S3 Meeting

A Hybrid System-level Prognostics Approach for Electronics-rich Systems With Online RUL Forecasting

Ahmad Al Mohamad

Supervisors

Université de Rouen Normandie & ESIGELEC-IRSEEM
Dr. Ghaleb Hoblos

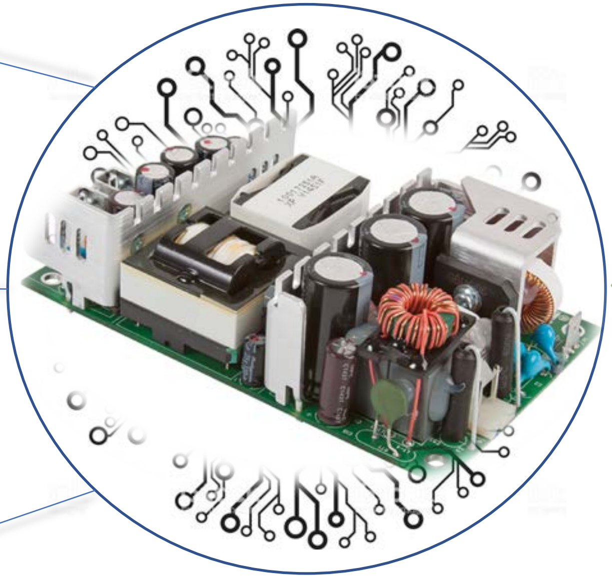
Universitat Politècnica de Catalunya & IRI
Dr. Vicenç Puig Cayuela

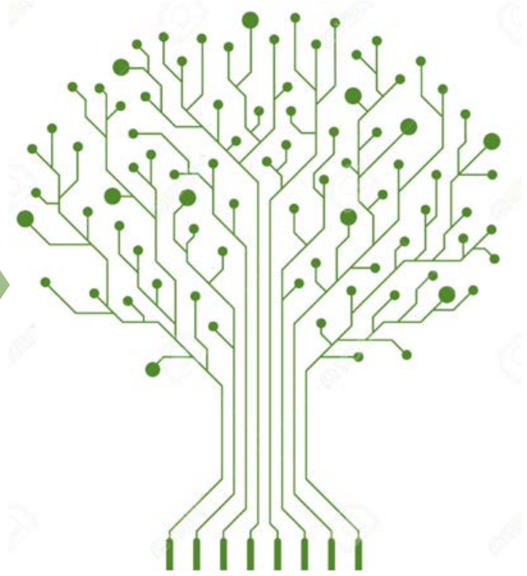
Agenda

- Introduction
- Failure mechanisms
- Case study
- Problem formulation
- PHM
- Results
- Conclusions
- Work in progress

