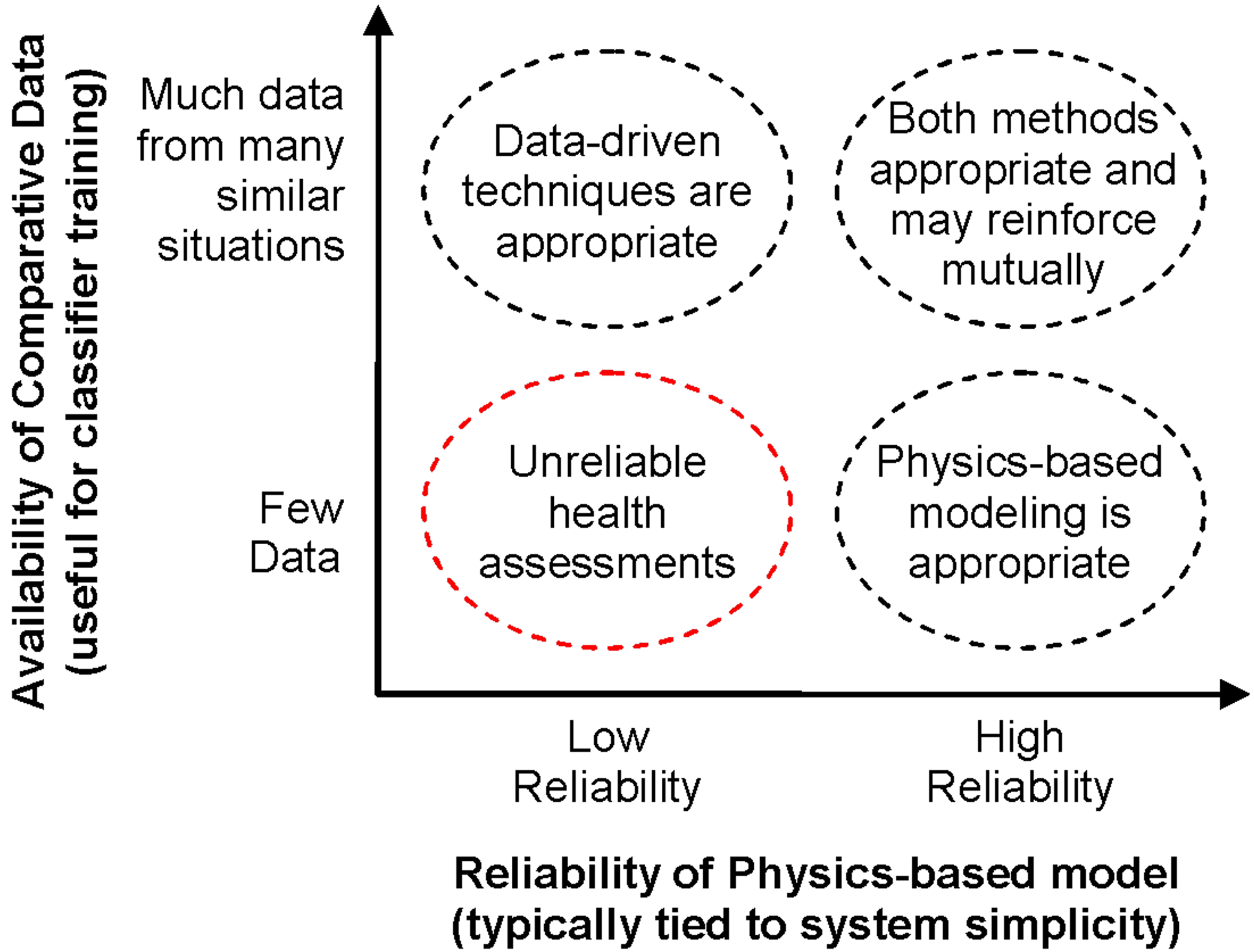






Understanding and Learning underlying Physics for Complex Systems

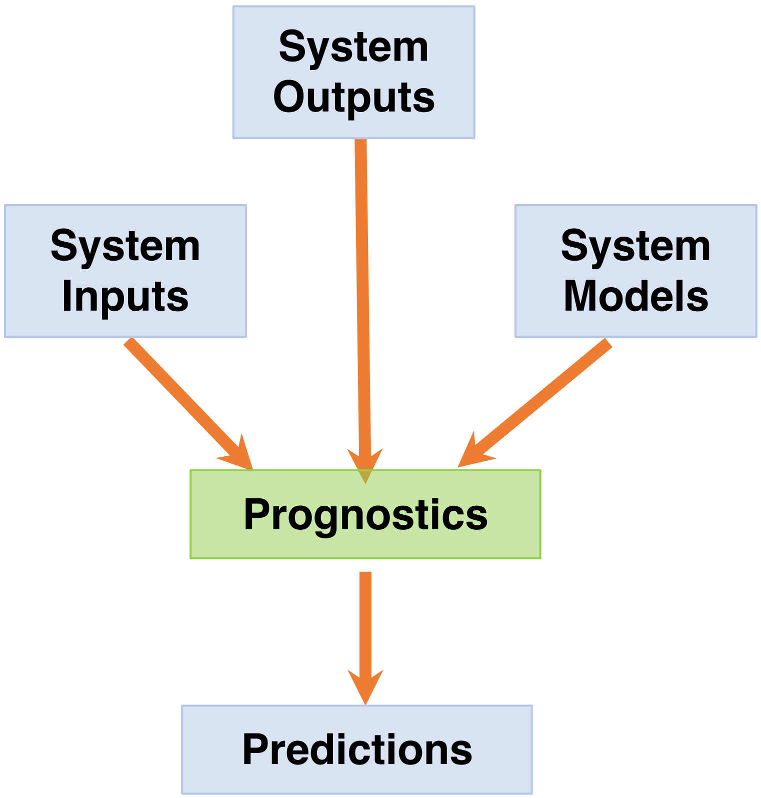
Dynamic Nonlinear Models



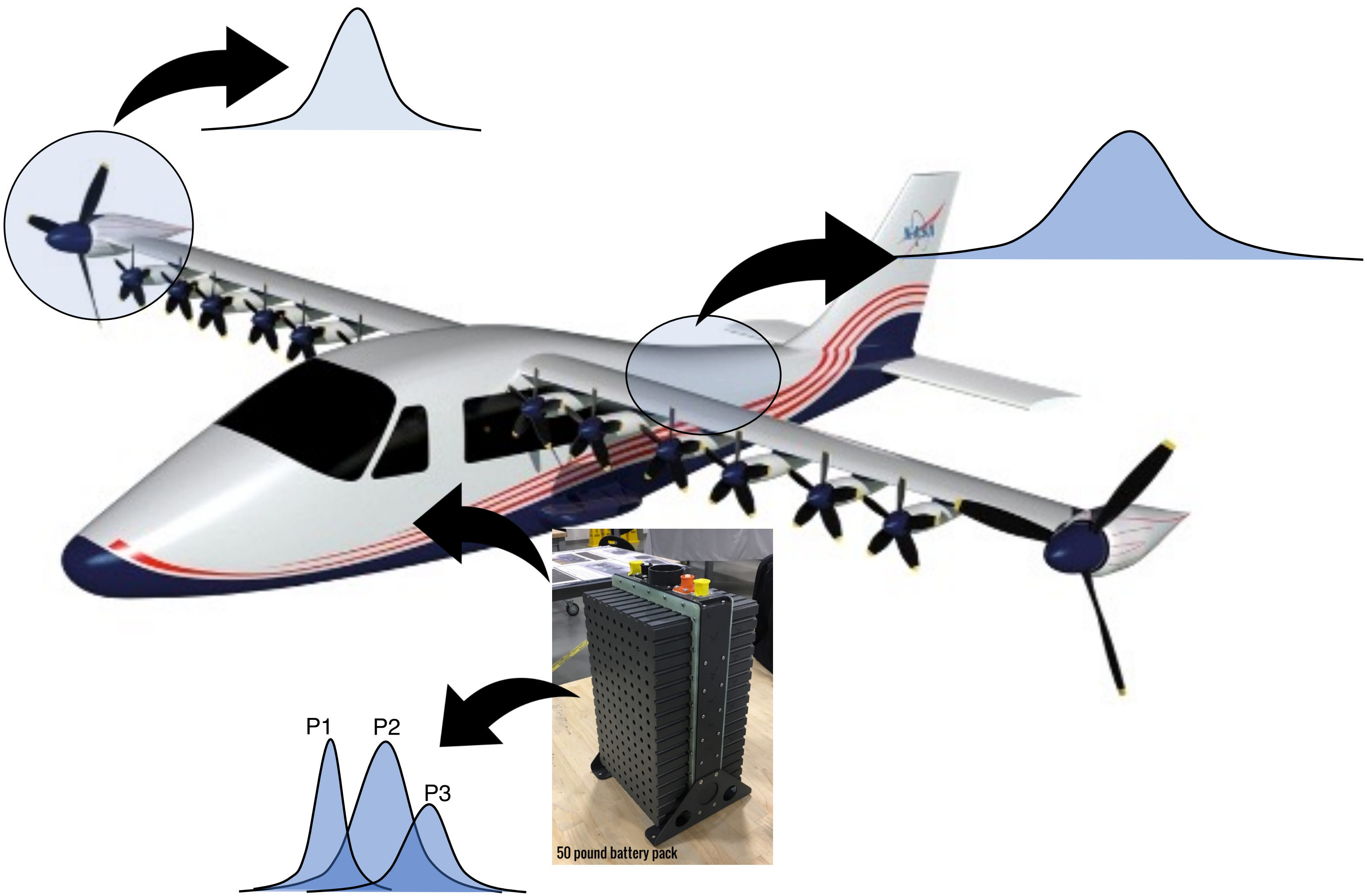
Source: Adapted from Inman et al. (2005

Why Model-Based Prognostics?

