Tutorial: Electronics PHM

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Agenda

- Introduction to Prognostics
- Introduction to Model-based Prognostics
- Research Approach for Prognostics of Electronics
- 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
- Closing Remarks

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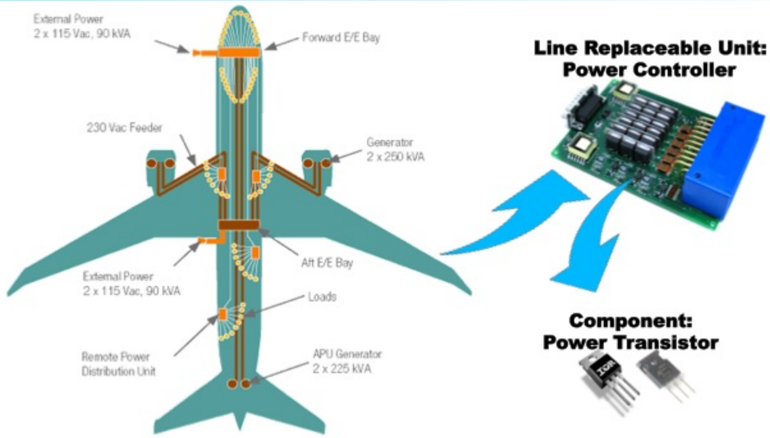
INTRODUCTION TO PROGNOSTICS

Motivation (1/2)

- Future aircraft systems will rely more on electronic components
- 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
  - The integrated navigation (INAV) module combines output of the GPS model and inertial measurement unit.
    - The filter capacitor of the power supply is the component which fails most often
      - faulty operation generates navigations errors in INAV
- Assumption of new functionality increases number of electronics 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

- Components under study:
  - **Power MOSFET**: IRF520Npbf, TO-220 package, 100V/9.27A
  - **IGBT**: IRG4BC30KD, TO-220 package, 600V/16A
  - **Electrolytic Capacitor:** 2200 uF, 10V

Definitions

- 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

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
    - Highrisk 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 & Cons

- 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

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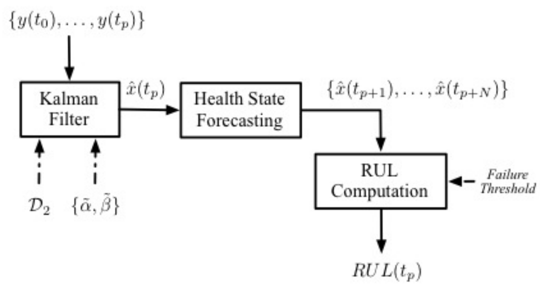
INTRODUCTION TO MODEL-BASED PROGNOSTICS

Model-based prognostics (1/2)

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

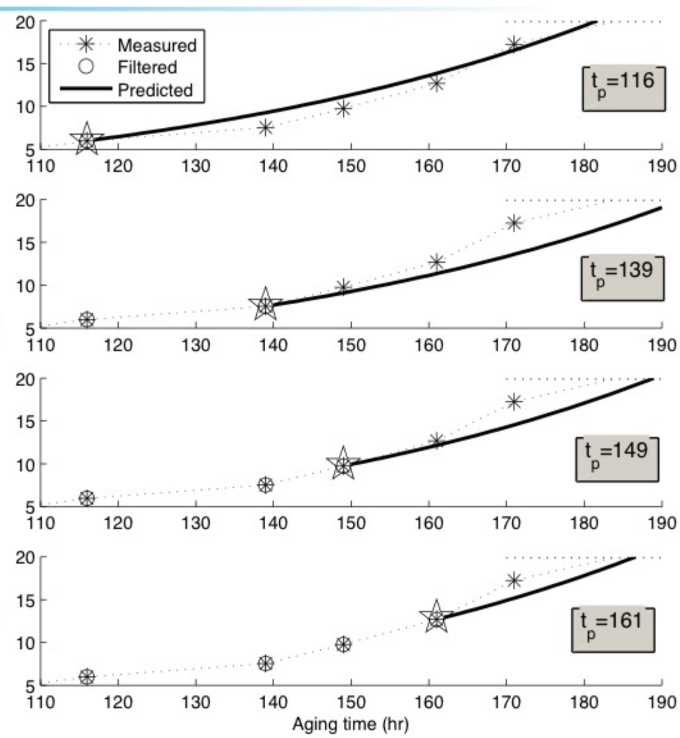
$$R(t_p) = t_{EOL} - t_p$$



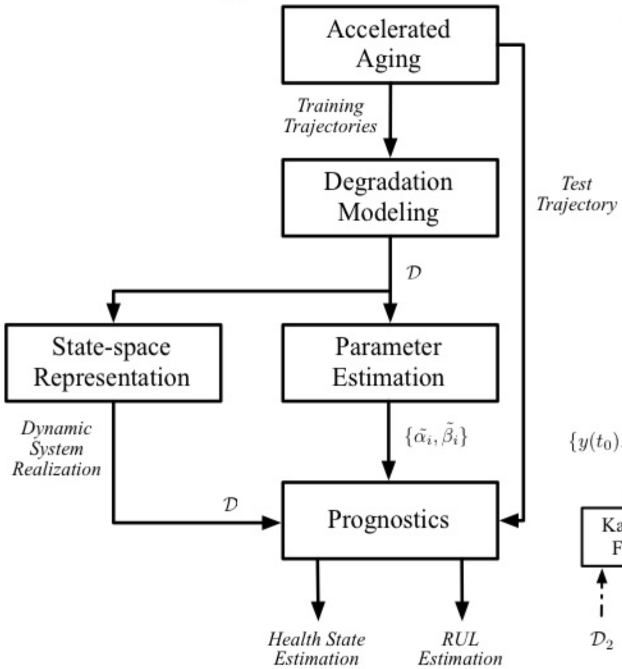
- State vector includes dynamics of the degradation process
- It might include nominal operation dynamics
- EOL defined at time in which performance variable cross failure threshold
- Failure threshold could be crisp or also a random variable

Model-based prognostics (2/2)

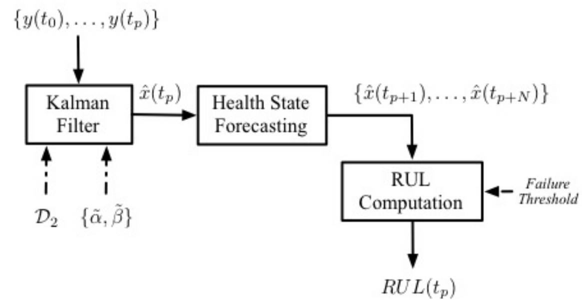
- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed



Methodology



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



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RESEARCH APPROACH FOR PROGNOSTICS OF ELECTRONICS

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 (CALCE)
  - Modeling of degradation process MOSFETs
  - Development of prognostics algorithms
- Prognostics for output capacitor in power supplies (Vanderbilt)
  - 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)
- Effects of ESD events of MOSFETS and IGBTs
- Effects of radiation on MOSFETS and IGBTs

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

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ACCELERATED AGING AS A PROGNOSTICS RESEARCH TOOL

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

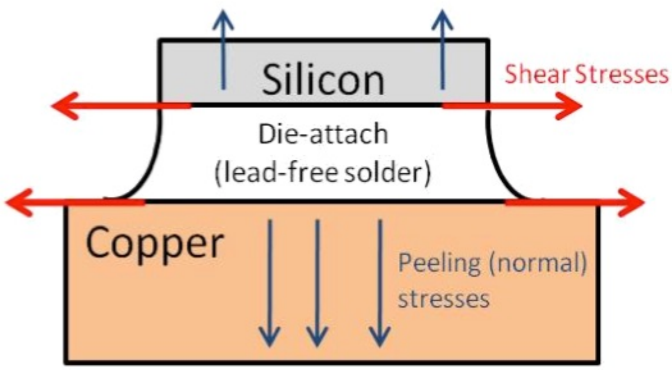
Thermal overstress aging of Power Transistors

Accelerated Aging Methodology

- The main strategy is the application of thermal overstress in the form of thermal cycles
- This is achieved by
  - Power cycling the devices without use of any external heat sink
  - Causing self heating during the power switching operation
- The goal is to induce package related failures like die-attach damage
- Failure is defined as
  - Latch up
  - Loss of gate control (failure to turn ON)
  - Thermal runaway

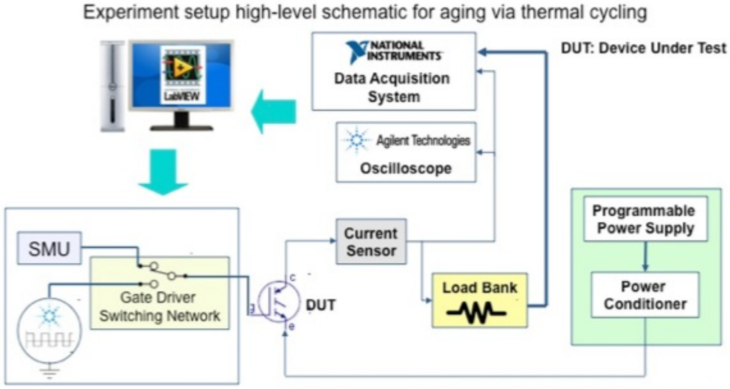
Thermal-Mechanical Stresses

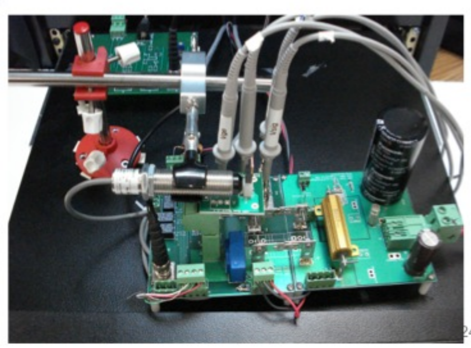
- The device structure can be regarded as a bi-metal assembly
  - Copper (internal heat sink) is the substrate
  - Silicon die is attached to the substrate with solder (die-attach)
- Thermally mismatched assembly due to difference in coefficient of thermal expansion (ppm/°C).
  - Copper: 16-18,
  - Silicon: 2.6-3.3, and
  - Lead-free Solder: 20-22.9