Introduction
Overview

Electrification





Introduction
Description

Active & passive components

High switching frequencies

Thermal & electrical overstress

Degradation

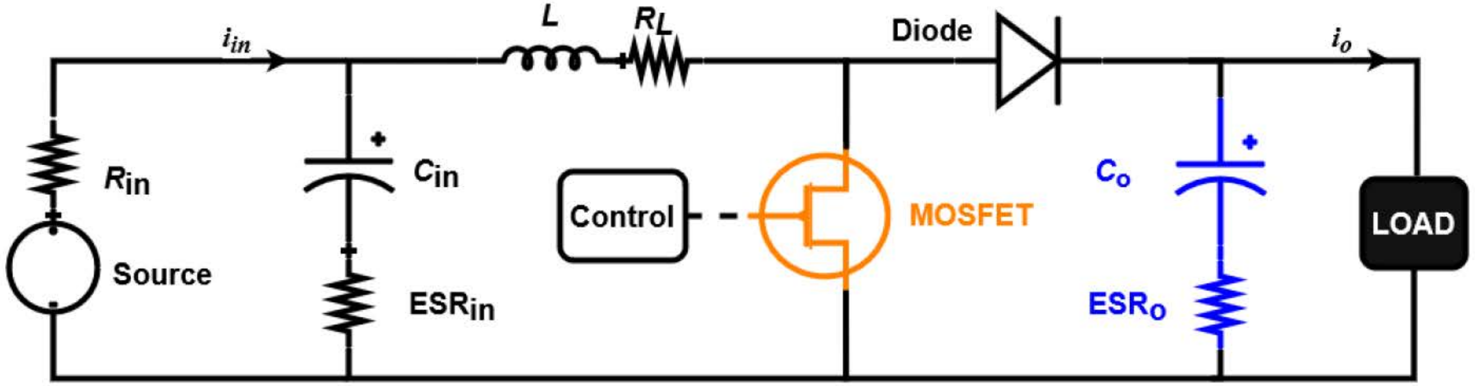
Faults

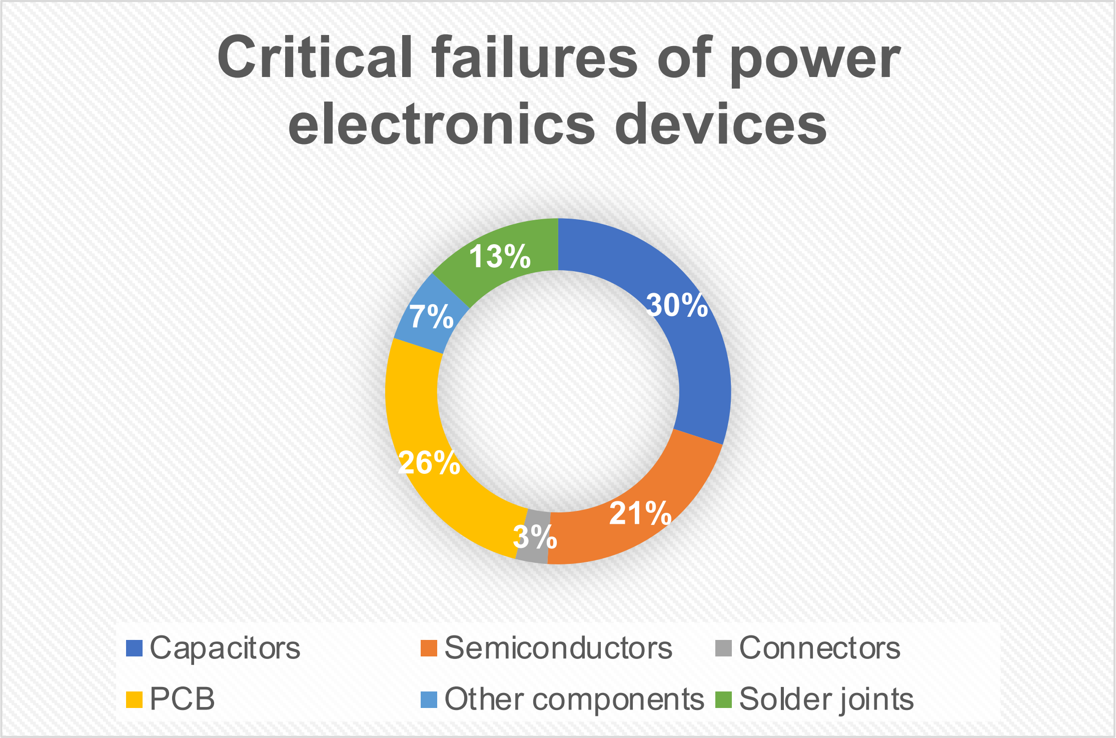
Diagnosis

Prognosis

Introduction

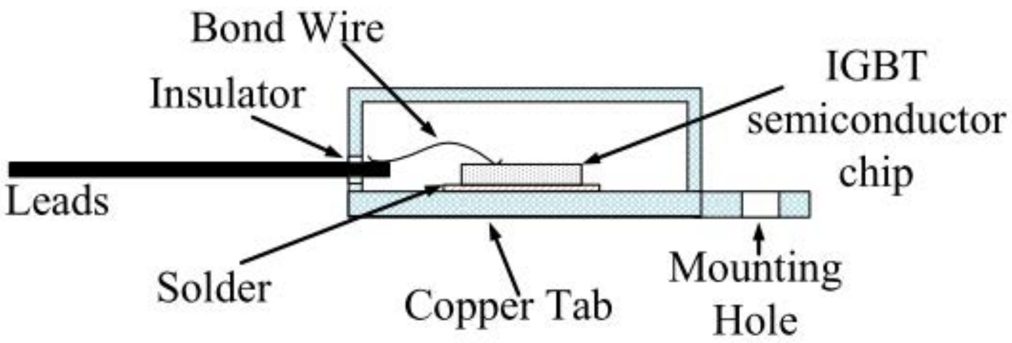
Converter & critical components

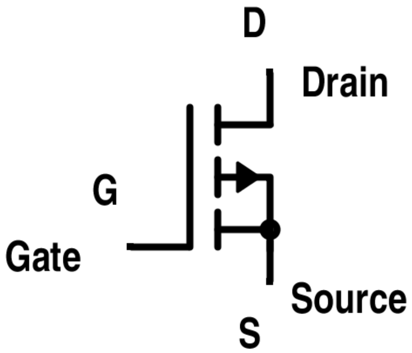




Failure Mechanisms

IGBT/MOSFET





Chip-related failures

- Electrical overstress
- Dielectric breakdown
- Electro-migration
- Latch-up

Package-related failures

- Solder fatigue
- Bond wire failure
- Aluminum reconstruction

Fault precursors

- ON Resistance (10%-17%)
- Gate threshold voltage Increases
- Threshold voltage increases
- Turn-Off time
- ON-state voltage

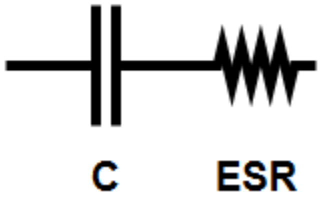
Failure Mechanisms

Electrolytic Capacitors

Failure mechanisms

Evaporation of the electrolyte which increases the pressure and decreases the oxide area in the capacitor unit due to thermal and electrical overstress.

$$C = \frac{2\, \varepsilon_R\, \varepsilon_o\, A_o}{t_o}$$



Fault precursors

- Increase in the ESR
- Decrease in the capacitance

$$\mathrm{ESR} = \frac{\rho_E\, t_o\, P_E}{2\, L\, W}$$

Failure Mechanisms

Accelerated Aging Experiments

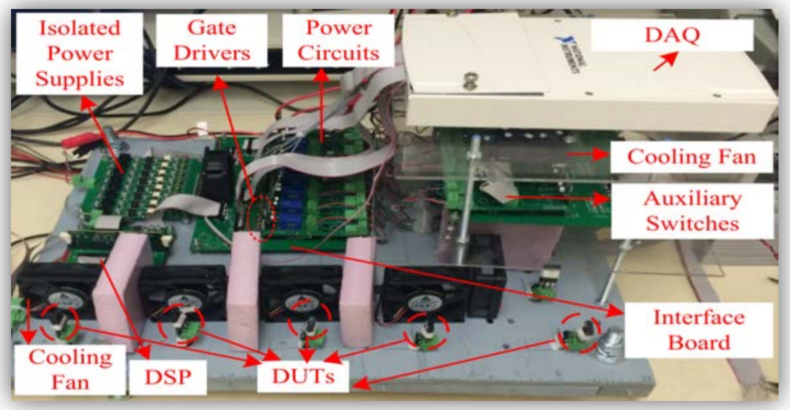
Accelerated aging experiments for power electronics are employed to extract the deterioration behaviors for fault modeling process.

Thermal overstress

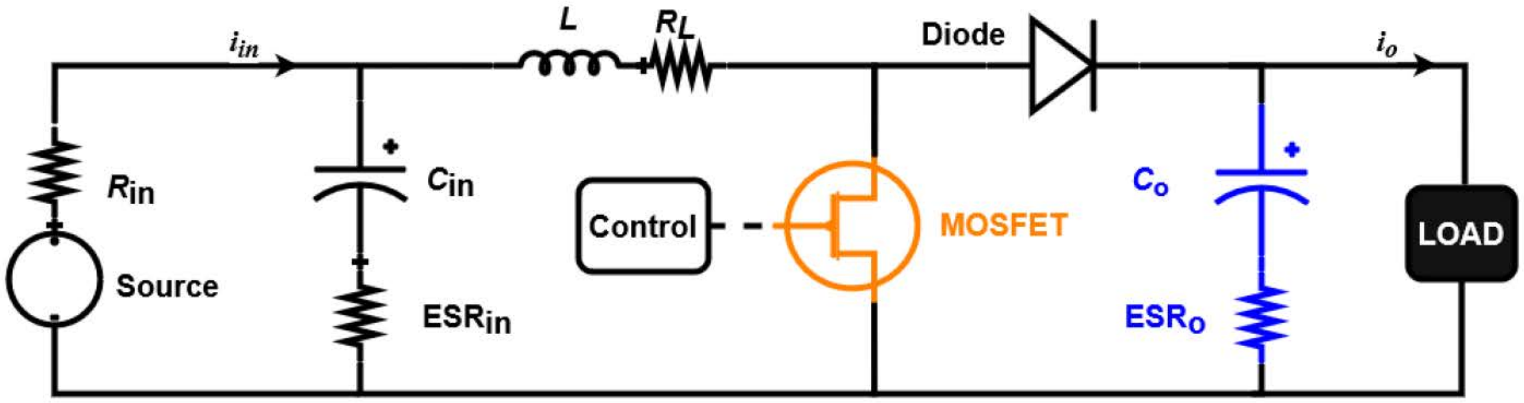
Apply high temperature in a special chamber on a system or components.

Electrical overstress

- Charge/discharge the capacitors with a voltage higher than the rated and small frequency.
- Switch the gate of the power device with a higher voltage than the rated.



