Communauté
UNIVERSITÉ Grenoble Alpes

PHD DEFENSE

Contribution to prognostics of PEM fuel cells: approaches based on degradation information at multiple levels

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Presented by

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Advisors

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gipsa-lab

FC LAB Research

eit InnoEnergy
Knowledge Innovation Communit

Outline

1. Background & motivation

ADAPTING THE STATE OF THE ART:

2. Remaining Useful Life prediction of PEM fuel cells
    - Particle Filtering-based RUL prediction
    - Taking into account reversible degradation

BEYOND THE STATE OF THE ART:

3. Multi-level prognostics using online inspection of degradation covariates
4. Multi-level prognostics using different sources of degradation information

5. Conclusion & perspectives

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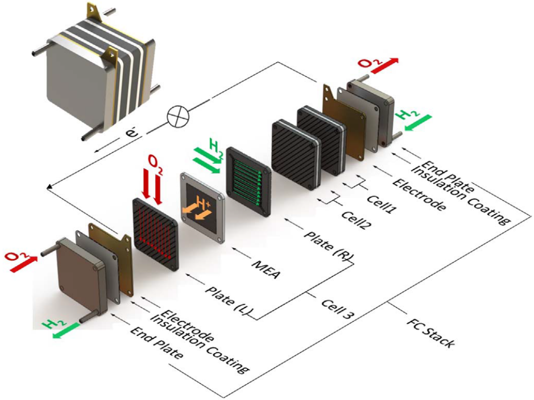
Part I

Background & Motivation

Proton Exchange Membrane (PEM) fuel cell

- Energy transition
  Hydrogen
- Promising alternative transition device
  Fuel Cells
- PEM Fuel Cell
  - Low temperature 80^oC-100^oC
  - Small size
    Single cell : 100 cm^2
    P $\approx$ 0.4 W/cm^2
  - High efficiency
    η $\approx$70%
  - Tailorable power
    ...

Stack and cell



- Anode:

$$H_2 \rightarrow 2H^+ + 2e^-$$

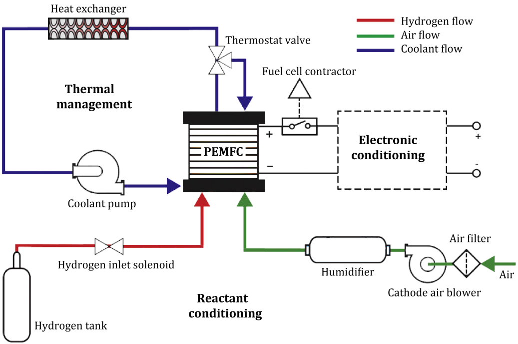
- Cathode:

$$\frac{1}{2}O_2 + 2H^+ + 2e^- \rightarrow H_2O$$

- Overall:

$$\frac{1}{2}O_2 + H_2 \rightarrow H_2O$$

Balance of Plant



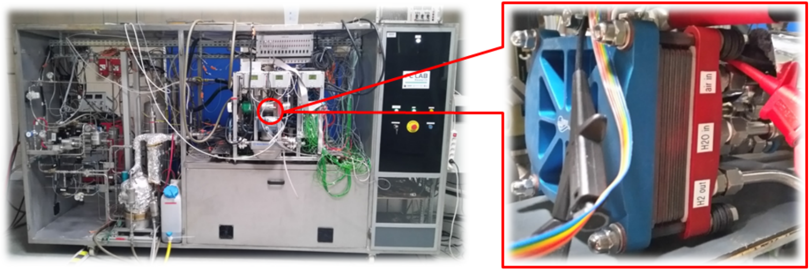
Subsystems

- Reactant conditioning
  tank, pumps, valves,. . .
- Electronic conditioning
  regulator, controller, . . .
- Thermal management
  heat exchanger, . . .

Balance of Plant

Heat exchanger

A PEM fuel cell test bench in FCLAB



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Challenges

Issues

- Poor health management (Faults)
- Materials and interfaces degradation (Aging)

Consequences

- Performance degradation
- Lifespan limitation

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- Poor health management (Faults)
- Materials and interfaces degradation (Aging)

Consequences

- Performance degradation
- Lifespan limitation

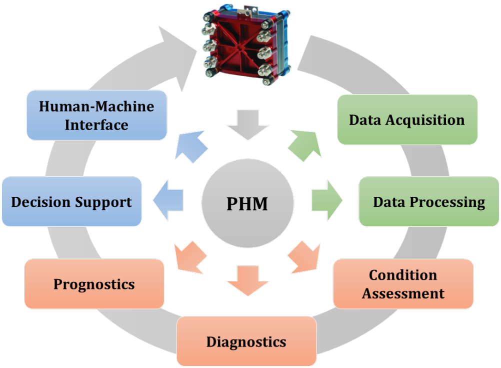
Challenges

- Enhance reliability
- Better manage lifespan

$\Rightarrow$ Prognostic and Health Management

Prognostics and Health Management (PHM)

- Recent dynamic approach to **monitor**, **analyze** and **master** the Remaining Useful Life (RUL) of industrial systems
- Pioneering technique in fuel cells technologies



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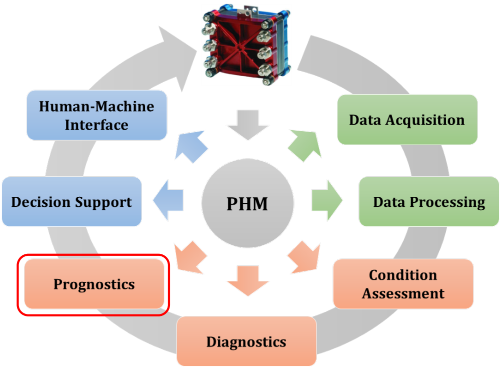

Remaining Useful Life (RUL)

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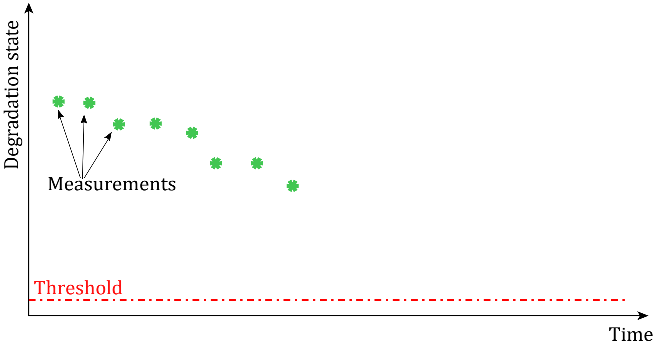

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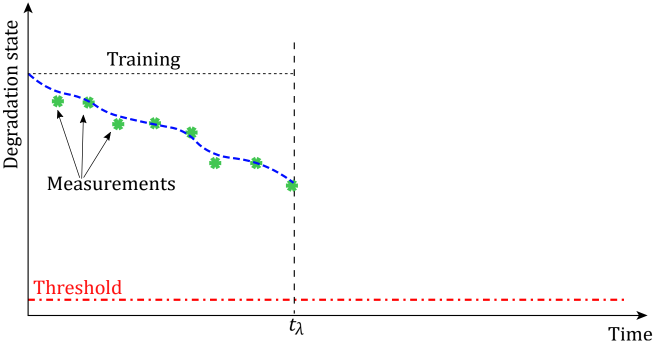

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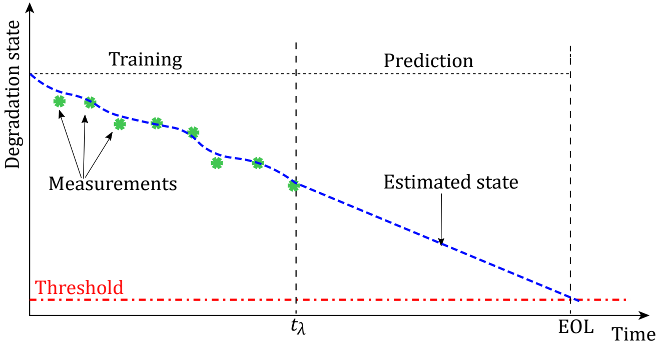

