



# RUBY Project **RUBY**

Robust and reliable general management  
tool for performance and durability  
improvement of fuel cell stationary units

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FUEL CELL STATE OF HEALTH FORECASTING USING  
ECHO STATE NETWORKS

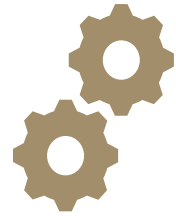
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**Context**



**Echo State Networks**



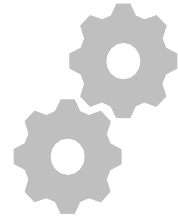
**Designed approach**



**Analyze of results**



**Context**



**Echo State Networks**



**Designed approach**



**Analyze of results**

## Limitation → Lifetime of fuel cells

### DOE objectives

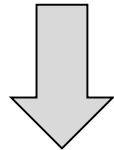
2020 : 40 000h Stationary / 5000h Vehicle

Ultimate : 80 000h / 8000h

### Tools :

Diagnosis → Detection of degrading conditions

Prognosis → Forecasting future performance

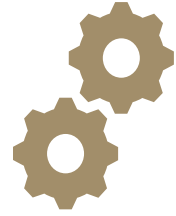


Control → Changes in operating conditions

# Echo State Networks



**Context**



**Echo State Networks**

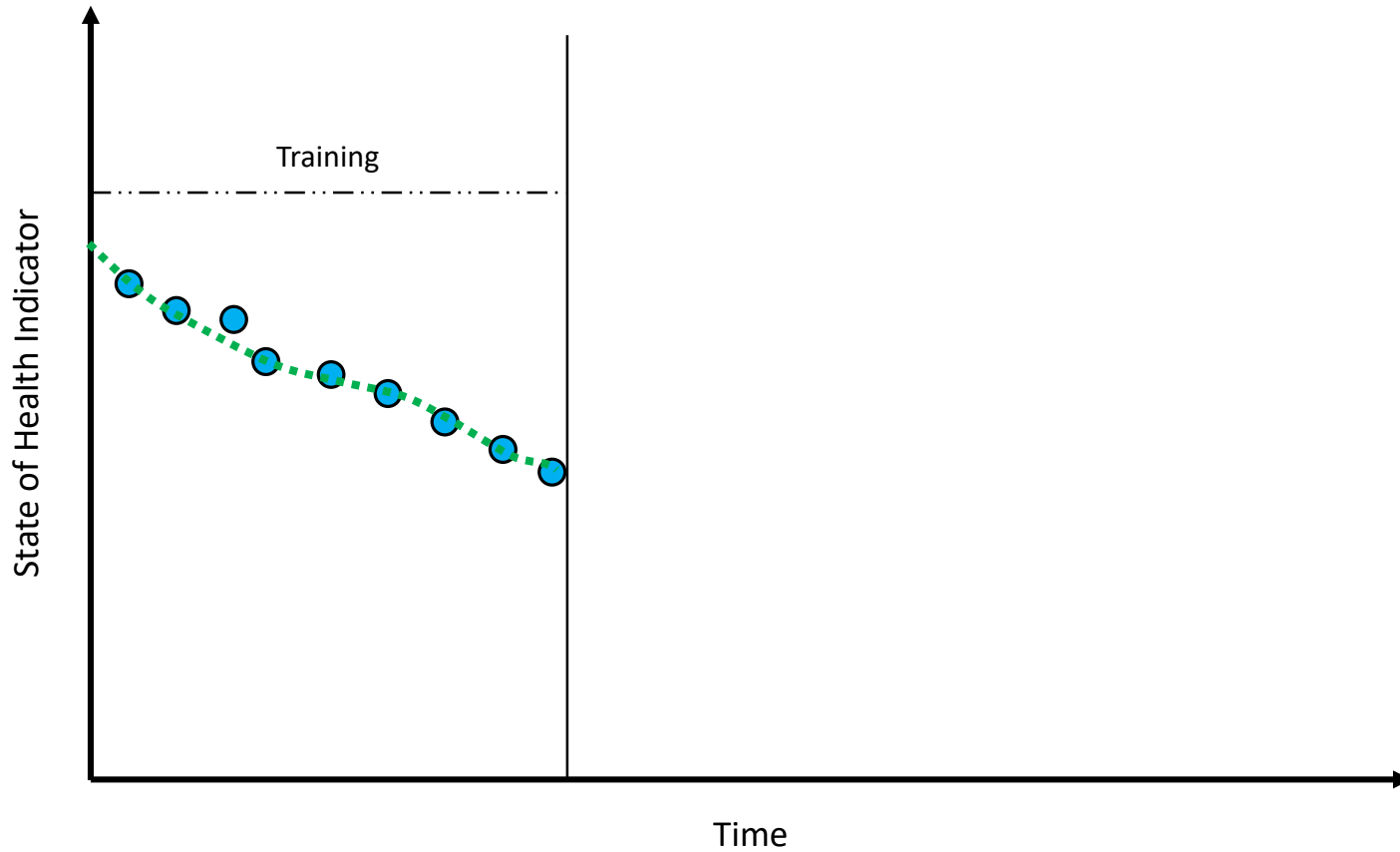


**Designed approach**



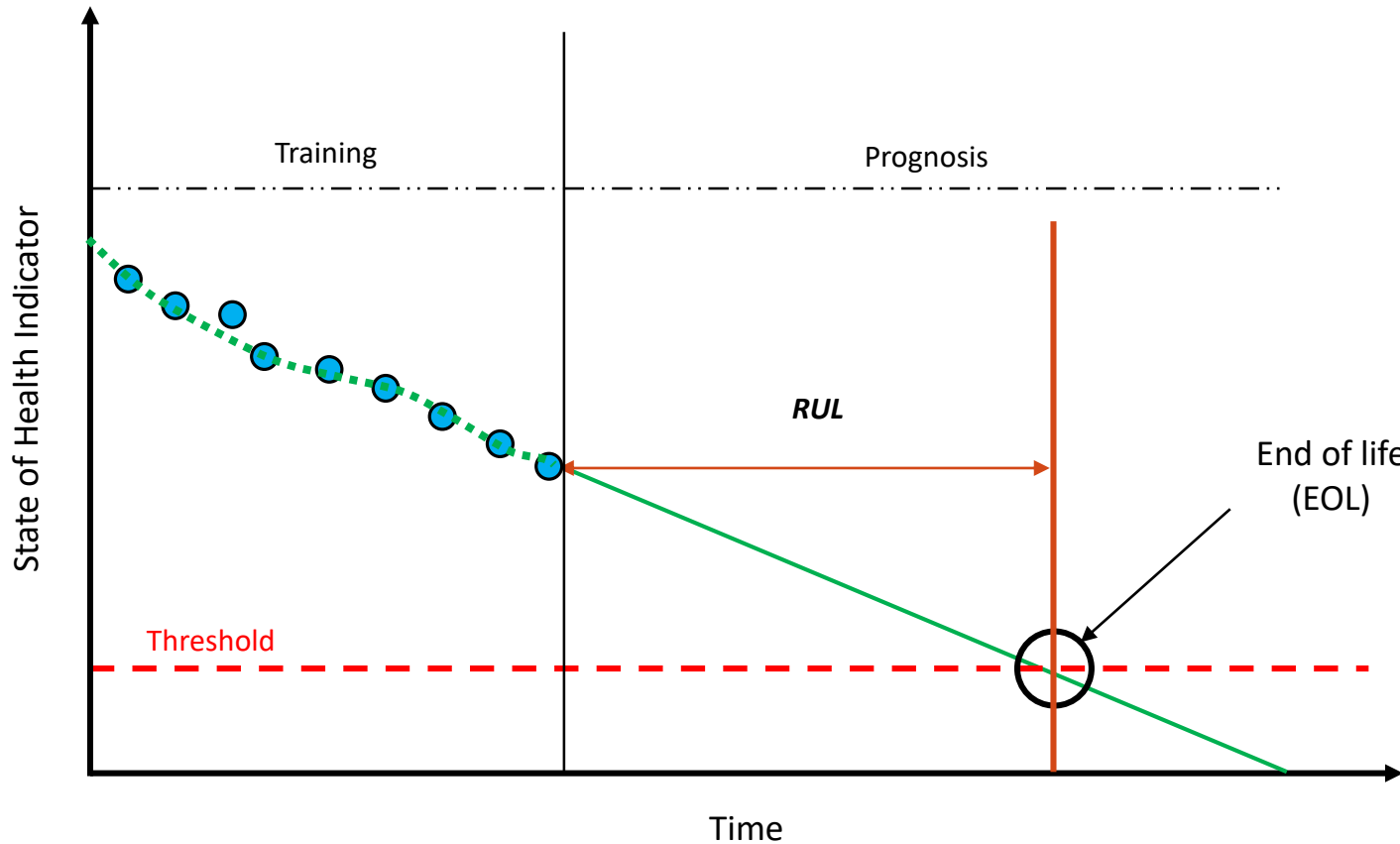
**Analyze of results**

# Prognosis principle



SoH indicator : e.g Stack voltage

# Prognosis principle



## Evaluation of the algorithm

Mean square error

$$\sqrt{\frac{1}{n} \cdot \sum_{t=1}^n (erreur)^2}$$

Percentage of mean absolute error

$$\frac{100}{n} \cdot \sum_{t=1}^n \left| \frac{Erreur}{vrai} \right|$$

## Evaluation of prediction

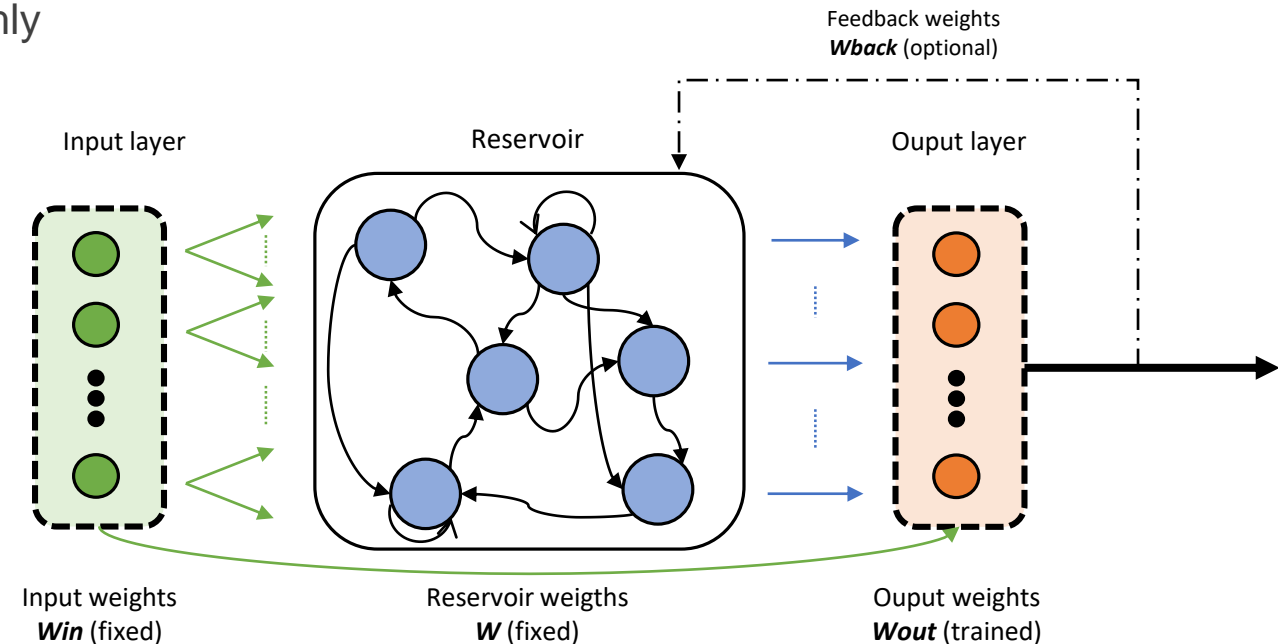
Performing several iterations

Confidence interval

# Echo State Network

## Echo State Network :

- Development: 2000s by Herbert Jaeger
- Derived from RNN
  - Replacement of RNN layers by a reservoir
- Specificities :
  - Propagation of information in a high dimensional space
    - Data separation
  - Setting the weights of recurrent connections randomly
  - Drive the network with only the output weights