System Description

Experiment setup high-level schematic for aging via thermal cycling

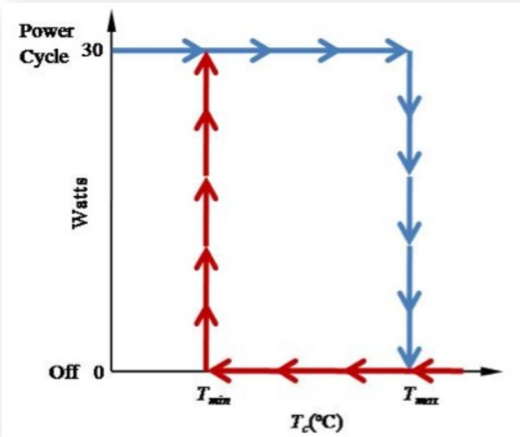




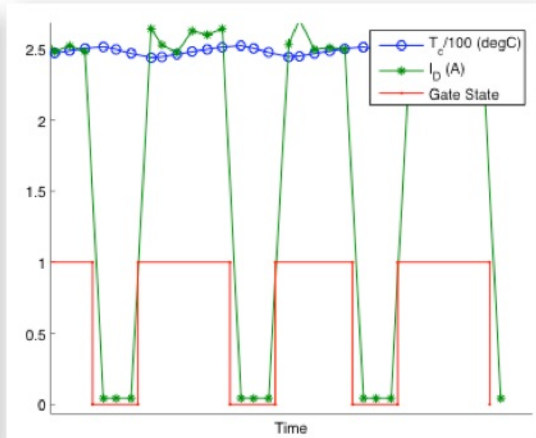
Aging Experiments

- Hysteresis control is used to provide thermal cycles needed for acceleration

Case temperature control law



Accelerated aging regime

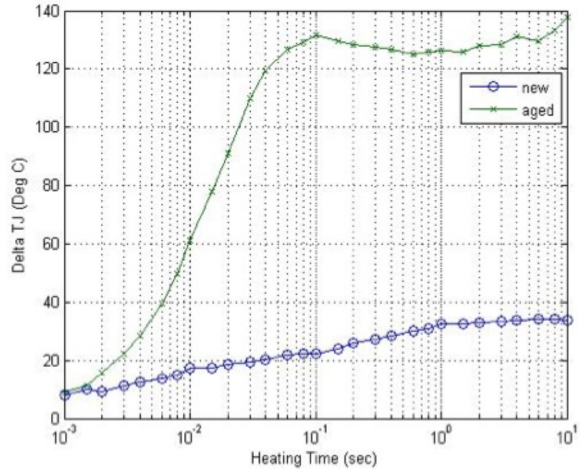


Die-Attach Damage Assessment (1/3)

- Collecting the ground truth data
  - Heat transfer performance due to thermal conduction decreases with die-attach damage
    - Voids, cracks, other mechanical damage
  - MIL-750 standard method 3161 provides a methodology for thermal impedance measurements for power MOSFET
    - Delta source-drain voltage method
    - Body diode is used to measure junction temperature
  - Heating curves can provide an assessment of the thermal characteristics of the die-attach

Die-Attach Damage Assessment (2/3)

- Results for Device #11
- 1 sec. heating time
- Same power applied to both tests (same heating profile)
- Steep slope starting at ~10ms is indicative of the die attach damage
- This method can be included as a BIT in order to periodically assess die-attach damage

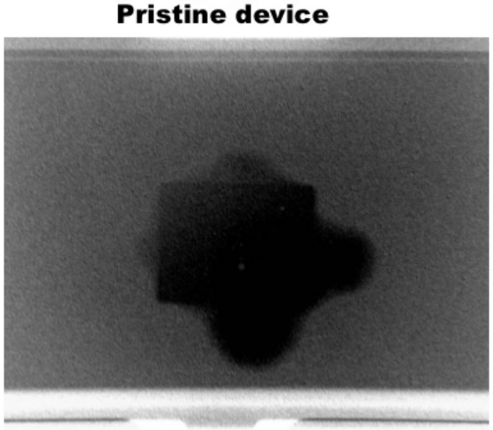


Aged device under thermal cycling heats up considerably faster than a pristine device

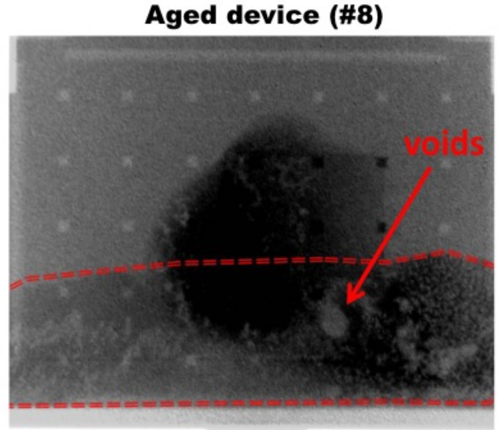
Die-Attach Damage Assessment (2/3)

- Damage of the die-attach interface can also be observed visually using failure analysis techniques like X-Ray (below) and Scanning Acoustic Microscopy

Pristine device



Aged device (#8)



Example: Electrical overstress aging of Power Transistors

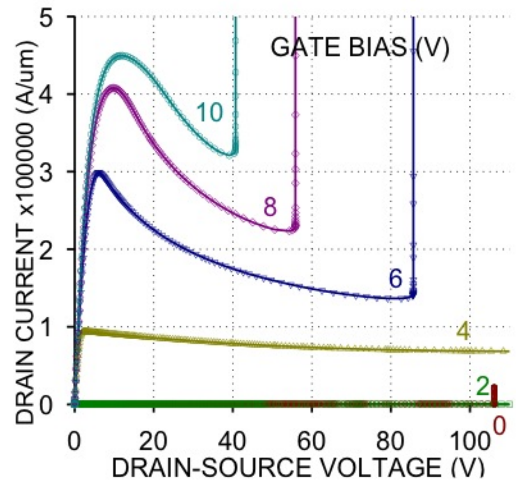
Accelerate aging strategy (1/3)

- The main strategy is the
  - 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 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 safe operation area boundary shifts closer to the origin as the temperature increases

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

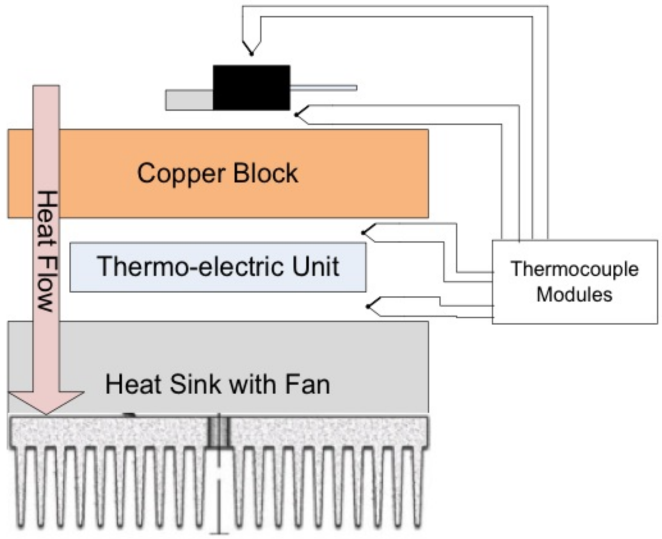


Aging system description (1/3)

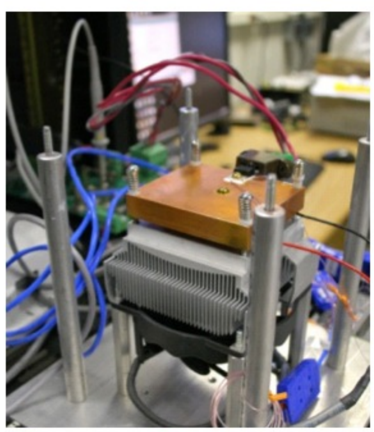
- Three main components in terms of hardware
  - Electrical operation unit of the device
    - custom made printed circuit boards for the instrumentation circuitry and gate drivers
    - commercially available power supplies and function generator to control the operation of the DUT
  - An in-situ measurement 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

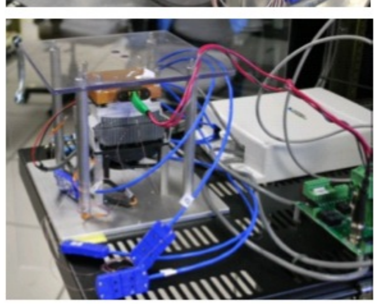
Aging system description (2/3)

Thermal block for measurement and control of device temperature



Aging system description (3/3)



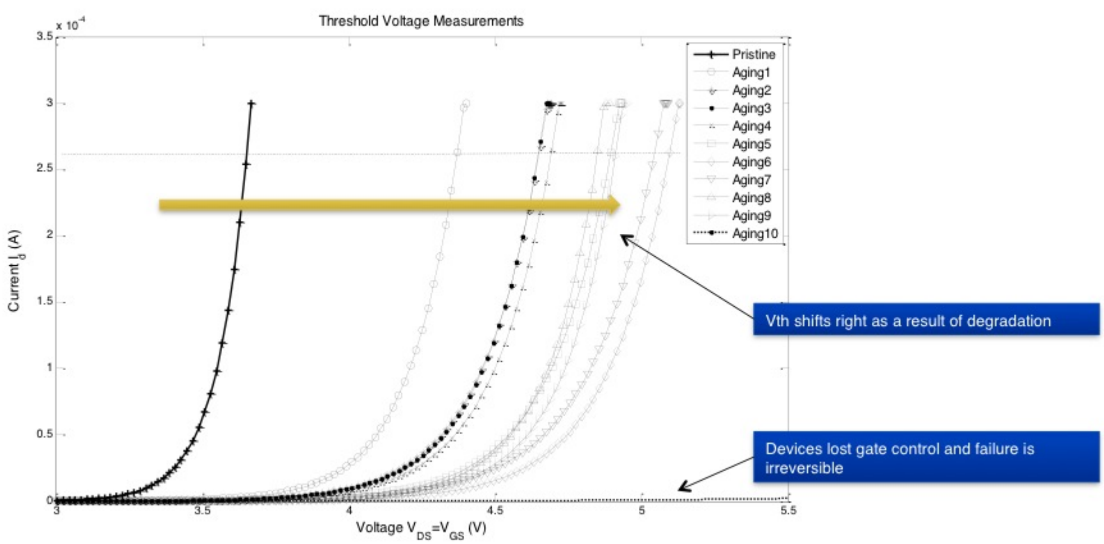


Experiment on power MOSFET (1/2)

- 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 (Vth)

