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Hybrid approach for predicting fuel cell future performance under dynamic load profile and variable operating conditions

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Outline

1. Introduction

2. Characterization of fuel cell (FC) aging

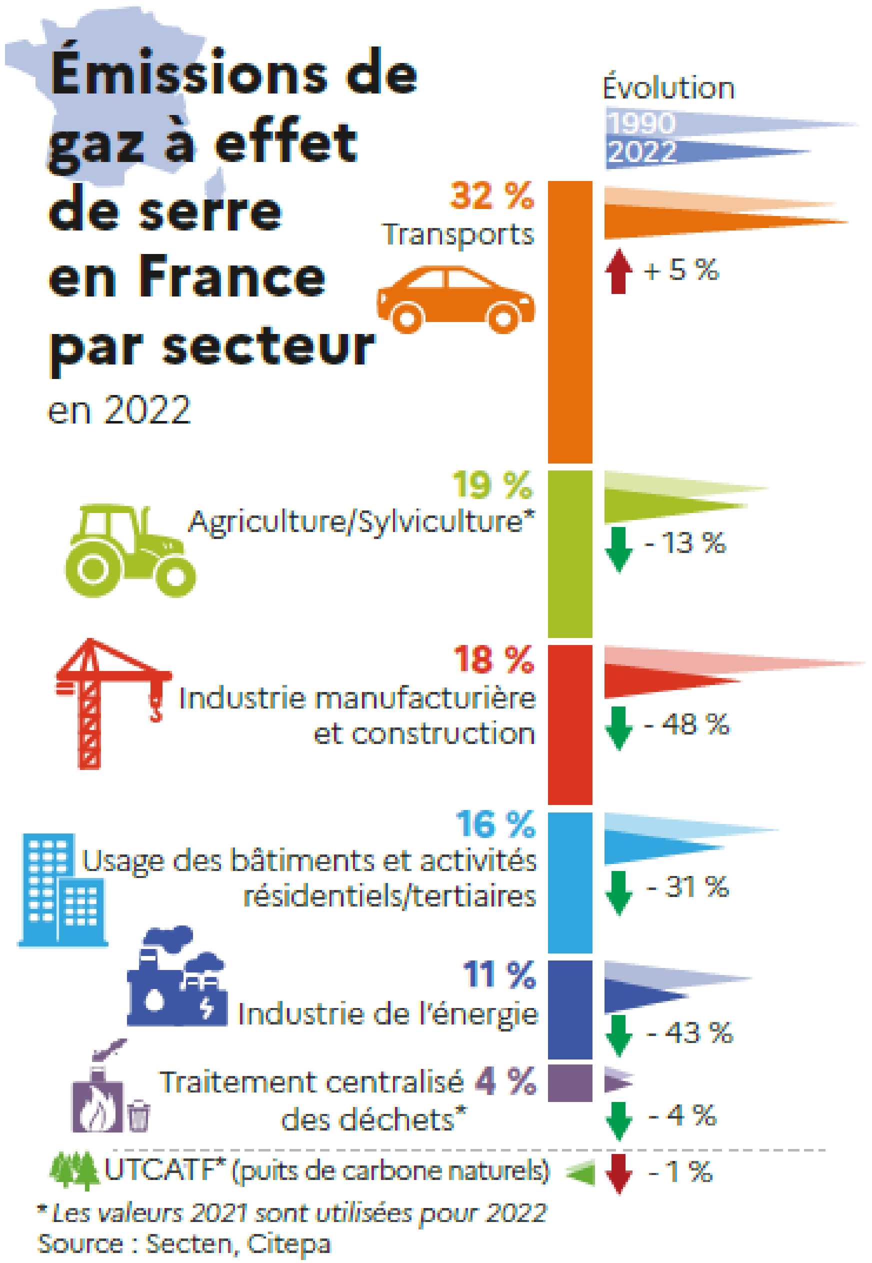
3. Hybrid approach for predicting the future performance of a FC

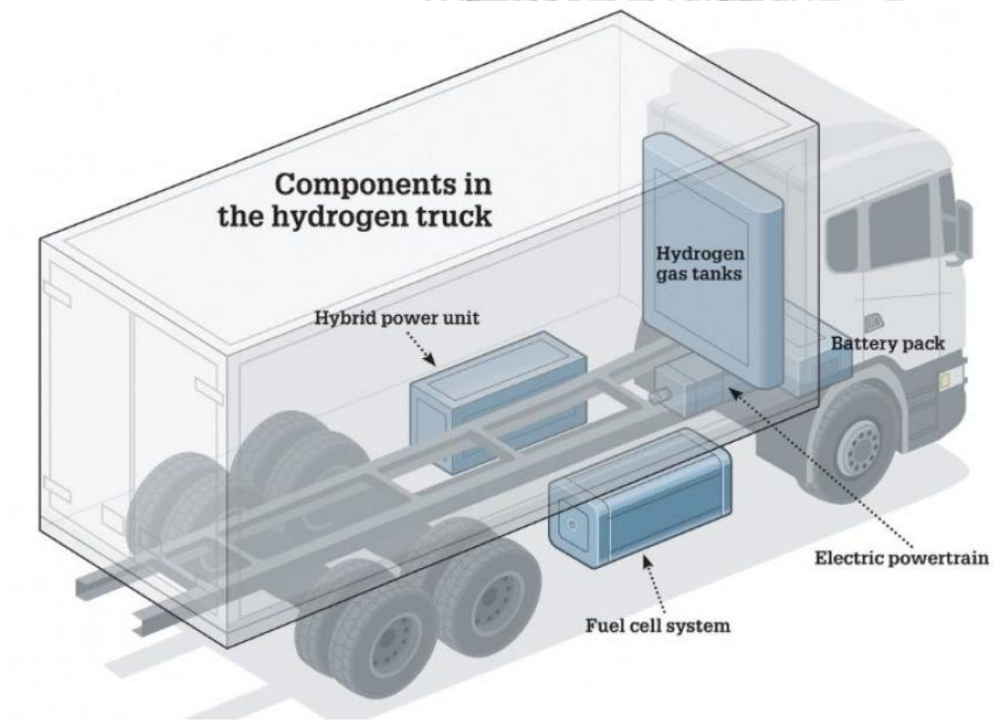
4. Conclusion and future work

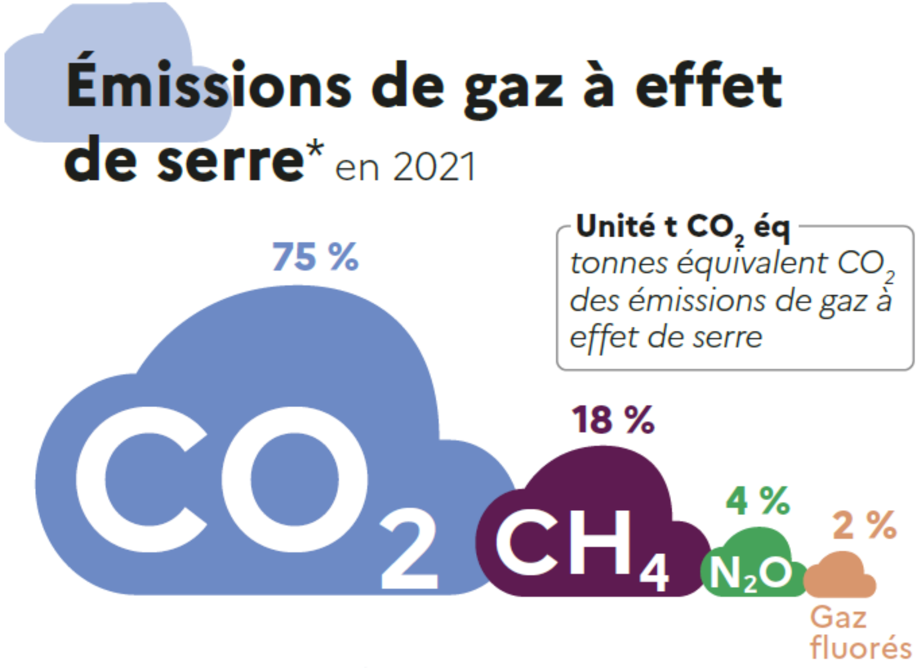
Part 1

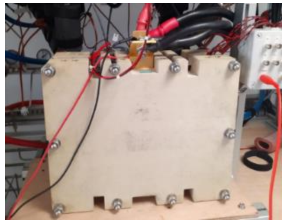
Introduction

Context of the thesis

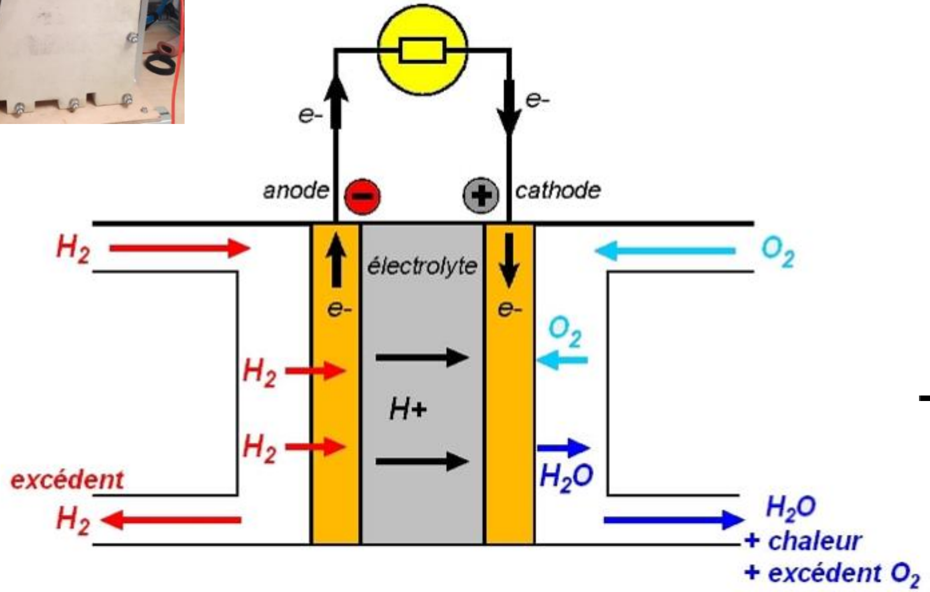








PEM fuel cell



Anode: $H_2 \longrightarrow 2H^+ + 2e^-$ (oxidation)