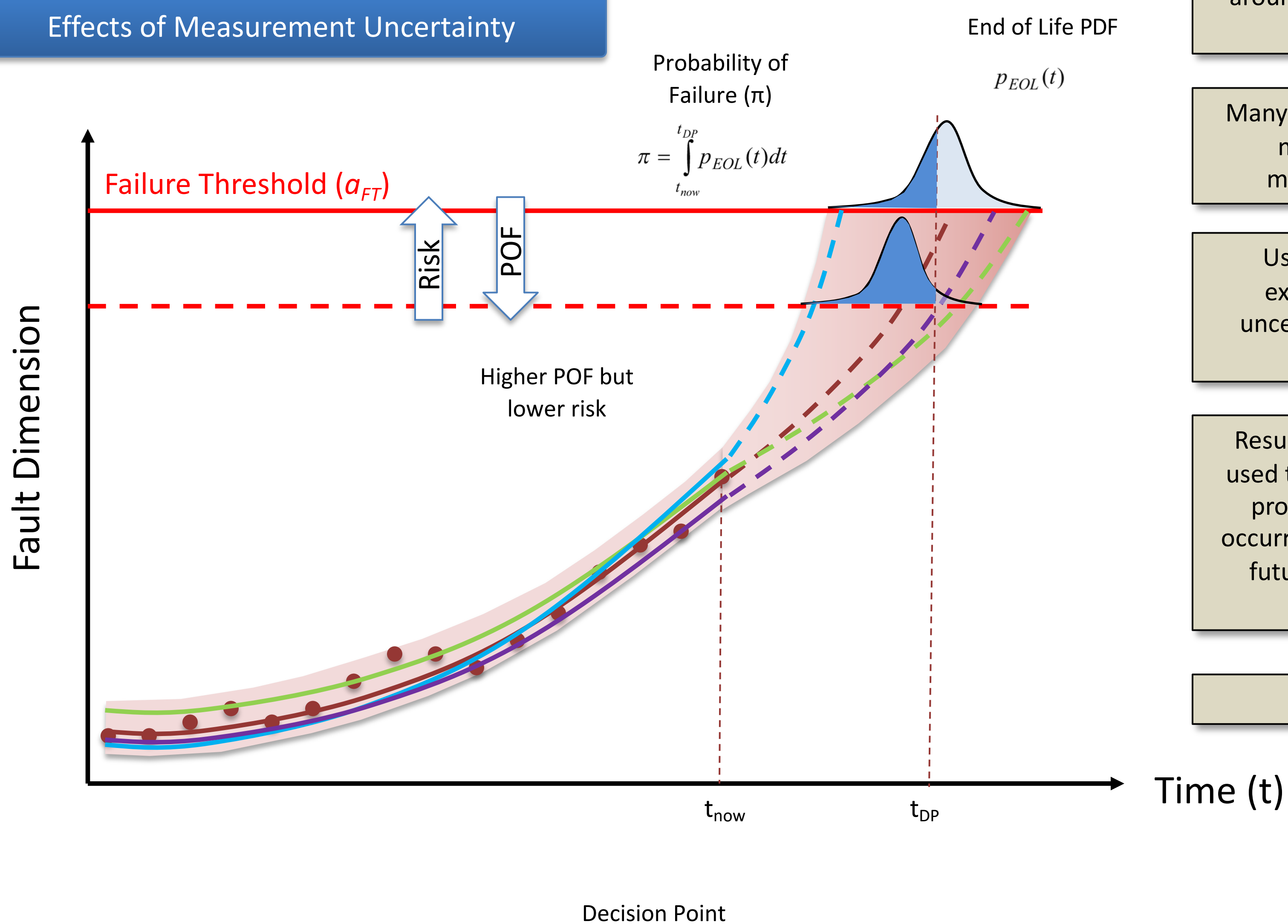
- With model-based algorithms, models are inputs
  - This means that, given a new problem, we use the same general algorithms
  - Only the models should change
- Model-based prognostics approaches are applicable to a large class of systems, given a model
- Approach can be formulated mathematically, clearly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



SYSTEM FAILURE PROGNOSIS


P1
P2
P3
50 pound battery pack

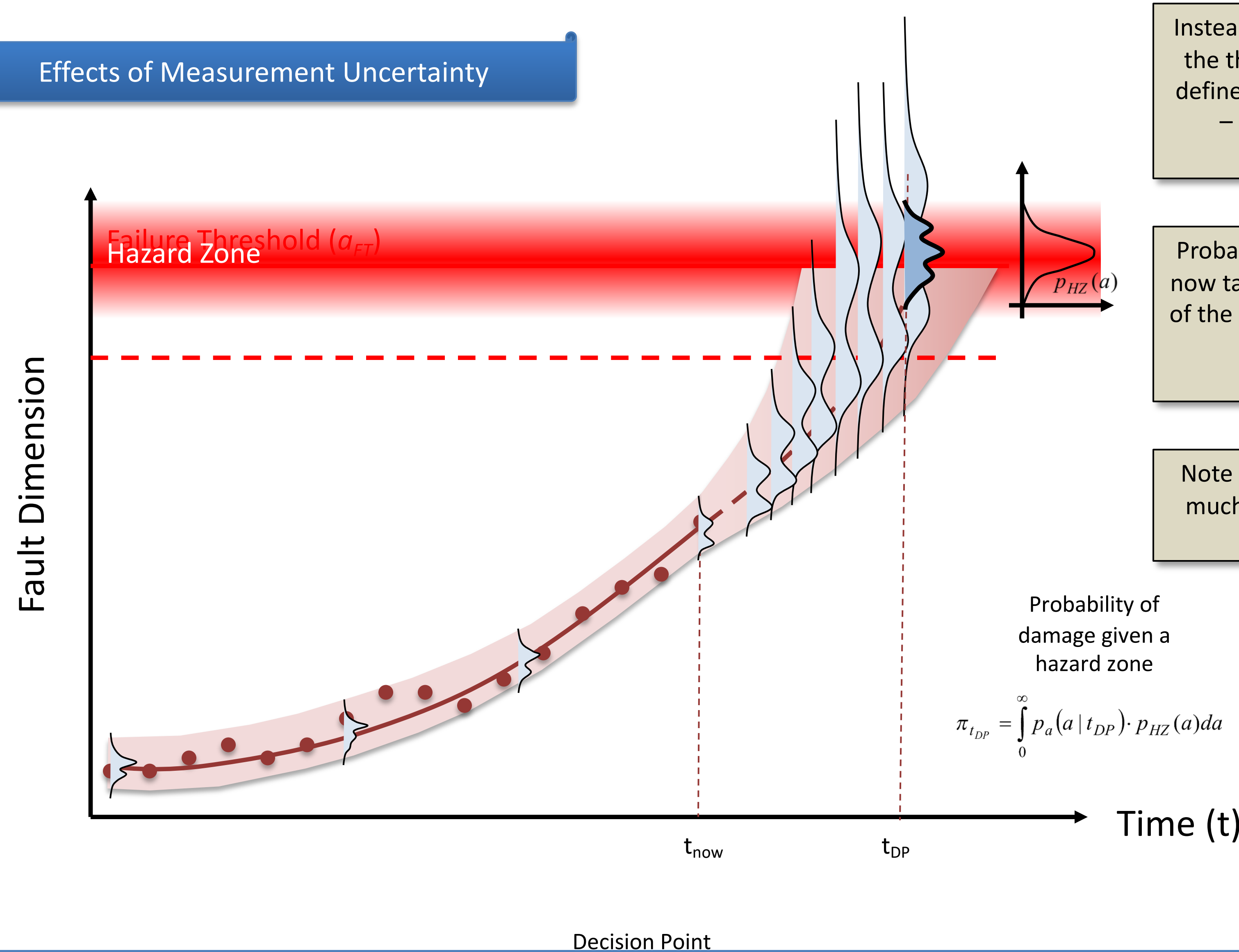
Effects of Measurement Uncertainty



- Band of uncertainty around measurement points
- Many possible Models may "fit" the measurements
- Use statistics to extrapolate the uncertainty into the future
- Resulting PDF can be used to determine the probability of EOL occurring between two future time points
- Risk vs POF

