Fuel Cells prognostics using Echo State Network

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***Abstract*— One remaining technological bottleneck to develop industrial Fuel Cell (FC) applications resides in the system limited useful lifetime. Consequently, it is important to develop failure diagnostic and prognostic tools enabling the optimization of the FC. Among all the existing prognostics approaches, data-mining methods such as artificial neural networks aim at estimating the process' behavior without huge knowledge about the underlying physical phenomena. Nevertheless, this kind of approach needs huge learning dataset. Also, the deployment of such an approach can be long (trial and error method), which represents a real problem for industrial applications where real-time complying algorithms must be developed. According to this, the aim of this paper is to study the application of a reservoir computing tool (the Echo State Network) as a prognostics system enabling the estimation of the Remaining Useful Life of a Proton Exchange Membrane Fuel Cell. Developments emphasize on the prediction of the mean voltage cells of a degrading FC. Accuracy and time consumption of the approach are studied, as well as sensitivity of several parameters of the ESN. Results appear to be very promising.**

Keywords*— *Prognostics, Proton Exchange Membrane Fuel Cell, Reservoir Computing, Echo State Network, Multi-steps ahead Prediction

I. INTRODUCTION

Condition-Based Maintenance (CBM) can be seen as a set of activities that aims at performing maintenance actions at the right time when needed. CBM appears to be a promising strategy since it enables increasing the availability of a system while reducing costs. Consequently, this thematic benefits from a growing interest, and "prognostics" is becoming a major research framework [1], [2].

According to the literature, three classes of prognostics approaches are commonly distinguished [2]. *1)* Model-Based prognostics aim at obtaining a physical model of the system's behavior [3]. This kind of approaches involves a high level of knowledge and supposes that the ageing process can be formalized into a mathematical form. *2)* Experience-based prognostics rely on statistical treatments and aims at calculating the probability of a failure to occur at any time [4]. The applicability of this kind of approach is however dependent on the representativeness of past experiences that do not always reflect current conditions. *3)* Data-driven prognostics aim at transforming real monitoring data into relevant indicators and trends that depict the health of a system [5], [6]. These approaches are a tradeoff between model-based and experience-based approaches. However, huge learning datasets are required in order to train artificial intelligence tools, which can lead to applicability problems: building a data-driven prognostics system can be time consuming, which impedes the transfer of such a technology to the industry. This is the problem addressed in this paper: how to go through a prognostics tool which is accurate enough to enable maintenance decision, and fast enough to be applicable in real world? More precisely, the aim of this paper is to study the application of a reservoir computing tool (the Echo State Network) as a prognostics system enabling the estimation of the Remaining Useful Life (RUL) of a Proton Exchange Membrane Fuel Cell (PEMFC).

The novelty consists in the use of an Echo State Network [7], [8] as a prognostics tool applied for low temperature fuel cells. An ESN is a neurons reservoir for which the learning step consists in a linear regression, keeping the same modeling capability of a Recurrent Neural Network (RNN) while saving the calculation time. Accuracy and complexity of the network are however dependent on some parameters that have to be well chosen. This aspect is discussed in the paper.

The paper is organized as follow. In a first part, data-driven prognostics is replaced within CBM strategy in order to define the limit of the study. Also, multi-steps ahead prediction strategies for this kind of prognostics approaches are defined. It enables formalizing the purpose of using ESN. In section III, the ESN tool is described. Mathematical backgrounds are given in order to define how the ESN can be used for prediction. Also, the problem of setting some parameters (reservoir design) is addressed. Before concluding, experiments are performed in order to discuss the usefulness of the ESN for prognostics purpose. Dataset used comes from experimental tests performed on a 20-cells PEMFC stack. The forecasts concern the mean cells voltage prediction, and the results appear to be promising

II. DATA DRIVEN PROGNOSTICS – MATHEMATICAL FORMALIZATION

A. Towards fast and accurate data driven prognostics

Condition-Based Maintenance (CBM) is an advanced maintenance system strategy improving reliability, security and costs of engineering systems. CBM architecture is used to be divided in seven layers / modules (Figure 1): *1)* row data acquisition, *2)* data processing (denoising, features extraction and selection), *3)* condition assessment, *4)* diagnostic, *5)* prognostics, *6)* decision making and *7)* presentation of results. Therefore, the whole aspects of failure analysis and prediction should be viewed as a set of activities that all must be performed. Nevertheless, this paper focuses on prognostics of

failures and only layers 1, 2 and 5 are addressed: data acquisition, signal processing and prognostics.