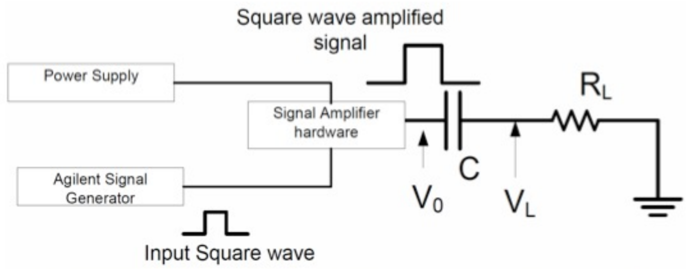


Example: Electrical overstress aging of Electrolytic Capacitors

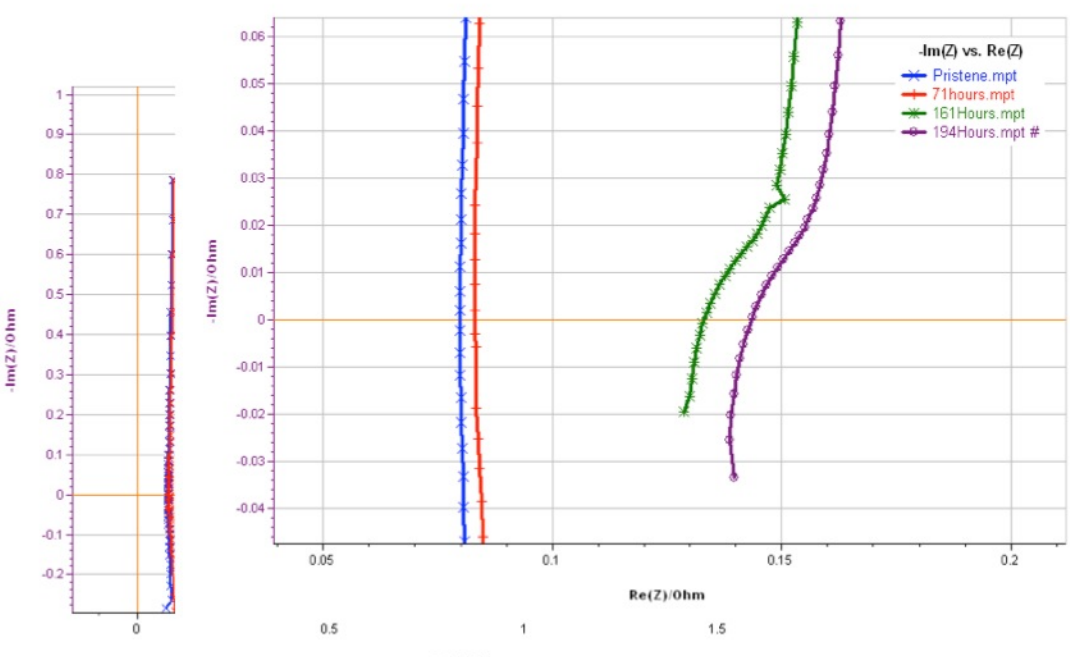
Accelerated aging system

- 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 hr
  - Square signal at 200 mHz with 12V amplitude and 100 ohm load

Electrical Overstress Aging System



Degradation observed on EIS measurements



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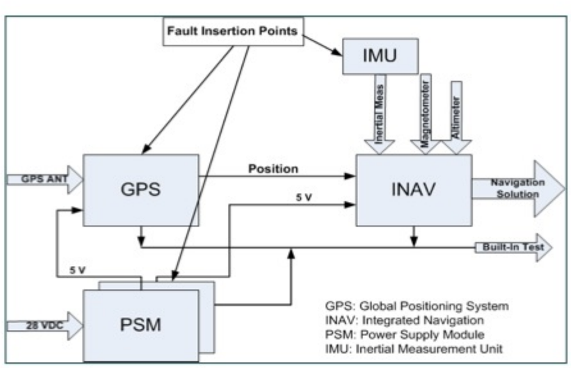
CASE STUDY I: PROGNOSTICS OF ELECTROLYTIC CAPACITORS

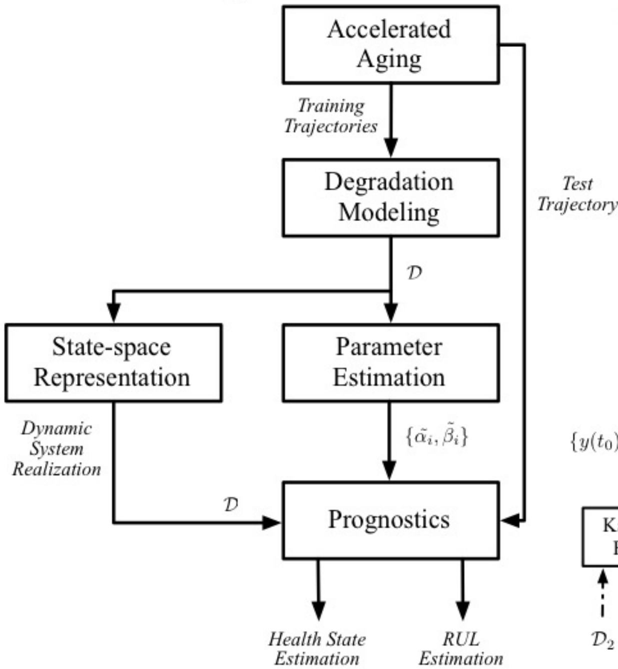
MODEL-BASED APPROACH EXAMPLE

Case Study: Avionics System

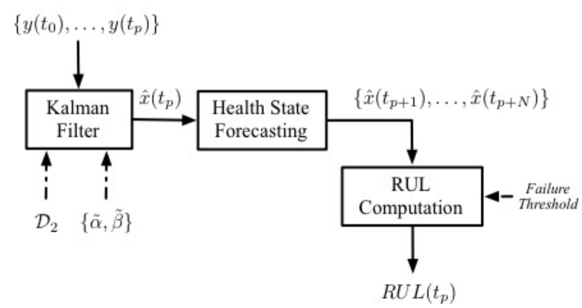
- Integrated Avionics systems consists of:
  - Global Positioning System (GPS) module
  - Integrated navigation (INAV) module combines output of the GPS model and Inertial measurement unit
  - Power Supply module



Methodology

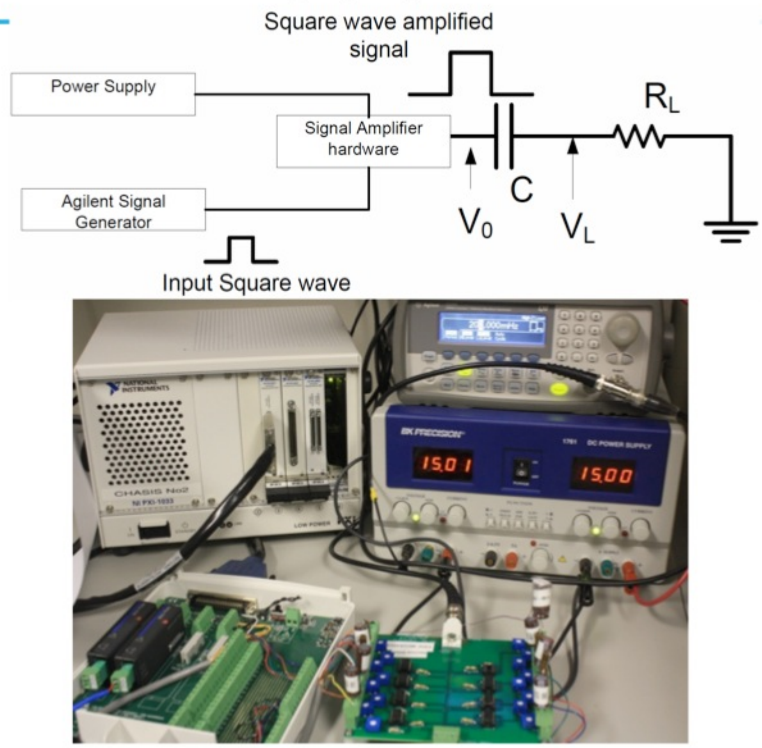


$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$y_k = Hx_k + v_k$$

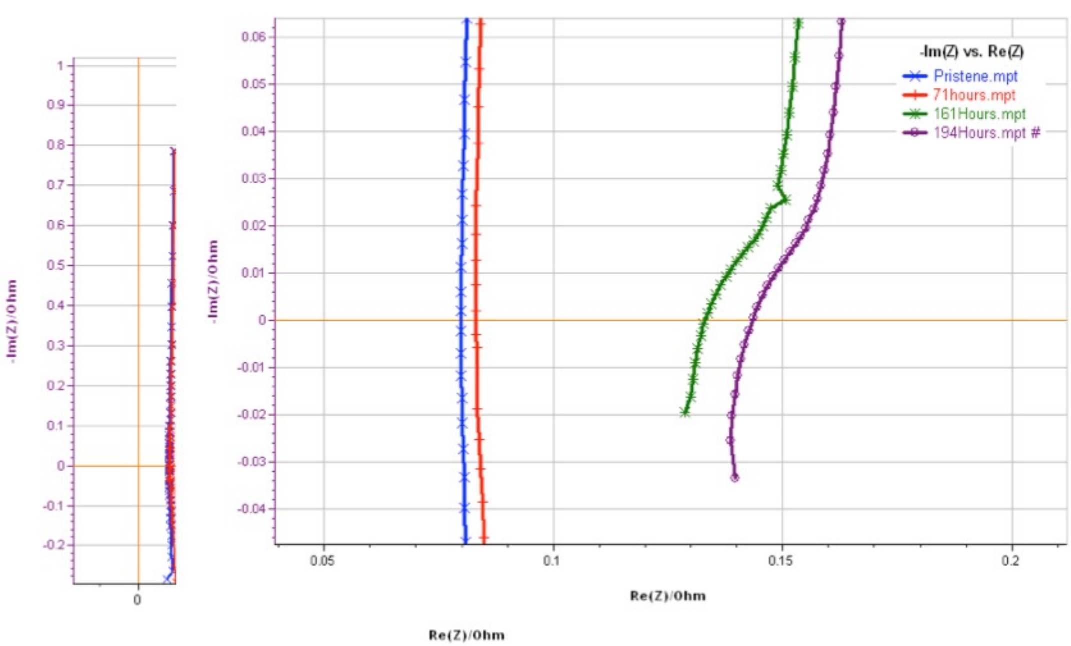


Accelerated Aging and Precursors of Failure Features

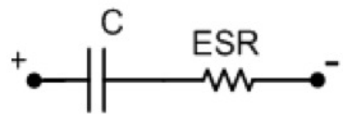
Electrical Overstress Aging System



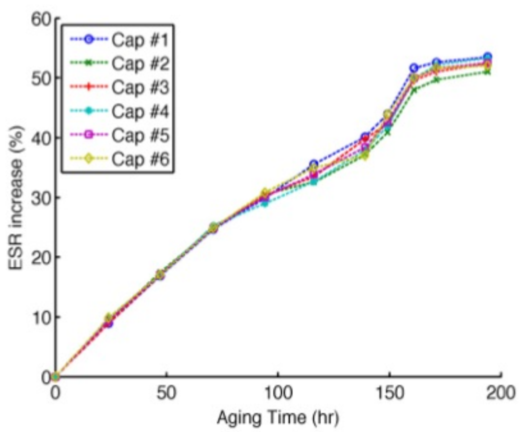
Degradation observed on EIS measurements