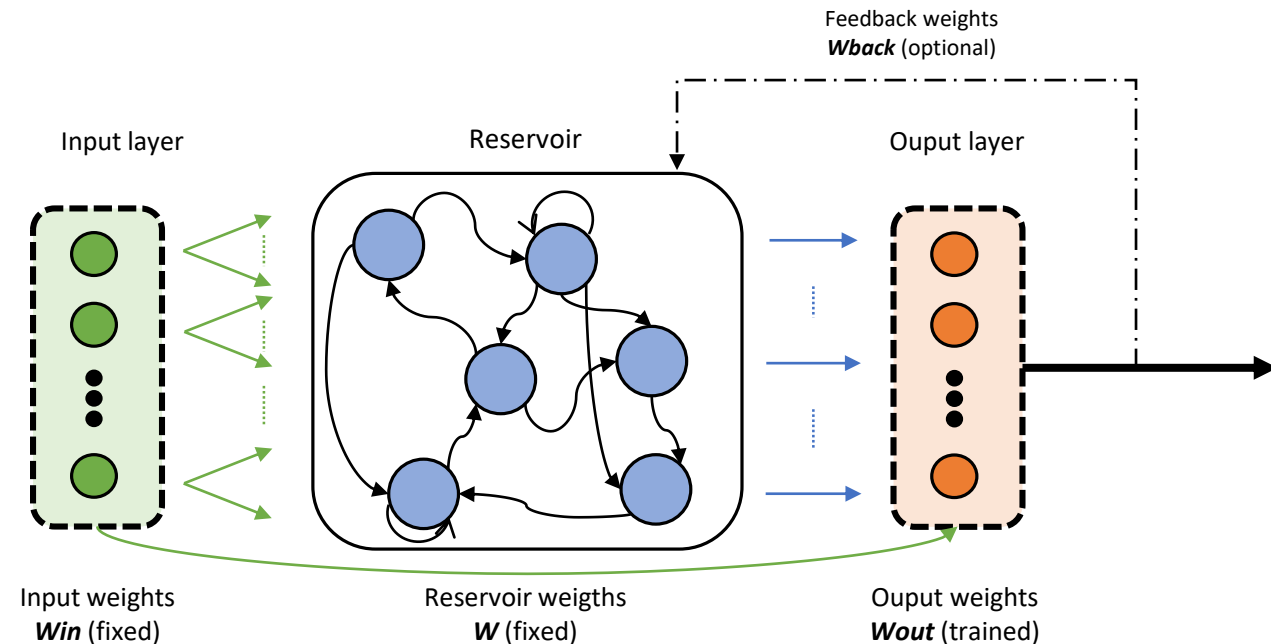




# Echo State Network - ESN

## ESN parameters

- Spectral radius
  - Matrix eigenvalue
  - Amplification of internal states as the network process information
  - High value → Strong amplification
  
- Leaky rate
  - Decay rate of information in the internal states over time
  - Low value → Retain mainly old information
  
- Connectivity
  - Percentage of non-zero weight in the reservoir matrix
  - Improves calculation times → Faster reservoir updates
  - Develops individual dynamics
  