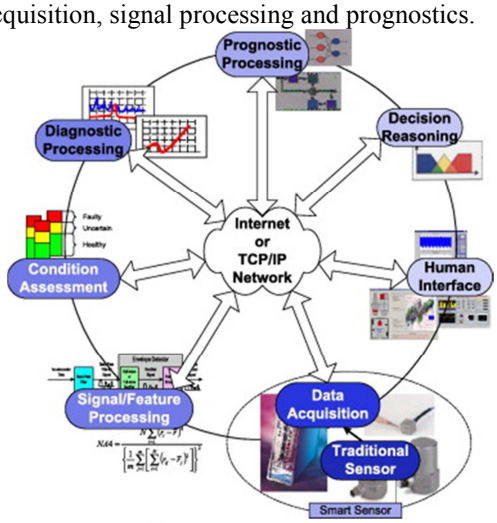


Figure 1: CBM Architecture [9]

In spite of some divergences in literature, prognostics can be defined as a process which objective is to estimate the Remaining Useful Life (RUL) of a system, i.e. the time before a failure occurs [10]. For that purpose, data-driven prognostics rely on the assumption that input-output data from the system are the major source of information to catch its behavior. Following that, these approaches are based on the real time exploitation of symptoms or indicators of degradations extracted from monitoring data (layers 1 and 2 of CBM architecture) which future evolution is determined by machine learning or data-mining approaches (see [11] for a taxonomy of useful approaches). From this point of view, data-driven prognostics approaches are very interesting since no prior on the behavior and no specific knowledge on the system's degradation are required. According to this, a particularly good trade-off between applicability and precision is reached. However, the learning time is one limit of this kind of application [12], as well as the need for sufficient learning datasets. This can be easily pointed out by considering prognostics based on Artificial Intelligence (AI) methods.

B. *Artificial Intelligence tools for prognostics*

Data-driven prognostics rely on the uses of an approximation tool from AI. This kind of system aims at approximating an input-output function. It can be seen as a black box model where the learning input and output target are known and the training phase consists in an optimization of the black box system parameters in order to fit the real function between the system input and output. Mathematically, it means that an input X and a corresponding output Y linked by the real function $\Gamma(.)$ can be written as:

$$Y = \Gamma(X) \quad (1)$$

And the estimation can be written as:

$$\hat{Y} = \hat{\Gamma}(X) \quad (2)$$

with $\hat{Y}$ the estimated output and $\hat{\Gamma}$ the approximated function obtained by a learning phase. In order to do that, $\hat{\Gamma}$ is expressed as a combination of a structure $f(.)$ and a set of parameters $[\theta]$ [12], previously explained by using a learning algorithm $La(.)$ (as shown in equation 3). It is easy to understand that the resulted error $\epsilon = Y - \hat{Y}$ must be as low as possible. This is the aim of the learning phase.

$$\{f, [\theta]\} \leftarrow La(X, Y) \quad (3)$$
$$\hat{\Gamma}(.) = f([\theta])$$

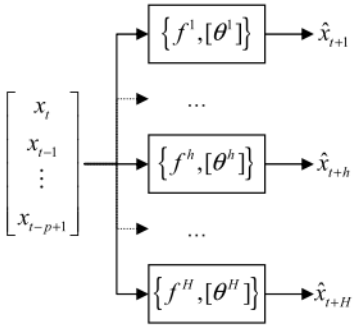
Finally, the estimation can be formalized as in equation (4):

$$\hat{Y} = f(X, [\theta]) \quad (4)$$

C. *Multi-steps prediction for prognostics*

A good designed maintenance system implies prediction at mid-term or long-term in order to schedule maintenance tasks. That's why a multi-step predictions system is necessary. According to [12], multi-step prediction can be divided in two main categories: prediction system designed with one output and prediction system designed for multiple outputs. In this article the Direct approach (Figure 3a) and the Parallel approach (Figure 3b) are considered.

a) Direct approach



b) Parallel approach

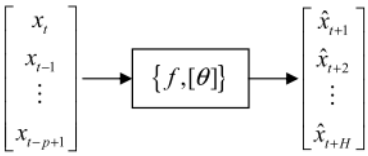


Figure 2: Representation of Direct and Parallel approach [12]

For the Direct approach, one model provides results for one forecasting horizon (called h). It means that the model does not provide forecasting values between t and $t+h$. To solve this drawback, several models have to be built at the same time, as shown in figure 3a and in equation (5). It results in a longer algorithm duration.

$$\hat{x}_{t+1} = f^1(x_t, x_{t-1}, \dots, x_{t+1-p}, [\theta^1])$$
$$\dots$$
$$\hat{x}_{t+h} = f^h(x_t, x_{t-1}, \dots, x_{t+1-p}, [\theta^h])$$
$$\dots$$
$$\hat{x}_{t+H} = f^H(x_t, x_{t-1}, \dots, x_{t+1-p}, [\theta^H]) \quad (5)$$

Another method consists in the use of only one model providing results for several differents forecasting horizons such as discribed by the Parallel approach. It consists in a calculation of all forecasting steps between t and $t+H$ with only one model, making the algorithm duration shorter than

for the Direct approach. Equation (6) is the mathematical representation of the Parallel approach:

$$\hat{X}_{t+1\to t+H} = [\hat{x}_{t+1}, \dots, \hat{x}_{t+H}] = f(x_t, \dots, x_{t+1-p}, [\theta]) \quad (6)$$

with $\{f, [\theta]\}$ representing the model optimised to provide all the forecasting steps between $[1, \dots, H]$ and p is the number of regressors used.