Case Study
DC-DC converter modeling



$$\begin{cases} \dot{x}(t+1) = A_s x(t) + B_s u(t) + \omega(t), \\ Y(t) = C_s x(t) + D_s u(t) + \upsilon(t), \end{cases}$$

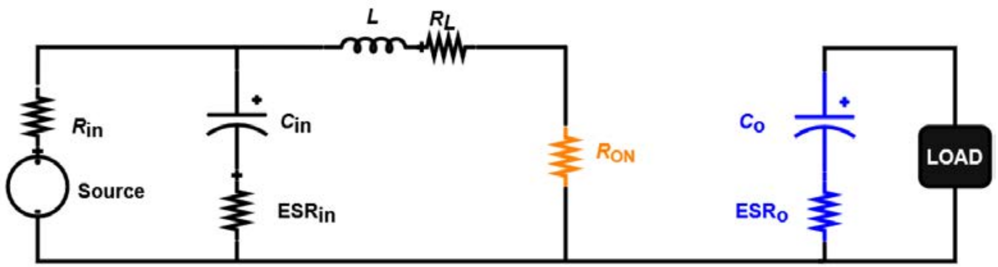
$$u = \begin{bmatrix} v_{\text{in}} \\ i_{\text{o}} \end{bmatrix}, \quad y = \begin{bmatrix} i_{\text{in}} \\ v_{\text{o}} \end{bmatrix}, \quad x = \begin{bmatrix} v_{C_{\text{in}}} \\ i_L \\ v_{C_{\text{o}}} \end{bmatrix}$$

Parameter	Variable	Symbol	Value	Units
Input resistance		R_{in}	0.01	Ω
Input capacitance		C_{in}	80	mF
Input capacitor resistance		ESR_{in}	100	mΩ
Inductance		L	146	μH
Inductor internal resistance		R_L	5	mΩ
MOSFET internal resistance		R_{ON}	1	mΩ
Output Capacitance		C_{o}	5	mF
Output capacitor resistance		ESR_{o}	80	mΩ
Switching frequency		f_s	15	kHz
Input voltage		v_{in}	200	V
Output current		i_{o}	100	A

Case Study

DC-DC converter modeling

ON-State operation

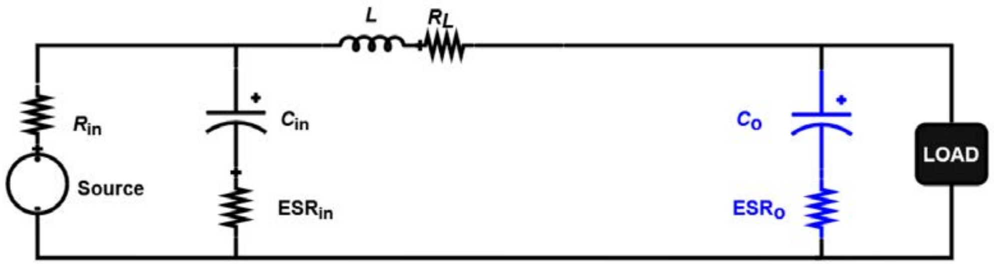


$$A_1 = \begin{bmatrix} \frac{-1}{C_{in} \cdot R_{iC_{in}}} & \frac{-R_{in}}{C_{in} \cdot R_{iC_{in}}} & 0 \\ \frac{R_{in}}{L \cdot R_{iC_{in}}} & \frac{-R_{in} \cdot \mathrm{ESR}_{in} + R_L \cdot R_{iC_{in}} + R_{ON} \cdot R_{iC_{in}}}{L \cdot R_{iC_{in}}} & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

$$B_1 = \begin{bmatrix} \frac{1}{C_{in} \cdot R_{iC_{in}}} & 0 \\ \frac{R_{C_{in}}}{L \cdot R_{iC_{in}}} & 0 \\ 0 & \frac{-1}{C_o} \end{bmatrix}, \quad C_1 = \begin{bmatrix} \frac{-1}{R_{iC_{in}}} & \frac{\mathrm{ESR}_{in}}{R_{iC_{in}}} & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

$$D_1 = \begin{bmatrix} \frac{1}{R_{iC_{in}}} & 0 \\ 0 & -\mathrm{ESR}_o \end{bmatrix},$$

OFF-State operation

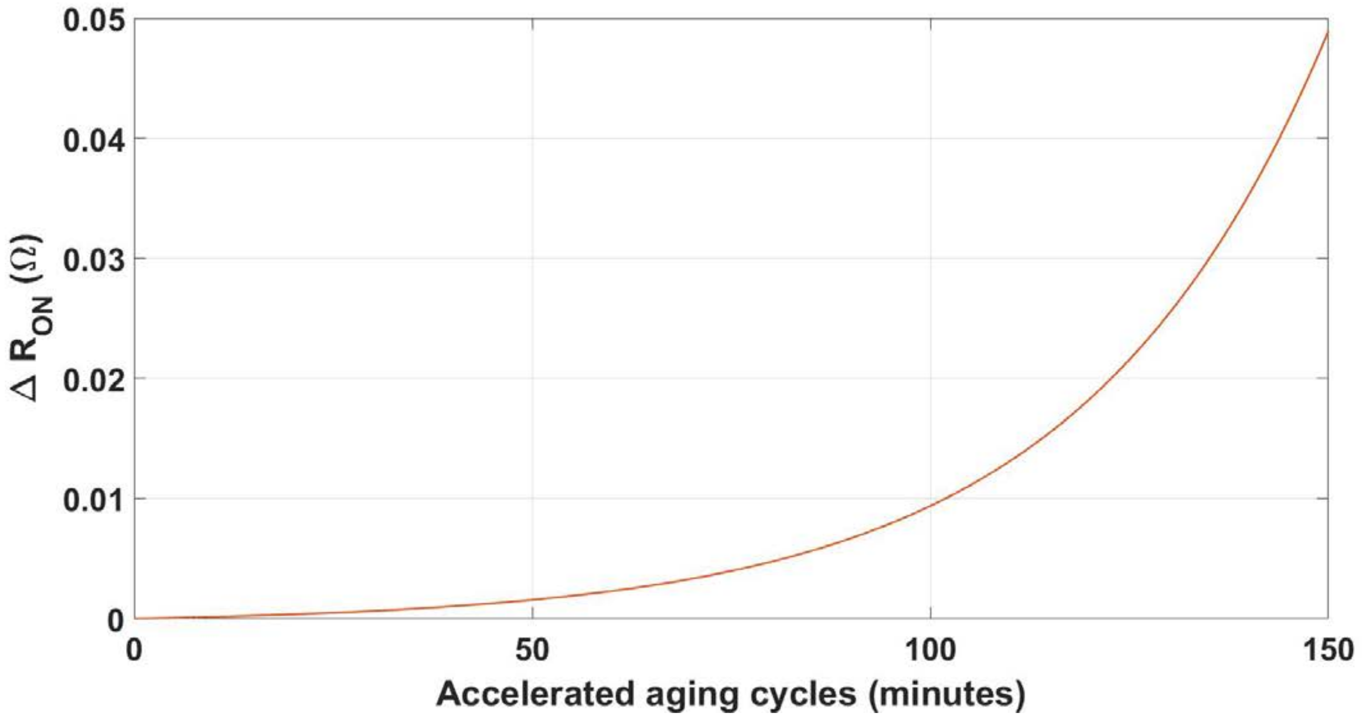


$$A_2 = \begin{bmatrix} \frac{-1}{C_{in} \cdot R_{iC_{in}}} & \frac{-R_{in}}{C_{in} \cdot R_{iC_{in}}} & 0 \\ \frac{R_{in}}{L \cdot R_{iC_{in}}} & \frac{-R_{in} \cdot \mathrm{ESR}_{in} + R_L \cdot R_{iC_{in}} + \mathrm{ESR}_o \cdot R_{iC_{in}}}{L \cdot R_{iC_{in}}} & \frac{-1}{L} \\ 0 & \frac{1}{C_o} & 0 \end{bmatrix},$$