- Number of neurons
  - Possibly very large > 1000 → Linear regression
  
- Initialization of weights
  - Random Uniform / Normal distribution



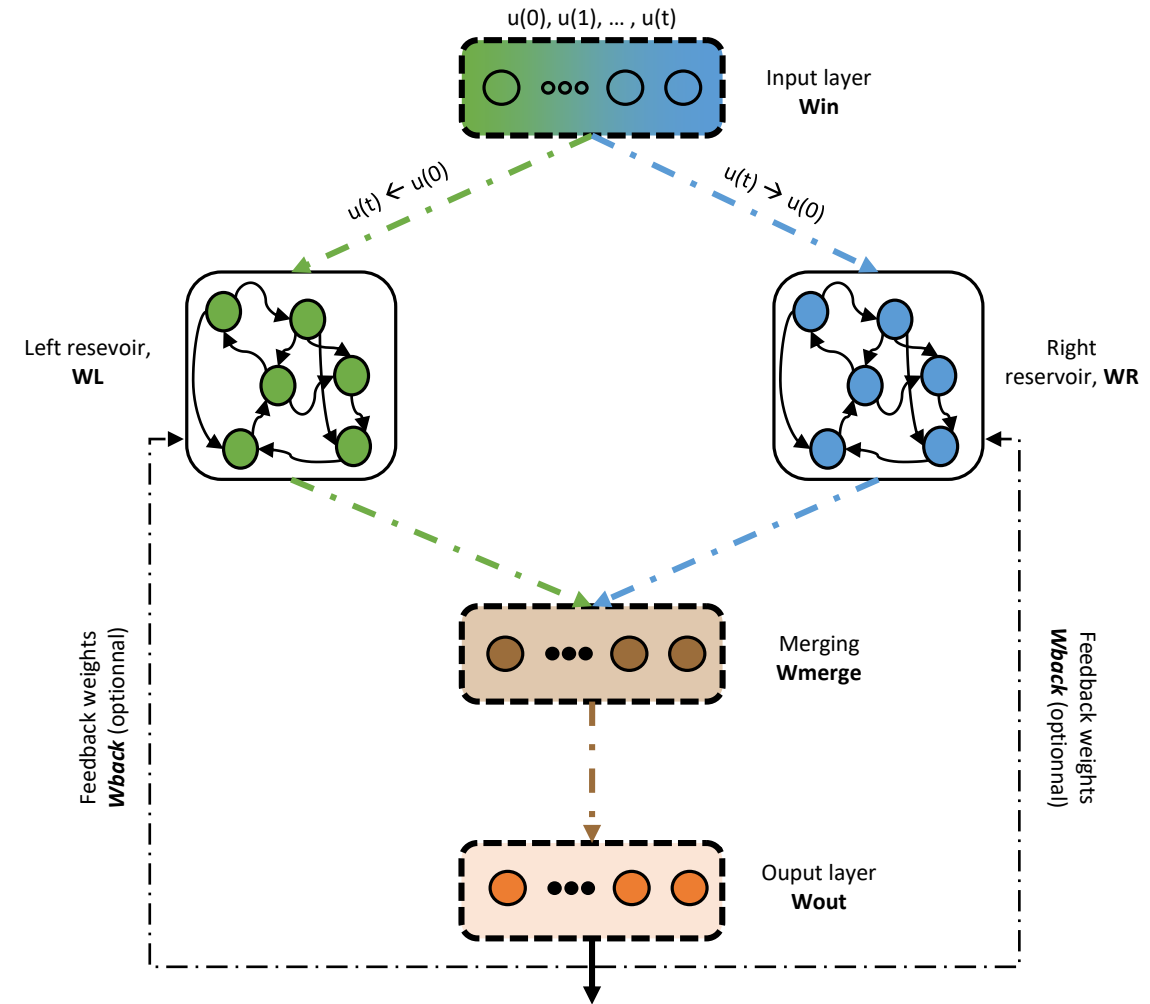
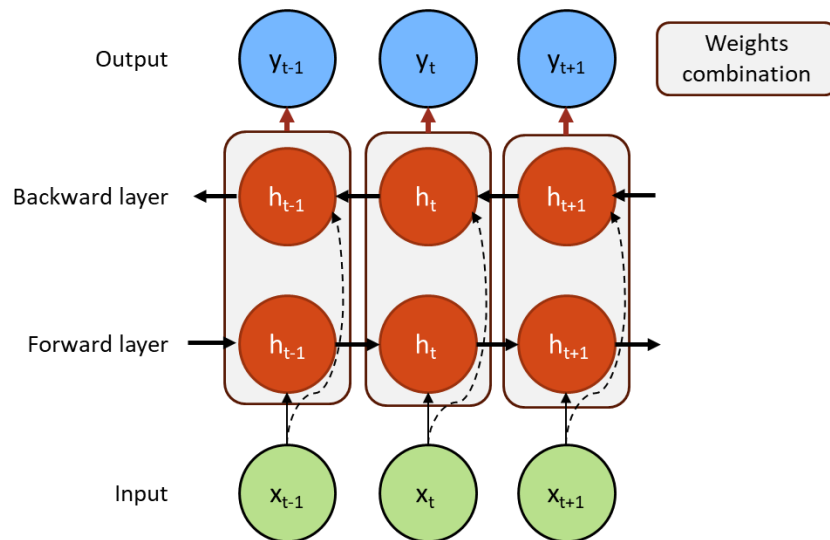
# Bidirectional Echo State Network - ESN

## Limitations of ESN:

- Difficult to learn long term dependencies → Focus on last time steps
- Don't memorize the context

## Solution: Bidirectional reservoir BiESN

- Double the number of reservoirs
- Sequence learning in chronological and reverse direction



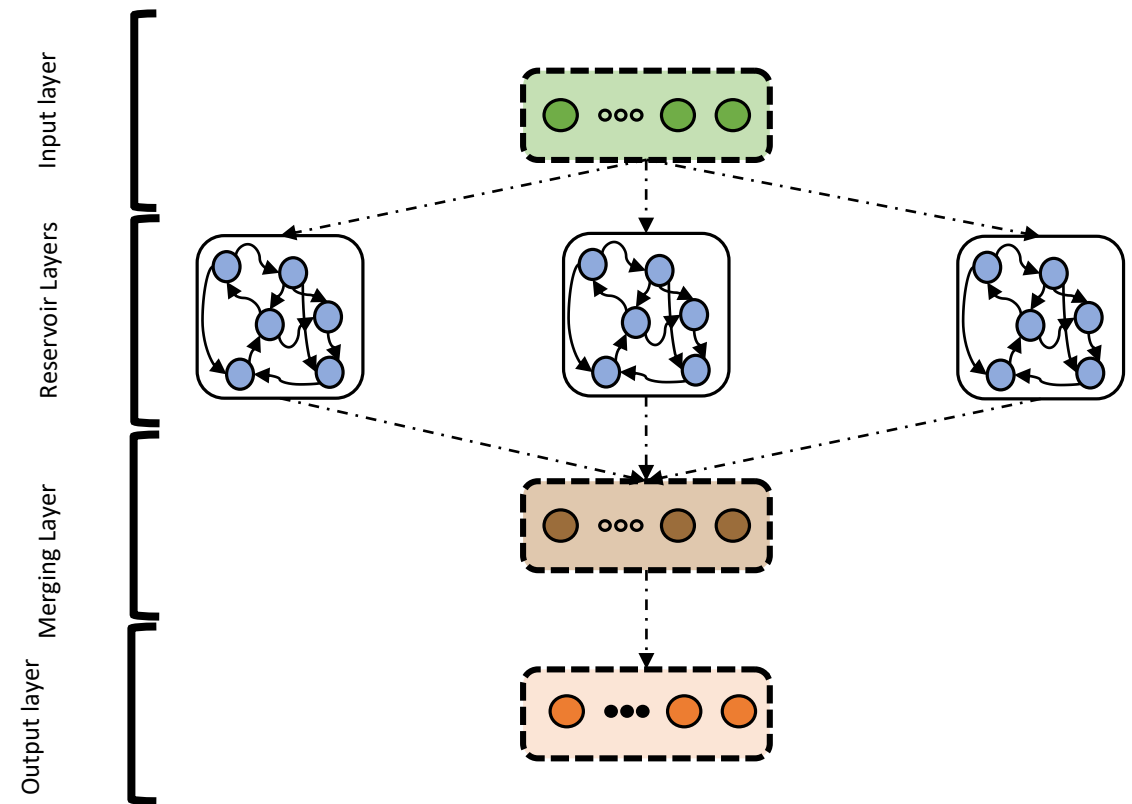
# Multi-reservoir ESN

Limitation of ESN:

- Complexity to find good reservoir parameters

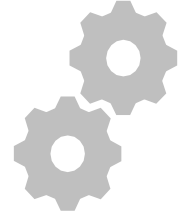
Solution: Multi-Reservoir :

- Use of reservoirs in parallel and/or in series
- Different parameters for each reservoir → more chances to capture the dynamics
- Decreasing burden of the parameter optimisation





**Context**



**Echo State Networks**



**Designed approach**

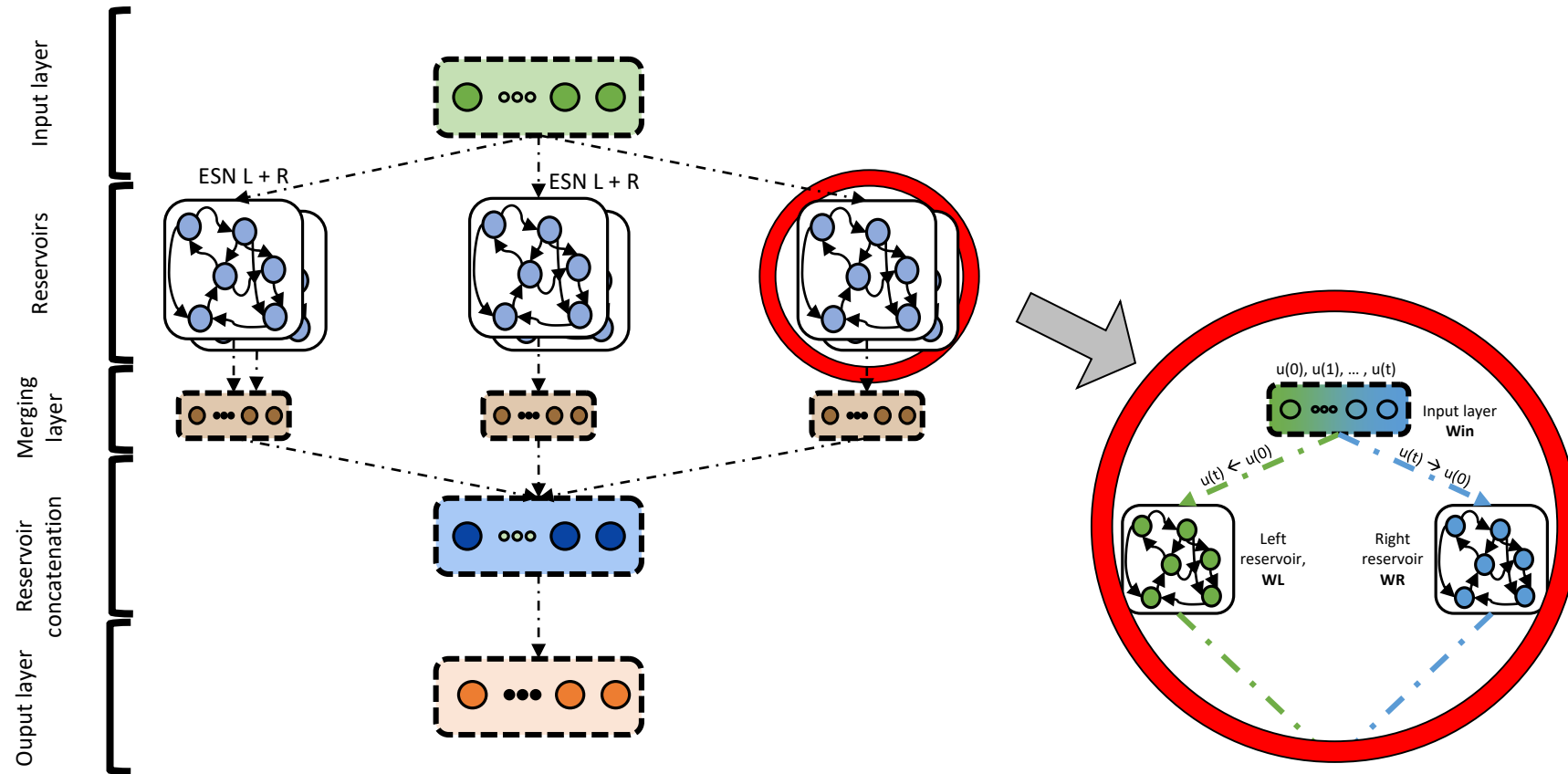


**Analyze of results**

# Designed approach - Network

## ESN Multi-reservoir bidirectional

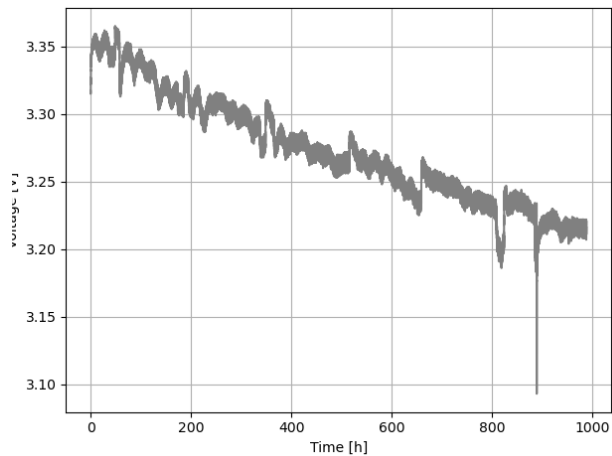
- 3 specialized bidirectional reservoirs: low, medium and high dynamics
  - Minimize reservoirs optimization
  - Maximizing detectable dynamics