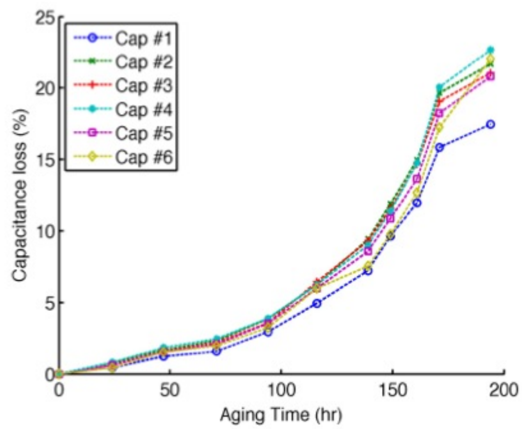


Degradation on lumped parameter model

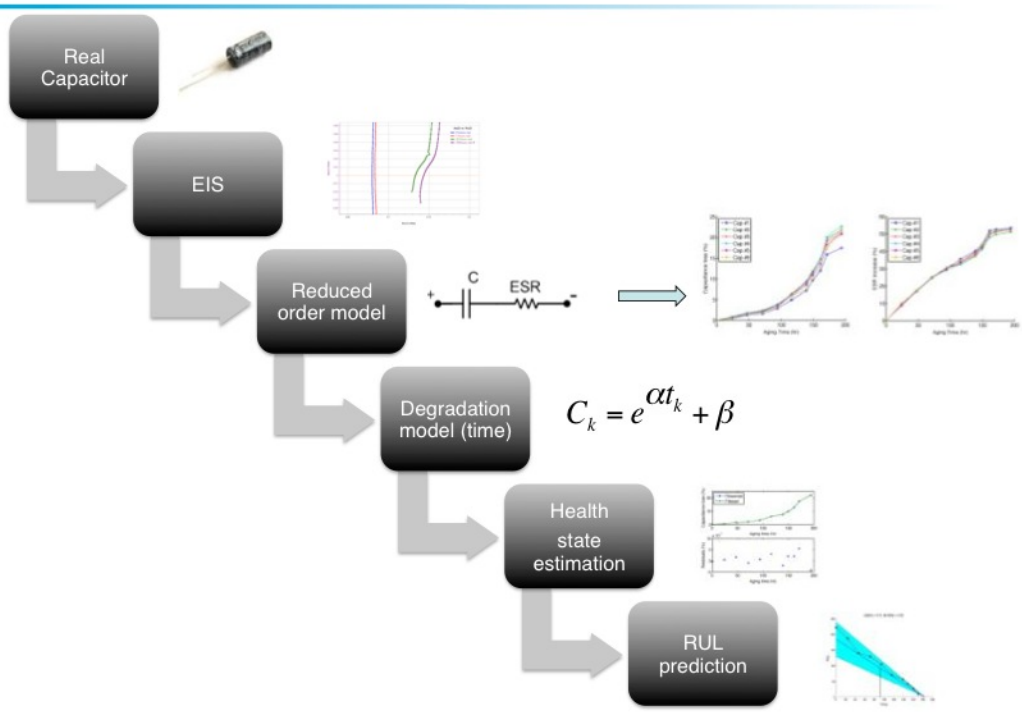


C and ESR are estimated from EIS measurements





Methodology

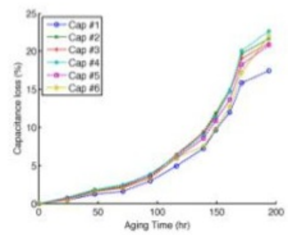


$$C_k = e^{\alpha t_k} + \beta$$

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 modeled 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

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

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

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

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

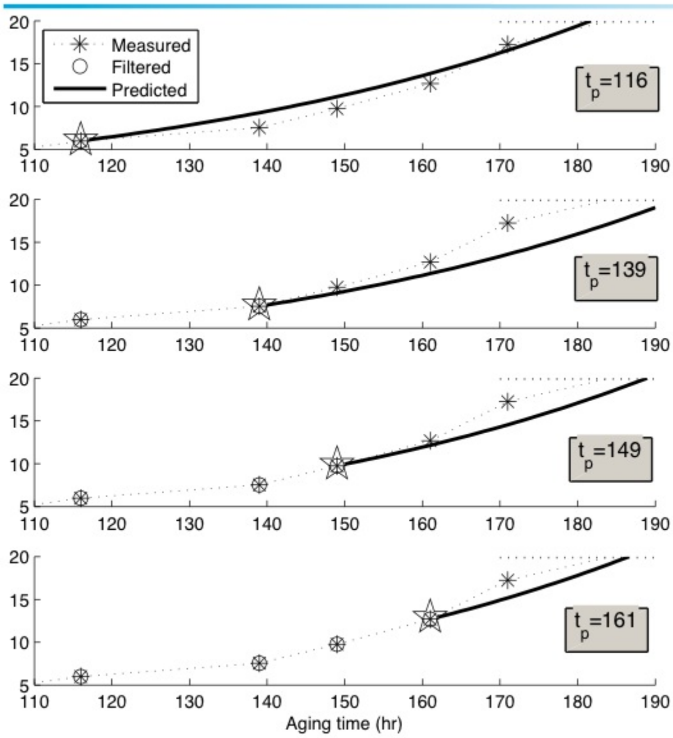
$$h = 1,\ u = 1.$$

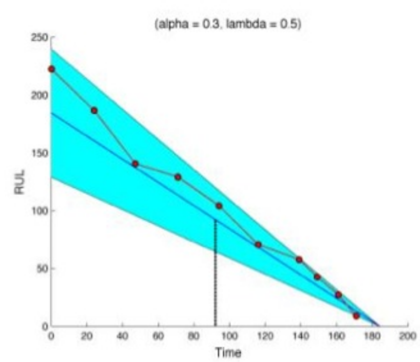
Prediction mode

- 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)

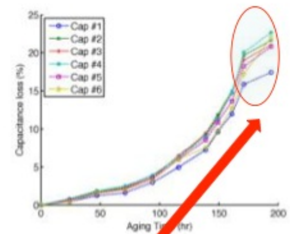




Relative Accuracy

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

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**



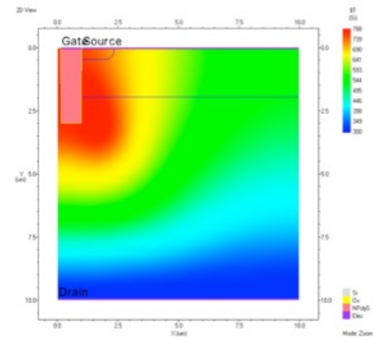
Electronics PHM

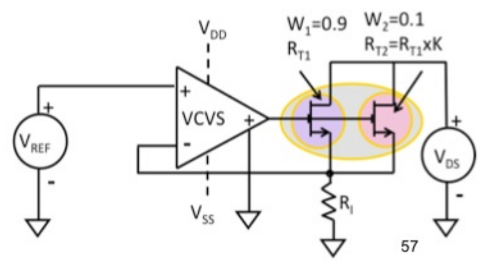
CASE STUDY II: PROGNOSTICS OF POWER TRANSISTORS

PRECURSORS OF FAILURE EXAMPLE

Modeling for Power MOSFET under electrical overstress

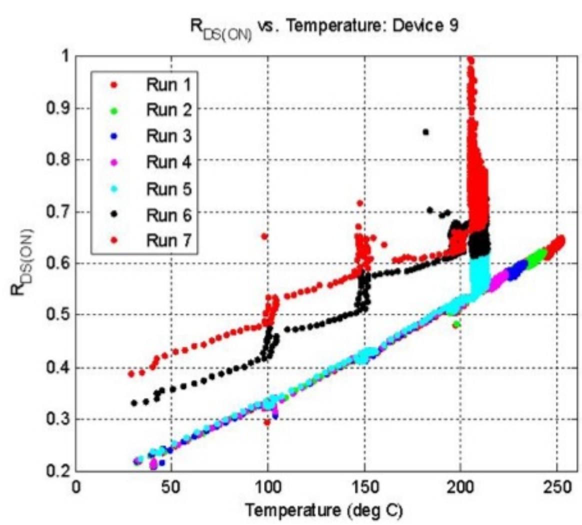
- Two-transistor model is shown to be a good candidate for a degradation model for model-based prognostics.
- The model parameters K, and W1 could be varied as the device degrades as a function of usage time, loading and environmental conditions.
- Parameter W1 defines the area of the healthy transistors, 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.





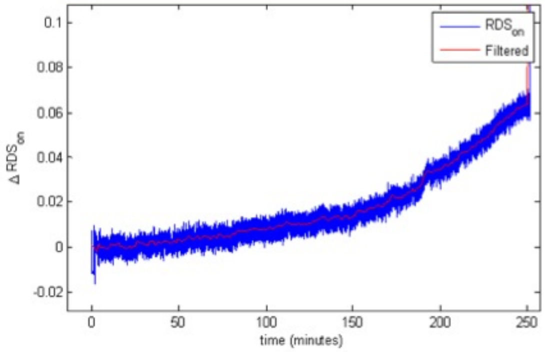
Precursor of Failure

- 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



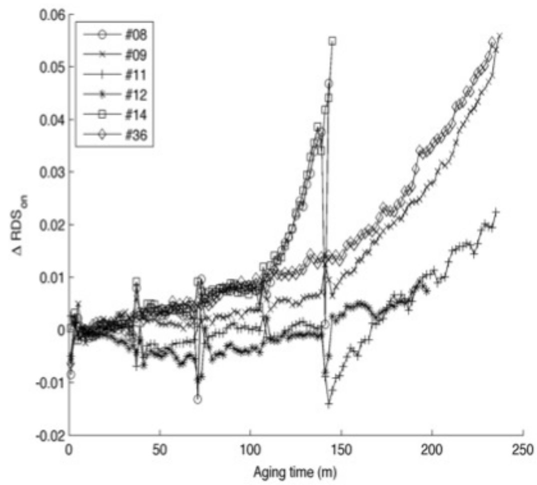
Degradation process data

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



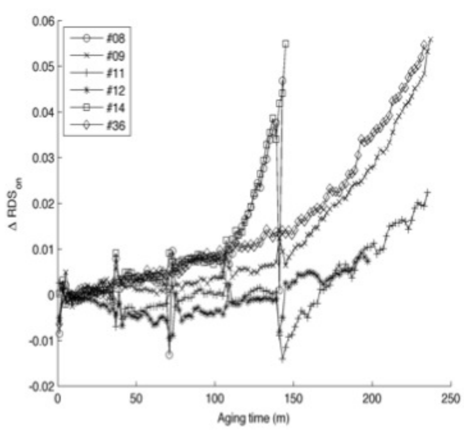
- Cases #08, #09, #11, #12 and #14 are used for algorithm development purposes.
- Case #36 is used to test the algorithms.