$$B_2 = \begin{bmatrix} \frac{1}{C_{in} \cdot R_{iC_{in}}} & 0 \\ \frac{\mathrm{ESR}_{in}}{L \cdot R_{iC_{in}}} & \frac{\mathrm{ESR}_o}{L} \\ 0 & \frac{-1}{C_o} \end{bmatrix}, \quad C_2 = \begin{bmatrix} \frac{-1}{R_i C_{in}} & \frac{\mathrm{ESR}_{in}}{R_{iC_{in}}} & 0 \\ 0 & \mathrm{ESR}_o & 1 \end{bmatrix},$$

$$D_2 = \begin{bmatrix} \frac{1}{R_{iC_{in}}} & 0 \\ 0 & -\mathrm{ESR}_o \end{bmatrix},$$

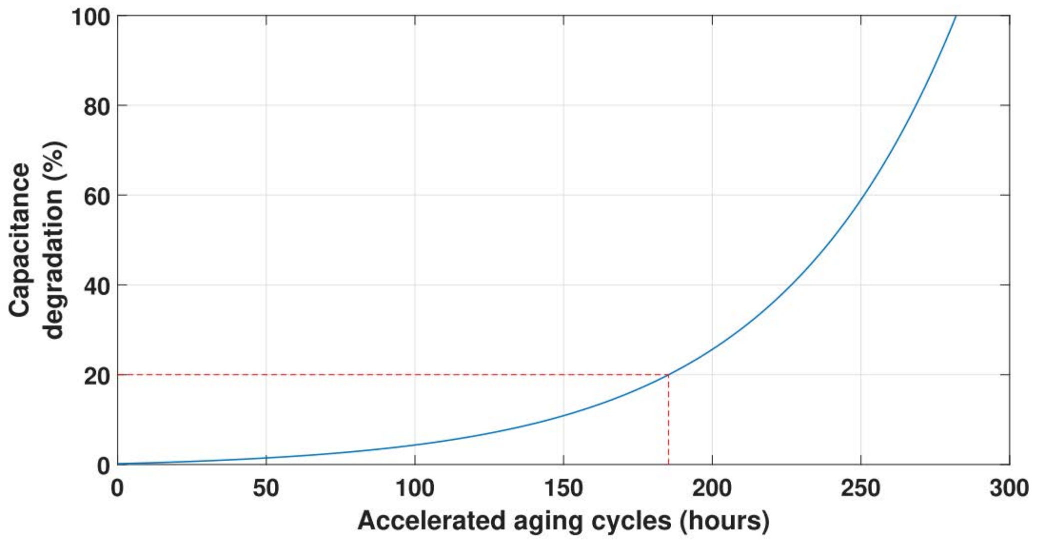
Case Study
Degradation Modeling: MOSFET



Empirical degradation model: $\Delta R_{\mathrm{ON}} = a_1(e^{b_1 t} - 1)$

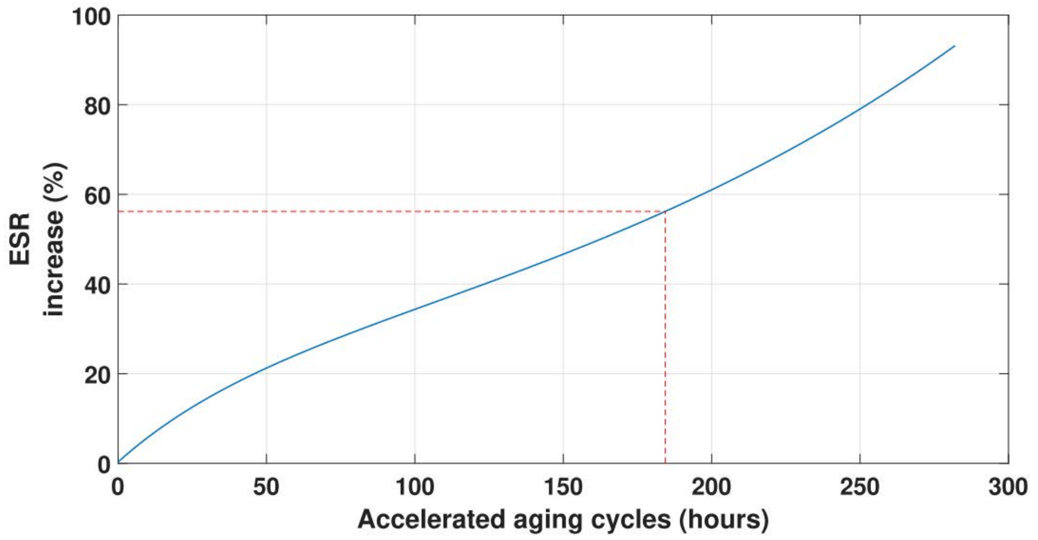
Case Study

Degradation Modeling: Capacitor



Empirical degradation models

$$C_{\mathrm{deg}}(t) = e^{a_2 t} + b_2$$

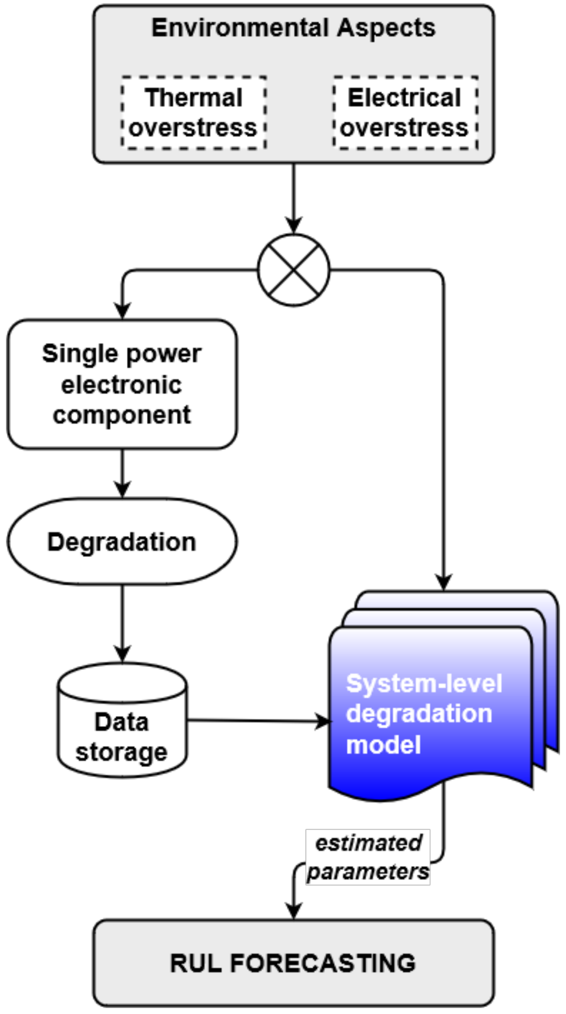


$$\mathrm{ESR}_{\mathrm{inc}}(t) = a_3 e^{b_3 t} + c_3 e^{d_3 t}$$

Problem Formulation

Problem statement

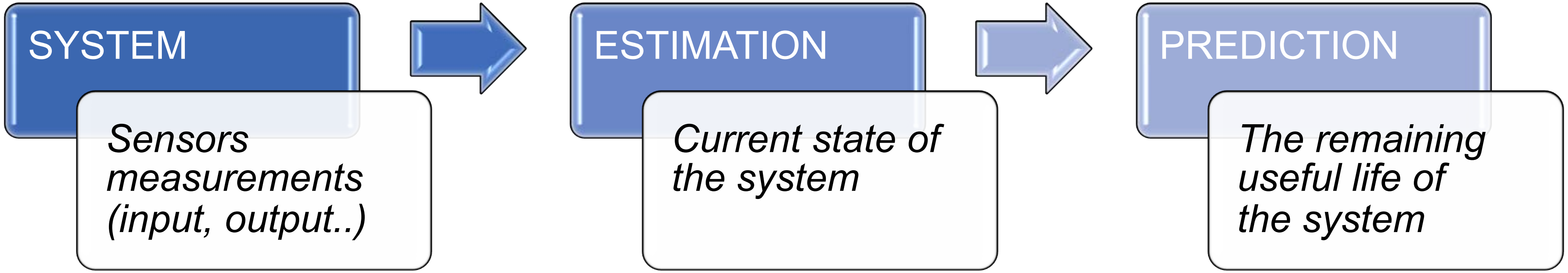
- Different degradation profiles with different time manifolds
- Single-component to System-level
- Fault threshold definition
- RUL of the system from components



Requirements

- Real measurements
- System's healthy and faulty behaviors
- Mathematical model
- Degraded parameters estimation

PHM
Definitions



Literature definitions:

Prognosis: forecasting of the remaining useful life of a component/subsystem/system…

Remaining useful life: the remaining time until system’s failure.

PHM
Motivation

Improve the reliability of the system

↓

Used with diagnosis to estimate the system’s safe working conditions and to clear faults before failures

Improve maintenance planning and reduce costs

↓

Eliminate unnecessary scheduled maintenance

Optimal working conditions

↓

Optimal operation planning in faulty conditions

Decrease cascading damage

↓

Avoid the continuous and fast deterioration of the system

PHM
Main goals

Provide advance warning of failures

Extend the life-time of the system

Forecast maintenance

Online diagnosis for intermittent faults

PHM