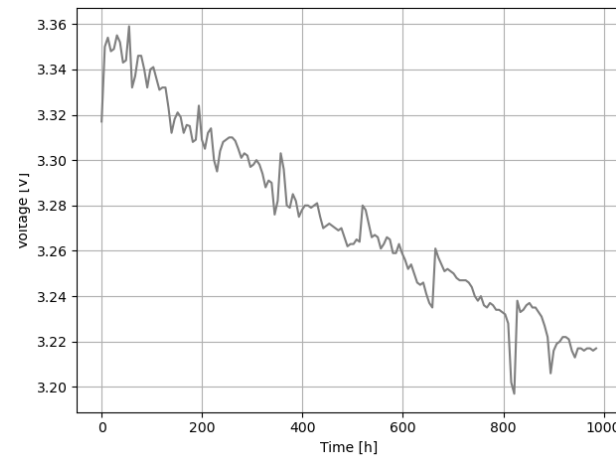
# Designed approach - Database

- From the 2014 IEEE PHM challenge → Open Database
- Long-term test (1000h) on two PEMFC-LT
  - 1st test: static state
    - Constant current 0.7 A/cm<sup>2</sup>
  - 2nd test: triangular current ripple
    - DC component 0.7 A/cm<sup>2</sup>
    - Triangular component 0.14 A/cm<sup>2</sup> peak to peak
- Only the static state is studied in this presentation
- Acquisition frequency: 1/30Hz
  - Choice to retain 1 pt / 6h with a rolling window → Only a trend is studied

Raw data

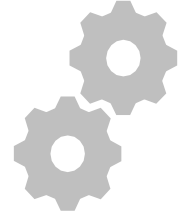


Data selected





**Context**



**Echo State Networks**



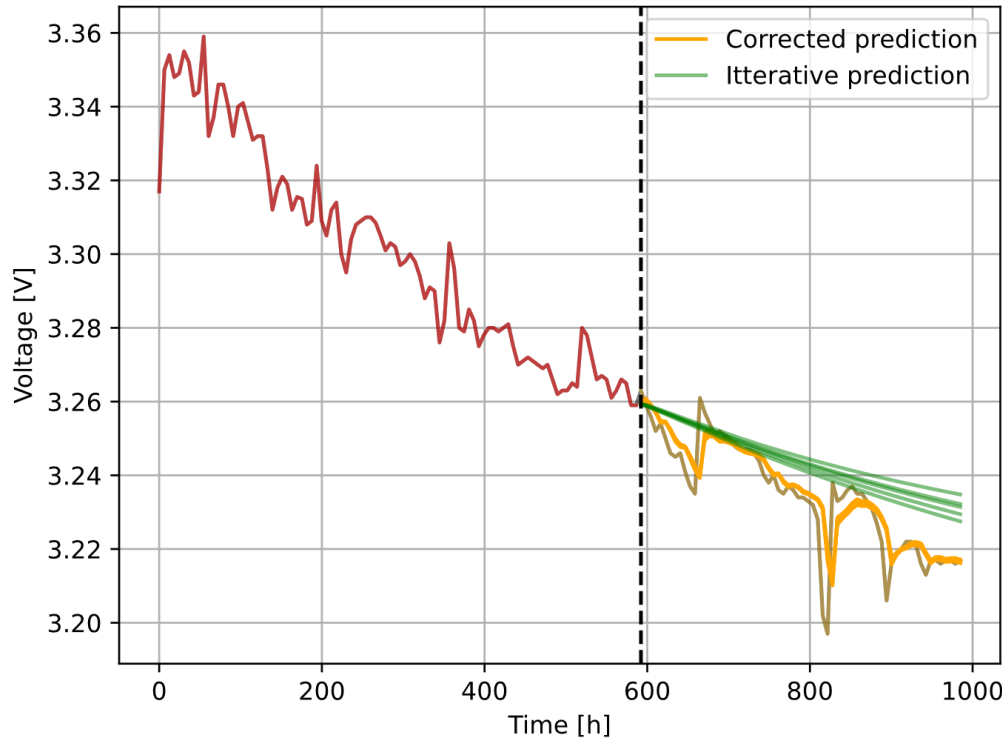
**Designed approach**



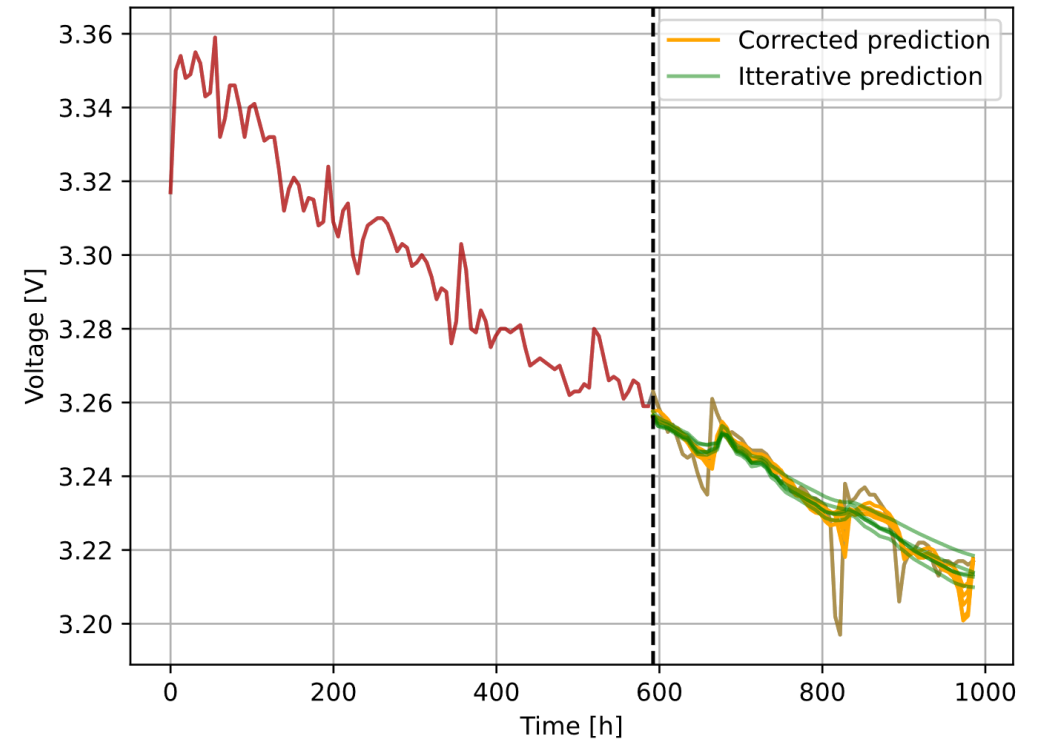
**Analyze of results**

# Results – Comparison with MR-Forward ESN

MR-Forward ESN (200neurons/reservoir)