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

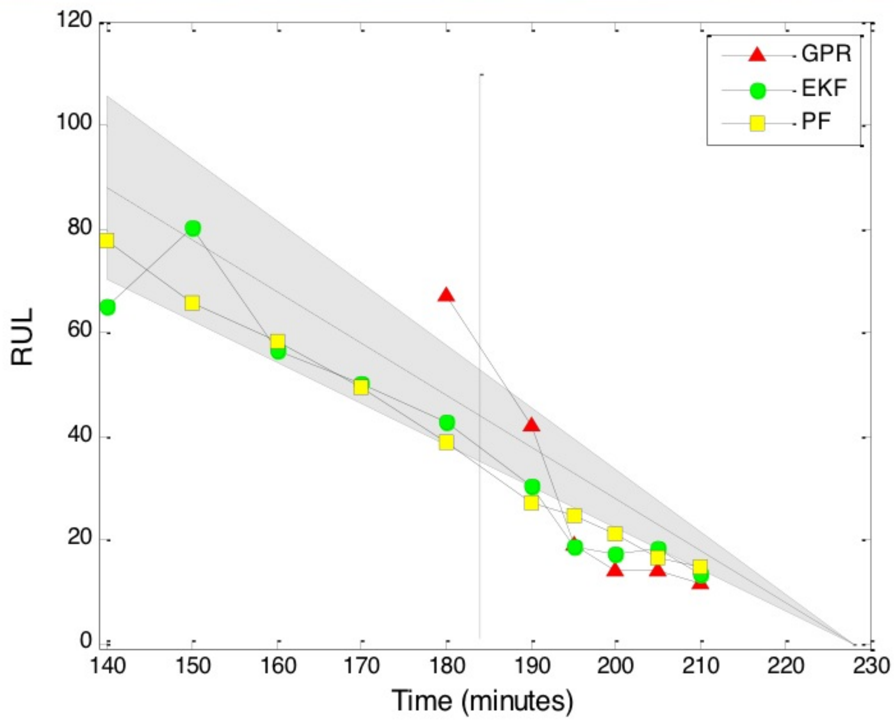
RUL Prediction Methodology Considerations

- 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



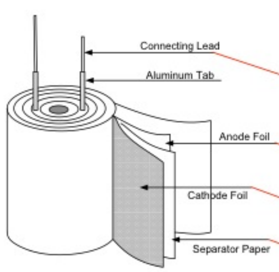
Electronics PHM

CASE STUDY III: PHYSICS-BASED PROGNOSTICS OF CAPACITORS

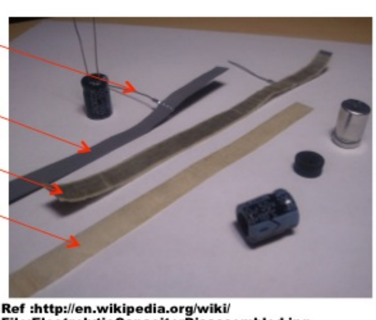
DEGRADATION MODELING EXAMPLE

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

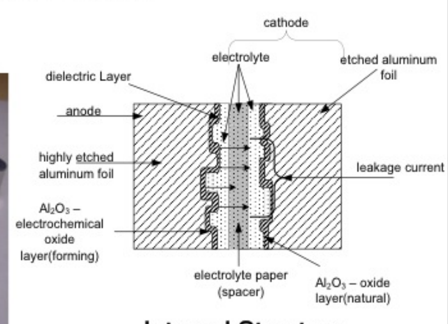


Physical Structure



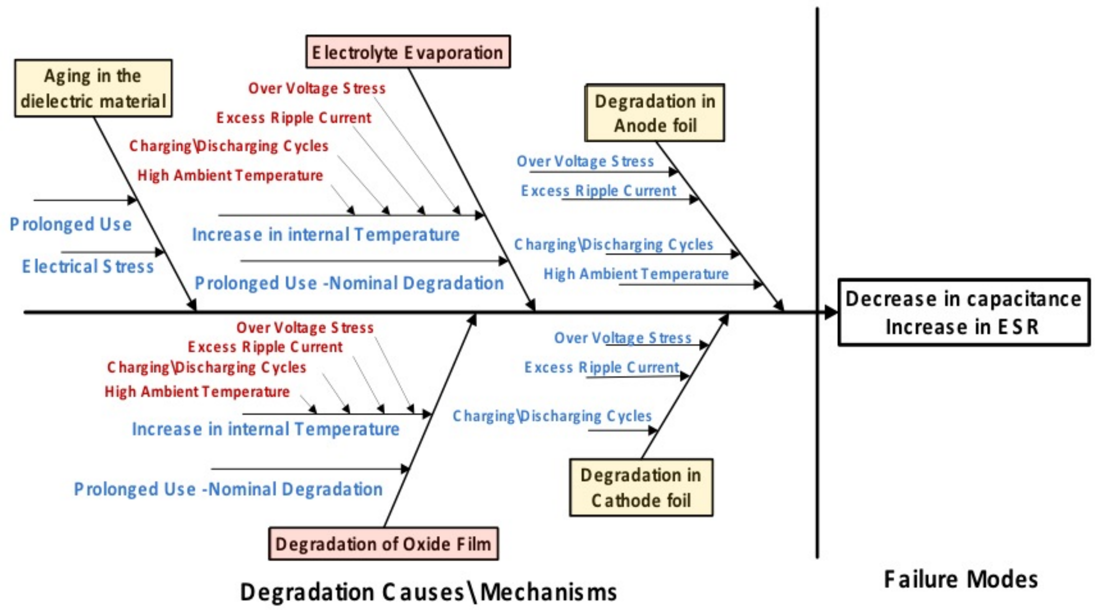
Ref :http://en.wikipedia.org/wiki/File:ElectrolyticCapacitorDisassembled.jpg

Open Structure

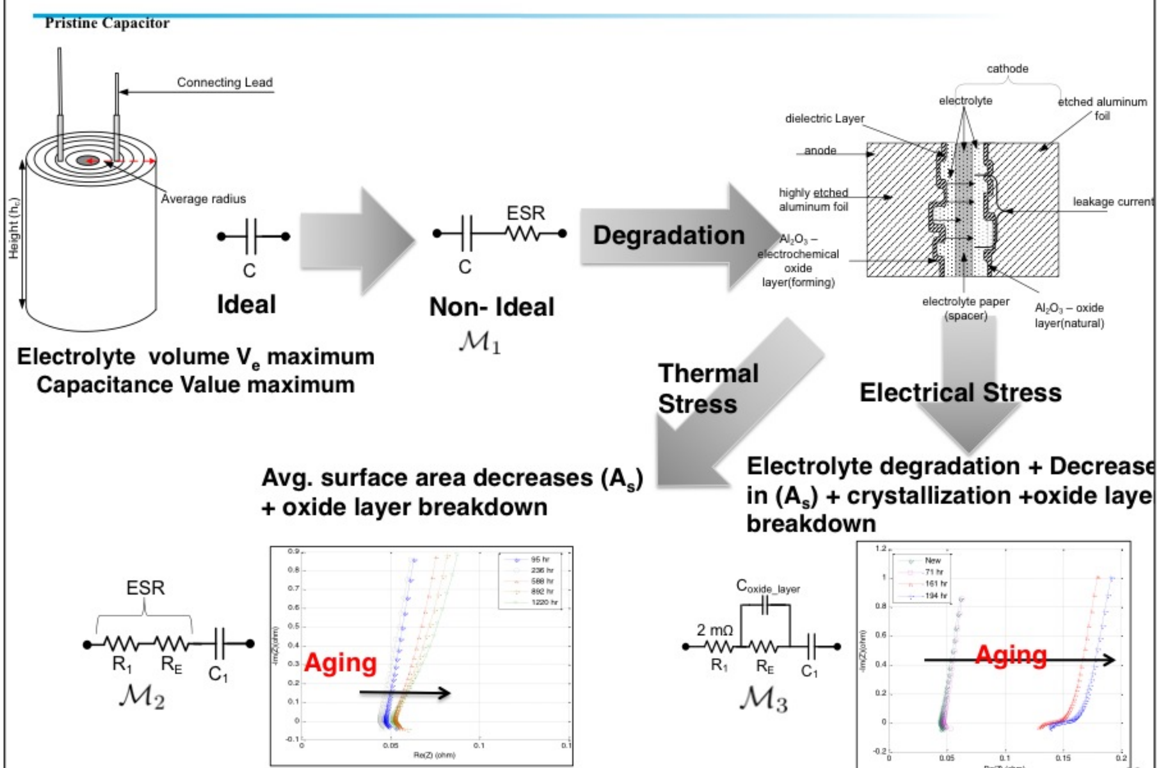


Internal Structure

Degradation Mechanisms



Capacitor Degradation Model



Empirical Model with static parameters

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

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

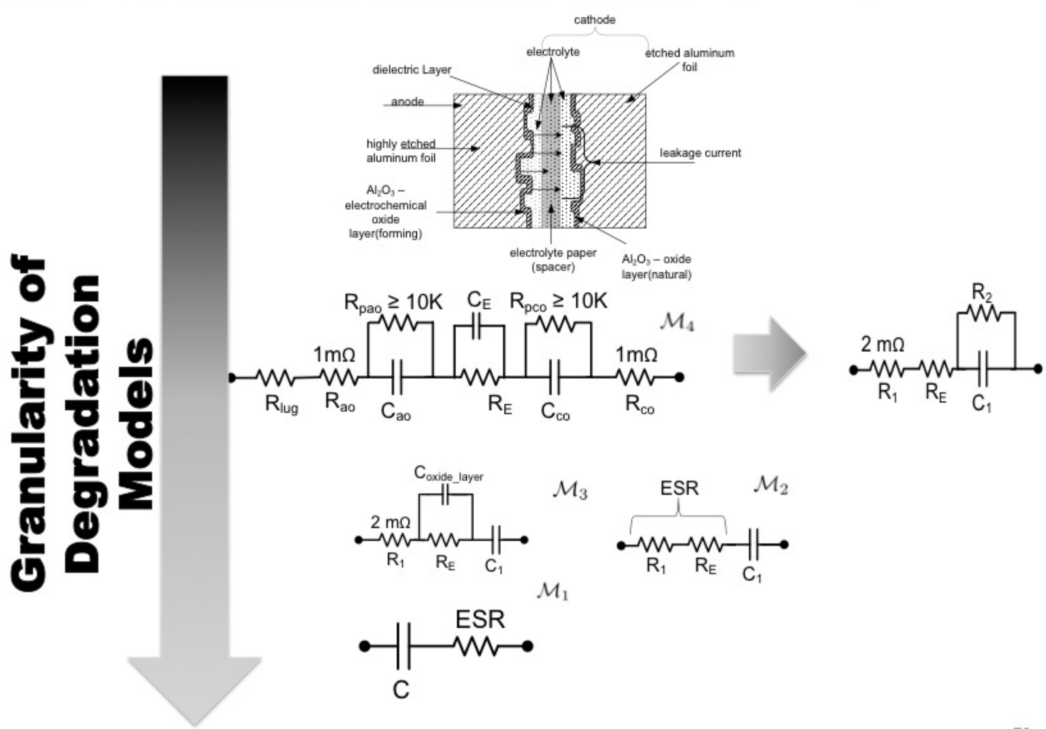
  - α and β are degradation model parameters estimated from the experimental data.
- The following system structure is used in the implementation of the filtering and the prediction using the Kalman filter.

$$x_k = A_k x_{k-1} + B_k u + v, \qquad A_k = (1 + \Delta_k),$$
$$y_k = h x_k + w, \qquad B_k = -\alpha\beta\Delta_k,$$
$$h = 1,$$
$$u = 1.$$

- 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 :

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

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:

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

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

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

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

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

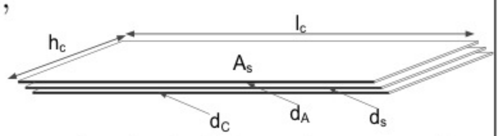
- Updated in capacitance degradation model :

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

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

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

Similarly Capacitace can be expressed as :

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

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)