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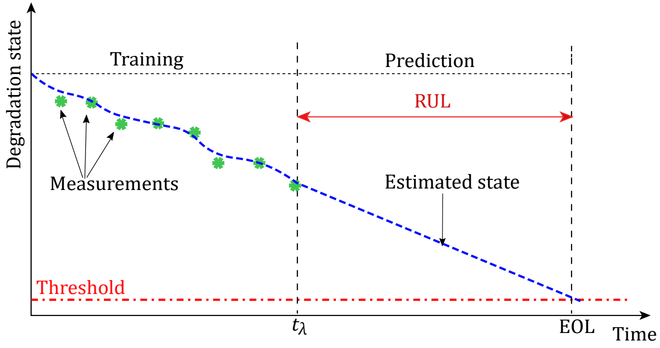

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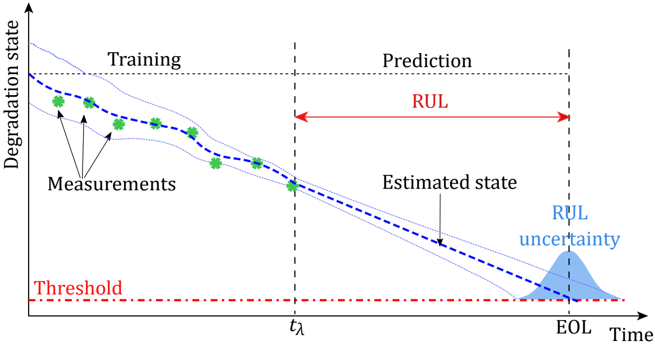
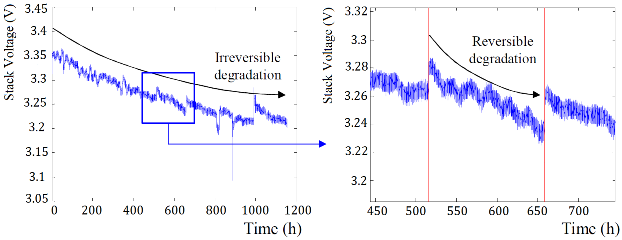


Difficulties

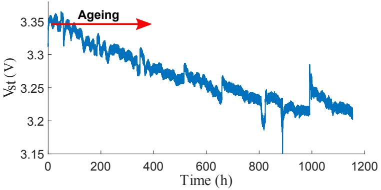


- Degradation can be different:
  - irreversible ($e.g.$ due to material deterioration)
  - reversible ($e.g.$ due to operating conditions)
- Degradation can be generated at different levels

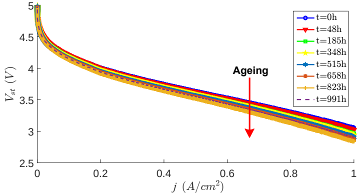
$\Rightarrow$ Observed from different measurements

Degradation measurements

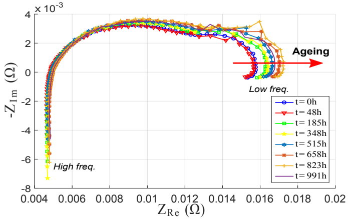
Stack voltage (or power)



Polarization curves



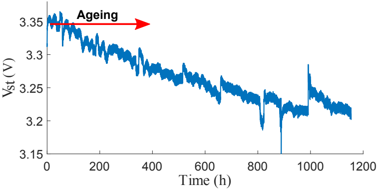
Electrochemical Impedance Spectroscopy (EIS)



- Classical measurements
  Voltage, Power
- State of Health (SOH) measurements
  EIS, Polarization

Degradation measurements

Stack voltage (or power)



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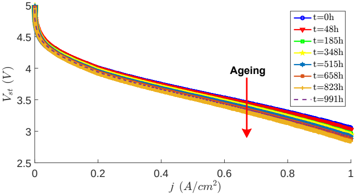

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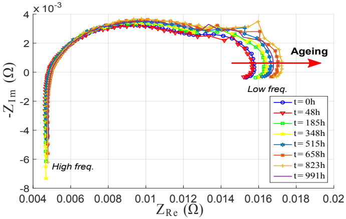

- Classical measurements
  Voltage, Power
- State of Health (SOH) measurements
  EIS, Polarization

$\Rightarrow$ Use multiple measurements

Objectives and contributions

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1. RUL prediction (on real application data) with taking into account both irreversible and reversible degradation

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   - Degradation covariate inspection scheme to gather additional information from measurements at different level

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   - An Ensemble-based approach to aggregate RUL predictions from different measurements at different levels

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2. Extension to multi-level prognostics
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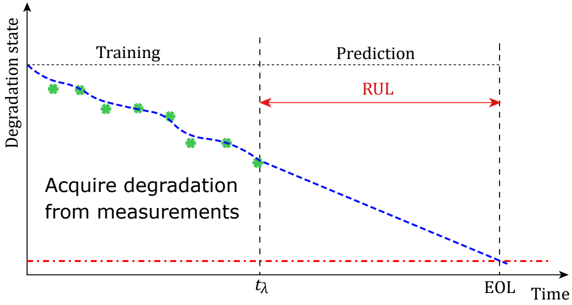
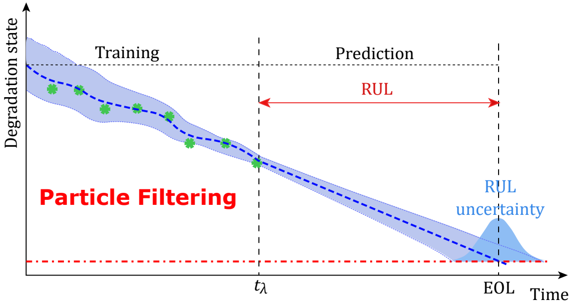
Part II

Remaining Useful Life Prediction of PEM fuel cell

Particle Filtering-based prognostics



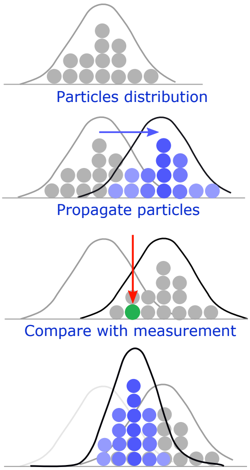
Particle Filtering-based prognostics



Estimator uses large amount of randomness to approach the truth

- Technique for implementing Recursive Bayesian filter by Monte Carlo sampling
- Nonlinear, non Gaussian model tracking

Particle Filtering (PF)



Particles with corresponding weights are used to form an approximation of PDF

1. Split initial state into particles

$$x_{t-1} \rightarrow \{x_{t-1}^i\}_{i=1}^N$$

2. Propagate particles through the transition function

$$x_t^i = f(x_{t-1}^i, \omega_{t-1}^i) \rightarrow p(x_t|x_{t-1})$$

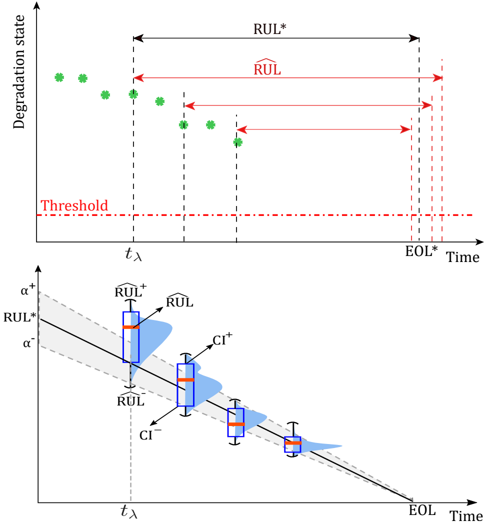
3. Importance sampling

$$W_t^i \propto p(z_t|x_t^i) \rightarrow x_t^{i*}$$

4. Re-sampling

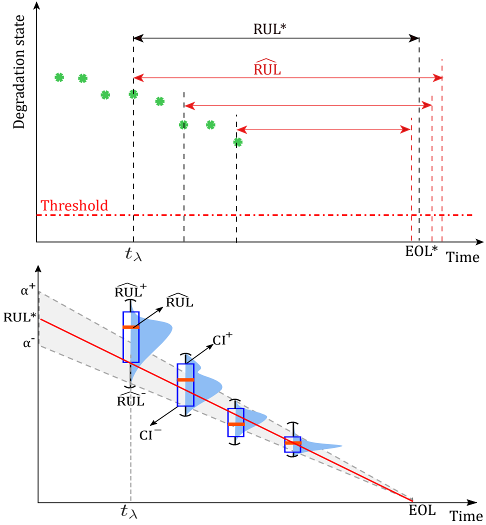
$$\{x_{t-1}^{i*}\}_{i=1}^N \rightarrow p(x_t^*|z_t)$$