Model-based Vs. Data-driven

Model-based	Data-driven
PROS	
• Intuitive results • Models are reusable • Computationally acceptable to implement	• Easy and fast to implement • Consider all relationships without prejudice
CONS	
• Requires a deep understanding of the system for modeling • High-fidelity models are computationally expensive	• Requires lots of data • Computationally expensive
TECHNIQUES	
• Population growth models • Paris-Eyring, Coffin-Manson…	• Neural network • Relevance vector machine • Gaussian process regression…

Proposed Approach: Estimation
AJEKF for parameter estimation

$$\begin{cases} x_{k+1} & = A(\delta_k)x_k + B(\delta_k)u_k + E_\omega \omega_k \\ y_k & = C(\delta_k)x_k + D(\delta_k)u_k + E_\upsilon \upsilon_k \end{cases}$$

$$x_k^{aug} = \begin{bmatrix} x^{old} \\ \delta \end{bmatrix}$$

The state-space equations:

$$x_{k^+} = A_k x_k + B_k u_k + \omega_k,$$

The prediction error covariance:

$$P_k = \frac{\partial f}{\partial x}\Big|_{\hat{x}_{k^-}} P_{k^-} \frac{\partial f^T}{\partial x}\Big|_{\hat{x}_{k^-}} + Q,$$

Kalman gain:

$$K_k = P_k(\frac{\partial g_{x_k}}{\partial x})^T \times [(\frac{\partial g_{x_k}}{\partial x})P_k \times (\frac{\partial g_{x_k}}{\partial x}) + R]^{-1}$$

The output equation:

$$y_k = C_k x_k + D_k u + \upsilon_k,$$

The filter equation:

$$\hat{x}_k = \hat{x}_k + K_k(Y_k - y_k),$$

The filter error covariance:

$$P_k = (I - K_k \frac{\partial g_{x_k}}{\partial x})P_k,$$

Proposed Approach: Estimation

AJEKF for parameter estimation

$$A_{avg} = A_1 \cdot d + A_2 \cdot (1 - d),$$
$$B_{avg} = B_1 \cdot d + B_2 \cdot (1 - d),$$
$$C_{avg} = C_1 \cdot d + C_2 \cdot (1 - d),$$
$$D_{avg} = D_1 \cdot d + D_2 \cdot (1 - d),$$

- *Duty cycle:* $d = 0.33$
- f_s=15 kHz
- Y_k is the measurement from the degraded model

Process noise auto-covariance:

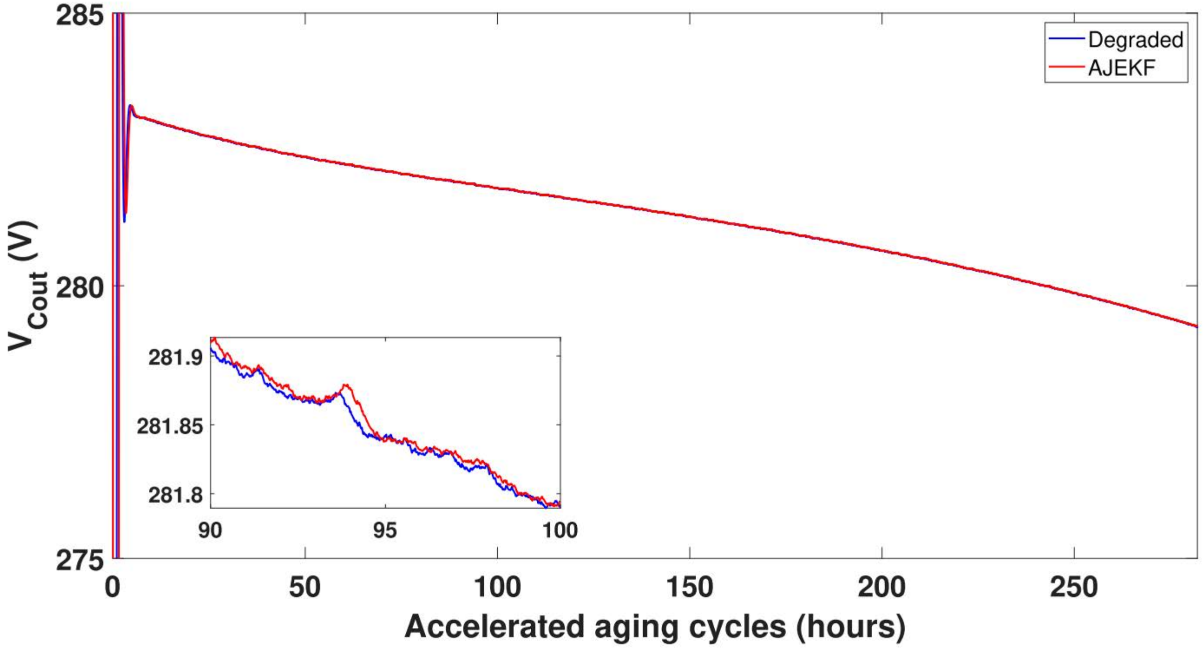
$$Q^{aug} = \begin{matrix} 10^{-5} & 0 & 0 & 0 \\ 0 & 10^{-5} & 0 & 0 \\ 0 & 0 & 10^{-5} & 0 \\ 0 & 0 & 0 & 10^{-5} \end{matrix}$$