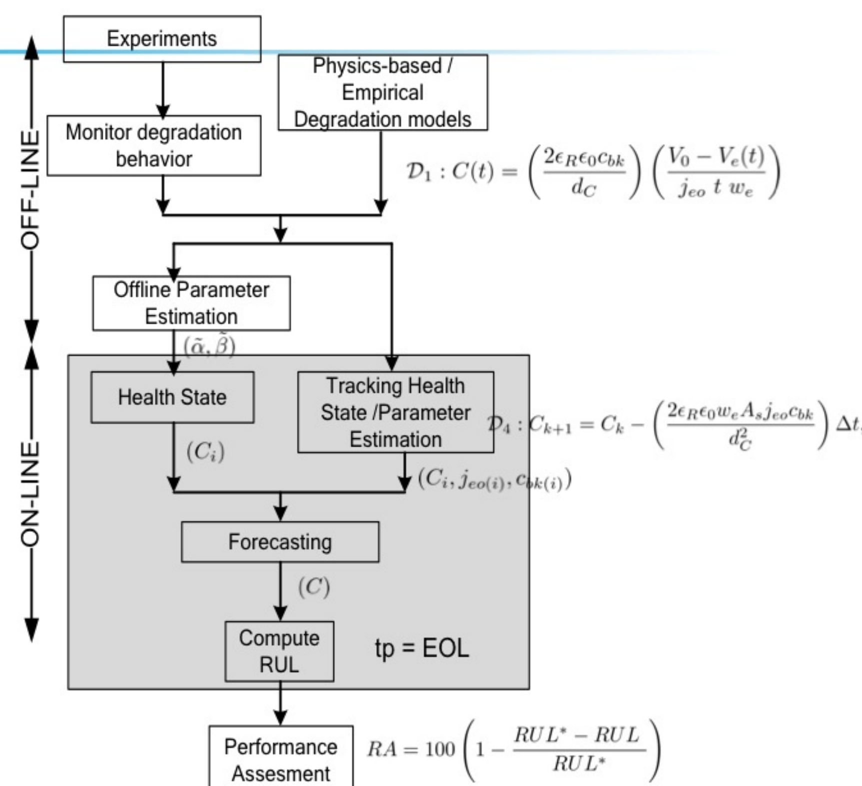
$$ESR = \frac{1}{2}\left(\frac{\rho_E d_C P_E e_{bk(t)}}{A_s}\right) \quad (8)$$

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

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



Unscented Kalman Filter for State Estimation

- Derived physics-based degradation model

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

- The following system structure is implemented for state estimation

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

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

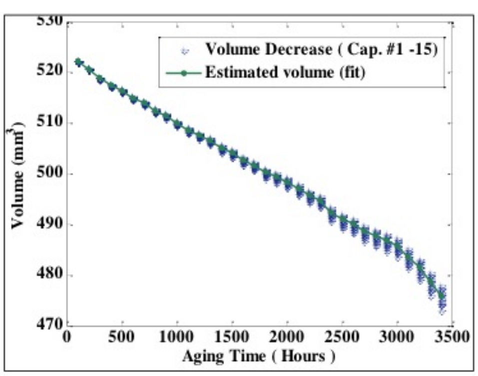
- The state variable (x_k) is the current health state at aging time (t_p)

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

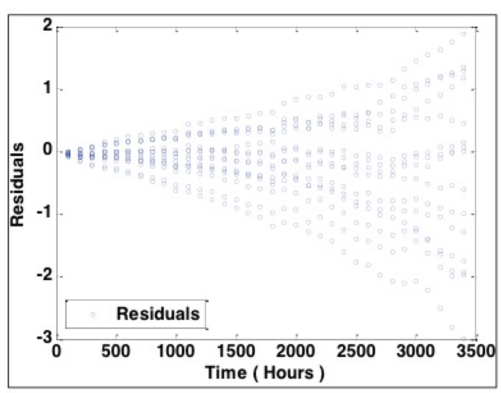
Electrolyte Volume Estimation for TOS Experiment

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



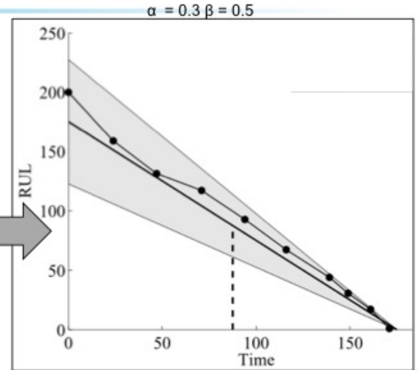
Volume estimation Error

RA Results – Discussion EOS Experiment

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

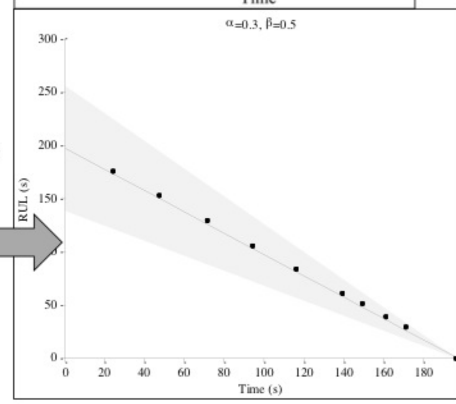
$$\mathcal{E}_1 : C_l(t) = e^{\alpha t} + \beta,$$



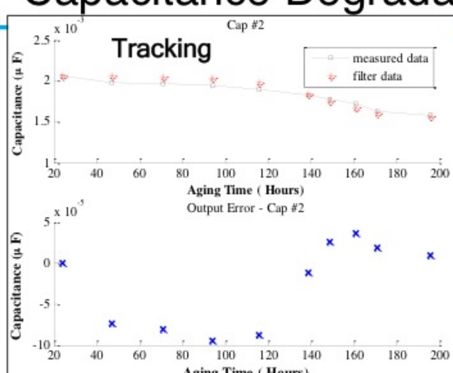
Capacitance - Over RA summary for model $\mathcal{D}_4$

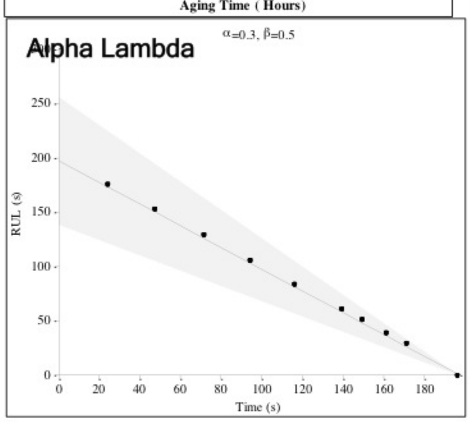
Aging Time	$\overline{RA}_a$
24	98.06
47	97.76
71	97.34
94	96.73
116	95.84
139	94.16
149	92.92
161	90.49
171	86.67

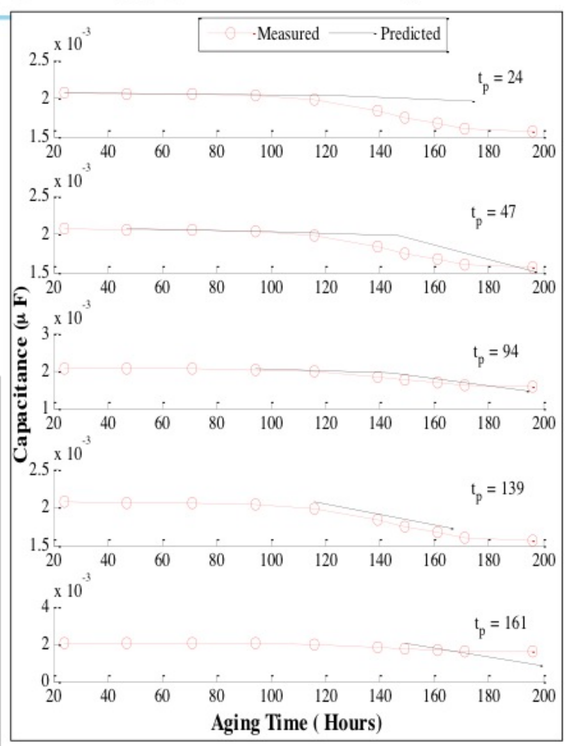
$$\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2}\right)\Delta t$$



RUL and Validation – EOS -Experiment – Capacitance Degradation Model $\mathcal{D}_4$