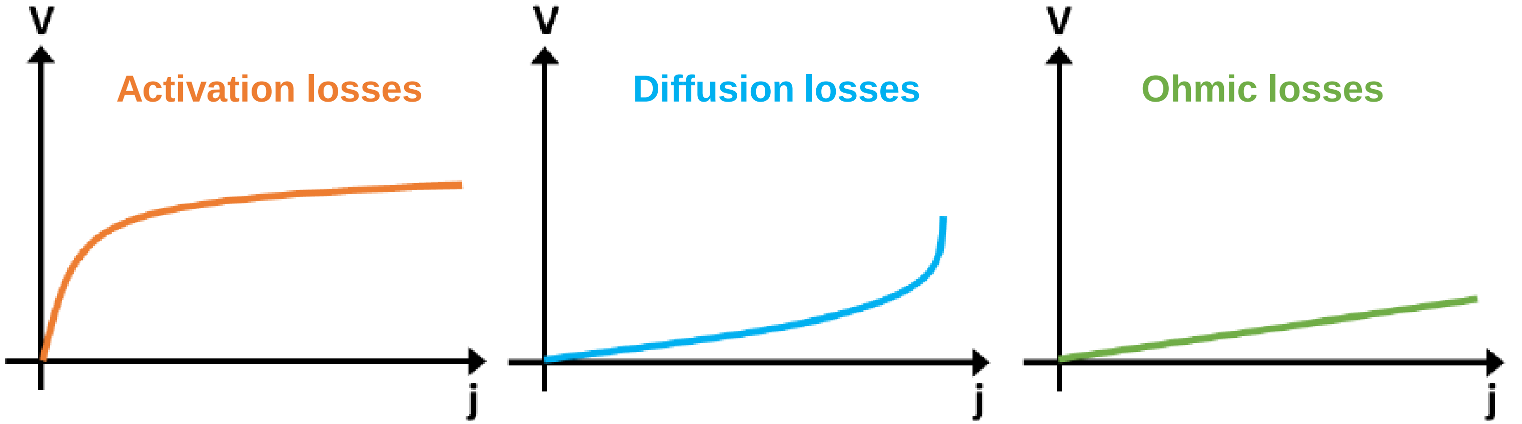
Cathode: $\frac{1}{2} O_2 + 2H^+ + 2e^- \longrightarrow H_2O$ (reduction)

Global equation:

$H_2 + \frac{1}{2} O_2 \longrightarrow H_2O$ + electricity + heat

Cost & Durability

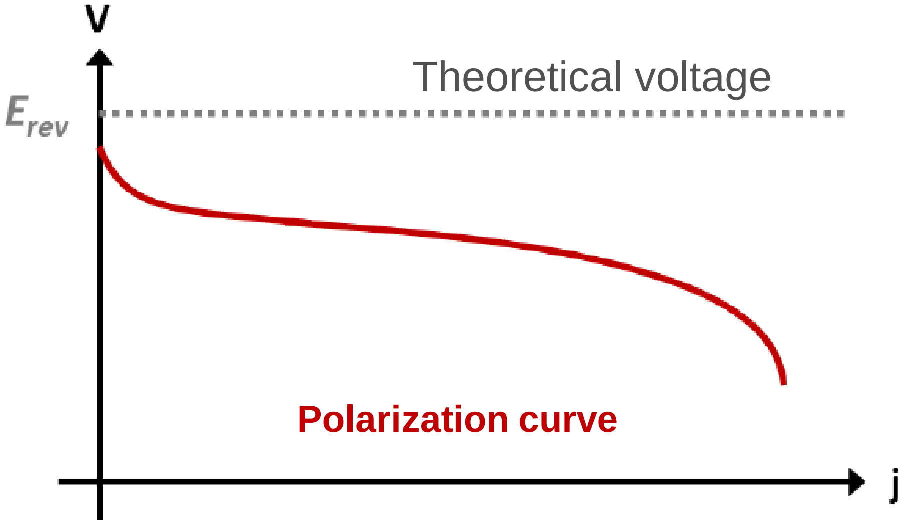
Irreversible losses affecting component voltage



To reach the activation energy

To supply reactants

Loss of charge of e^- and H^+ ions

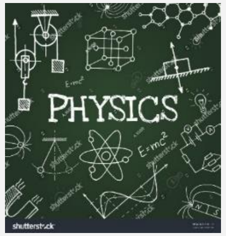


$$U_{cell} = E_{rev} - \eta_{act} - \eta_{diff} - \eta_{ohm}$$

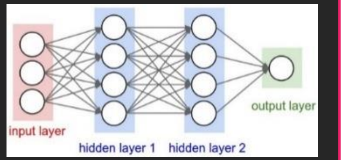
Modeling approach

Three main approaches for aging modeling

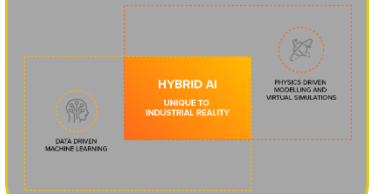
Model-based methods



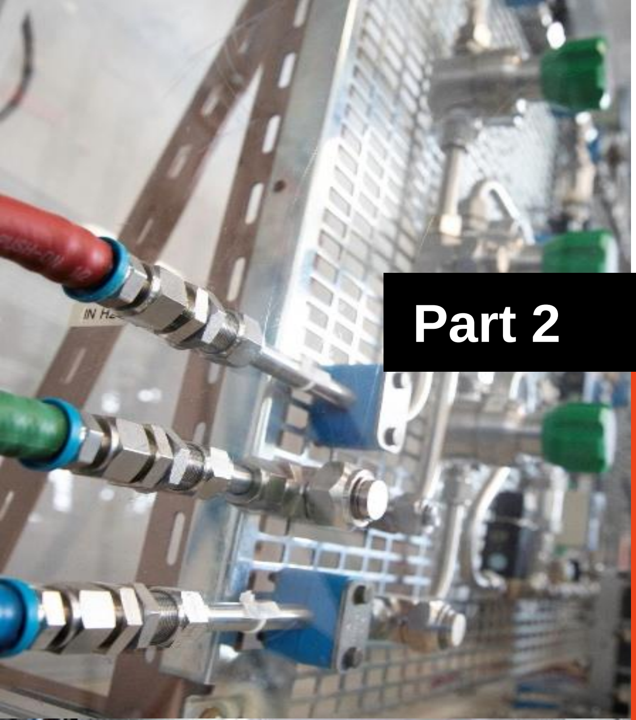
Data-driven methods



Hybrid methods



- Propose statistical / machine learning methods,
- Integrating knowledge from physical models,
- Predict the future performance of a fuel cell.



Part 2

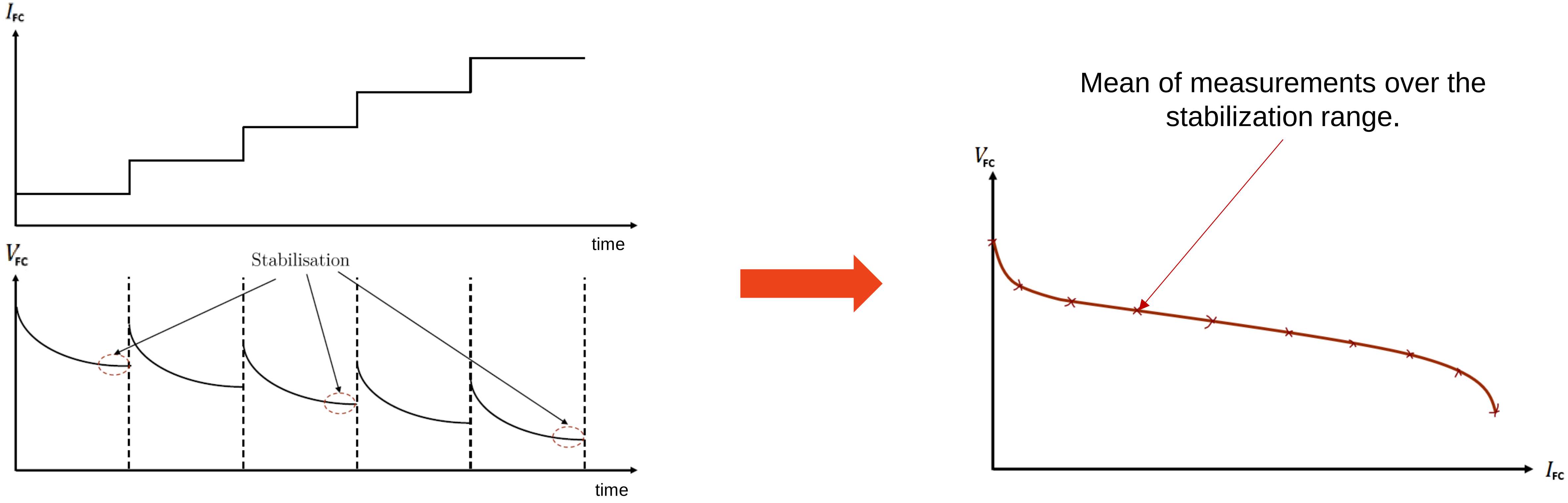
Characterization of fuel cell (FC) aging

Laplace

Polarization curve

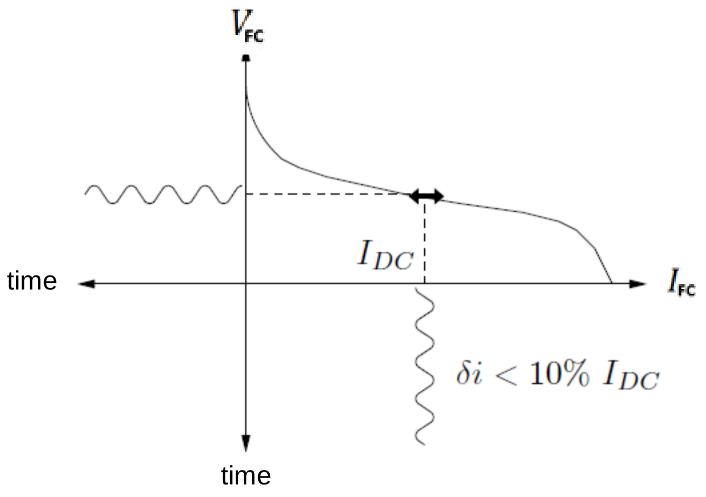
- Provides information on the fuel cell's static behavior.