* Abhinav Saxena; PHM 2011, Montreal, Canada

Effects of Measurement Uncertainty



Instead of a single value, the threshold could be defined as a distribution – “Hazard Zone’

Probability of damage is now taken as the integral of the product of the two PDF’s

Note that “Risk” is now much more difficult to quantify

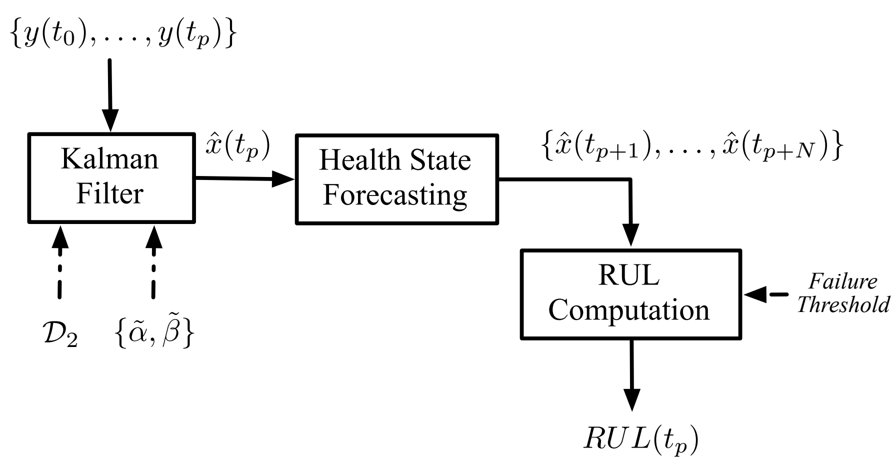
* Abhinav Saxena (Ph.D.); PHM 2011, Montreal, Canada

INTRODUCTION TO MODEL-BASED PROGNOSTICS

Model-based prognostics (1/2)

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

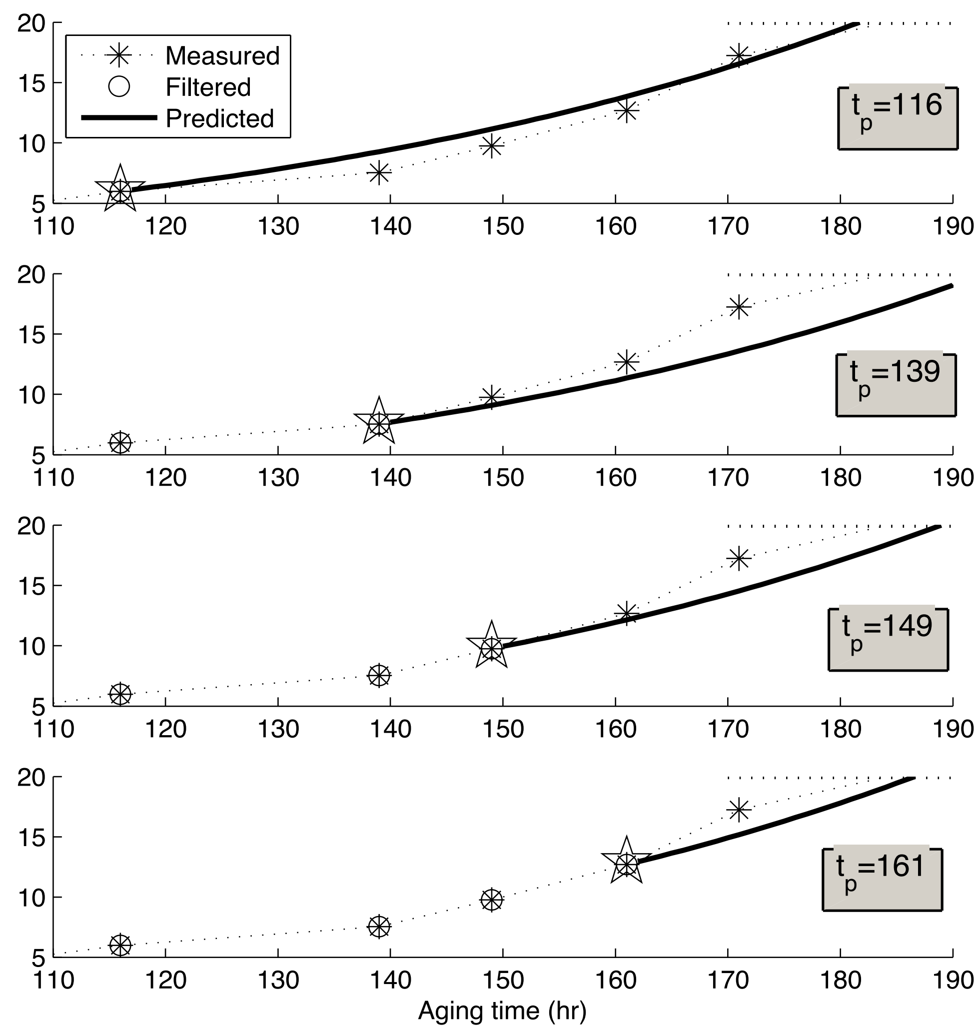
$$R(t_p) = t_{EOL} - t_p$$



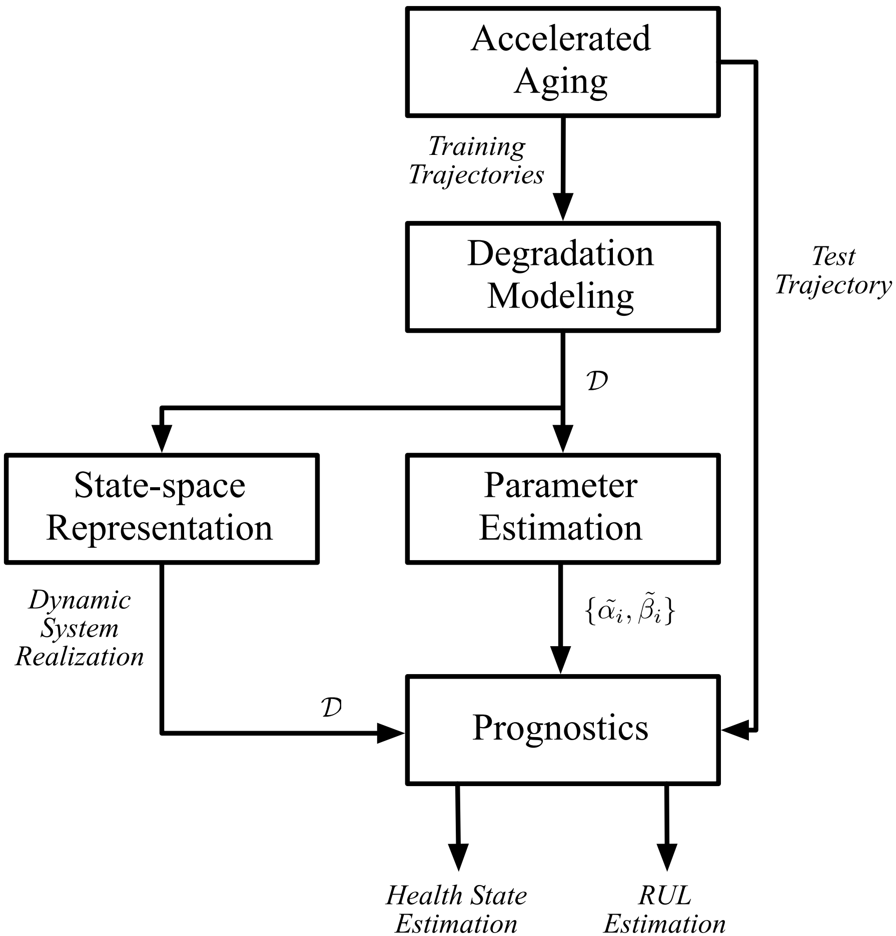
- State vector includes dynamics of the degradation process
- It might include nominal operation dynamics
- EOL defined at time in which performance variable cross failure threshold
- Failure threshold could be crisp or also a random variable

Model-based prognostics (2/2)

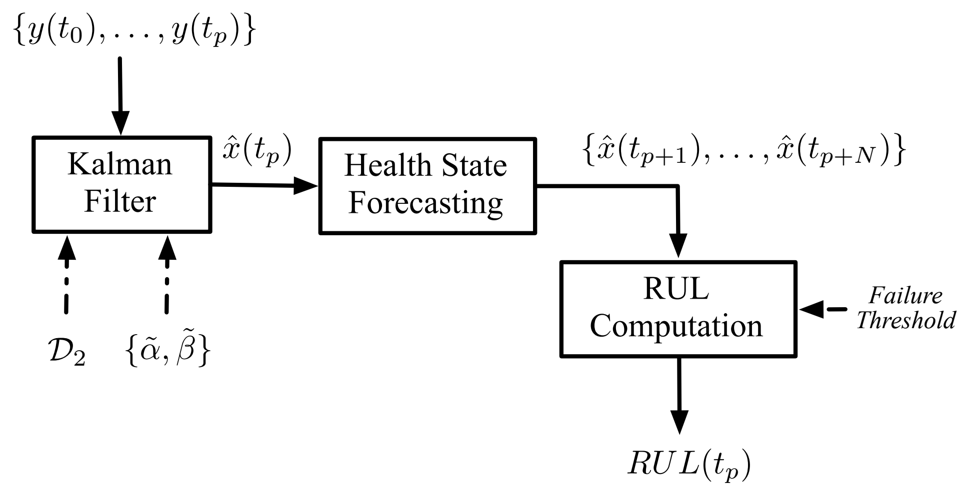
- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed