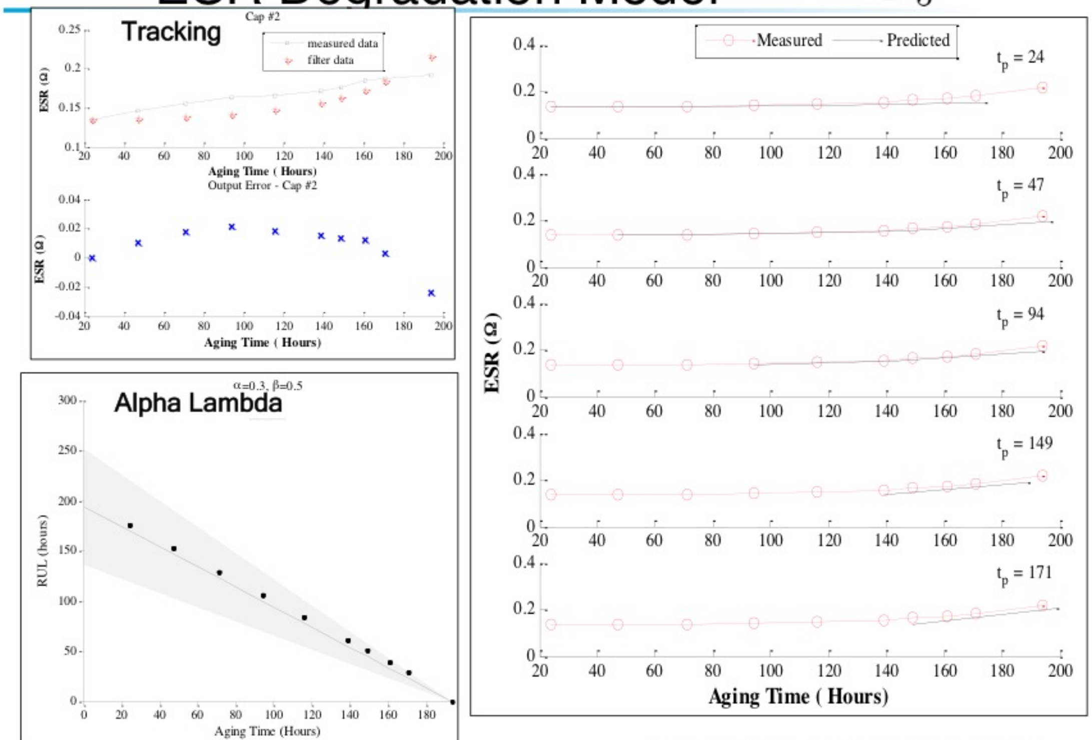






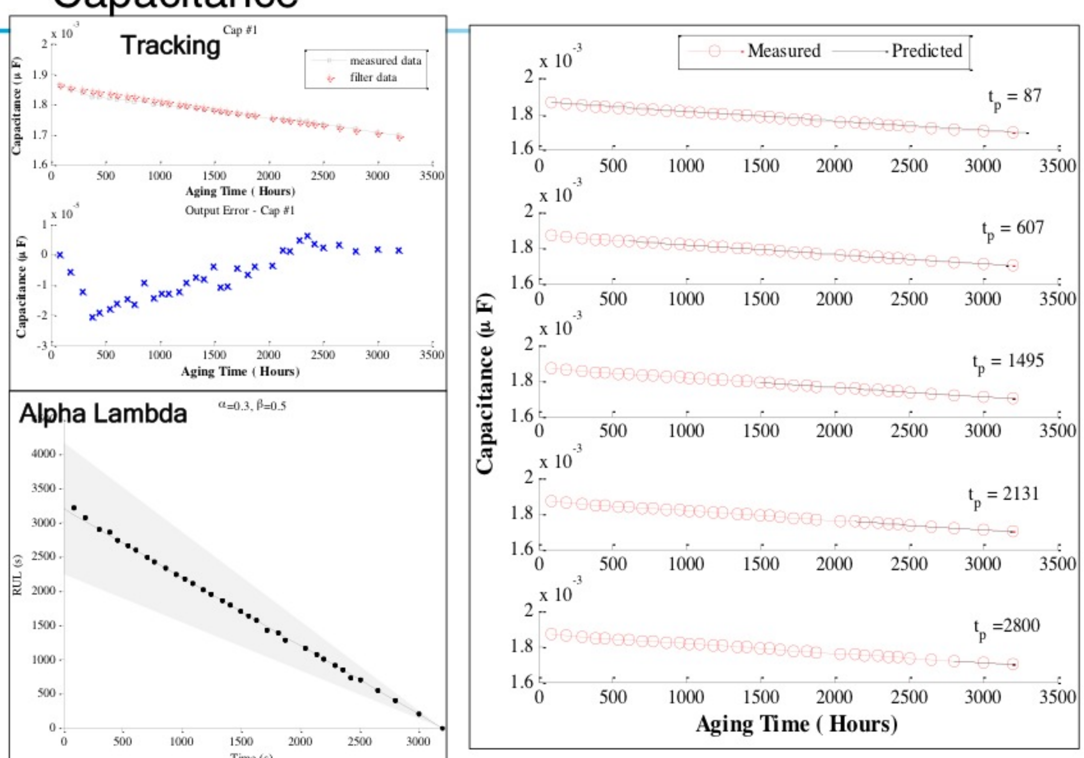
Predictions at different aging time

RUL and Validation – EOS -Experiment – ESR Degradation Model $\mathcal{D}_5$



Predictions at different aging time

RUL and Validation – TOS -Experiment - Capacitance



Predictions at different aging time

Electronics PHM

CLOSING REMARKS

Remarks (1/2)

- Electronics PHM Maturity (scientific and engineering challenges still present)
- 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 processes is key

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
- A success in Electronics PHM in an real usage application will require the right team

Acknowledgments

- To my colleague **Dr.Chetan Kulkarni** for our collaboration in Prognostics for Capacitors
- To my colleagues **Dr. Kai Goebel** and **Dr. Abhinav Saxena** for sharing material from previous tutorial to complement this one
- To **Impact Technologies** for helping to set up a vision and research direction for Electronics PHM and for multiple collaborations in related topics

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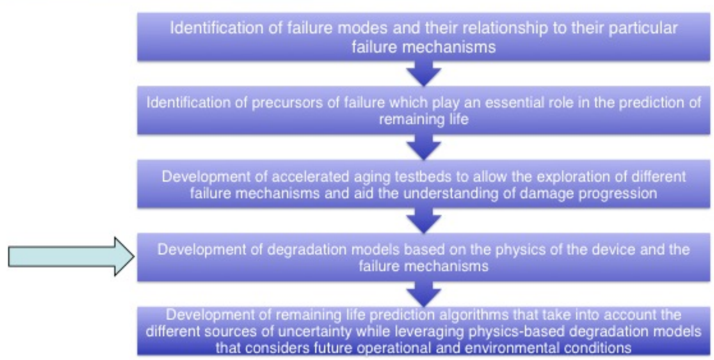
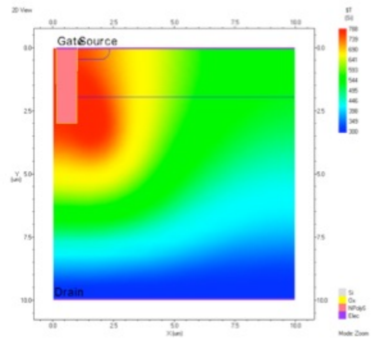


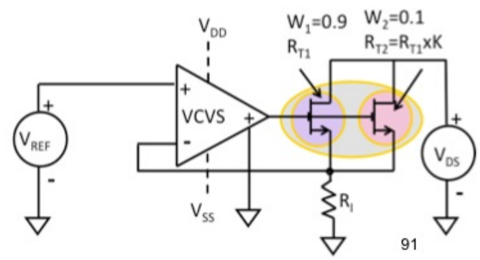
Prognostics for Electronics

PROGNOSTICS MODEL DEVELOPMENT

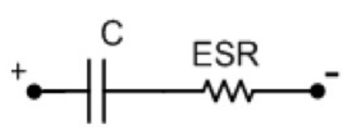
Modeling for Power MOSFET under electrical overstress

- 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.

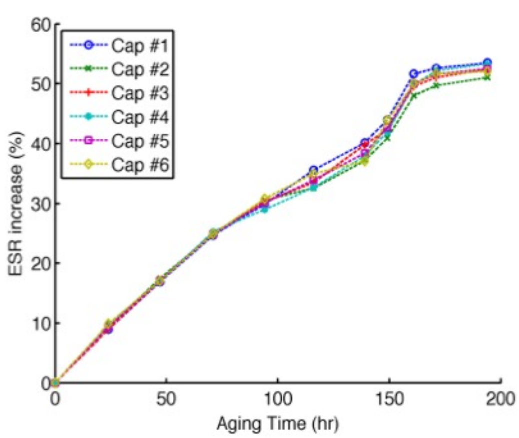


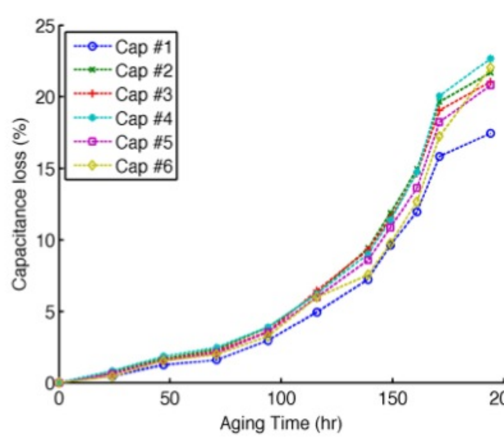


Degradation modeling for Capacitor (1/2)



C and Equivalent Series Resistance (ESR) are estimated from EIS measurements

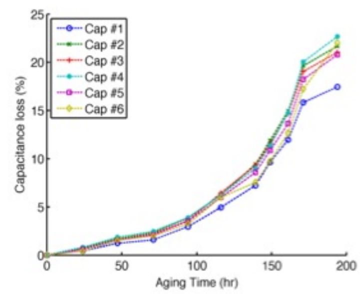




Degradation modeling for Capacitor (2/2)

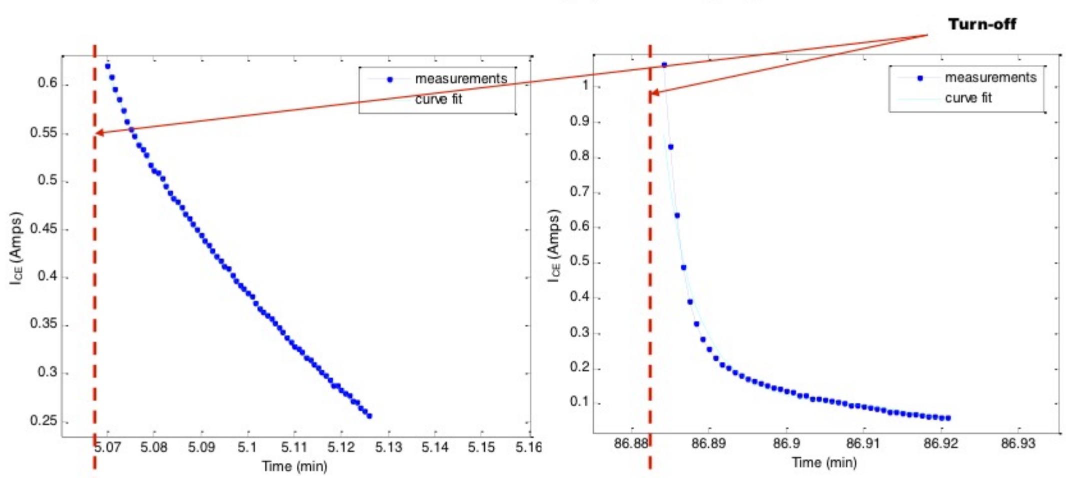
- Empirical model based on observed degradation from capacitance parameter
- Using accelerated aging data to estimate degradation model parameters
- Assumed exponential model based on capacitance loss
- Parameter estimation with least-squared regression

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



Degradation modeling of IGBT under thermal stress (1/2)

- Failure precursors observed in collector current I_{CE}
  - The tail current falls more sharply after aging

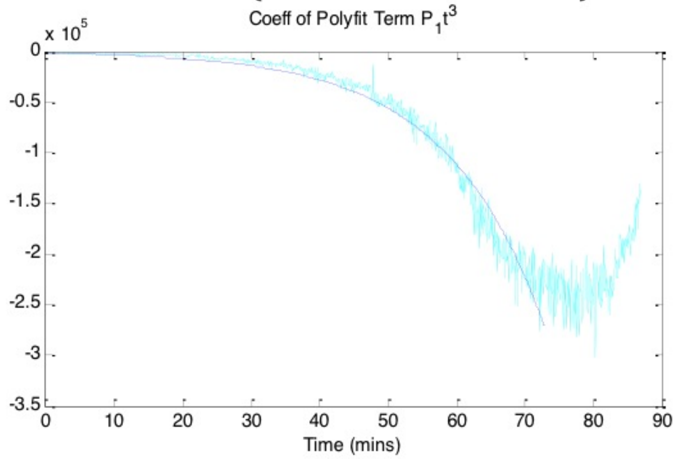


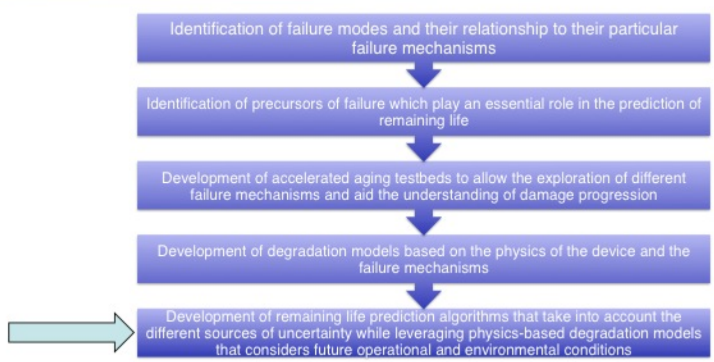
Change in IGBT Off-state Current Decay with Aging