Measurement noise auto-covariance:

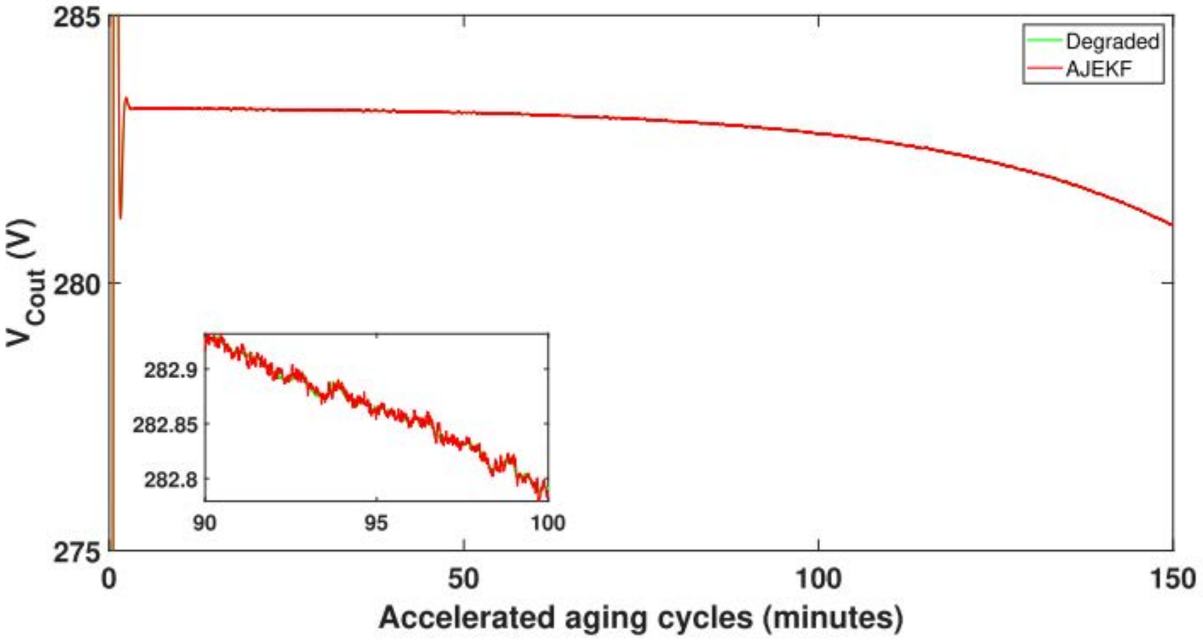
$$R = \begin{matrix} 10^{-3} & 0 \\ 0 & 10^{-3} \end{matrix}$$

Results

Affected states



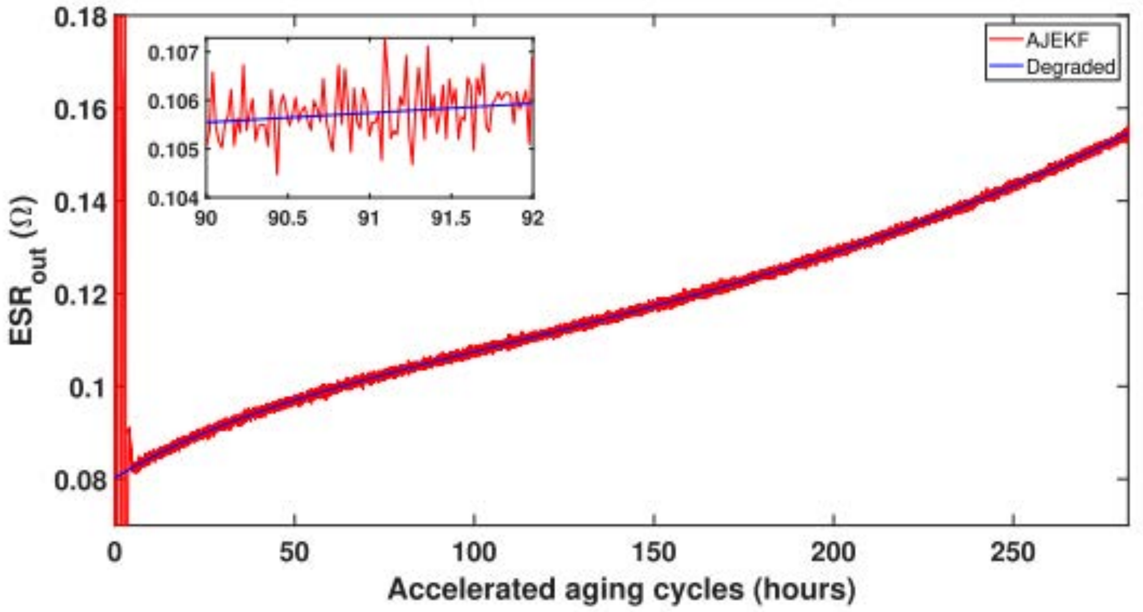
Output capacitance voltage during capacitor degradation