Methodology



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



RESEARCH APPROACH

Research Approach

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

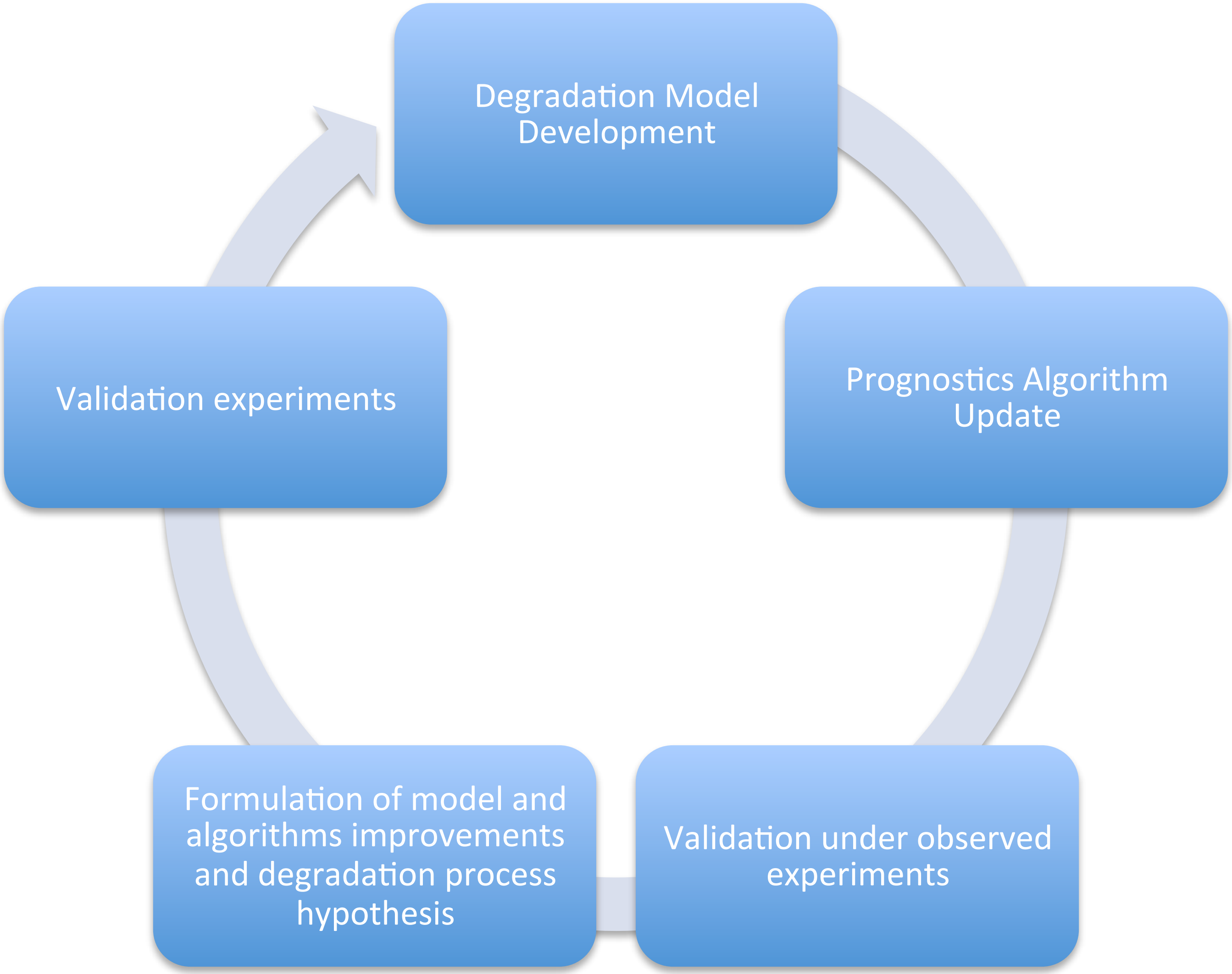
Identification of precursors of failure which play an essential role in the prediction of remaining life

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

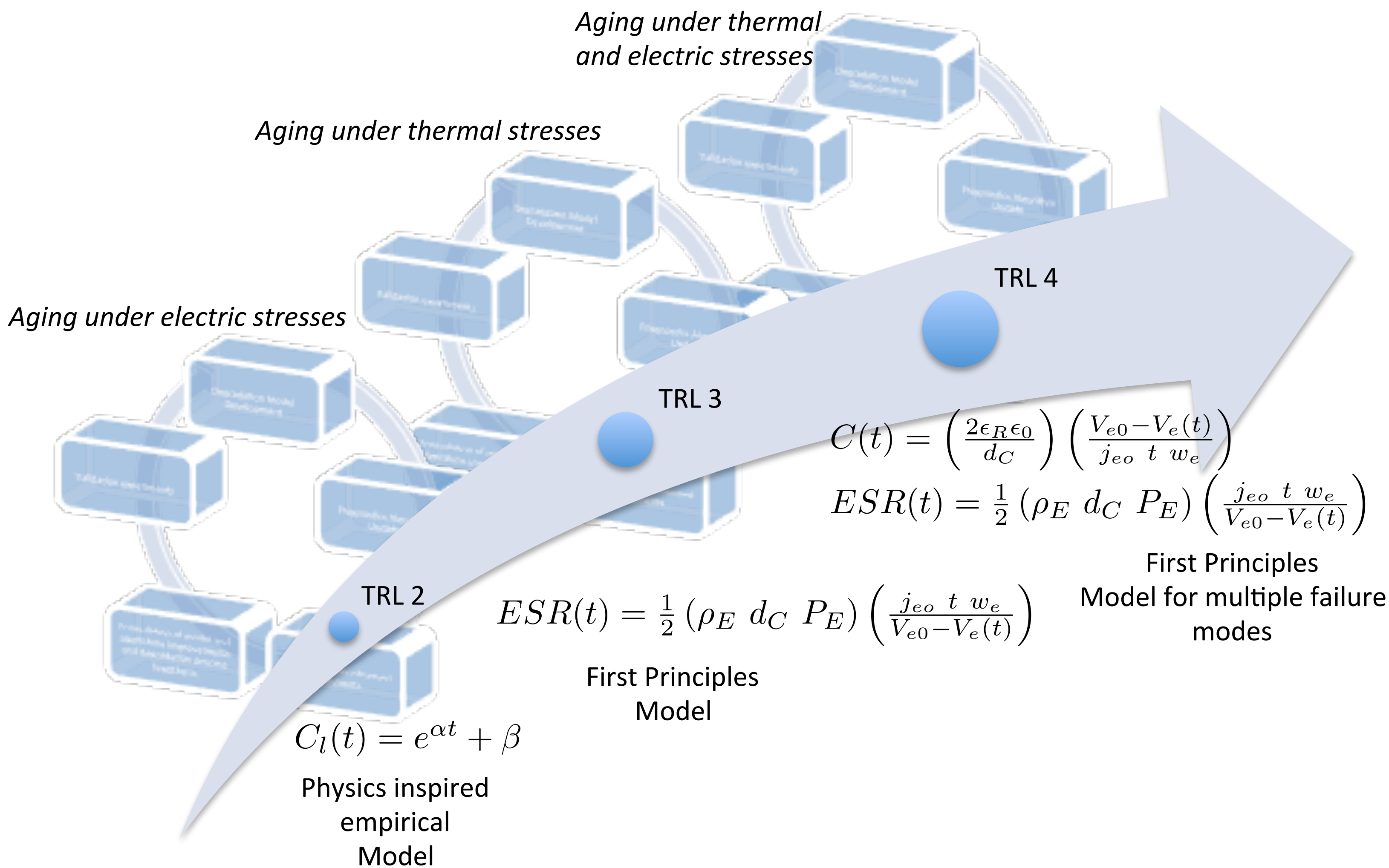
Development of degradation models based on the physics of the device and the failure mechanisms