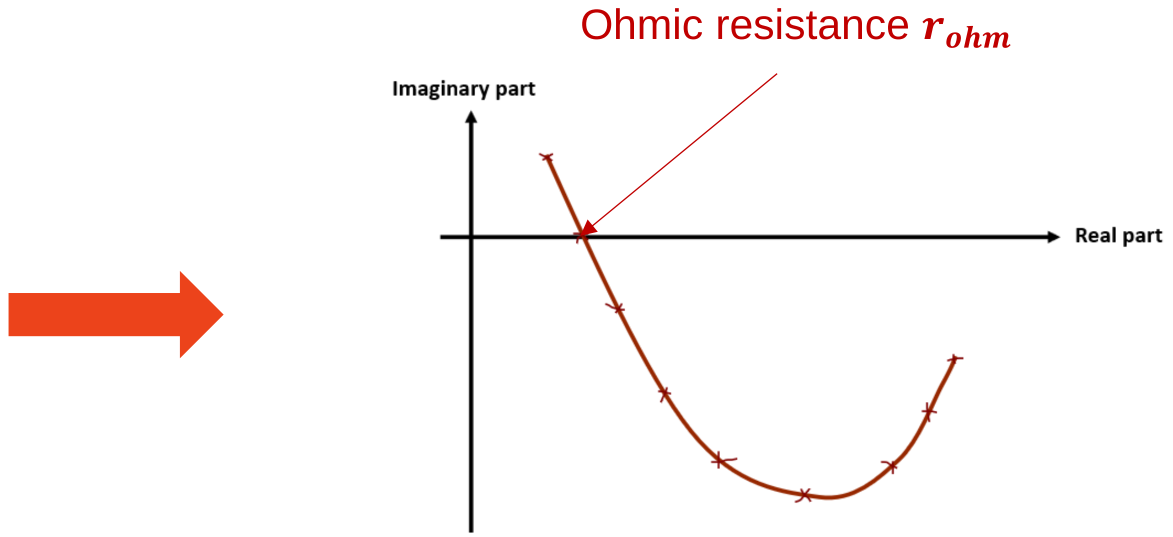
- Under stable operating conditions (temperature, pressure, humidity, ...).



Electrochemical impedance spectroscopy

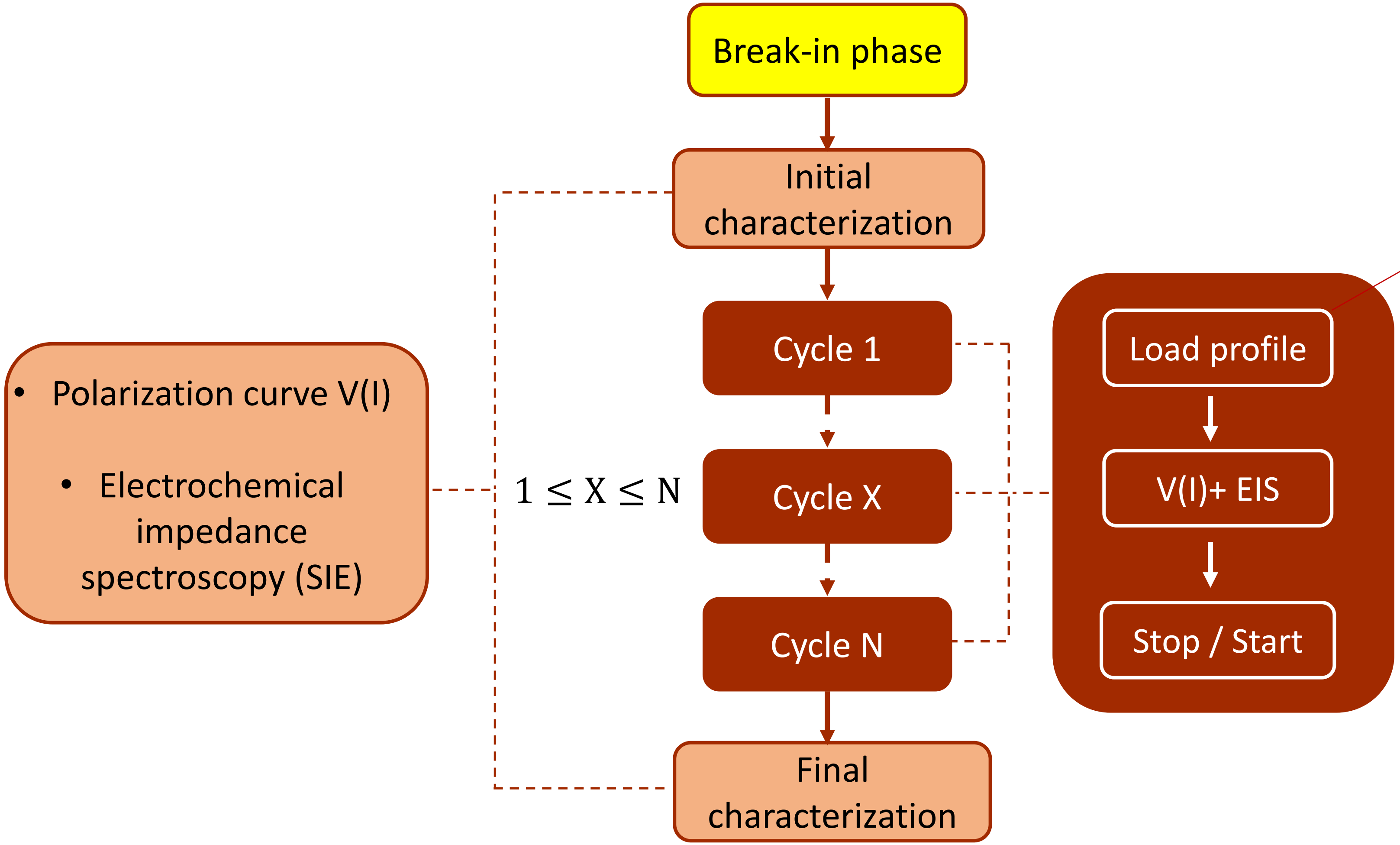
- Provides information on the dynamic behavior of the FC, around an operating point.
- Application of low-amplitude sinusoidal current disturbances with frequency variation.