Prognostic performance



Prognostic metrics

Prognostic performance

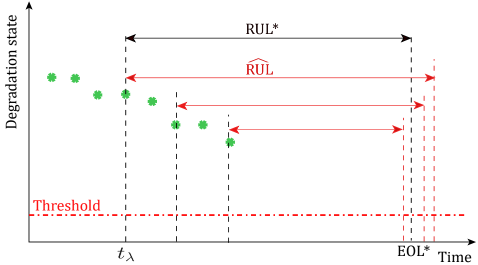


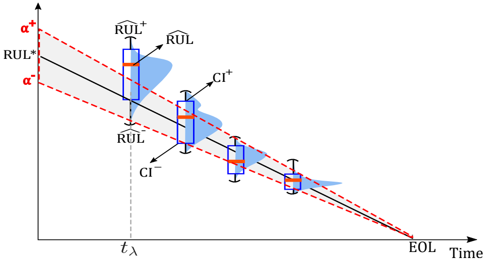
Prognostic metrics

- Accuracy index

$$Acc_\lambda = 1 - \frac{|RUL_\lambda^* - \widehat{RUL}_\lambda|}{RUL_\lambda^*}$$

Prognostic performance





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$$Acc_\lambda = 1 - \frac{|RUL^*_\lambda - \widehat{RUL}_\lambda|}{RUL^*_\lambda}$$

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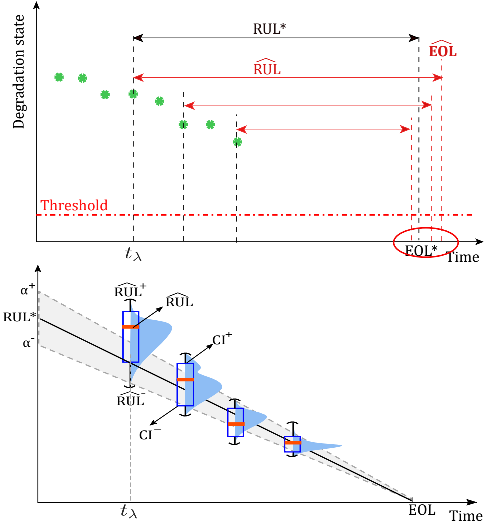
$$\alpha Ac_\lambda = p\left(\alpha^-_\lambda \leq \widehat{RUL}_\lambda \leq \alpha^+_\lambda\right)$$

Prognostic performance



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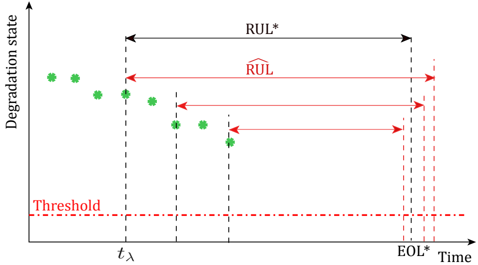
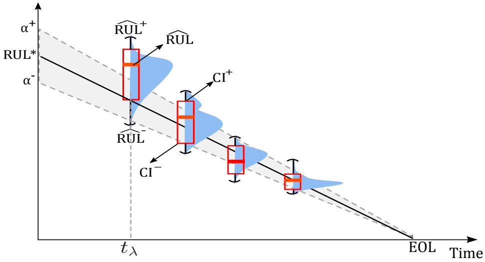
- Steadiness index

$$Std_\lambda = \frac{\sqrt{var(\widehat{EOL}_{(\lambda-L):\lambda})}}{EOL^*}$$

Prognostic performance





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$$Std_\lambda = \frac{\sqrt{var(\widehat{EOL}_{(\lambda-L):\lambda})}}{EOL^*}$$

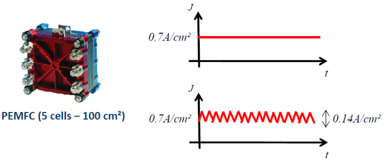
- Precision index

$$Prc_\lambda = \frac{\widehat{RUL}^{CI+}_\lambda - \widehat{RUL}^{CI-}_\lambda}{RUL^*_\lambda}$$

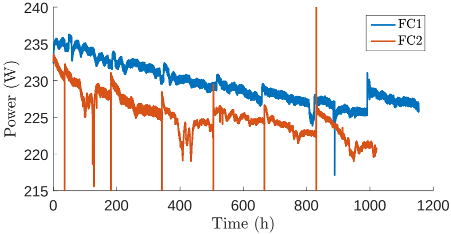
Application data (test bench FCLAB)

- Two PEM fuel cell stacks under operation degrade
- Stack power measurements are used as the degradation indicator

FC1 - Long-term test without current ripples



FC2 - Long-term test with high frequencies current ripples



Application data (test bench FCLAB)

- Two PEM fuel cell stacks under operation degrade
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Degradation state models

- Pure logarithmic:
  $x_k = -\alpha \cdot ln(t_k/t_{k-1}) + x_{k-1}$
- Log-linear:
  $x_k = -\alpha \cdot ln(t_k/t_{k-1}) - \beta \cdot (t_k - t_{k-1}) + x_{k-1}$
- Linear:
  $x_k = -\beta \cdot (t_k - t_{k-1})) + x_{k-1}$
- Polynomial:
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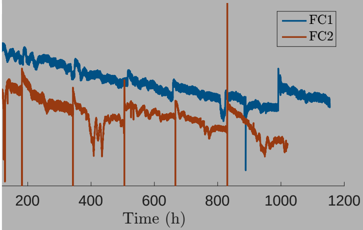

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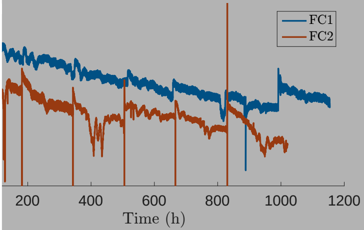
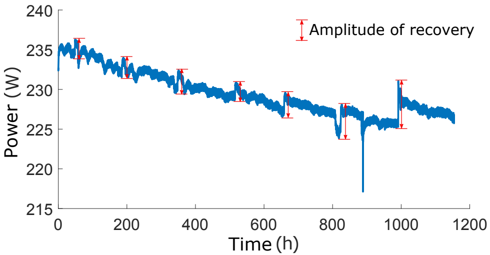


Difficulty

Reversible degradation



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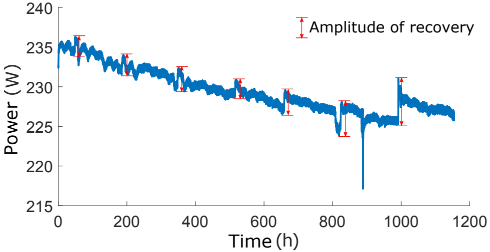
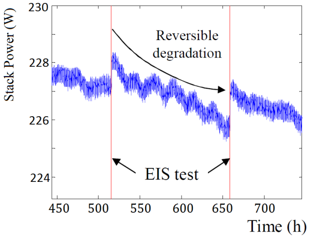
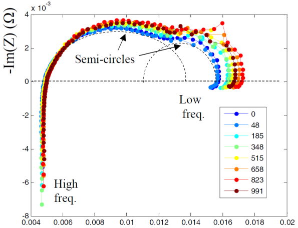