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

Algorithm Maturation through Validation



Algorithm Maturation through Validation

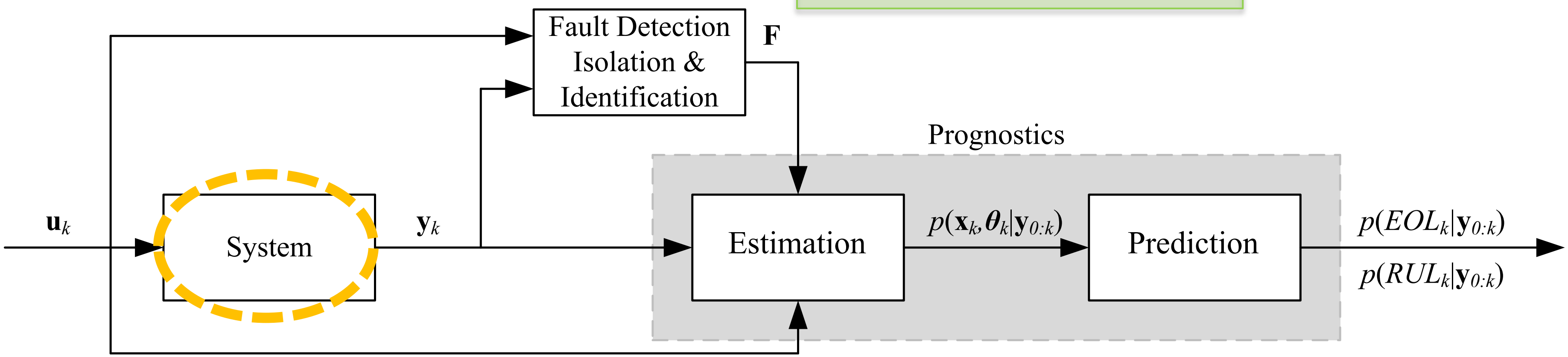


ARCHITECTURE

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

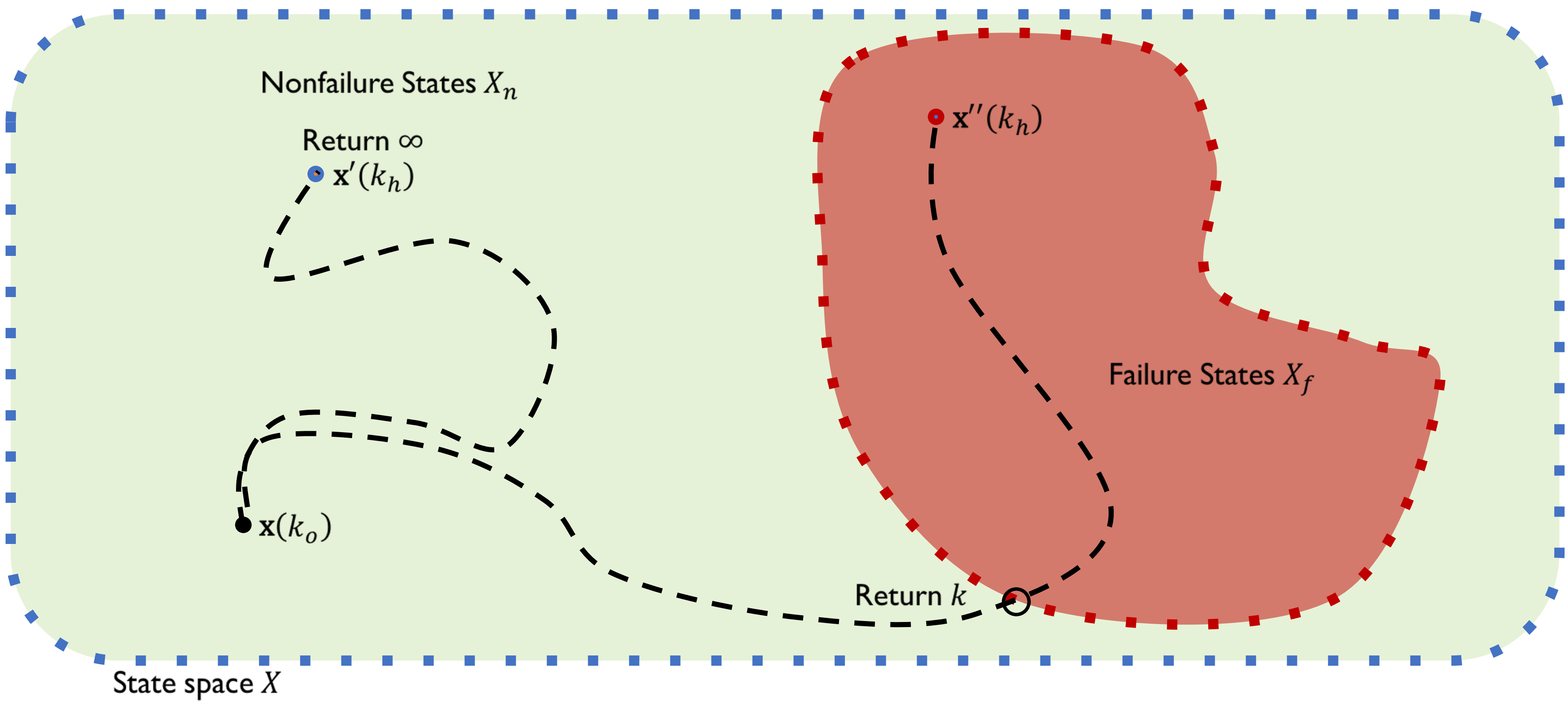
System Model

- 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
  - $T_f : \mathbb{R}^{n_x} \rightarrow \{true, false\}$
  - 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: Compute EOL



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*

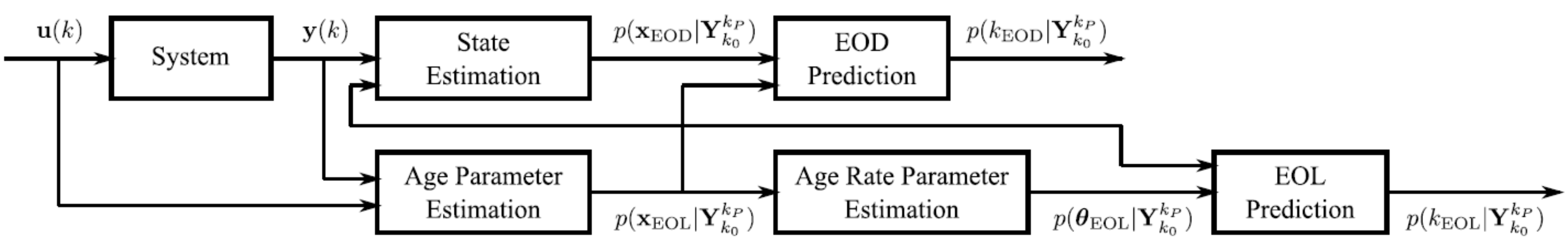
else

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)

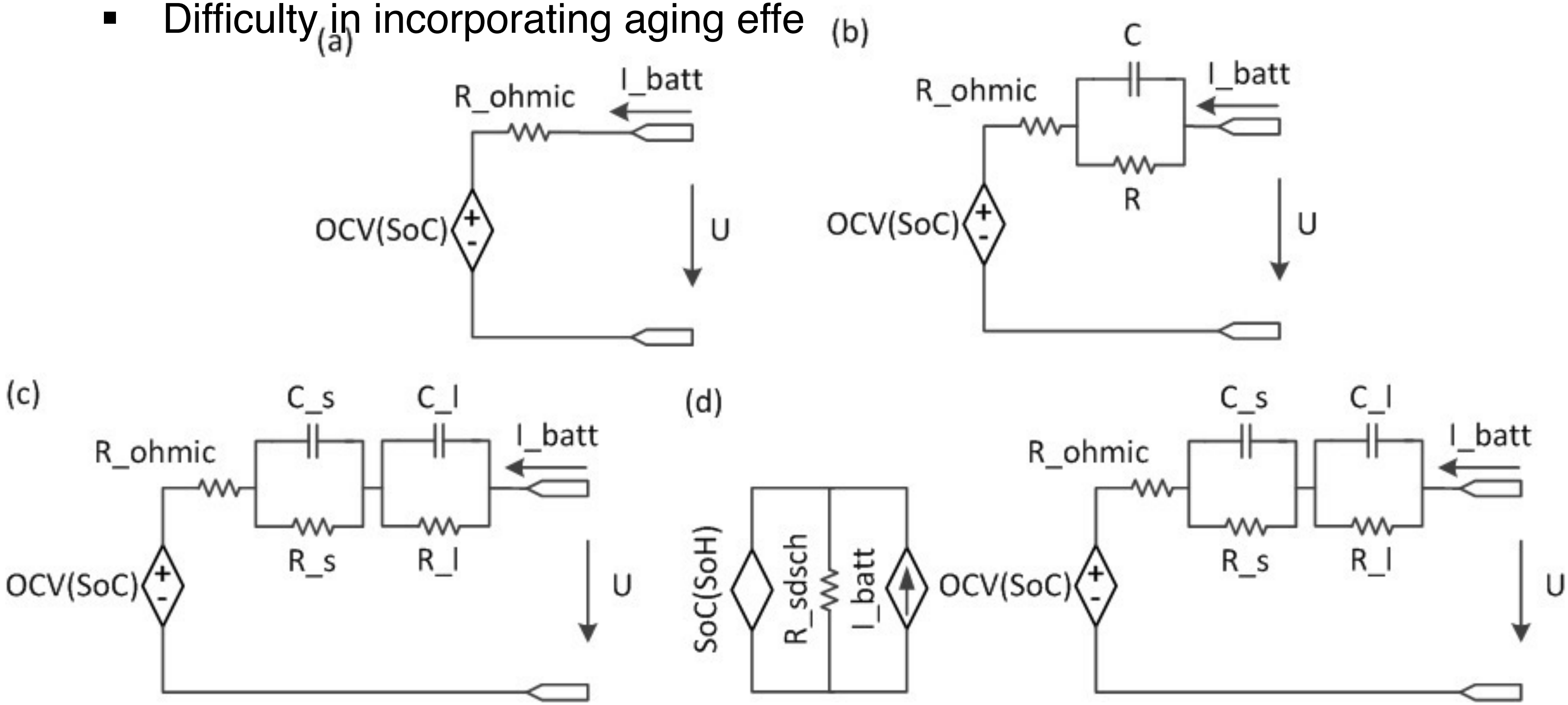
Prediction

- 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)