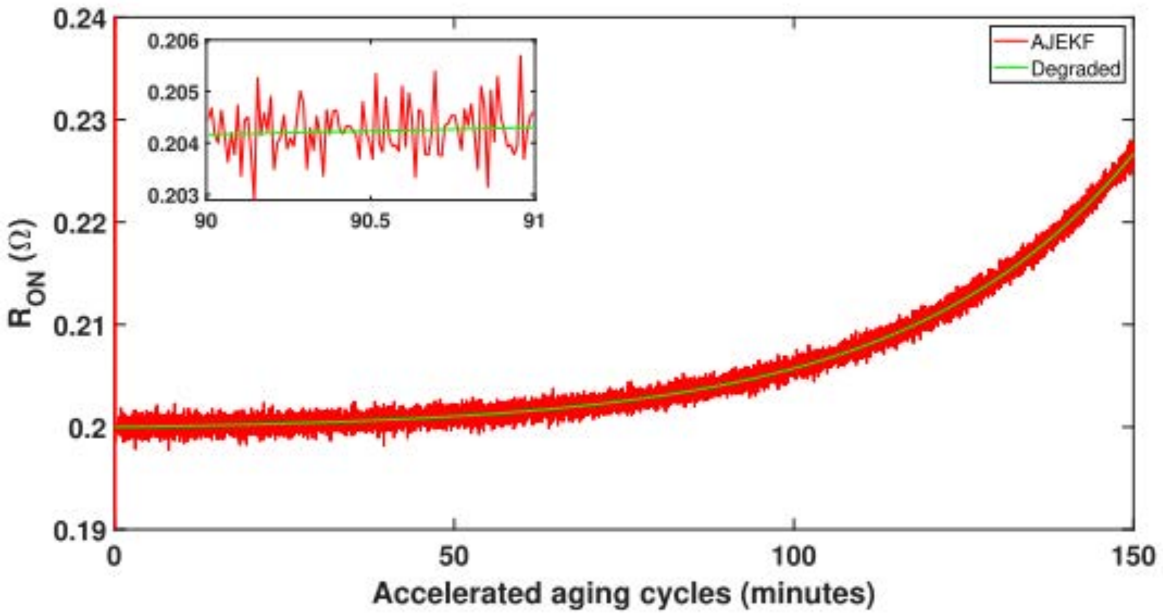
Output capacitance voltage during MOSFET degradation

Results

Estimated parameters



ESR estimation during capacitor degradation



RON estimation during MOSFET degradation

Proposed Approach: Prediction

RUL forecasting algorithm

Contribution:

- The RUL forecasting algorithm is completely independent of the degradation behaviors.
- Its reliability depends on the parameter estimation.

Assumption:

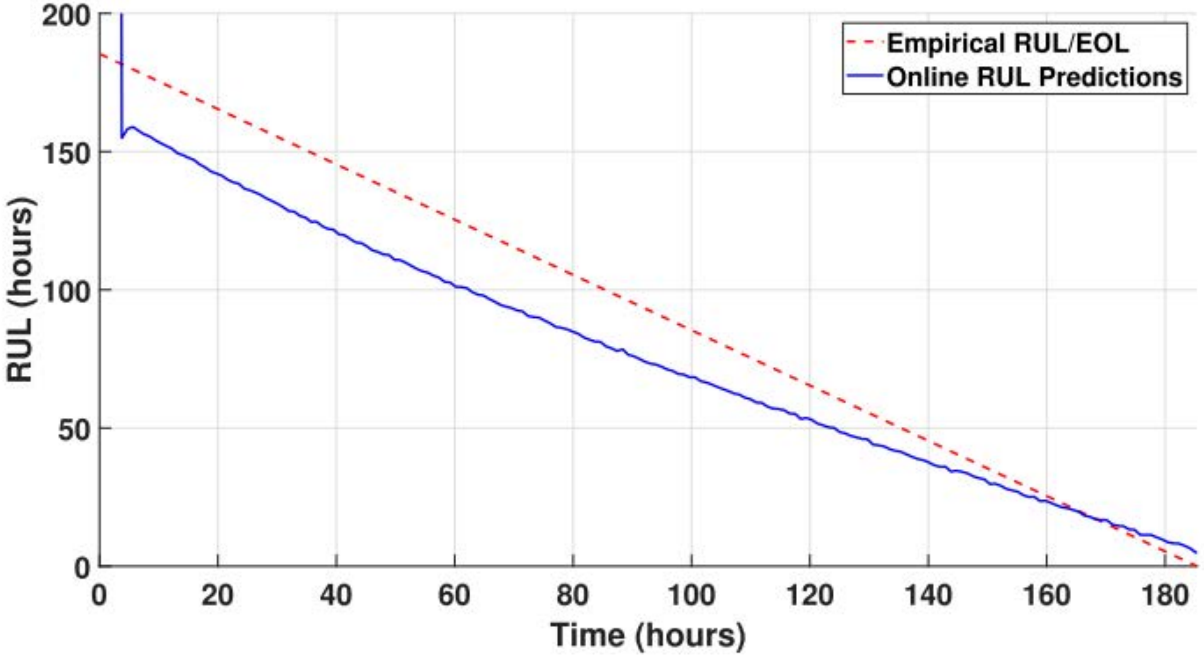
- At k=1, the EoL of the system is considered the same as the expected operation time by the user.
- It is also considered as the threshold of parameter degradation.

RUL Forecasting Algorithm

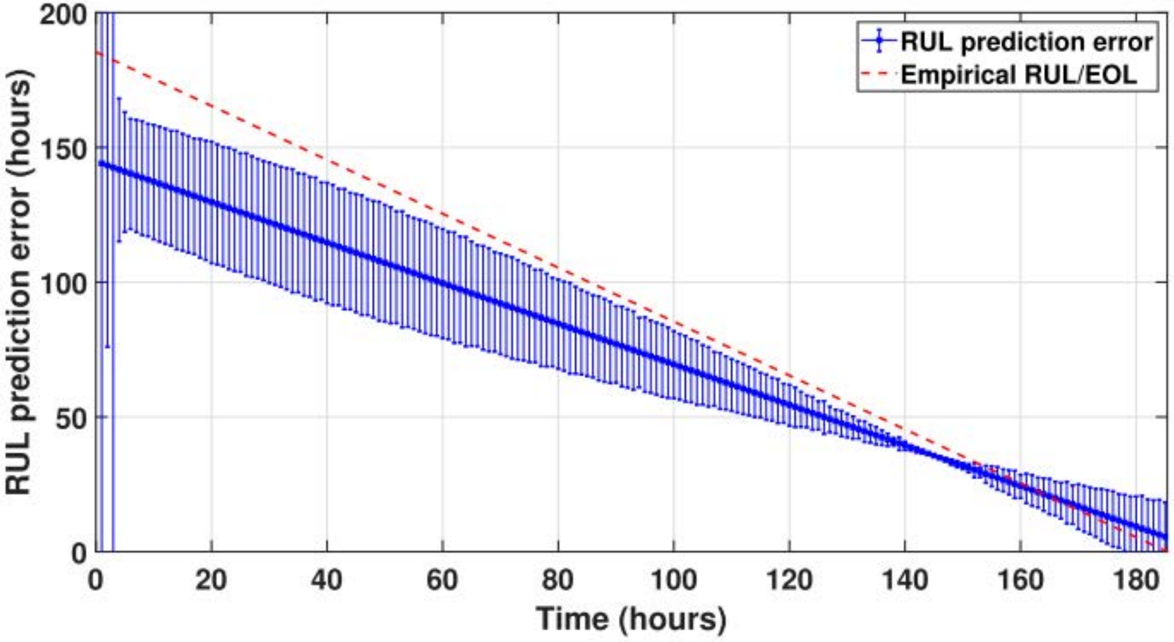
1. Consider a random polynomial equation with unknown variables
2. At time t proposed by the user as the EoL, the degradation is 100%
3. The second equation considers the estimated parameter to calculate the degradation percentage at each measurement time
4. Computation of the variables of the polynomial equations
5. Update and calculation of EoL
6. Computation of RUL: EoL-measurement time
7. Update the variables and repeat until reaching the threshold