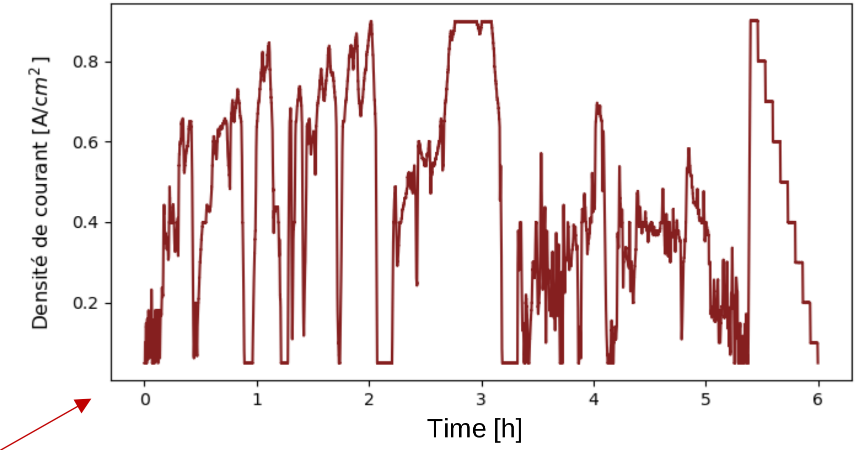




Nyquist diagram

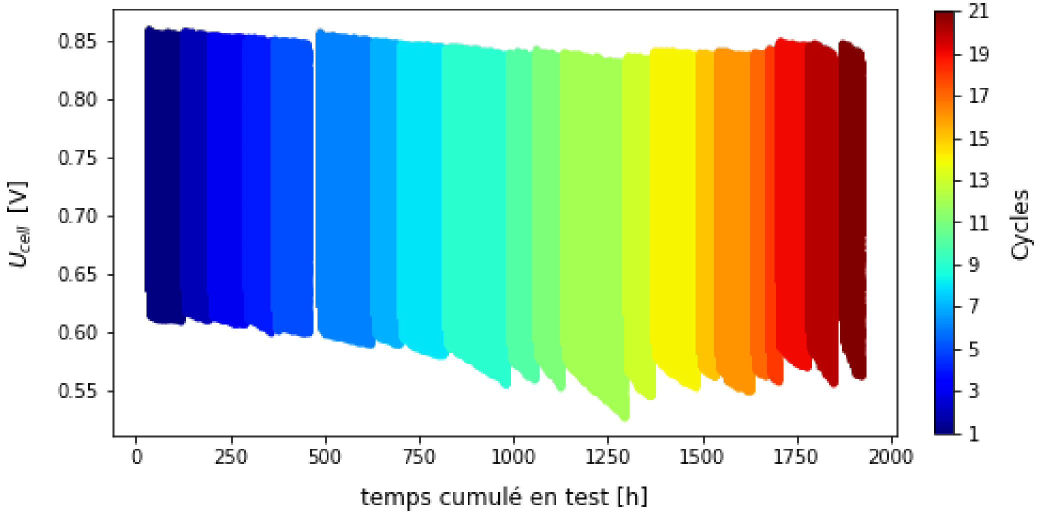
Description of the aging campaign





Data

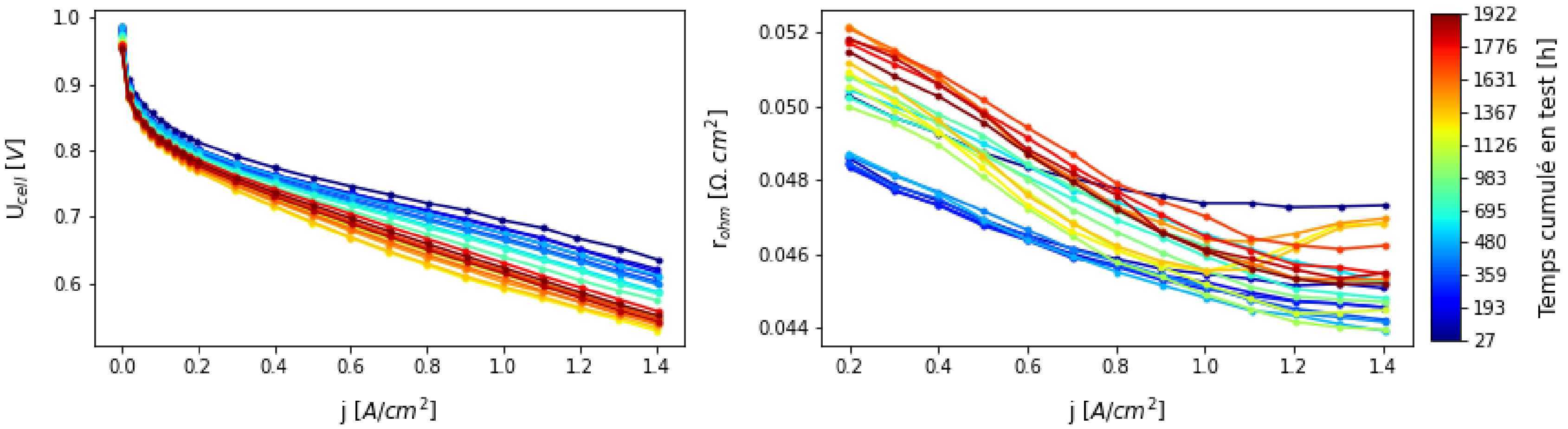
Voltage over time under load profile



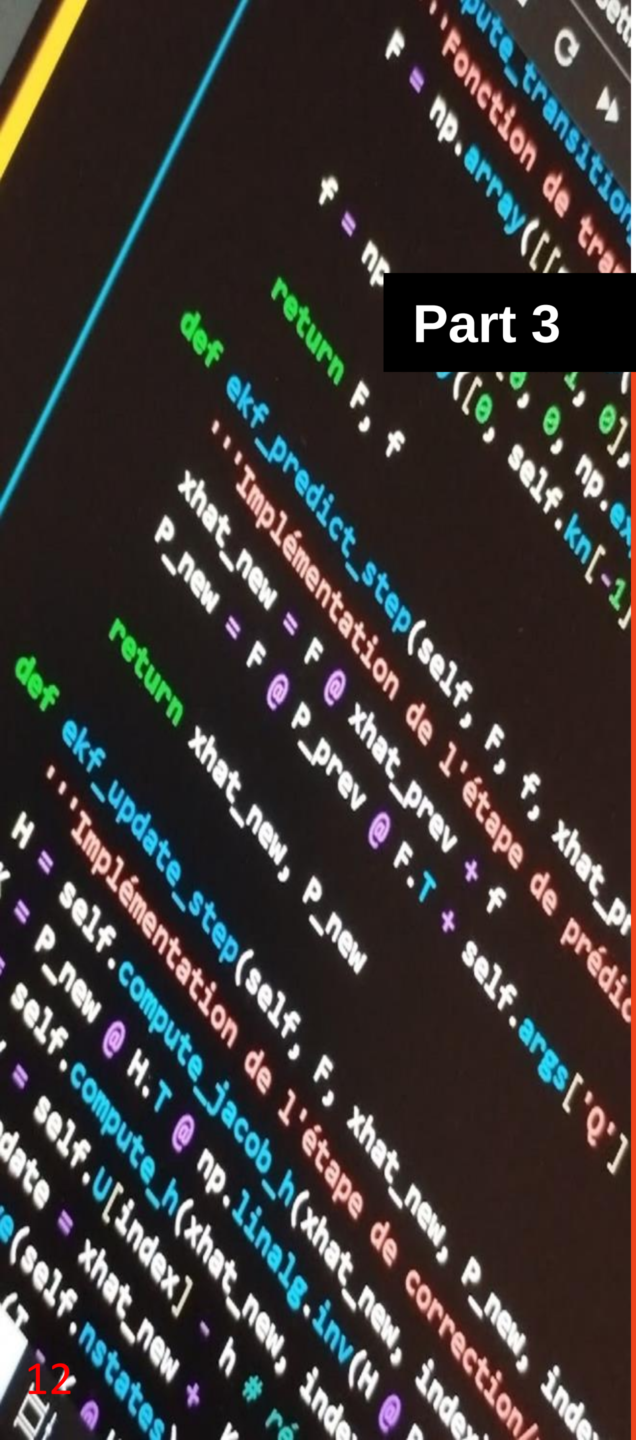
Operating conditions

Temperature, Pression, …

Polarization curves and ohmic resistances over time



$$U_{cell}(j) = E_{rev}(P,T) - \frac{RT}{2\alpha F}\ln\left(\frac{j + \boldsymbol{j_n}}{\boldsymbol{j_0}}\right) - \boldsymbol{r_{diff}} \times j - \boldsymbol{r_{ohm}(j)} \times j$$



Part 3

Hybrid approach for predicting the future performance of a FC

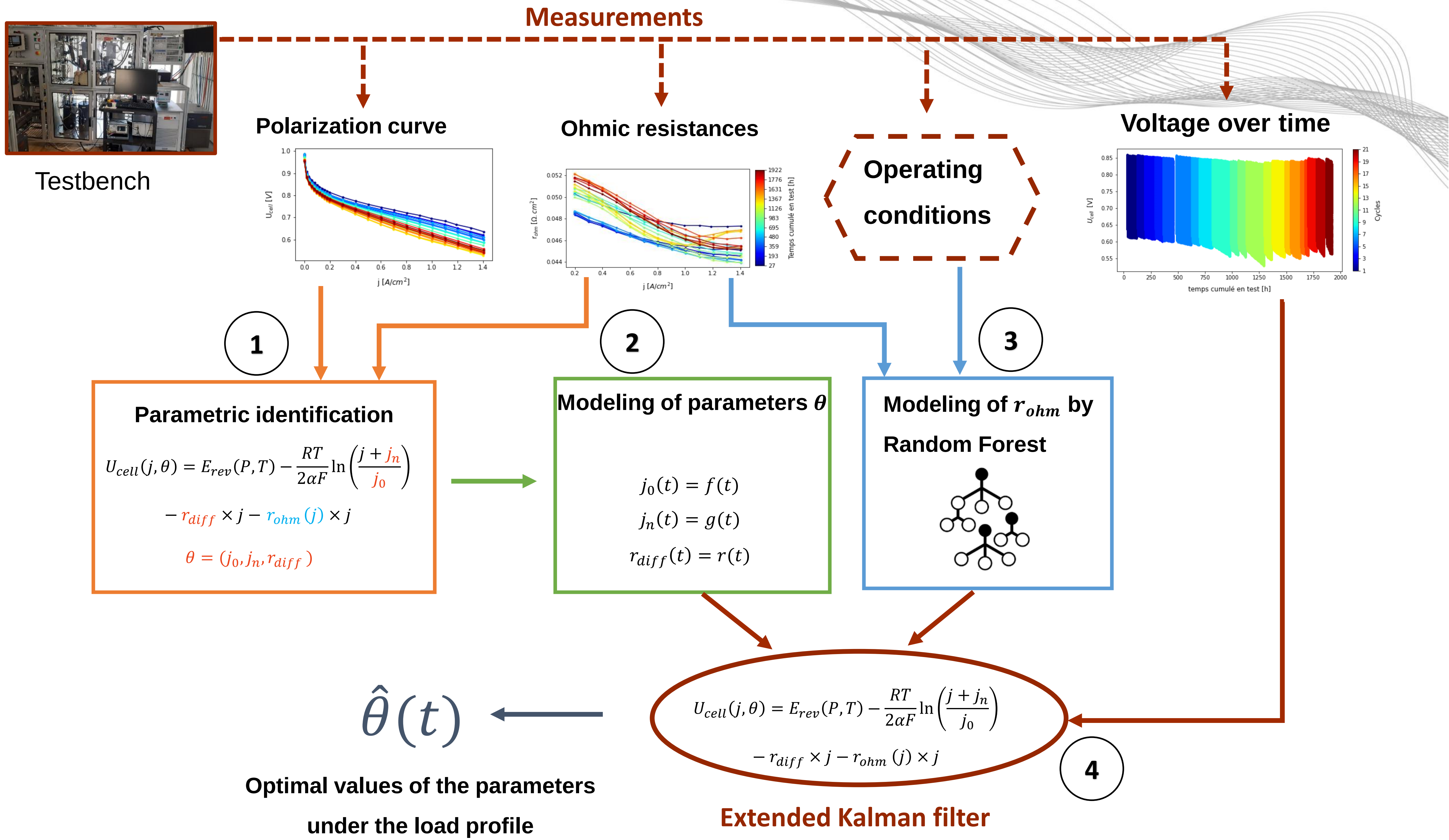
Laplace

Model

$$U_{cell}(j) = E_{rev}(P,T) - \frac{RT}{2\alpha F}\ln\left(\frac{j + \boldsymbol{j_n}}{\boldsymbol{j_0}}\right) - \boldsymbol{r_{diff}} \times j - \boldsymbol{r_{ohm}(j)} \times j$$

- Parameters j_0, j_n and r_{diff} vary over time.
- Ohmic resistance $\boldsymbol{r_{ohm}(j)}$ depend on the current and is sensitive to operating conditions.
- These can only be estimated at chararcterization phase

- How to estimate them under load profile ?
- How to predict their future values ?



Measurements
Testbench
Polarization curve
U_{cell} [V]
j [A/cm²]
Ohmic resistances
r_{ohm} [Ω cm²]
j [A/cm²]
Temps cumulé en test [h]
Operating conditions
Voltage over time
U_{cell} [V]
temps cumulé en test [h]
Cycles
1
2
3
Parametric identification
$U_{cell}(j,\theta) = E_{rev}(P,T) - \frac{RT}{2\alpha F}\ln\left(\frac{j+j_n}{j_0}\right)$
$- r_{diff} \times j - r_{ohm}(j) \times j$
$\theta = (j_0, j_n, r_{diff})$
Modeling of parameters θ
$j_0(t) = f(t)$
$j_n(t) = g(t)$
$r_{diff}(t) = r(t)$
Modeling of r_{ohm} by Random Forest
$\hat{\theta}(t)$
Optimal values of the parameters under the load profile
$U_{cell}(j,\theta) = E_{rev}(P,T) - \frac{RT}{2\alpha F}\ln\left(\frac{j+j_n}{j_0}\right)$
$- r_{diff} \times j - r_{ohm}(j) \times j$
4
Extended Kalman filter

- The forget gate:

$$\mathbf{f}_t = \sigma\left(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1} + \mathbf{b}_f\right)$$

- The input gate:

$$\mathbf{i}_t = \sigma\left(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1} + \mathbf{b}_i\right)$$

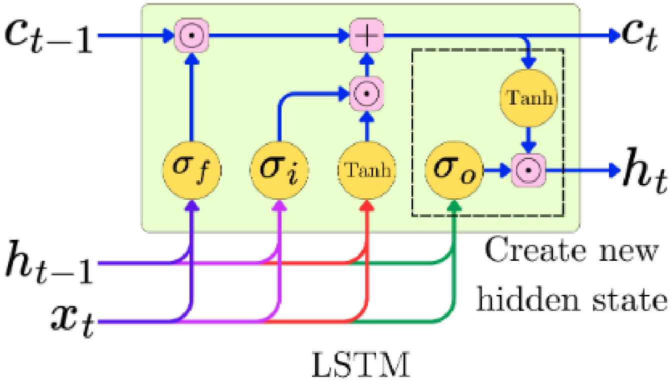
- The output gate:

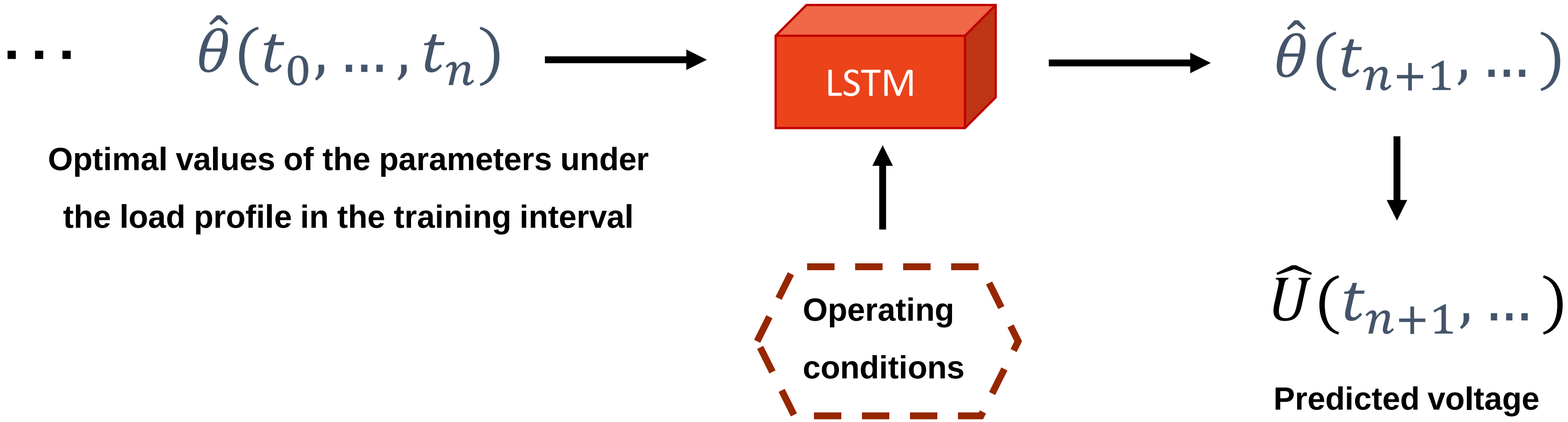
$$\mathbf{o}_t = \sigma\left(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1} + \mathbf{b}_o\right)$$

$$\tilde{\mathbf{c}}_t = \tanh\left(W_c \mathbf{x}_t + U_c \mathbf{h}_{t-1} + \mathbf{b}_c\right)$$

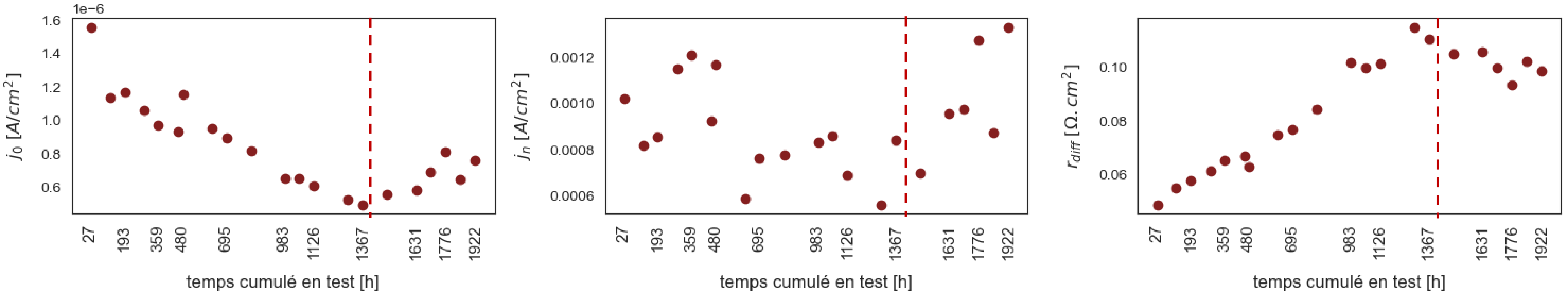
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$





Parameters identification



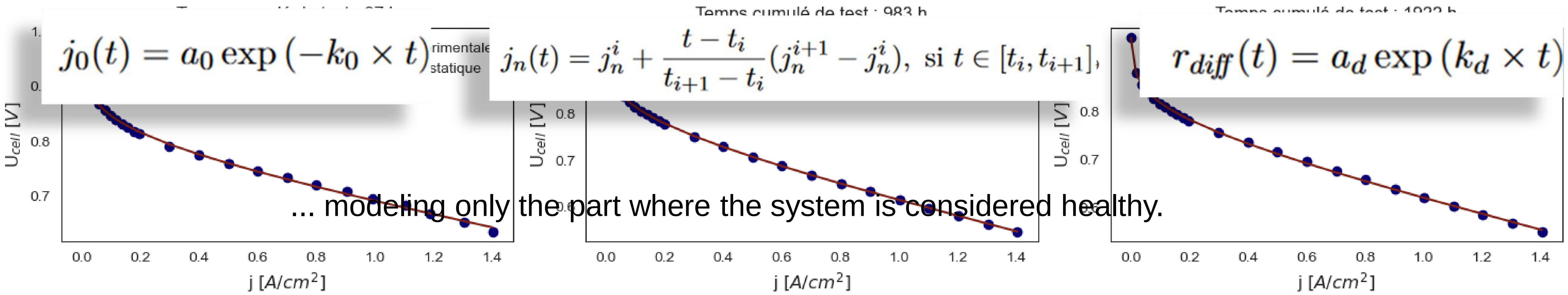
- Good fit of model parameters to experimental data..
- 0.3% mean relative error

Proposed temporal evolution laws

$$j_0(t) = a_0 \exp\left(-k_0 \times t\right)$$

$$j_n(t) = j_n^i + \frac{t - t_i}{t_{i+1} - t_i}(j_n^{i+1} - j_n^i), \text{ si } t \in [t_i, t_{i+1}],$$

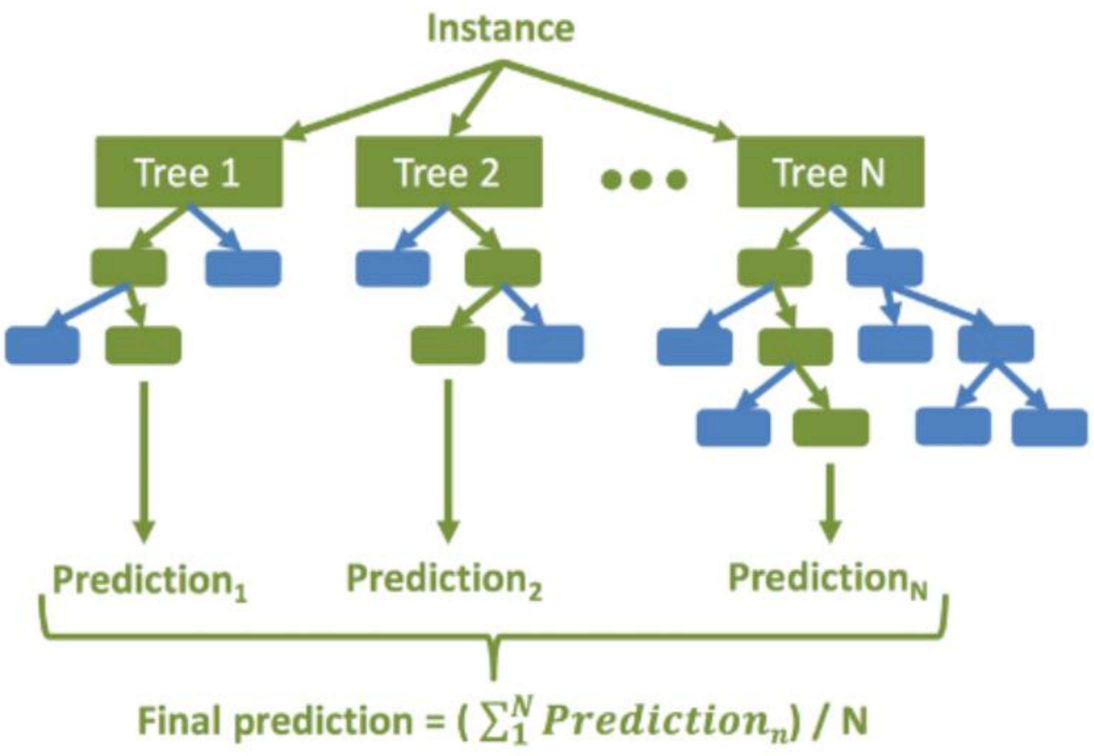
$$r_{diff}(t) = a_d \exp\left(k_d \times t\right)$$



... modeling only the part where the system is considered healthy.