CASE STUDY : PROGNOSTICS OF LI-ION BATTERIES

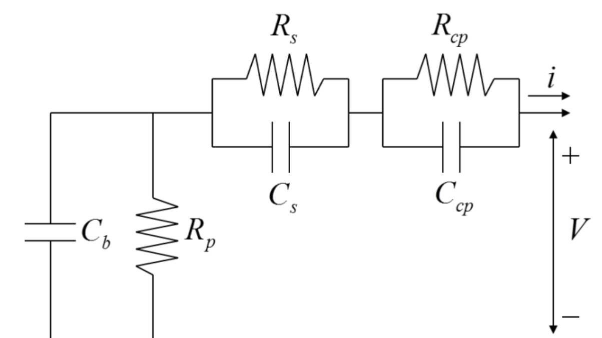
Battery Modeling

- Equivalent Circuit Empirical Models
  - 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



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

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

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

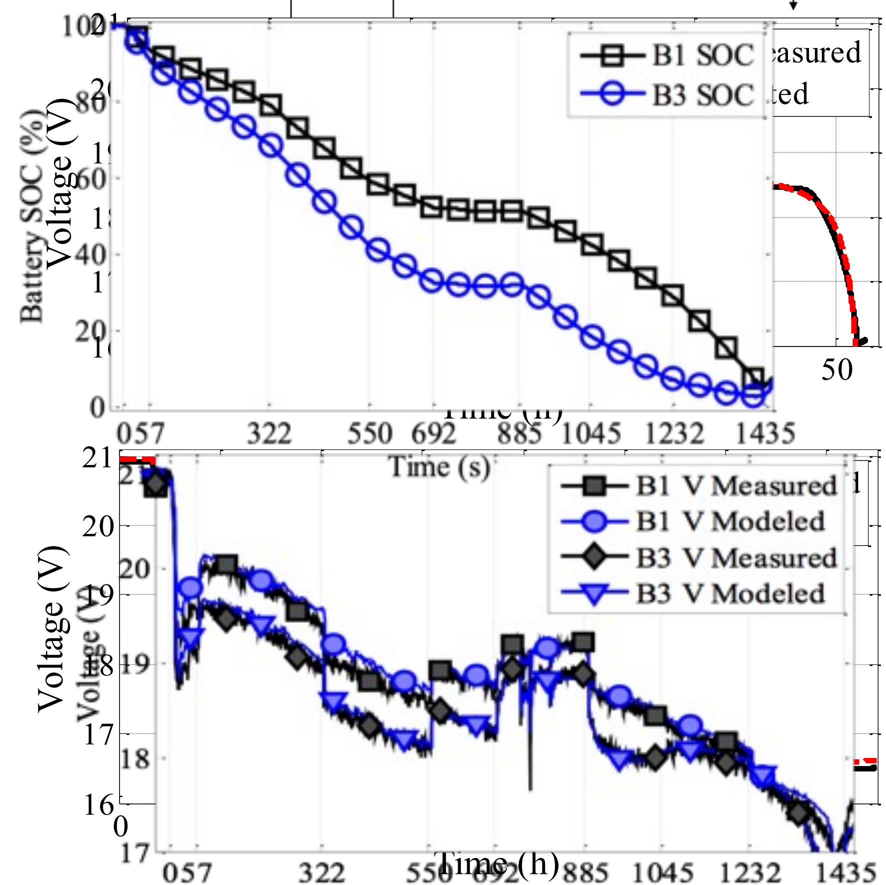
- Two laboratory loading experiments are used to fit the following parameterization coefficien

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

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

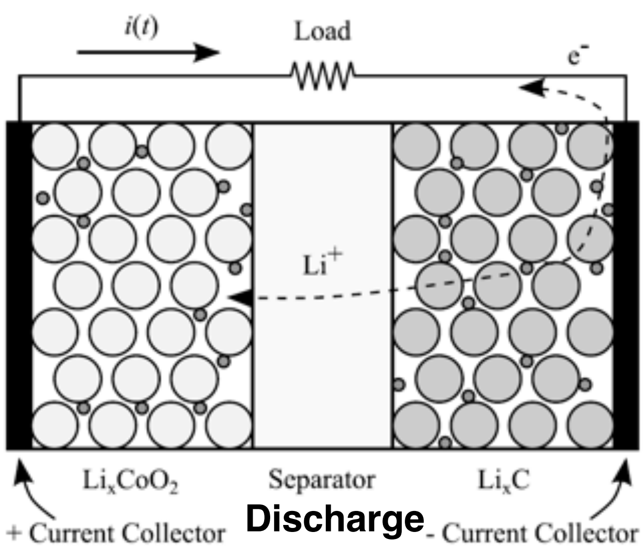
$$C_{cp} = C_{cp0} + C_{cp1} \cdot \exp\left(C_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

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



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:

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

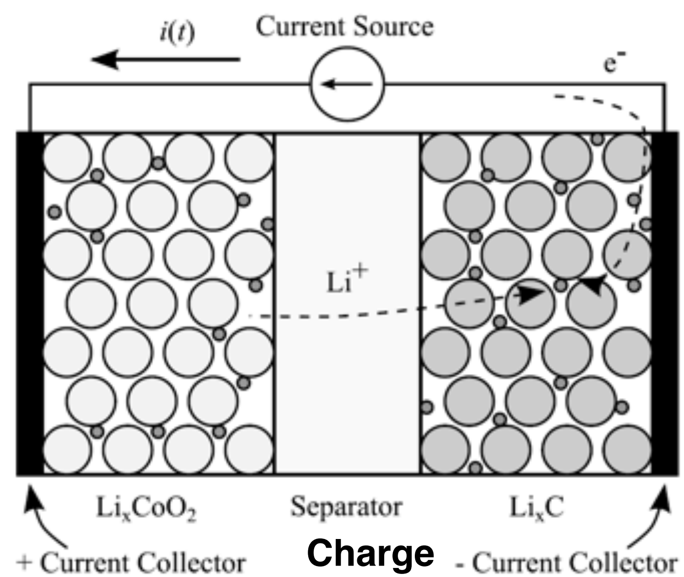
Oxidation at neg. electrode:

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

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:

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

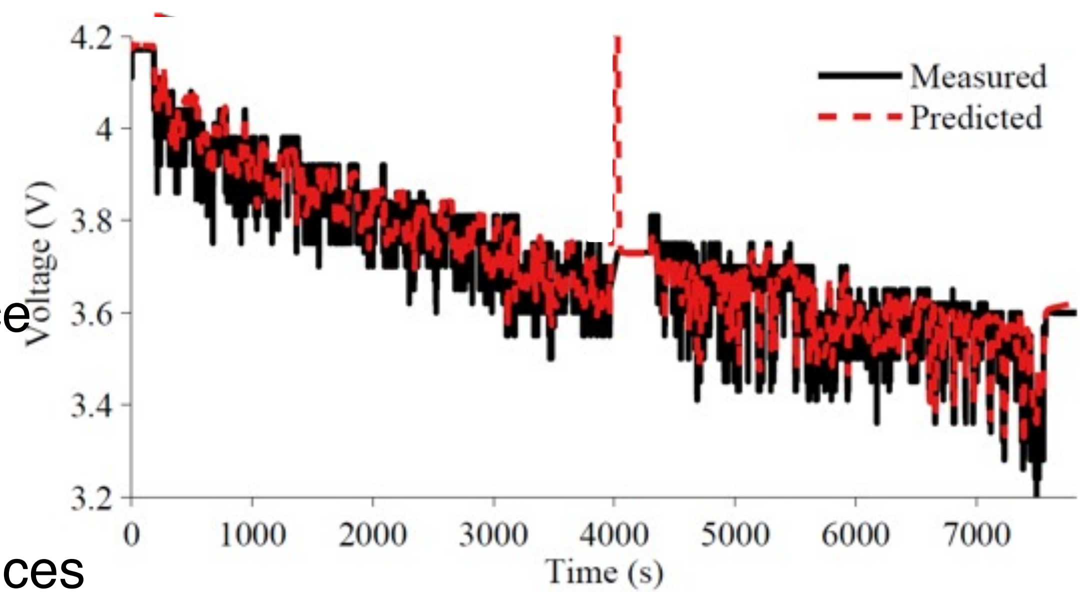
Current flows – to +

Electrons flow + to –

Lithium ions flow + to –

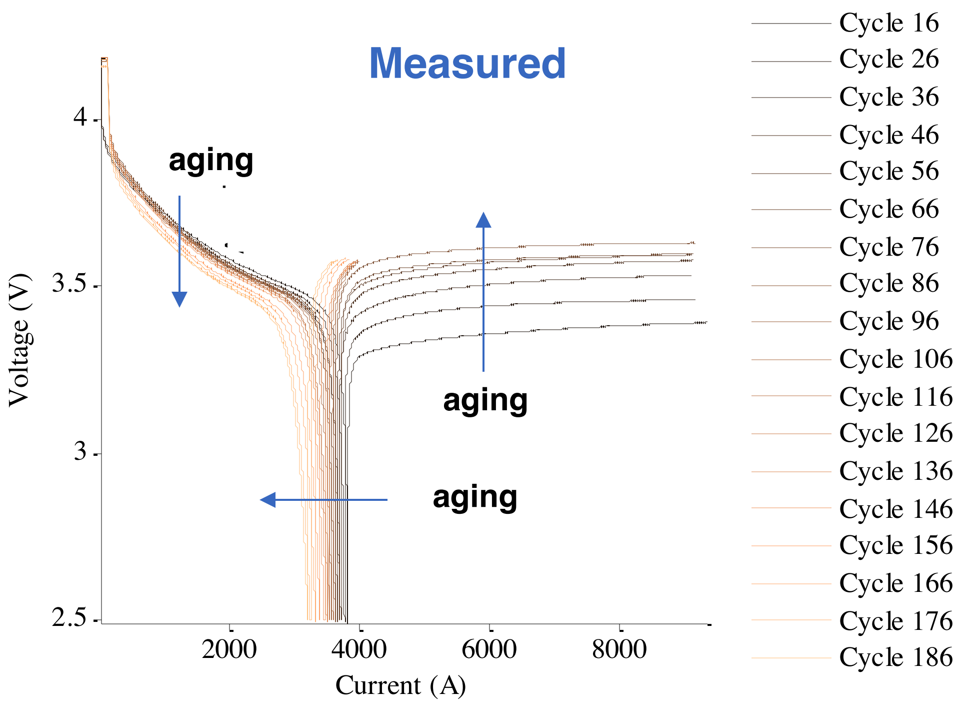
Electrochemical Li-ion Model

- 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

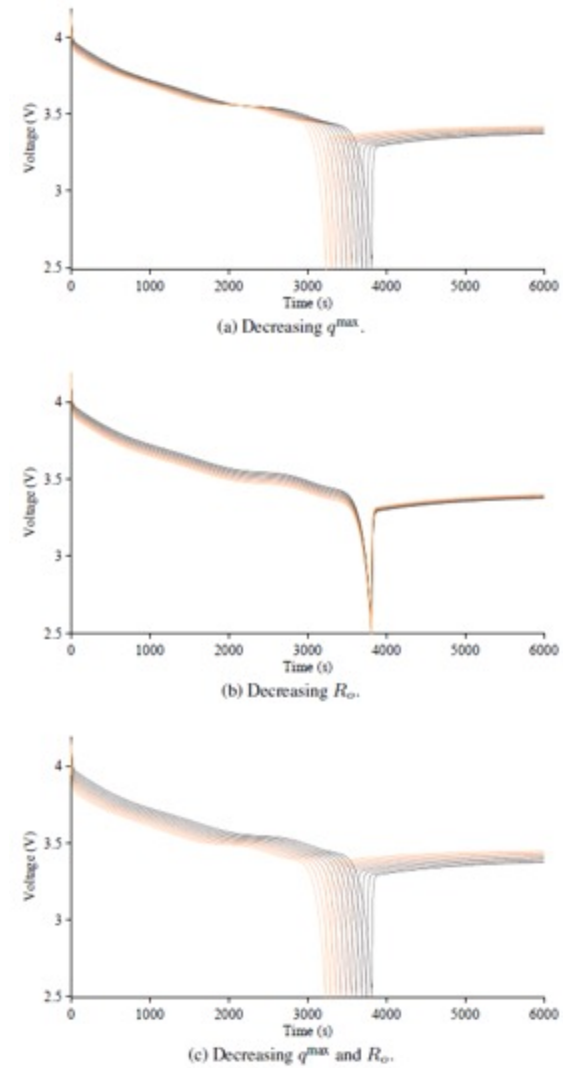


Battery Aging

- 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

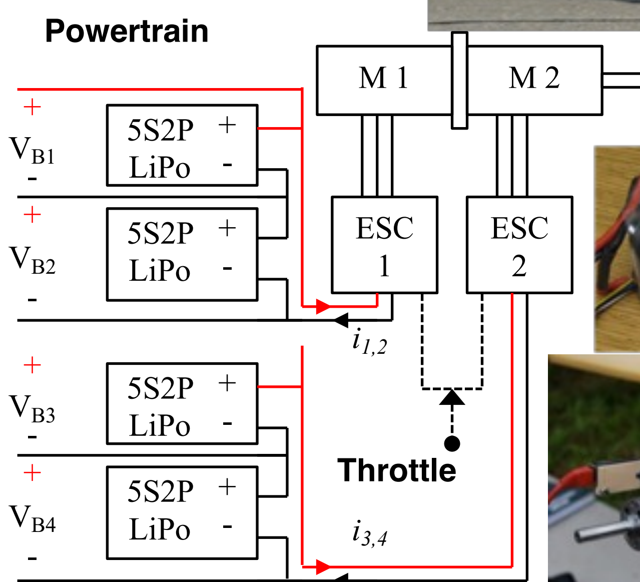


Simulated



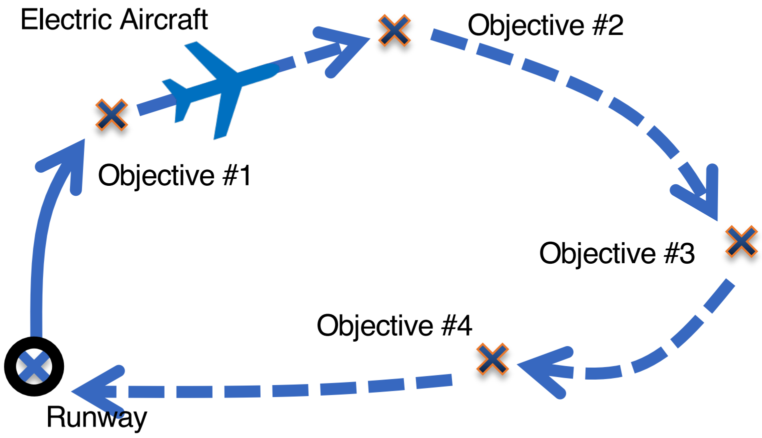
Edge 540-T

- 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



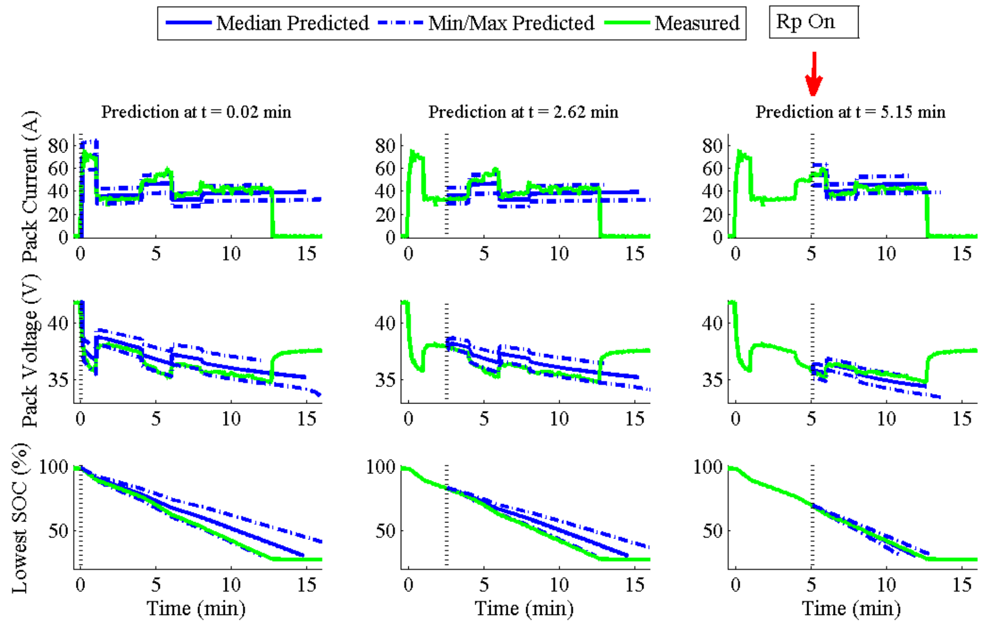
Edge UAV Use Case

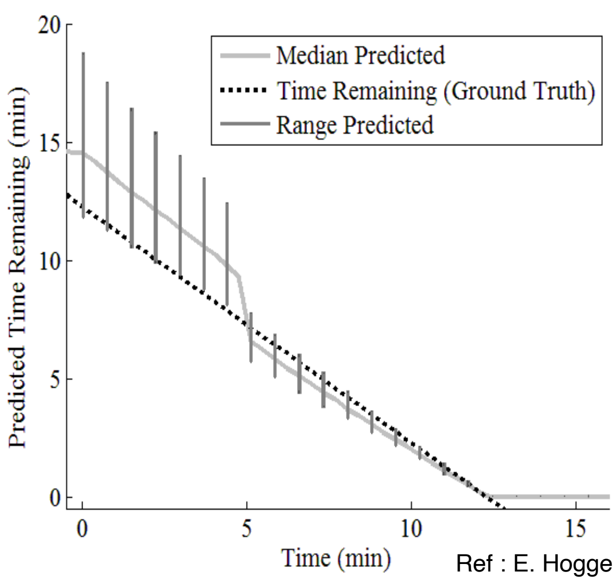
- Piloted and autonomous missions, visiting waypoints
- Require 2-minute warning for EOD so pilot/autopilot has sufficient time to land safely
  - This answer depends on battery age
  - Need to track both current level of charge and current battery age
  - Based on current battery state, current battery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



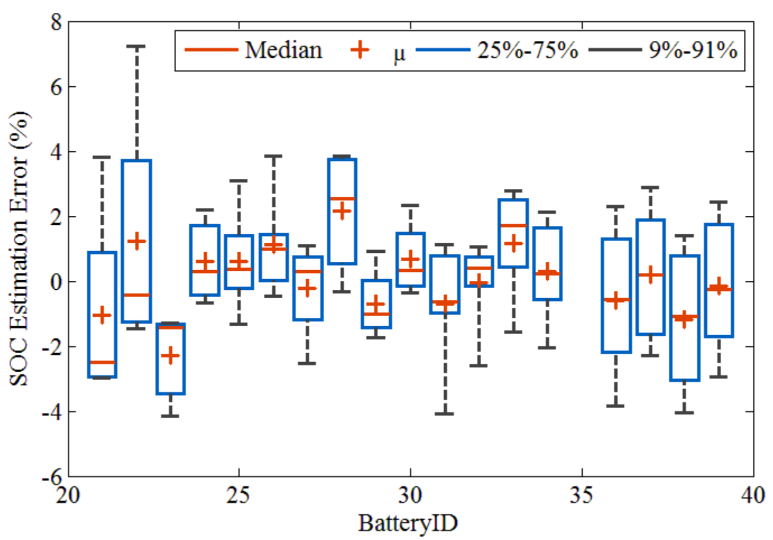


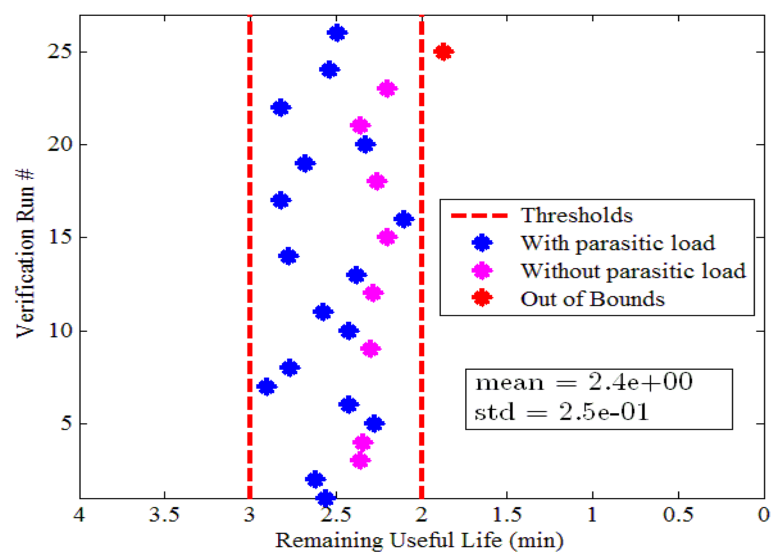
- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

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*





Data Sets Available for Download

- https://www.nasa.gov/content/prognostics-center-of-excellence-data-set-repository

Randomized Battery Usage Data Set
Publications using this data set

Description	Batteries are continuously cycled with randomly generated current profiles

MOSFET Thermal Overstress Aging Data Set
Publications using this data set

Description	Run-to-failure experiments on Power MOSFETs under thermal overstress.
Format	
Datasets	
Dataset Citation	
Publication Citation	

Capacitor Electrical Stress Data Set - 2
Publications using this data set

Description	Capacitors were subjected to electrical stress at 10V. DataSet Reference document can be downloaded here
Format	The set is in .mat format and has been zipped.
Datasets	+ Download Capacitor Electrical Stress Data Set - 2 (2087 downloads)
Dataset Citation	J. Celaya, C. Kulkarni, G. Biswas, and K. Goebel "Capacitor Electrical Stress Data Set - 2", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	J. Celaya, C. Kulkarni, G. Biswas, and K. Goebel, "Towards A Model-based Prognostics Methodology for Electrolytic Capacitors: A Case Study Based on Electrical Overstress Accelerated Aging", International Journal of Prognostics and Health Management. 2012 Vol 3 (2) 004.

Tools Available for Download

ProgPy

ProgPy Python Packages 1.4.0 documentation

Search the docs ...

ProgPy Guide
- prog_models Guide
- prog_algs Guide
- prog_server Guide

API Reference

Release Notes

Glossary

Developers Guide & Project Plan

Theme by the Executable Book Project

ProgPy Guide

This page is a general guide for ProgPy. ProgPy consists of three packages: prog_models, prog_algs, prog_server. To access a guide specific to the package you're using, select it in the menu below.

prog_models | prog_algs | prog_server

What is Prognostics

ProgPy uses the following definition for prognostics:

Prognostics