Degradation modeling of IGBT under thermal stress (1/2)

- Empirical model based on degradation data
- Parameters need to be estimated

$$I_{CE}(t) = \exp\{P_1 t^3 + P_2 t^2 + P_3 t + P_4\}$$



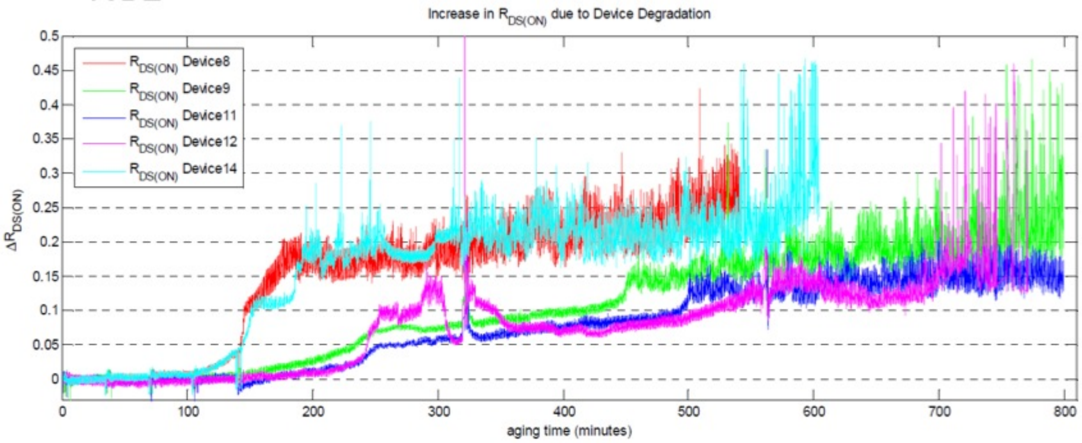


Prognostics for Electronics

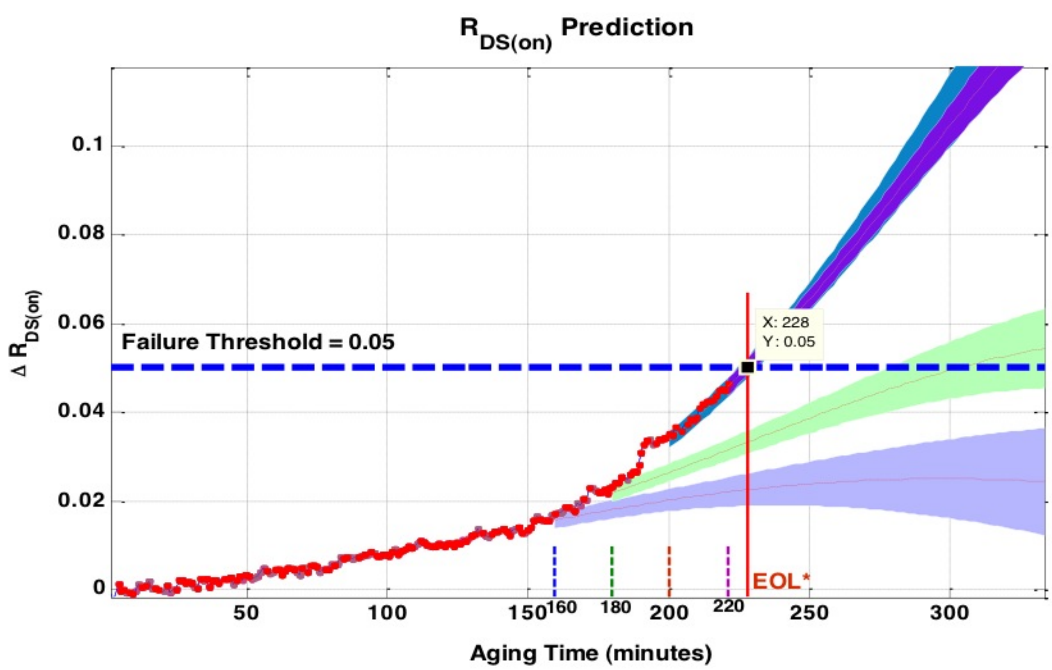
PREDICTION OF REMAINING LIFE

Data-driven prognostics for Power MOSFETs under thermal stress

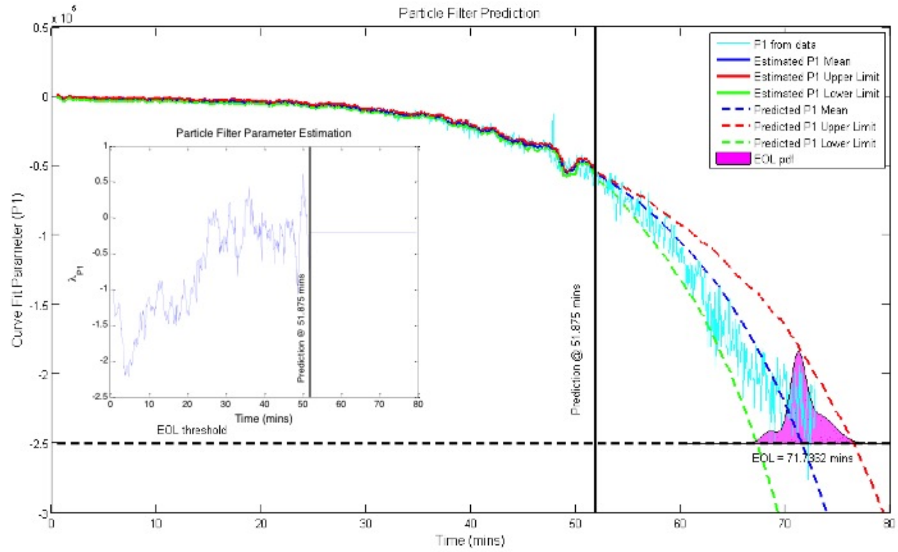
- Change in ON-resistance as a function of aging time
- Normalized based on pristine condition values
- $RDSON = RDSON_{nominal} + RDSON_{temperature} + RDSON_{degradation}$
- Gaussian Process Regression Algorithm used to predict RUL



Data-driven prognostics for Power MOSFETs under thermal stress



Prognostics with Particle Filter for IGBT under thermal stress



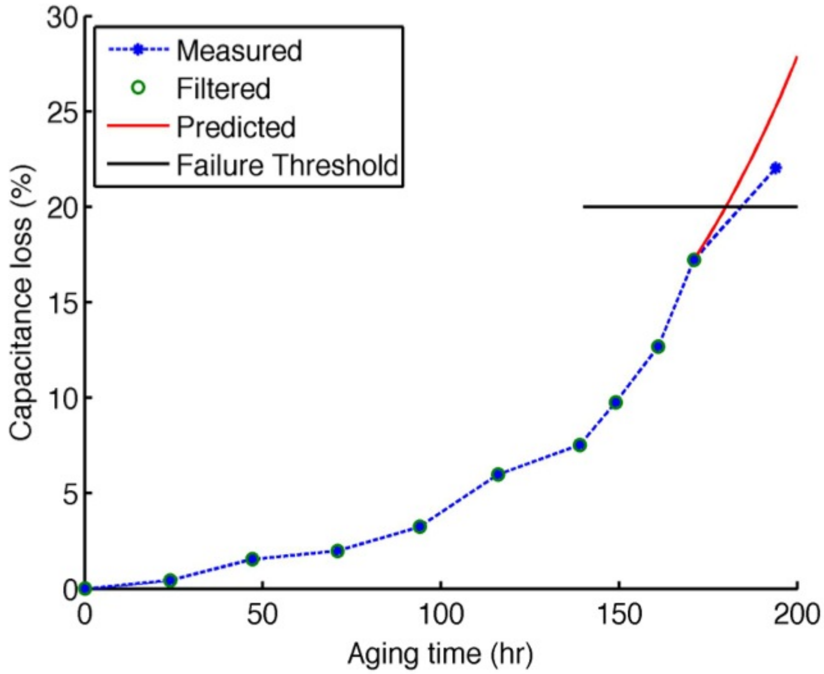
Kalman Filter based prognostics for Capacitor under electrical overstress

Real Capacitor → EIS → Reduced order model → Degradation model (time) → Health state estimation → RUL prediction

- EIS: • Potentiostat
- Reduced order model: • Lumped parameter model based on passive electrical elements
- Degradation model (time): • Empirical model based on exponential function
- Health state estimation: • Kalman filter (tracking)
- RUL prediction: • Kalman filter (forecasting)

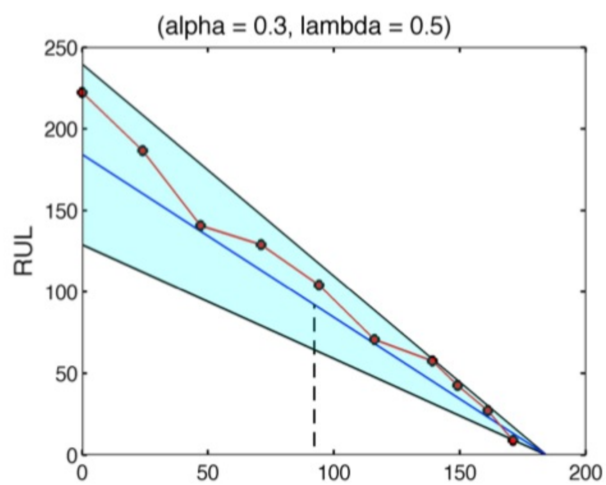
- Implementation of prognostics algorithm with Kalman filter
- Capacitance loss considered as state variable
- EIS measurements and lumped parameter model used to obtained measured capacitance loss values
- Empirical degradation model used to generate the state transition equation
- Use Cap #6 to test predictions
- Failure threshold of 20% drop on capacitance based on MIL-C-62F

Kalman Filter based prognostics for Capacitor under electrical overstress



Kalman Filter based prognostics for Capacitor under electrical overstress

RUL forecasting time (hr)	RUL estimate (hr)	Ground truth (hr)
0	222.2	184.24
24	186.55	160.24
47	140.66	137.24
71	128.98	113.24
94	104.18	90.24
116	70.71	68.24
139	57.58	45.24
149	42.61	35.24
161	27.20	23.24
171	8.94	13.24



Prognostics for Electronics

DISCUSSION AND CLOSING REMARKS

Discussion

- Accelerated aging methodologies for electrolytic components have been designed and accelerated aging experiments have been carried out.
- The methodology is based on imposing electrical and/or thermal overstresses via electrical power cycling in order to mimic the real world operation behavior.
- Data are collected in-situ and offline in order to periodically characterize the devices' electrical performance as it ages.
- The data generated through these experiments are meant to provide capability for the validation of prognostic algorithms (both model-based and data-driven).
- Furthermore, the data allow validation of physics-based and empirical based degradation models for this type of capacitor. A first set of models and algorithms has been designed and tested on the data.

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Questions

THANK YOU!

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