MR-BiESN (100neurons/reservoir)



Corrected forecasting → Only predict next timestep → no bias

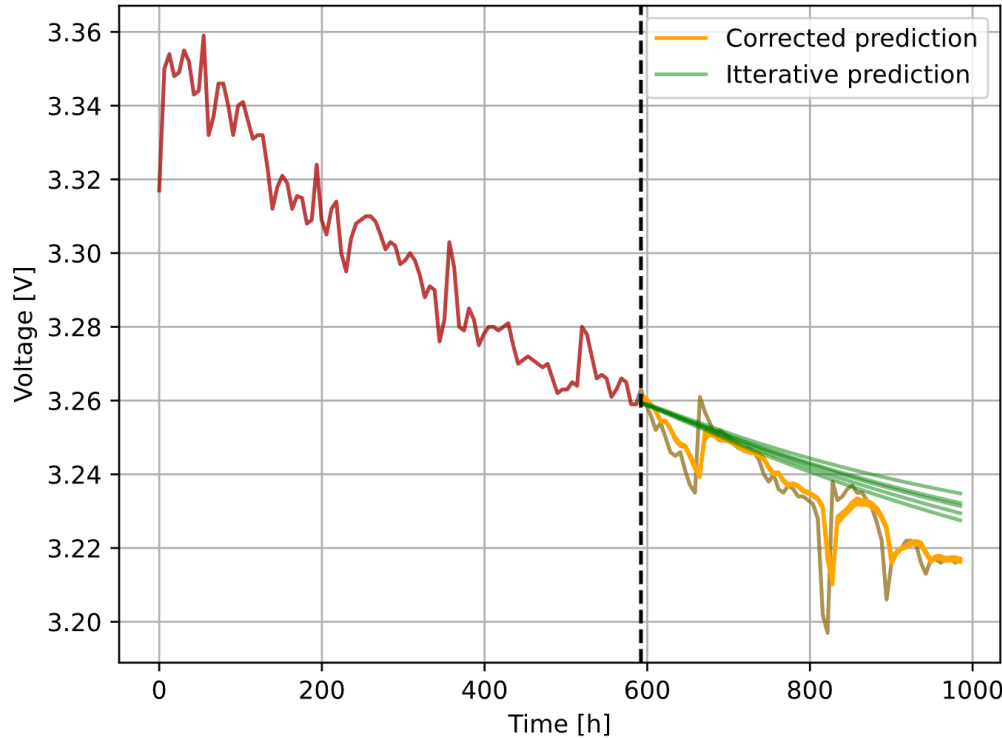
- MR-BiESN is slightly less able to predict the next timestep
  - Backward layer learn information on past history “less” relevant
- MR-Forward ESN is focus on last historical data
  - Correspond more to corrected forecasting as bias is not accumulated

Forward ESN ≥ Bidirectional ESN

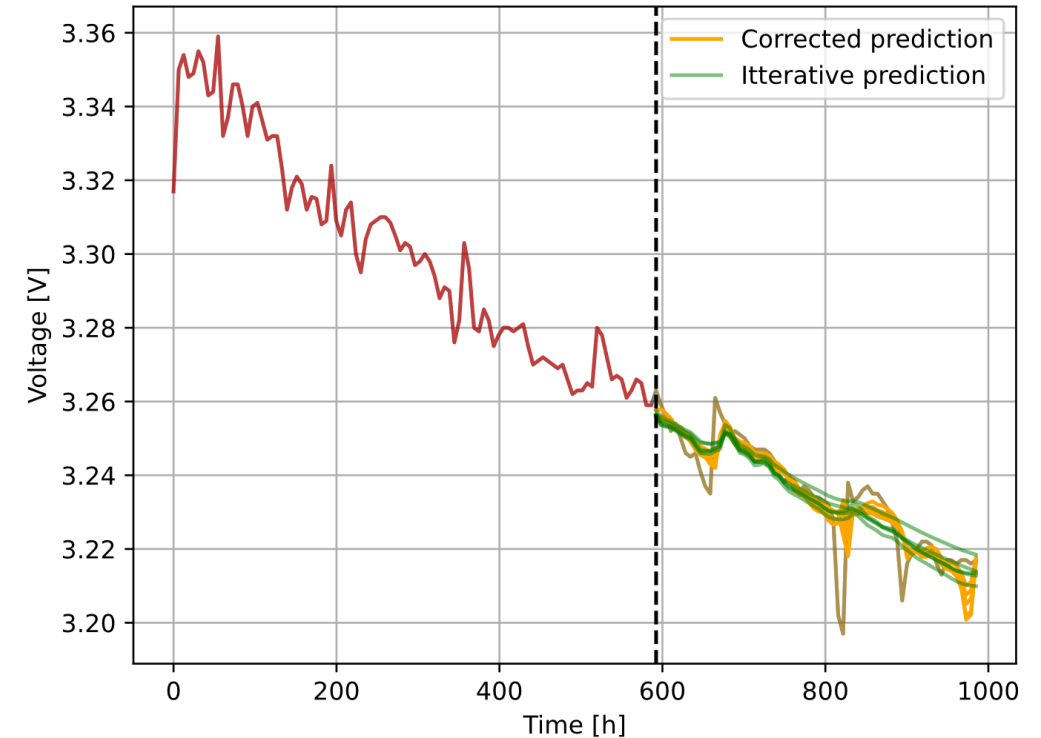


# Results – Comparison with MR-Forward ESN

MR-Forward ESN (200neurons/ reservoir)