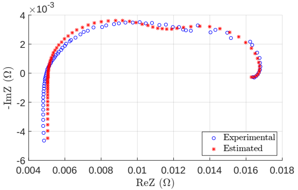


Use information from characterization measurement
$\Rightarrow$ Electrochemical Impedance Spectroscopy

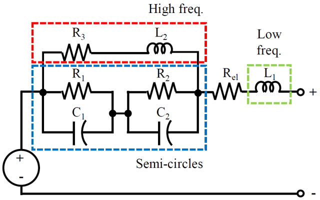
Electrochemical Impedance Spectroscopy (EIS) data

EIS measurements





Equivalent Circuit Model [1]



Polarization resistance

$$R_{pol} = \frac{(R_1 + R_2) \cdot R_3}{R_1 + R_2 + R_3} + R_{el}$$

[1] Kim, T. et al., (2014). A degenerated equivalent circuit model and hybrid prediction for state-of-health (SOH) of PEM fuel cell. In: *2014 International Conference on Prognostics and Health Management. pp. 1-7.*

State transition model

Hypothesis

- Reversible degradation is related to R_{pol}
- R_{pol} can be estimated from EIS

$$x_c = x_k + \alpha_1(R_{pol}) \cdot exp\left(-\beta_1(R_{pol}) \cdot (t_k - t_{k-1})\right)$$
$$x_k = \alpha \cdot (t_k - t_{k-1})^2 - \beta \cdot (t_k - t_{k-1}) + x_{k-1}$$

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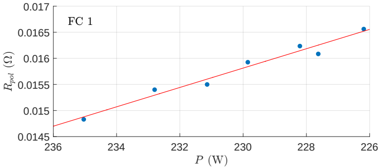
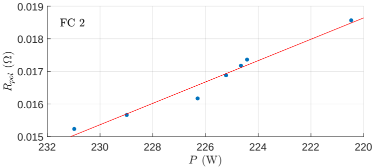
R_{pol} vs. Power (FC1)



R_{pol} vs. Power (FC2)



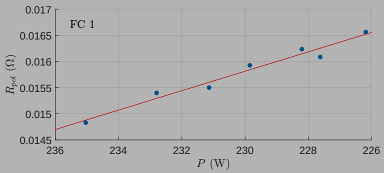
State transition model

Hypothesis

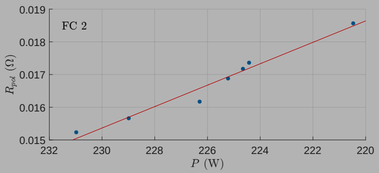
- Reversible degradation is related to R_{pol}
- R_{pol} can be estimated from EIS

$$x_c = x_k + \alpha_1 \cdot \frac{R_{pol}(c)}{R_{pol}(0)} \cdot exp\left(-\beta_1 \cdot \frac{R_{pol}(c)}{R_{pol}(0)} \cdot (t_k - t_{k-1})\right)$$

R_{pol} vs. Power (FC1)

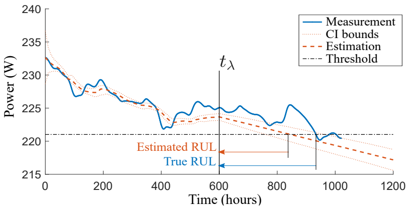


R_{pol} vs. Power (FC2)

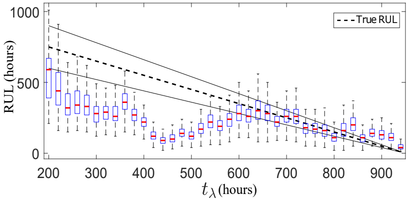


Results (FC2)

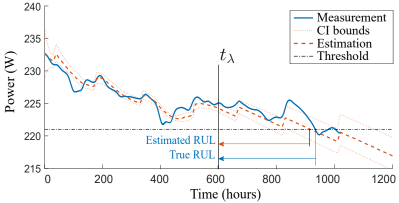
Estimation with classical model



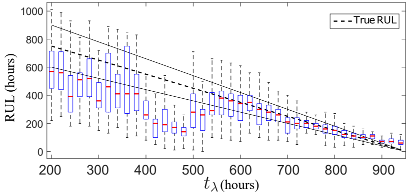
RUL predictions with classical model



Estimation with proposed model

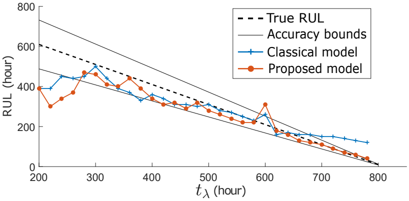


RUL predictions with proposed model

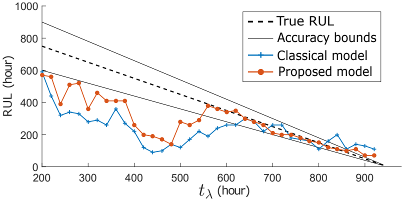


Prognostic performance

RUL predictions of FC1



RUL predictions of FC2



Performance metrics

	FC 1				FC 2			
	Acc	aAc	Prc	Std	Acc	aAc	Prc	Std
Classical	0.67	0.29	0.89	0.06	0.48	0.11	0.69	0.17
Proposed	0.86	0.42	0.68	0.06	0.72	0.34	0.74	0.12

Summary

Challenge accomplished:

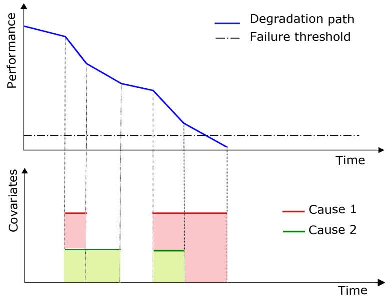
- RUL predictions of PEM fuel cell application with taking into reversible degradation
- Reversible degradation has been investigated by using the information of R_{pol}
- Prediction quality has been improved by using additional information from SOH characterization

How to generalize the use of degradation related information
$\Rightarrow$ Introduce **covariates** to the degradation model

Part III

Multi-level Prognostics Using Online Inspection of Degradation Covariates

Problem statement



Degradation

- Continuously monitored with simple measurements
- Affected by the change of covariates

Assumption

Possible to inspect the covariates with extra cost

Objective

Use the information of covariates for RUL prediction

How?

Design a degradation covariate inspection scheme

- When and how to apply an inspection on covariates (that costs)
- Ensure the prognostic quality
- Minimize the inspection cost

General modeling assumptions

General modeling assumptions

- Evolution of the degradation follows a stochastic process:

$$x_k = f_k(x_{k-1}, \Theta_k)$$

- Impacts of covariates on the degradation model parameter can be quantified and modeled:

$$\Theta_k = g_k(c_k)$$

General modeling assumptions

- Evolution of the degradation follows a stochastic process:

$$x_k = f_k(x_{k-1}, \Theta_k)$$

- Impacts of covariates on the degradation model parameter can be quantified and modeled:

$$\Theta_k = g_k(c_k)$$

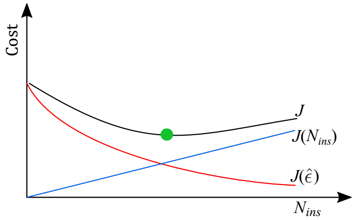
$\Rightarrow$ Possible to update the degradation model by inspecting the degradation covariate with cost

Cost of the covariate inspection

Global cost

$$J = J_{inspection}(N_{ins}) + J_{estimation}(\hat{\epsilon})$$

- Inspection incurs application cost
- Inaccurate estimation leads to prognostic quality cost



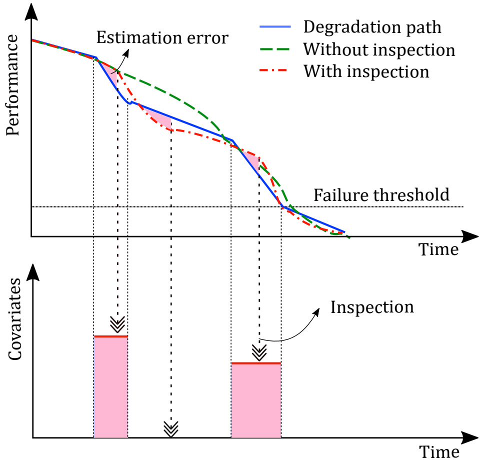
Find the optimal trade-off

Method

Two decision variables:

- inter-inspection period $\tau \rightarrow$ number of inspections N_{ins}
- error threshold $ET \rightarrow$ estimation error $\hat{\epsilon}$

Covariates inspection schemes



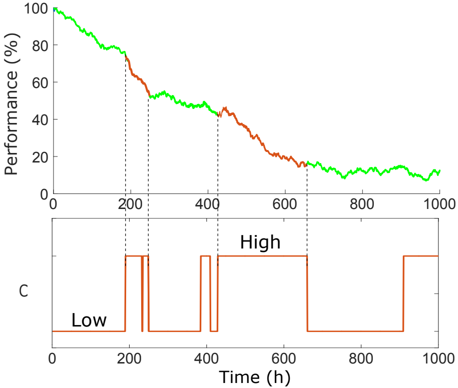
Periodic inspection

Performed regularly at fixed time intervals τ

Online inspection

Triggered online when the accumulated estimation error reaches an error threshold ET

Degradation example



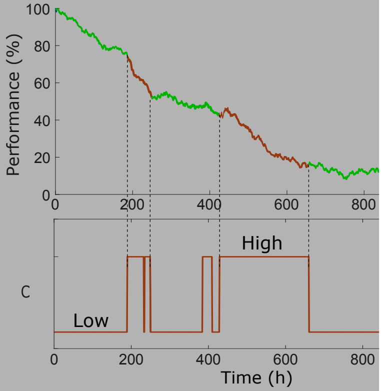
Simulated by a state transition function [2]:

$$x_k = x_{k-1} \cdot exp(-b_k(c_k) \cdot \Delta t)$$

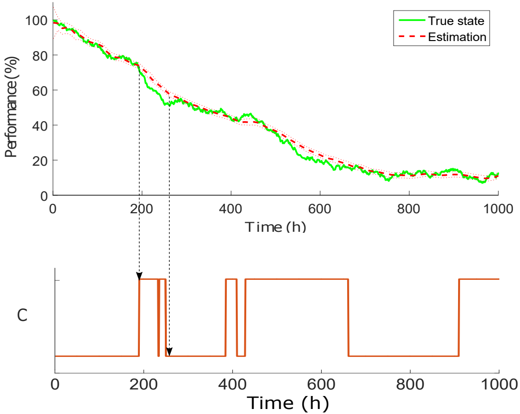
The presence of covariate c_k impacts the degradation behavior by changing trend parameter b_k.

[2] An, D., Choi, J.H., and Kim, N.H. (2013). Prognostics 101: A tutorial for particle filter-based prognostics algorithm using Matlab.*Reliab. Eng. Syst. Saf.*, 115, 161-169.

Degradation example

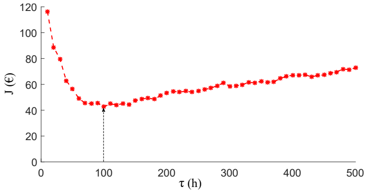


Degradation estimation examples



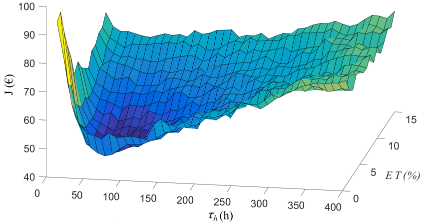
Decision variables

Periodic inspection



Inter-inspection period $\tau^* \simeq 100h$

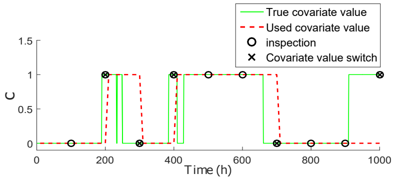
Online inspection



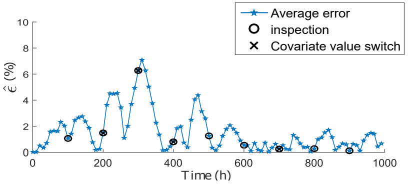
Error threshold $ET^* = 4\%$
Minimum inter-inspection period $\tau_h^* = 50h$

Different inspection schemes

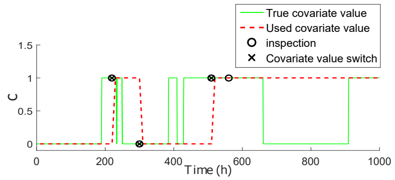
Periodic covariate inspection



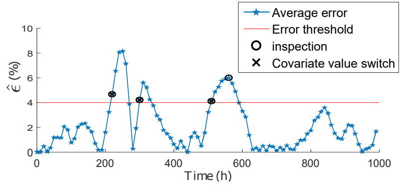
Error of periodic inspection



Online covariate inspection

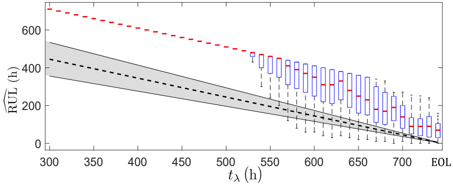


Error of online inspection

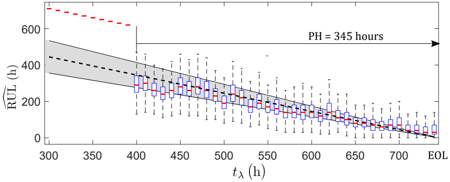


RUL predictions results

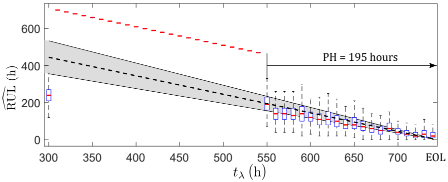
RUL predictions without inspection



∼ with periodic inspection



∼ with online inspection



Cost and prognostic performance

	Without inspection	Periodic $\sim$	Online $\sim$
Acc	0	0.54	0.27
αAc	0	0.53	0.36
$\hat{\epsilon}(\%)$	69.19	20.73	28.91
N_{ins}	–	215	110
J (€)	692	422	399

Summary

Challeng accomplished:

- RUL prediction using the information from inspections of covariate
- Two covariate inspection schemes: online and periodic
- Online inspection scheme helps to minimize the cost by avoiding unnecessary inspection

$\Rightarrow$ A different way of using degradation related information at different levels

Part IV

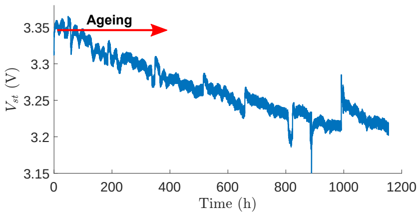
Multi-level Prognostics Using Different Sources of Degradation Information[3]

POLITECNICO
MILANO 1863

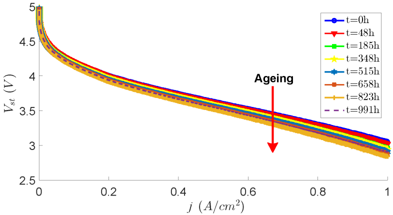
[3] Work in this section has been partly done during an international mobility in the **Laboratory of signal and risk analysis (LASAR)** at *Politecnico di Milano*

Problem statement

Stack voltage vs. time



Polarization measurement



Degradation of a stack observed from different measurements:

- External measurement: measured frequently, "poor quality" (voltage)
- Internal characterization: less frequently, "good quality" (polarization)

Objective

Aggregate RUL predictions from both measurements to improve global RUL quality

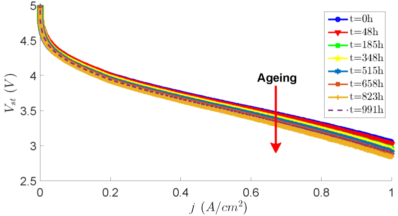
Polarization model

The output voltage of a stack at a given current density J [4]:

$$V_{st}(J) = n \cdot \{E - r \cdot J - A \cdot ln(\frac{J}{j_0}) - m_1 \cdot exp(m_2 \cdot J)\}$$

V_{st}: stack voltage
n: number of cells in the stack
E: open circuit voltage
r: internal resistance
J: operating current density
A: Tafel coefficient
j_0: exchange current density

m_1 and m_2: mass-transfer constants



Time impact on model parameters

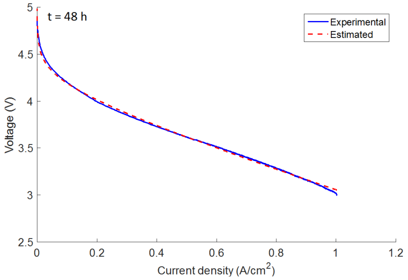
[4] J. Larminie and A. Dicks, *Fuel cell systems explained*. Wiley, 2003.