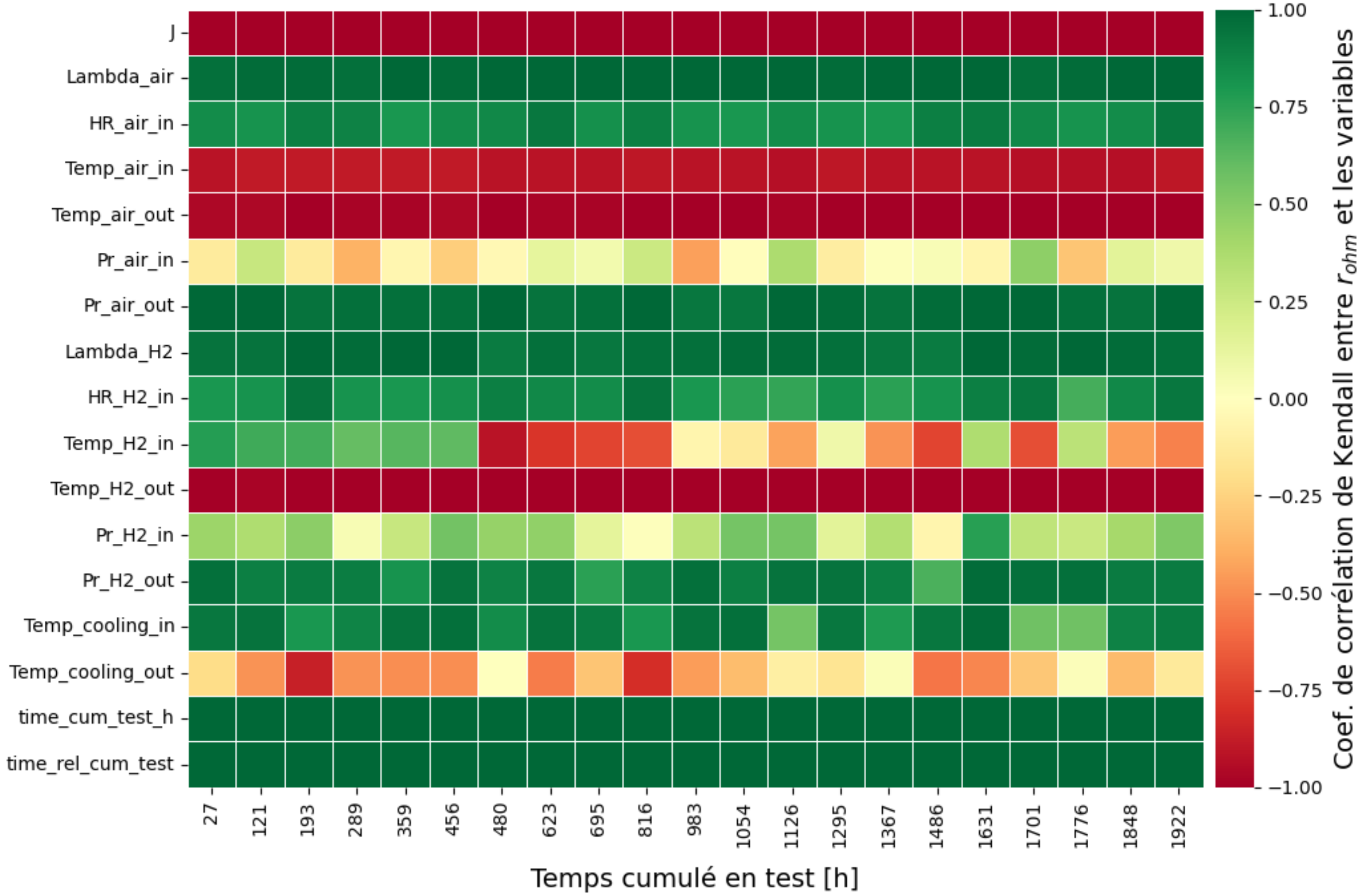
Modeling of the ohmic resistance

Random Forests



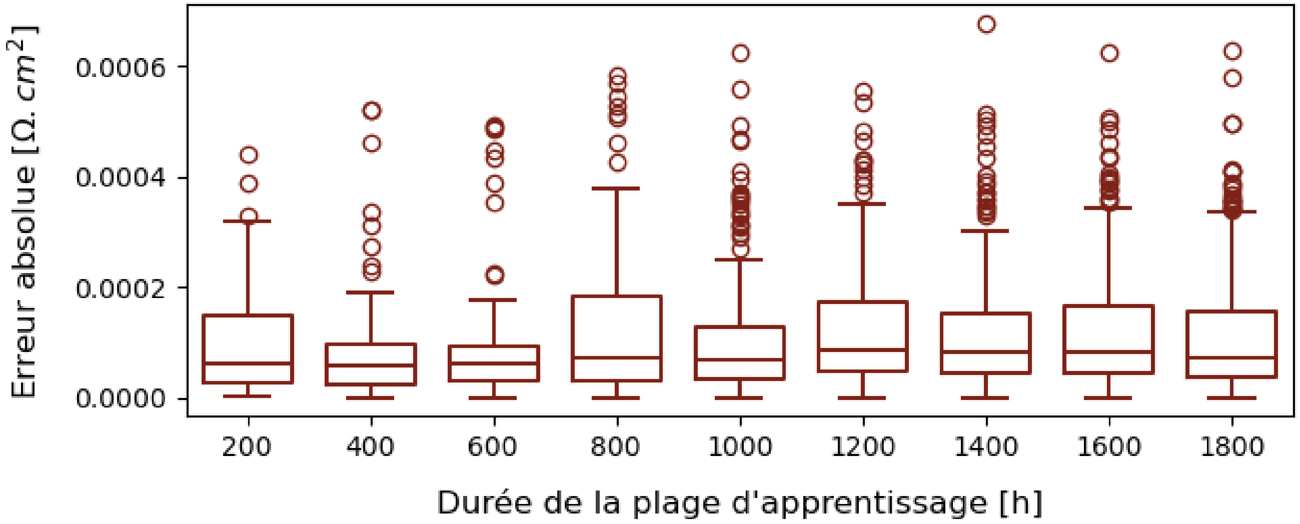
Aggregation of decision trees

Selection of features



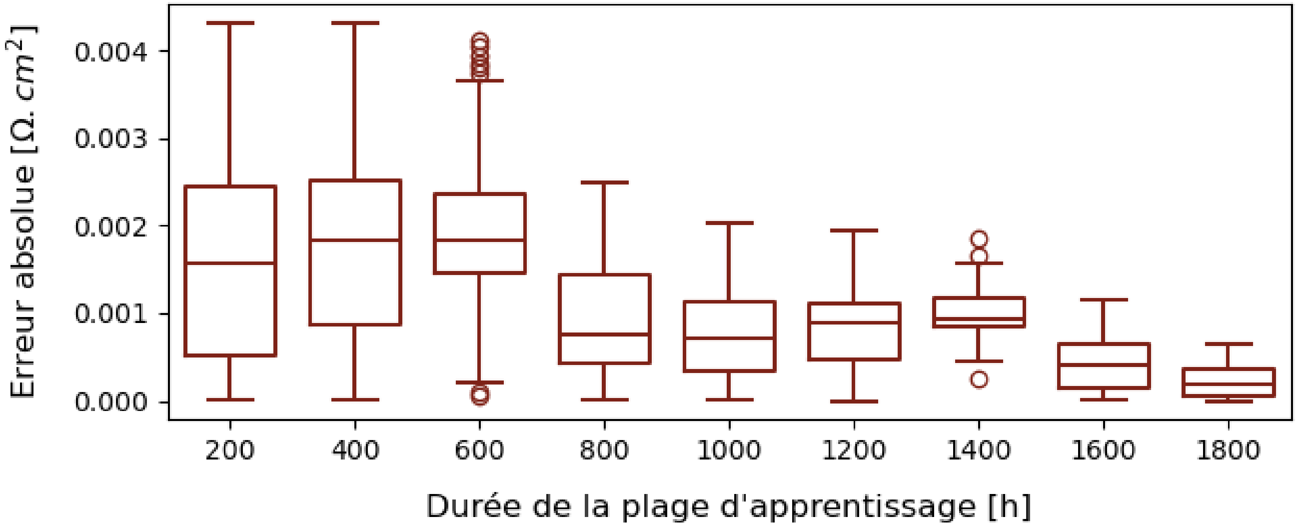
Distribution of errors according to learning time

Learning set



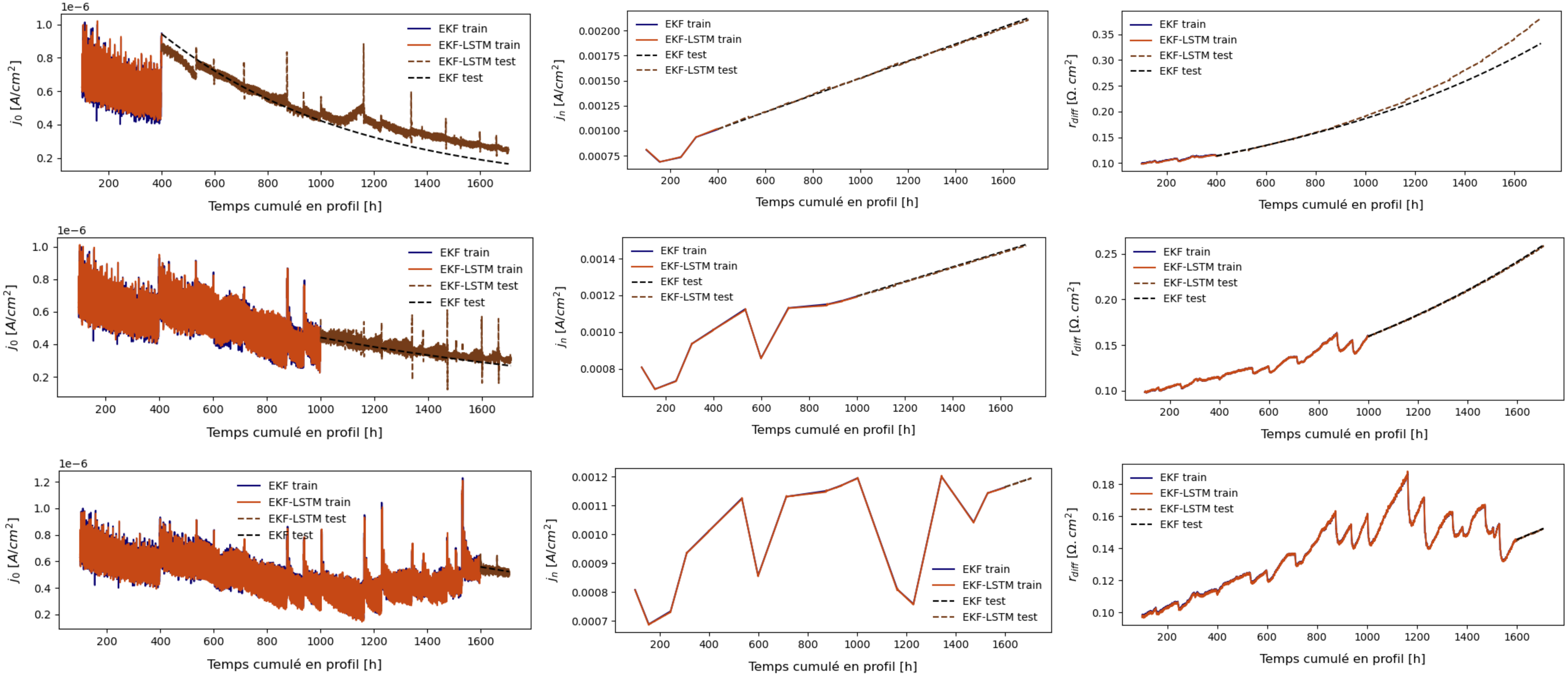
- Good precision on the learning set.
- Maximum mean relative error: 0.2 %.