Prediction of (a) future performance and/or (b) the time at which one or more events of interest occur, for a system or a system of systems

This is similar to those described in [1]. This approach is intended to be generic, capable of describing system behavior based on physical principles (i.e., physics-based), learning from data (i.e., data-based), or hybrid

Contents

https://nasa.github.io/progpy/guide.html

CLOSING REMARKS

- Prognostics helps enable
  - Systems safe and efficient
  - Decision making
- 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
    - Hybrid Approach
- **Requirements for autonomous systems**
- **Framework still in early stages and needs maturation**
- Health Management and Safety Working Group

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.

[5] C. Kulkarni, J. Celaya, G. Biswas, and K. Goebel, "Physics Based Degradation Models for Capac- itor Prognostics under Thermal Overstress Conditions", International Journal of Prognostics and Health Management, 2013 Vol 4 (1) 005.

[6] G. Sonnenfeld, K. Goebel, and J. R. Celaya, "An agile accelerated aging, characterization and scenario simulation system for gate controlled power transistors," in *IEEE AUTOTESTCON 2008*, pp. 208–215, 2008.

[7] J. R. Celaya, N. Patil, S. Saha, P. Wyscoki, and K. Goebel, "Towards accelerated aging methodologies and health management of power MOSFETs," in *Annual Conference of the Prognostics and Health Management Society, 2009*, (San Diego, CA), 2009.

[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.

[11] P. Wysocki, V. Vashchenko, J. Celaya, S. Saha, and K. Goebel, “Effect of electrostatic discharge on electrical characteristics of discrete electronic components,” in *Annual Conference of the Prognostics and Health Management Society, 2009*, (San Diego, CA), 2009.

[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.

[16] S. Saha, J. Celaya, B. Saha, P. Wysocki, and K. Goebel, “Towards modeling the effects of lightning injection on power MOSFETs,” in *Annual Conference of the Prognostics and Health Management Society 2010*, (Portland, OR), 2010.

[17] S. P. Bharadwaj, A. E. Ginart, I. N. Ali, P. W. Kalgren, J. Celaya, and S. Poll, “Solar cells aging estimation based on impedance characterization,” in *IEEE Aerospace Conference 2011*, (Big Sky, MT), 2011.

Publications (3/3)

[18] J. R. Celaya, C. Kulkarni, G. Biswas, and K. Goebel, “Towards prognostics of electrolytic capacitors,” in *AIAA Infotech@Aerospace 2011*, (St. Louis, MO), 2011.

[19] J. R. Celaya, A. Saxena, V. Vashchenko, S. Saha, and K. Goebel, “Prognostics of power MOSFET,” in *23rd International Symposium on Power Semiconductor Devices and ICs*, (San Diego, CA), 2011.

[20] 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 test: MOSFETS in “ON” state,” *NASA Technical Memorandum*, 2011.

[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.

[23] E. Hogge et al, “Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft”, PHM 2015

[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

THANK YOU!

chetan.s.kulkarni@nasa.gov

https://www.nasa.gov/content/prognostics-center-of-excellence