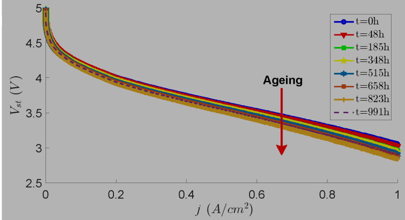
Polarization model

The output voltage of a stack at a given current density J [4]:

$$V_{st}(J) = n \cdot \{E - r \cdot J - A \cdot ln(\frac{J}{j_0}) - m_1 \cdot exp(m_2 \cdot J)\}$$

Identify model parameters





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m_1 and m_2: mass-transfer constants

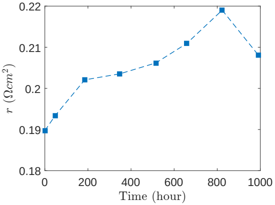
Time impact on model parameters

Parameters estimation results

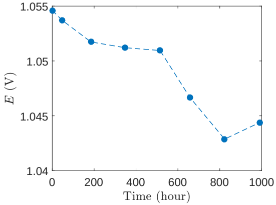
Time (h)	E (V)	r (Ω cm^2)
0	1,055	0,190
48	1,054	0,193
185	1,052	0,202
348	1,051	0,204
515	1,051	0,206
658	1,047	0,211
823	1,043	0,219
991	1,044	0,208

[4] J. Larminie and A. Dicks, *Fuel cell systems explained*. Wiley, 2003.

SOH degradation model



$$r(t) = r_0 \cdot (1 + \gamma(t))$$



$$E(t) = E_0 \cdot (1 - \gamma(t))$$

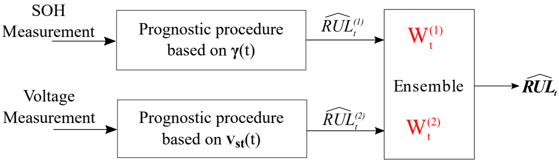
SOH degradation model $\gamma(t)$ of a PEM fuel cell [5]

- Definition: degradation rate of $E(t)$ and $r(t)$
- Assumption: availability of a procedure which returns an estimation of $\gamma(t)$ from polarization measurements

[5] Bressel et al.,"Remaining Useful Life Prediction and Uncertainty Quantification of Proton Exchange Membrane Fuel Cell Under Variable Load," *IEEE Trans. Ind. Electron.*, vol.63, no.4, pp.2569-2577, 2016.

RUL aggregation

- SOH degradation $\gamma(t)$
- Voltage degradation $V_{st}(t)$ driven by $\gamma(t)$



$$\widehat{RUL}_t = \sum_{i=1}^{M} W_t^i \cdot \widehat{RUL}_t^i$$

$$p(\widehat{RUL}_t) = \sum_{i=1}^{M} W_t^i \cdot p(\widehat{RUL}_t^i)$$

$\widehat{RUL}_t$: the ensemble outcome for the RUL prediction
RUL_t^i: RUL prediction by each i^{th} individual model
M: the number of models

W_t^i: local weights (non-negative and sum to 1).

Local weight W_t determination

$$\widehat{RUL}_t = W_t^{(1)} \cdot \widehat{RUL}_t^{(1)} + W_t^{(2)} \cdot \widehat{RUL}_t^{(2)}$$

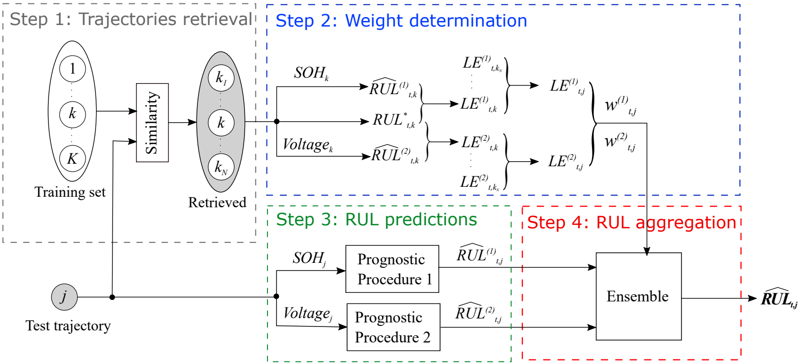
Why: to benefit from both measurements

- “good” RUL quality $\rightarrow$ large weight
- “poor” RUL quality $\rightarrow$ small weight

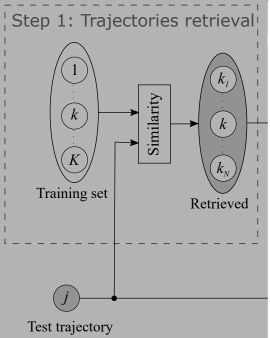
How

- Evaluated **locally** on a similar training set (historical data)
- Weights are recomputed at each time step

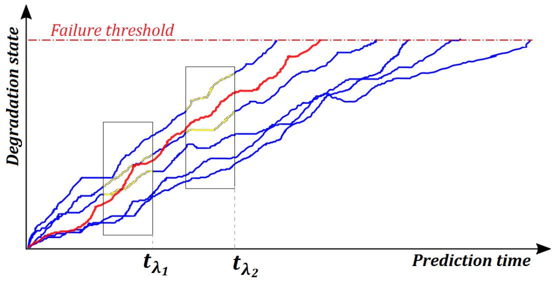
Ensemble-based approach



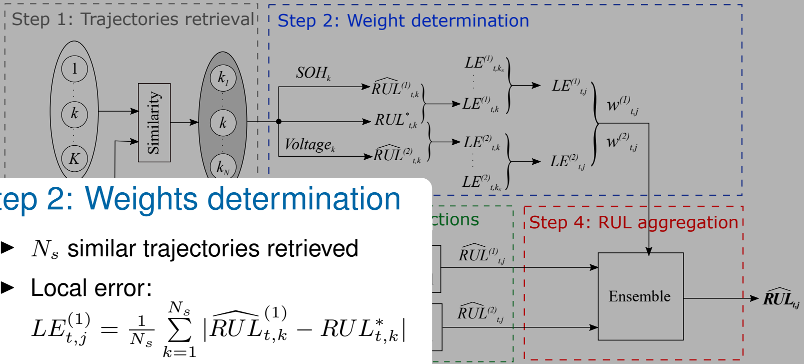
Ensemble-based approach



Step 1: Trajectories retrieval



Ensemble-based approach



Step 2: Weights determination

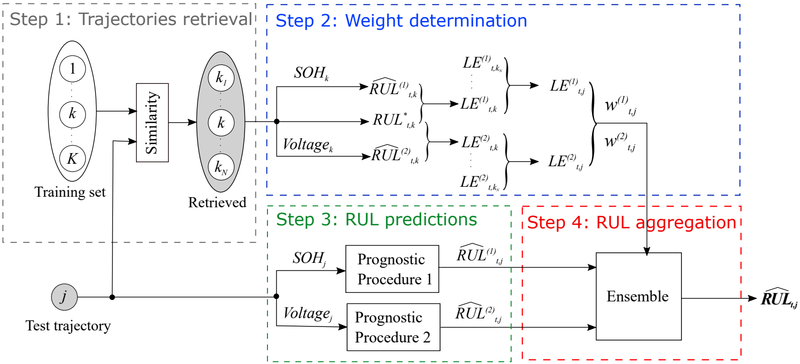
- N_s similar trajectories retrieved
- Local error:

$$LE^{(1)}_{t,j} = \frac{1}{N_s} \sum_{k=1}^{N_s} |\widehat{RUL}^{(1)}_{t,k} - RUL^{*}_{t,k}|$$