Test set

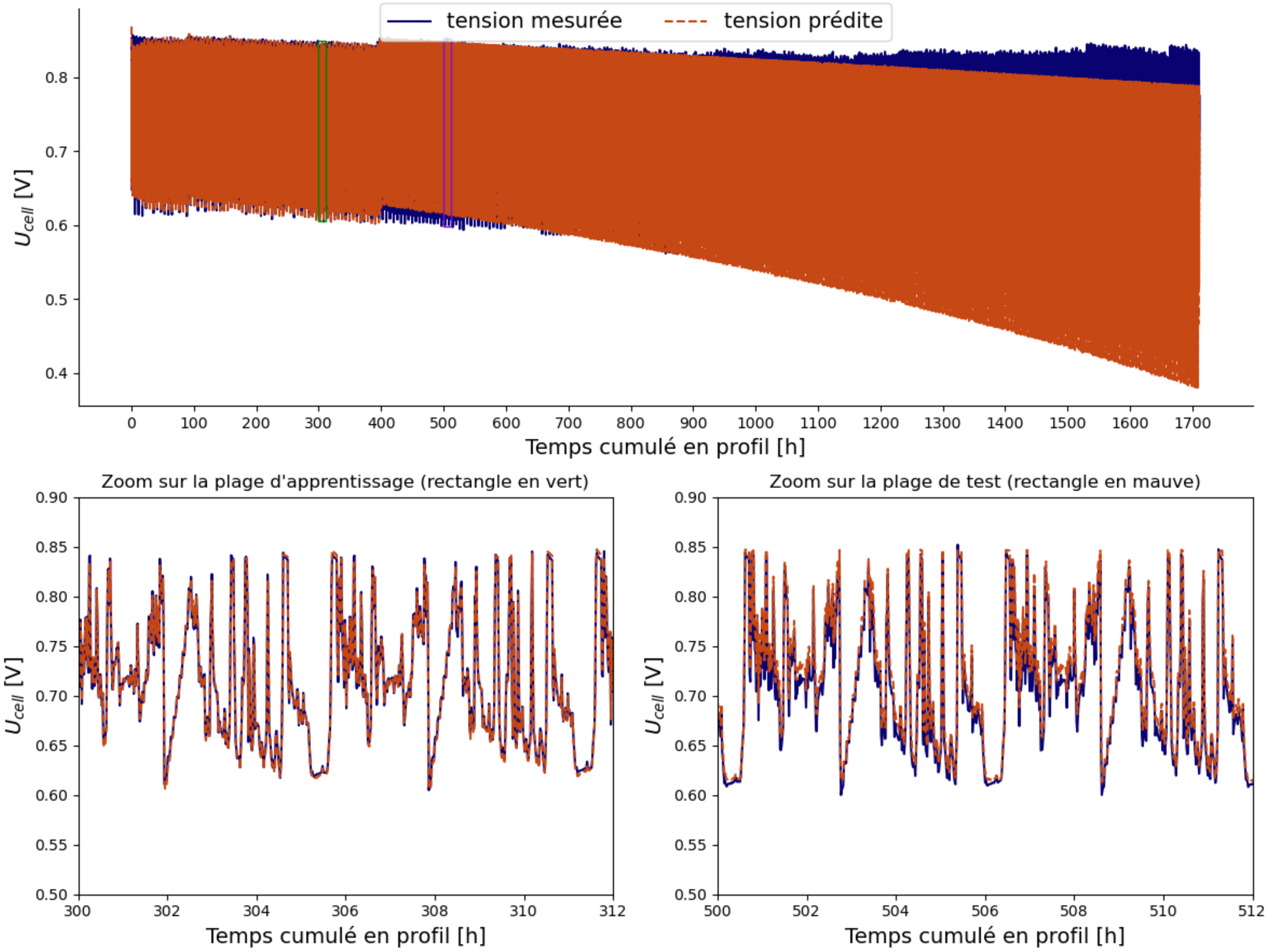


- Performance increases with learning time.
- Good ability to infer.
- Maximum mean relative error: 3.7%.

Estimation and prediction of state variables



Future performance prediction



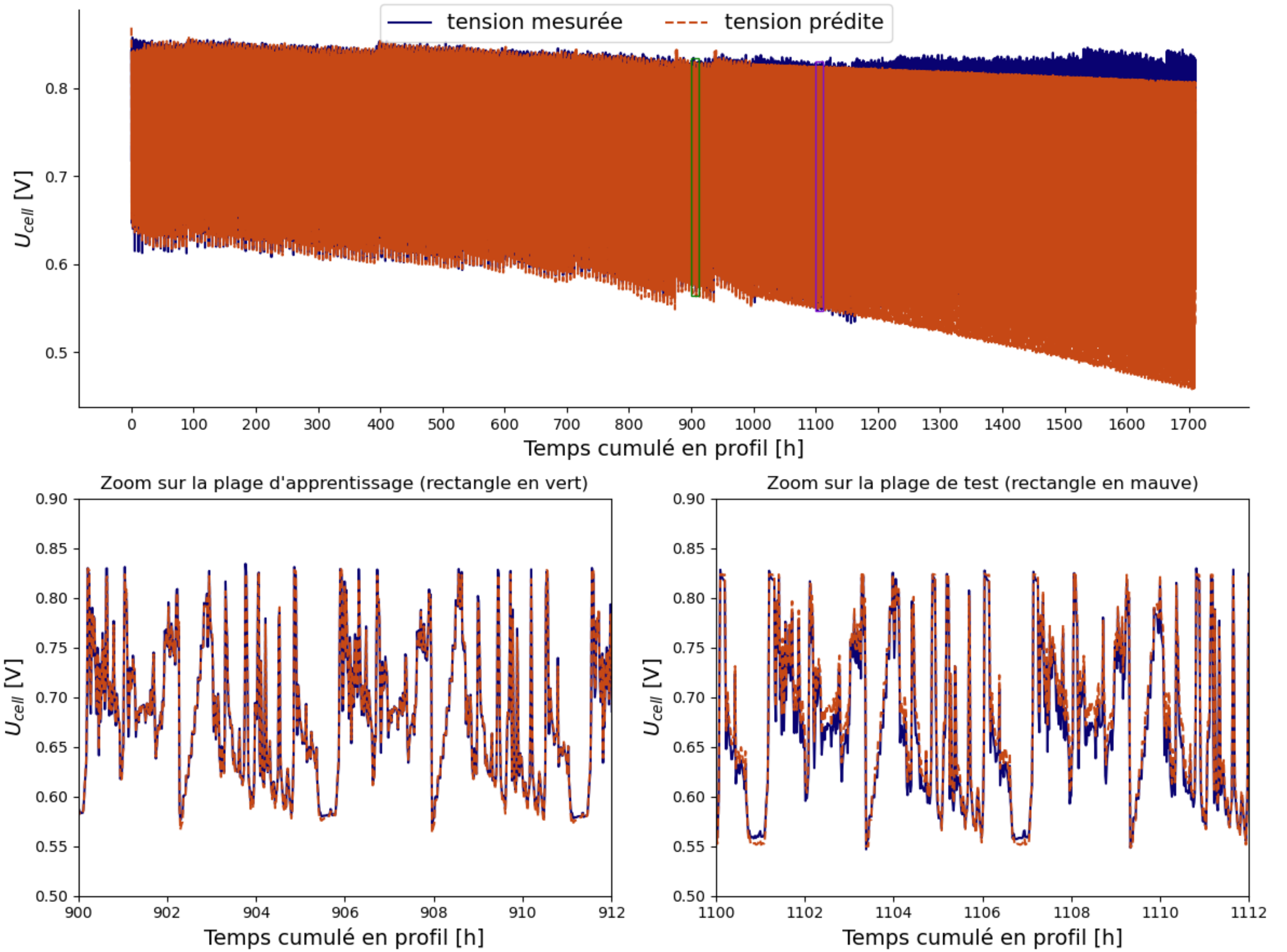
Learning on 400 hours

- Very satisfactory estimation on the learning interval

Better accuracy over the shortest forecast horizons.

- Tendency to underestimate the predicted voltage on the test sample at long horizons.