Return RUL at each measurement

Results
RUL Forecasting

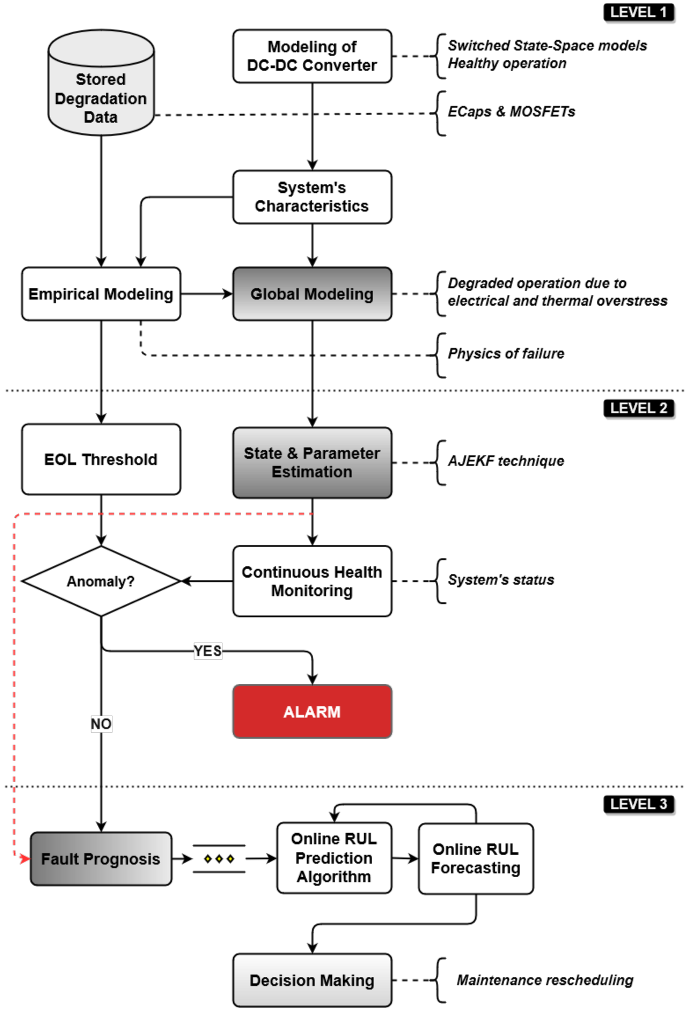


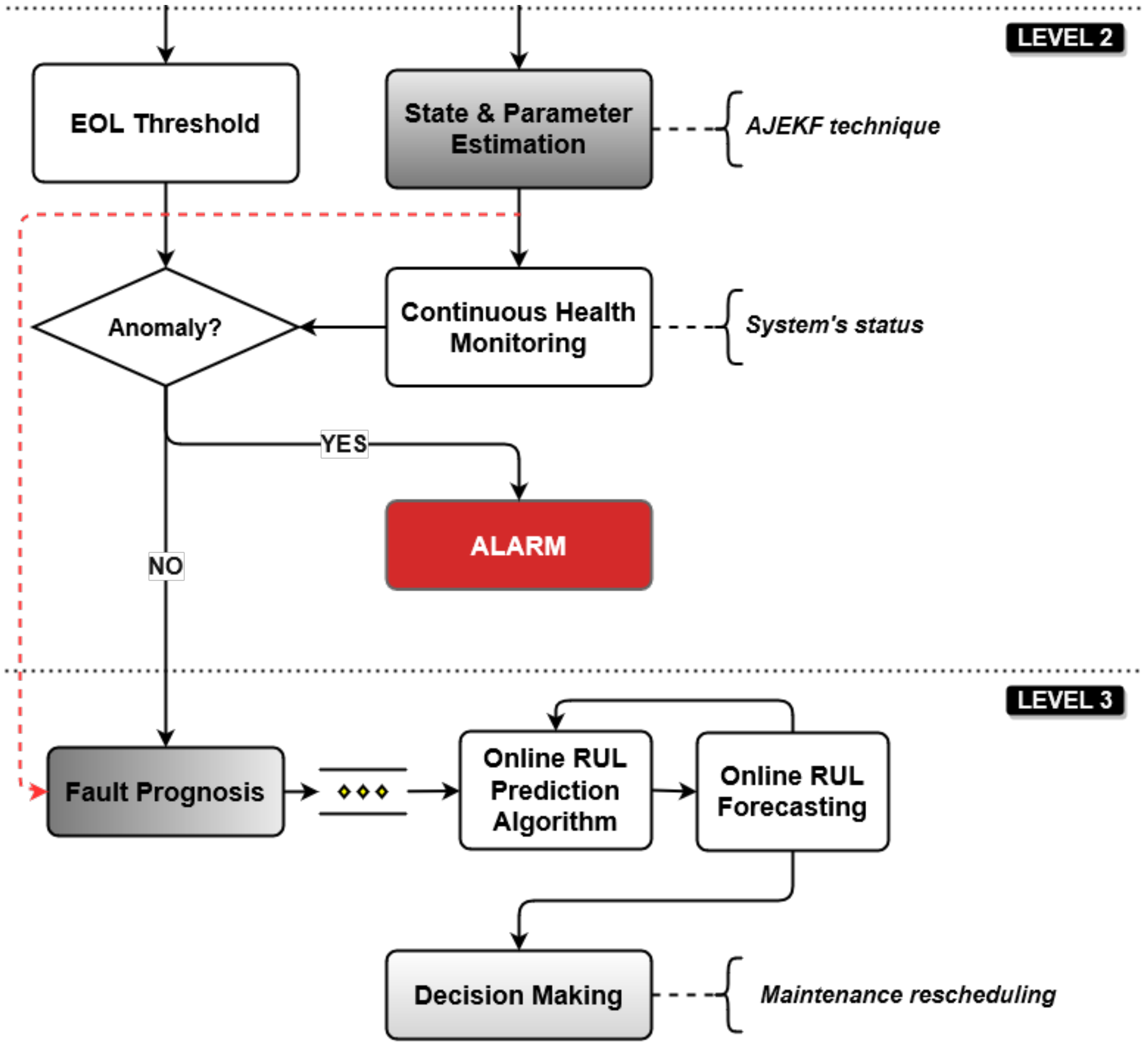
Online RUL forecasting during capacitor degradation



Error of online RUL prediction

PHM
Methodology





Conclusions

- The online RUL technique is independent of the degradation behaviors.
- Statistical degradation data are critical for the empirical models design.
- The reliability of the RUL forecasting depends on the estimation precision.
- The EoL of the system is related to the first EoL of a critical component.

Work in Progress

- Working on set-memberships and zonotopic approaches for RUL forecasting.
- Validating the simulation results with real application testbench.
- Testing a technique to emulate the degradation of real power electronic devices without harming the system.