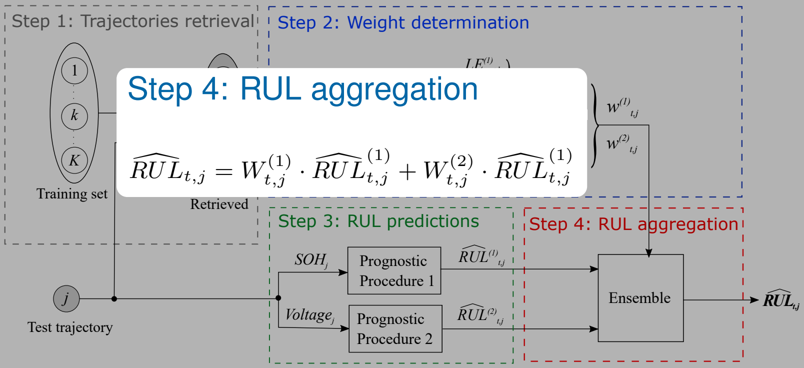
- Local weight:

$$W^{(1)}_{t,j} = \frac{1/LE^{(1)}_{t,j}}{1/LE^{(1)}_{t,j} + 1/LE^{(2)}_{t,j}}$$

Ensemble-based approach



Ensemble-based approach



Step 4: RUL aggregation

$$\widehat{RUL}_{t,j} = W^{(1)}_{t,j} \cdot \widehat{RUL}^{(1)}_{t,j} + W^{(2)}_{t,j} \cdot \widehat{RUL}^{(1)}_{t,j}$$

Numerical experiment

Simulation objective

Produce realistic signals:

- signal variability and randomness from stack to stack
- dependency between two types of measurement

Simulated signals synthesis

- Two types of measurement: $\gamma(t)$ and $V_{st}(t)$
- Ad hoc simulations based on dependent stochastic processes (Gamma process)

Simulated signals

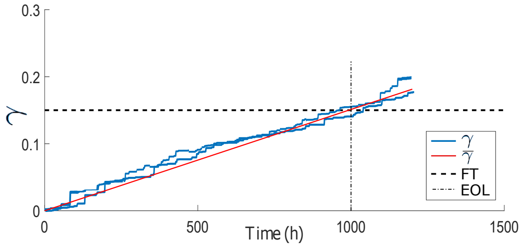
Simulated signals

- SOH degradation $\gamma(t)$

Simulated signals

- SOH degradation $\gamma(t)$

SOH degradation



Simulated signals

- SOH degradation $\gamma(t)$
- Voltage degradation $V_{st}(t)$ driven by $\gamma(t)$

$$V_{st}(t) = f\left(E(t), r(t), J(t)\right) \begin{cases} E(t) = E_0 \cdot (1 - \gamma(t)) \\ r(t) = r_0 \cdot (1 + \gamma(t)) \end{cases}$$

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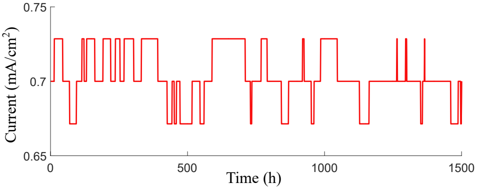
Loading current



Simulated signals

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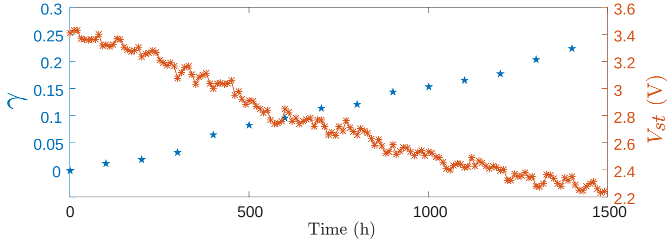
Simulated signals

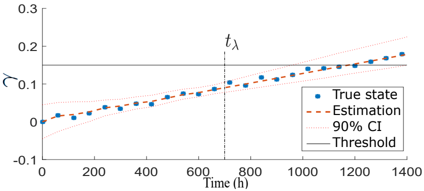
- SOH degradation $\gamma(t)$
- Voltage degradation $V_{st}(t)$ driven by $\gamma(t)$