Future performance prediction

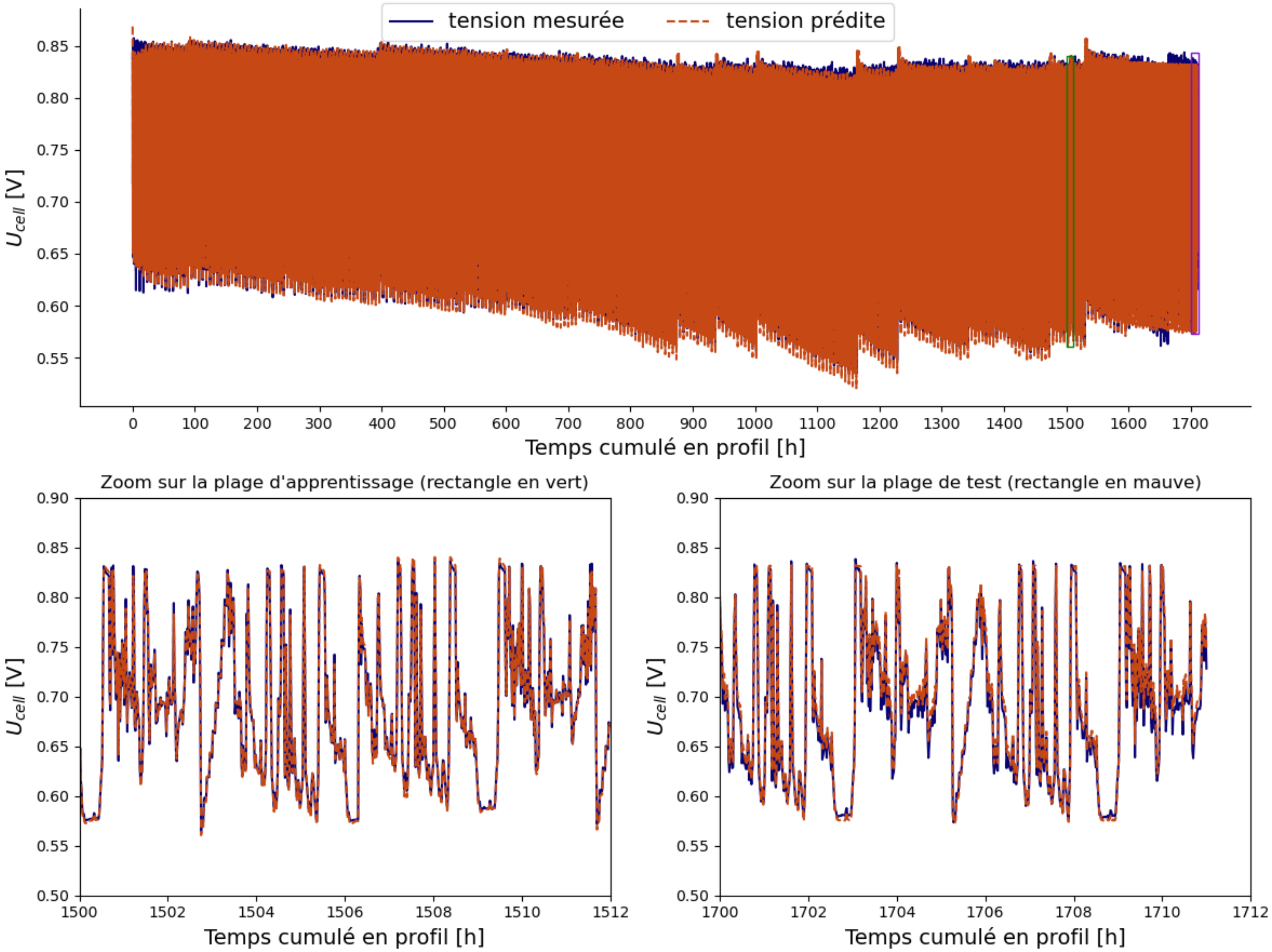


Learning on 1000 hours

- Improved predictions at long horizons as learning time increases.

- Less pessimistic predictions for performance.

Prédiction des performances futures

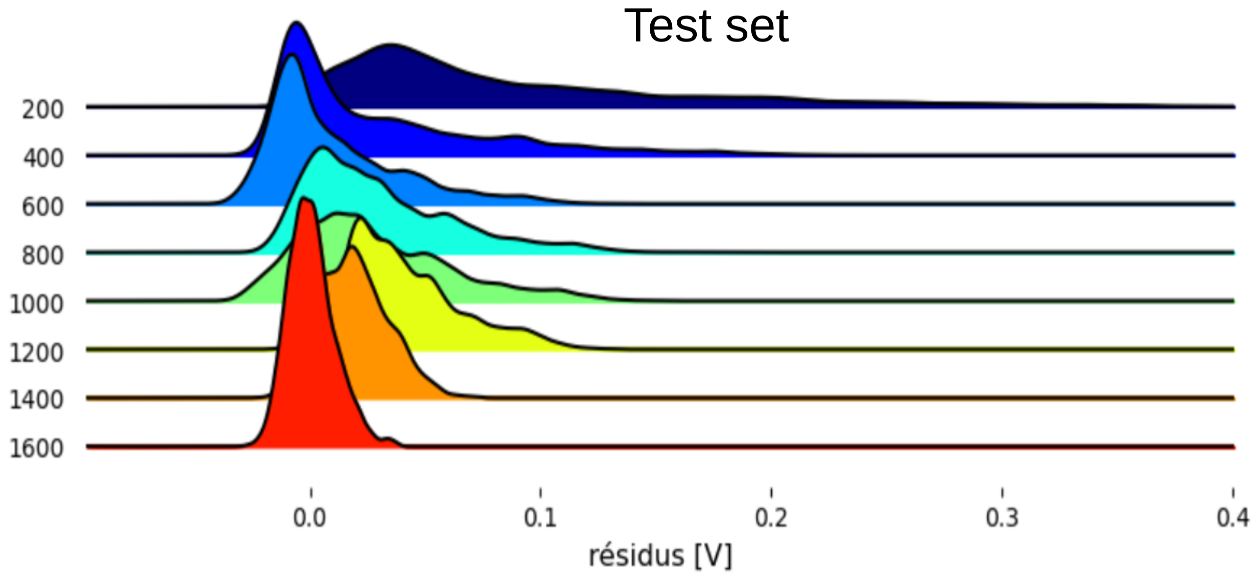


Learning on 1600 hours

Adaptation to reversible phenomena in the learning phase

- Sign of robustness of the extended Kalman filter.

Distribution of residuals for different learning time (y axis)



Mean and median errors on the test set

Durée d'apprentissage [h]	200	400	600	800	1000	1200	1400	1600
Moyenne [V]	$8{,}6\times10^{-2}$	$2{,}8\times10^{-2}$	$\mathbf{9{,}7\times10^{-3}}$	$2{,}9\times10^{-2}$	$2{,}8\times10^{-2}$	$4{,}0\times10^{-2}$	$1{,}7\times10^{-2}$	$\mathbf{5{,}9\times10^{-4}}$
Médiane [V]	$5{,}9\times10^{-2}$	$9{,}4\times10^{-3}$	$\mathbf{5{,}5\times10^{-4}}$	$2{,}1\times10^{-2}$	$2{,}1\times10^{-2}$	$3{,}5\times10^{-2}$	$1{,}6\times10^{-2}$	$\mathbf{-2{,}8\times10^{-4}}$

- Satisfactory order of magnitude: a few tens of millivolts on average.

Part 4

Conclusion and future work

Laplace

Conclusion

- Proposal of a hybrid approach for predicting the future performance of a fuel cell.
- Modeling of the ohmic resistance by Random Forests.
- Estimation of the internal parameters of the physical model using a Kalman filter.
- Learning the variation of internal parameters using LSTM.
- Overall satisfactory results.

- Test adaptive filtering algorithms.
- Developing an LSTM (or other types of RNN) with physical constraints during training.

Merci pour votre attention !

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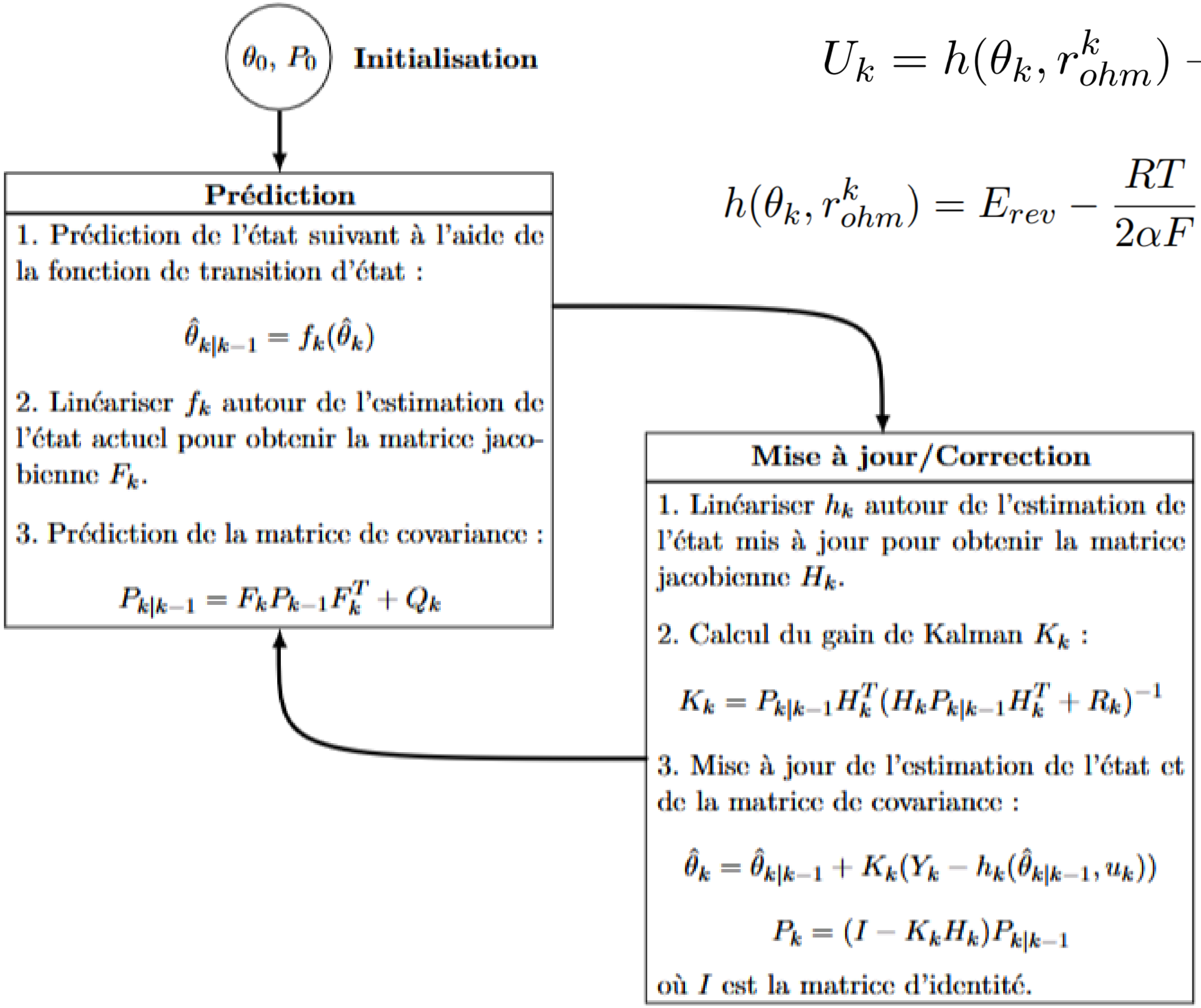

FIGURE 2.28 – Étapes du filtre de Kalman étendu (EKF).

$$U_k = h(\theta_k, r_{ohm}^k) + V_k,$$

$$h(\theta_k, r_{ohm}^k) = E_{rev} - \frac{RT}{2\alpha F} \ln\left(\frac{j + j_n^k}{j_0^k}\right) - r_{ohm}^k(j) \times j - r_{diff}^k \times j,$$

$$\theta_{k+1} = \mathbf{F}_k \theta_k + \mathbf{f}_k + W_k,$$

$$\mathbf{F}_k = \begin{bmatrix} \exp(-k_0 \Delta t) & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \exp(k_d \Delta t) \end{bmatrix}, \quad \mathbf{f}_k = \begin{bmatrix} 0 \\ k_n \Delta t \\ 0 \end{bmatrix}$$

$$H_k = \frac{\partial h(\theta_k, r_{ohm}^k)}{\partial \theta_k} = \begin{bmatrix} \frac{RT}{2\alpha F j_0^k} & -\frac{RT}{2\alpha F (j + j_n^k)} & -j \end{bmatrix}$$