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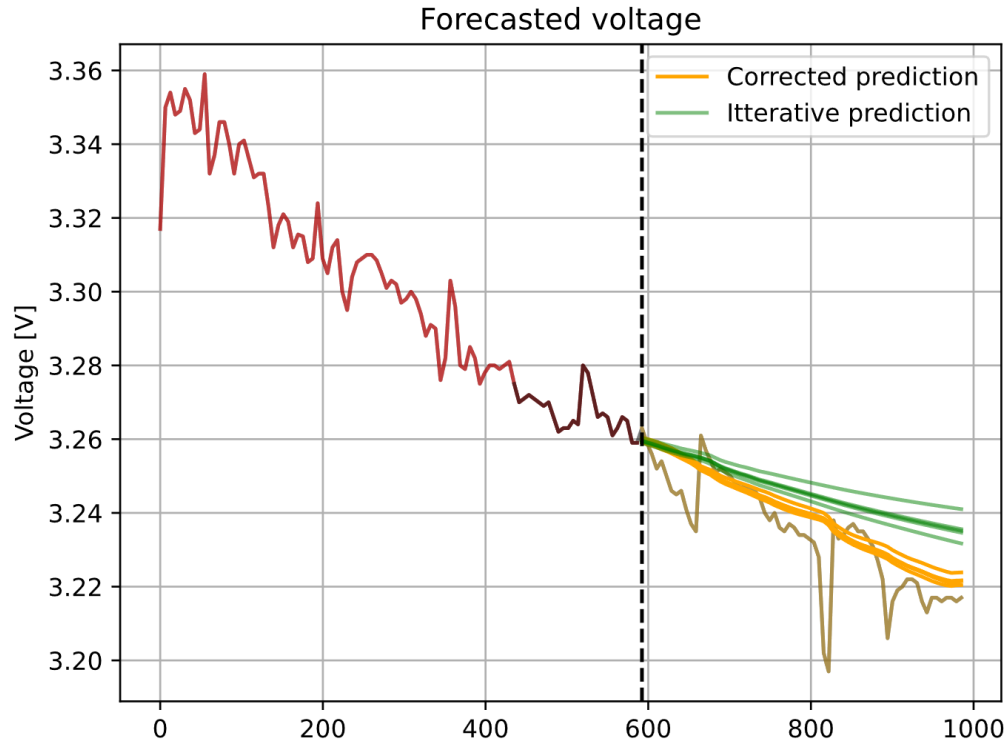
Iterative forecasting → prediction is used as new input

- MR-BiESN network catches periodic recovering process
  - Linear trend with recovering
- MR- One Way ESN catches only global trend

Bidirectional ESN >> Forward ESN

# Comparison with BiLSTM

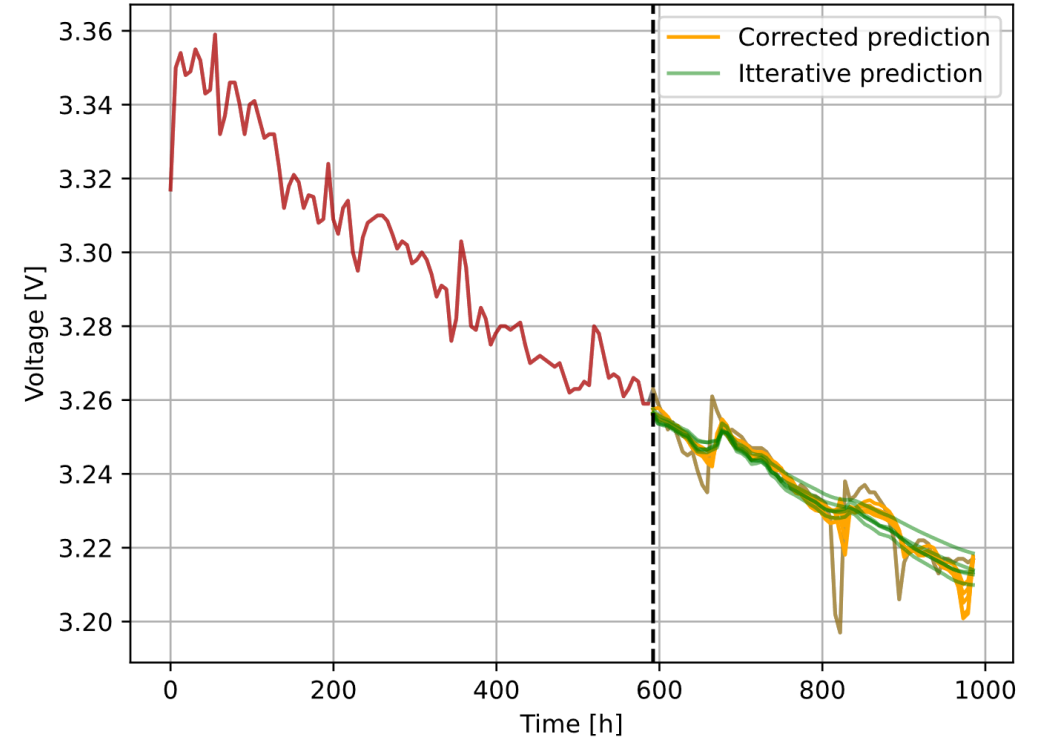
3 BiLSTM stacked (100neurons/reservoir)



LSTM: 563 401 trainable parameters

- Need more iterations to converge (x3)
- Results seems underfit → underfitted
- Lack of data

MR-BiESN (100neurons/reservoir)



MR-BiESN network: 601 trainable parameters

- Better performances for small dataset

# Conclusion

- Synthesis:
  - Principle of Echo State Networks
  - Prognostic approach based on data only
  - Study case on a fuel cell
- Designed approach advantages
  - Dynamics correctly captured
  - Better performances than BiLSTM for small databases --> Most used Network for forecasting
  - Ability to improve by re-optimizing with recent data
  - Can be applied to many systems
- Future prospect:
  - Generalization of the method with other databases