Measurements $\gamma(t)$ and $V_{st}(t)$

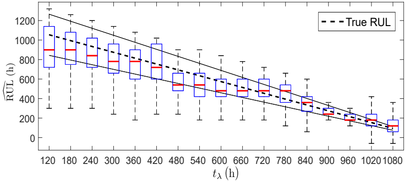


RUL prediction results

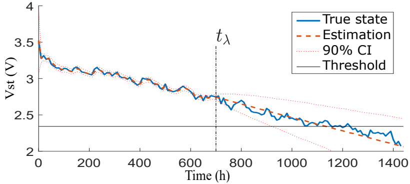
Estimation of $\gamma(t)$



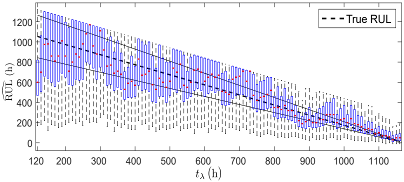
RUL predictions based on $\gamma(t)$



Estimation of $V_{st}(t)$

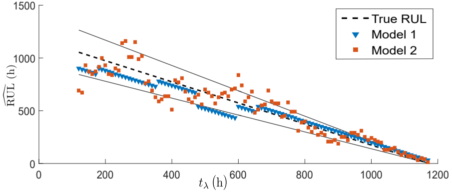


RUL predictions based on $V_{st}(t)$



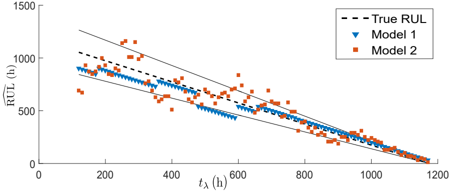
RUL aggregation

Individual RUL

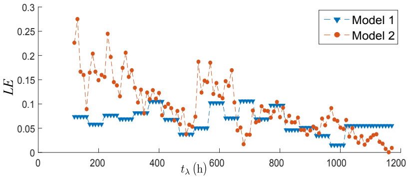


RUL aggregation

Individual RUL

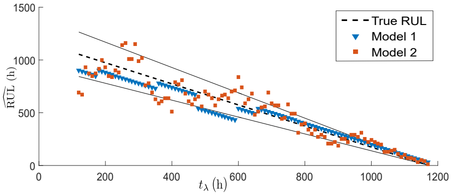


Local error LE

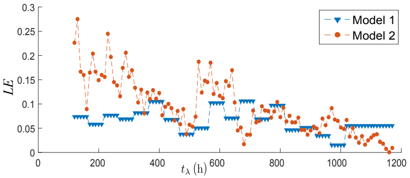


RUL aggregation

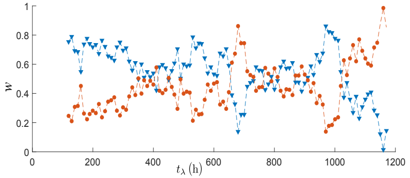
Individual RUL



Local error LE

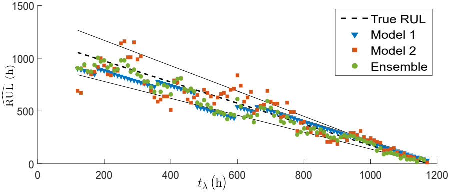


Local weight w

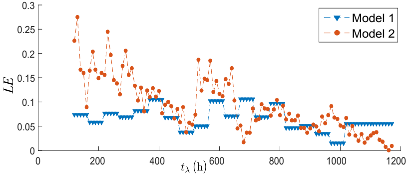


RUL aggregation

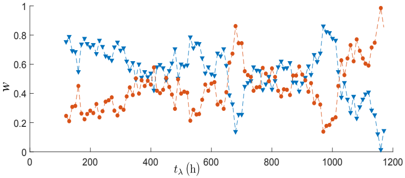
Aggregated RUL



Local error LE

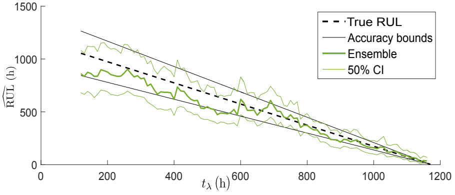


Local weight w

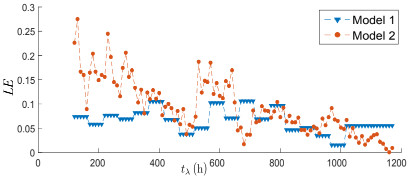


RUL aggregation

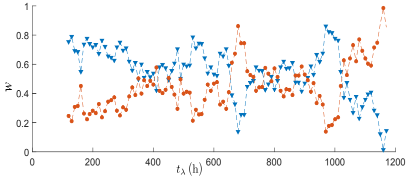
Aggregated RUL uncertainty



Local error LE



Local weight w



Performance evaluation

Average performance on 50 test trajectories:

Performance	Model 1	Model 2	Ensemble	
			Point value	PDF
Acc	0.52	0.12	0.55	0.56
αAc	0.31	0.24	0.54	0.49
Std	0.16	0.14	0.07	0.07

* Prediction quality is improved with different configurations

- different process variances
- different signals' dependencies

Summary

- RUL prediction quality has been evaluated on historical data
- Weights have been locally associated to individual predictions from two different measurement signals
- Aggregated results provided better quality than individual ones
- Ready for the application in PEM fuel cell when data requirement is met

Part V

Conclusion & Perspectives

General conclusion

Three main contributions:

1. Developed a PF-based approach for RUL prediction of PEM fuel cell using deeper characterization information
2. Proposed an online inspection of degradation covariate at different level to adapt RUL prediction
3. Proposed an Ensemble-based approach using degradation information at different levels to improve the RUL prediction quality

General conclusion

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Perspectives

Short term

- Data involves varying usage profile for both development and validation
- Inspection schemes based on simple cost function
  $\rightarrow$ consideration of more impacts, $e.g.$ timeliness

Long term

- Validation of developed approaches with real-life data should be envisaged to become commercially attractive
- Not limited to the framework of PEM fuel cell
  $\rightarrow$ adapt and extend to other applications

Thank you !

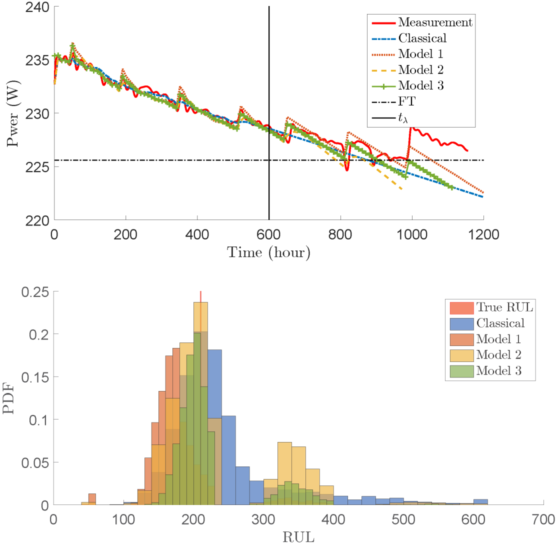
Publications

- Zhang D, Cadet C, Yousfi-Steiner N and Bérenguer C (2017) PEMFC RUL Prognostics Considering Degradation Recovery Phenomena. *Journal of Risk and Reliability*, revised.
- Zhang D, Cadet C, Yousfi-Steiner N and Bérenguer C (2017) A Study of Online Inspection for Multi-level Prognostics. In: *IFAC-PapersOnLine*, 50(1), pp.13716-13721. DOI: 10.1016/j.ifacol.2017.08.2549.
- Zhang D, Baraldi P, Cadet C, Yousfi-Steiner N, Bérenguer C and Zio E (2017) A Study of Local Aggregation of An Ensemble of Models for RUL Prediction. In: *The 10th International Conference on Mathematical Methods in Reliability (MMR 2017)*, July 3-6, 2017, Grenoble, France.
- Zhang D, Cadet C, Yousfi-Steiner N, Druart F and Bérenguer C (2017) PHM-oriented Degradation Indicators for Batteries and Fuel Cells. *Fuel Cells*, 17(2), pp.268-276. DOI: 10.1002/fuce.201600075.
- Zhang D, Cadet C, Yousfi-Steiner N and Bérenguer C (2016) Some Improvements of Particle Filtering Based Prognosis for PEM Fuel Cells. In: *IFAC-PapersOnLine*, volume 49. pp.162-167. DOI: 0.1016/j.ifacol.2016.11.028.
- Zhang D, Cadet C, Yousfi-Steiner N and Bérenguer C (2015) PHM-oriented degradation indicators for PEM fuel cells:What can be learnt from battery State of Charge estimation . In: *Proc. 6th International Conference on Fundamentals & Development of Fuel Cells*, Paper 190. Feb 2015, Toulouse, France.

Part VI

Appendix

RUL uncertainty



Proposition 1

Two indicators $V_{st}(t)$ and $\gamma(t)$ are generated from the same realization of a Gamma degradation process, with different additive noises.

$$\overline{\gamma}(t) = \overline{\gamma}(t-1) + \Gamma(\overline{\alpha}\Delta t, \overline{\beta})$$

$$\gamma^i(t) = \gamma^i(t-1) + \Gamma(\alpha^i \Delta t, \beta^i)$$

$$\begin{cases} \gamma_1^i(t) = \gamma^i(t) + \mathcal{N}(0, \sigma_1^2(t)) \\ \gamma_2^i(t) = \gamma^i(t) + \mathcal{N}(0, \sigma_2^2(t)) \end{cases} \rightarrow \begin{cases} \gamma_{meas}^i(t) = \gamma^i(t) + \mathcal{N}(0, \sigma_{\omega_1}^2(t)) \\ V_{st}{}_{meas}^i(t) = V_{st}^i(t) + \mathcal{N}(0, \sigma_{\omega_2}^2(t)) \end{cases}$$

Proposition 2

Two indicators $V_{st}(t)$ and $\gamma(t)$ are simulated from two different degradation processes, yet the two processes are dependent processes by construction.

$$\begin{matrix} G_1(\alpha_1,\beta) \\ G_2(\alpha_2,\beta) \end{matrix} \rightarrow \left\{ \begin{matrix} a_1 = \alpha_1 - \rho\sqrt{\alpha_1\alpha_2} & \rightarrow g_1^i(a_1,\beta) \\ a_2 = \alpha_2 - \rho\sqrt{\alpha_1\alpha_2} & \rightarrow g_2^i(a_2,\beta) \\ a_1 = \rho\sqrt{\alpha_1\alpha_2} & \rightarrow g_1^i(a_3,\beta) \end{matrix} \right\} \rightarrow \begin{matrix} G_1^i = g_1^i + g_3^i \\ G_2^i = g_2^i + g_3^i \end{matrix}$$

$$\begin{cases} \gamma_1^i(t) = \gamma_1^i(t-1) + G_1^i \\ \gamma_2^i(t) = \gamma_2^i(t-1) + G_2^i \end{cases} \rightarrow \begin{cases} \gamma_{meas}^{i}(t) = \gamma^i(t) + \mathcal{N}(0,\sigma_{\omega_1}^2(t)) \\ V_{st\,meas}^{\;i}(t) = V_{st}^i(t) + \mathcal{N}(0,\sigma_{\omega_2}^2(t)) \end{cases}$$