An AI tool is choosen in order to fit the real function. In this paper, the AI tool choosed is the ESN thus the function f^h represents the ESN and $[\theta]$ the main parameters of an ESN (detailed in the following part).

III. ESN AS AN EFFICIENT PREDICTION SYSTEM

A. Backgrounds of ESN

ESN is included into the Reservoir Computing (RC) scientific area, which is a specific Artificial Neural Network (ANN) architecture using a neurons reservoir enabling a better representation of human intelligence paradigm. Moreover, an ESN uses the parameter α called Echo State Property (ESP) that makes the reservoir dynamic. This kind of neural networks was introduced by Jaeger works about ESN in 2001 [7], [8]. However, the term of RC appeared only in 2006 after the creation of others "reservoir" neural network architectures such as liquid-state machines [13] and BackPropagation-Decorrelation networks [14].

An ESN (Figure 3) consists in a large number of neurons located in a so-called "reservoir", with a randomly (and fixed) connectivity between each other. The reservoir (called W_{res}) and several weights matrix (detailed as following) are defined. The Input-Reservoir weight matrix, called W_{inp}, is created randomly and also fixed. It makes the link between the input of the network and the reservoir. The Reservoir-Output weight matrix is called W_{out} and makes the link between the reservoir and the output. Those elements are the main components for a basic use of ESN. This model can be improved by adding another optional matrix, named W_{feed}, which represents the retroaction of the outputs. To summarise, for the basic structure, there are two fixed matrix, W_{inp} and W_{res}, and only W_{out} has to be trained. Consequently the training consists in a very simple linear regression. It is one of the main advantages of the ESN: the training duration. The ESN application domains are various. They can be founded in medical [15], economic [16] and optical applications [17].

B. Mathematical formulation and learning scheme

The first step is to design the reservoir (detailed in part C) and then the calculation to optimize the network can start. This step begins with the reservoir output calculation for the training sequence. The update of the reservoir is calculated as following [18]:

$$\tilde{x}(n) = f(W_{inp}.u(n) + W_{res}.x(n-1)) \quad (7)$$

where $\tilde{x}$ is the update of the reservoir, $u(n)$ the input of the ESN and $x(n-1)$ is the previous output of the reservoir.

Then it is possible to calculate the reservoir output x(n) by using the echo state property α:

$$x(n) = (1-\alpha).x(n-1) + \alpha.\tilde{x}(n) \quad (8)$$

This calculation makes it possible to calculate the network output as shown in equation (9):

$$y(n) = W_{out}.x(n) + W_{feed}.y(n-1)) \quad (9)$$

Nevertheless the W_{feed} matrix is optional thus the output formula for a basic structure ESN is:

$$y(n) = f(W_{out}.x(n)) \quad (10)$$

The learning algorithm consists in reducing the Mean Square Error (MSE) between the computed values for the training data set $y_{predicted}$ and the targets y_{target}:

$$MSE = \frac{1}{N}.\sum_1^N (y_{target}(n) - y_{predicted}(n))^2 \quad (11)$$

Also equivalent to:

$$MSE = \frac{1}{N}.\sum_1^N (y_{target}(n) - f(W_{out}.x(n)))^2 \quad (12)$$

Where N is the number of dismissed samples, due to the initial condition of the different matrix . The goal is now to find the best W_{out} weights matrix corresponding to the lowest MSE possible result, achieved by a linear regression.

C. Reservoir design

The design of the ESN reservoir consists in the configuration of several parameters:

- The number of reservoir neurons N_{res}:

The number of reservoir neurons is one of the most important parameters. To find a better linear combination of the signals in order to find the best target, it is better to define a large reservoir (it is not uncommon to find a reservoir containing more than 10^4 neurons [19]).

- The reservoir connectivity c:

To obtain best results, the reservoir neurons are not all connected. For this reason, a connectivity parameter has to be designed. It represents the percentage of non-zero weights in the reservoir and can take values between 0 and 1. For example, the following matrix in Table 1, with a connectivity c= 0.25 (i.e. ¼ of connections have non-zero values) represents the links between neurons. As we can see, the output of neuron #1 is linked to the input of neuron #2 by a weight of 0.58.

Table 1: Example of a reservoir matrix (4 neurons)

	1	2	3	4
1	0	**0.58**	0	0
2	0	0	0	0
3	0	0.75	0	0.25
4	0.22	0	0	0

- The spectral radius

Mathematically, the spectral radius of a square matrix corresponds to the maximum value of this matrix eigenvalues. In ESN, the spectral radius is used to scale the non-zero elements of W_{res}. The principle is to create the W_{res} matrix randomly with a connectivity parameter, and calculate the spectral radius of the matrix created. Then, the W_{res} matrix is divided by the spectral radius previously calculated. Hence, the result of this division gives a matrix with a spectral radius

of 1. The last step consists in the multiplication of this matrix by the spectral radius chosen by the user. The W_{res} matrix is now created with the desired scaling.

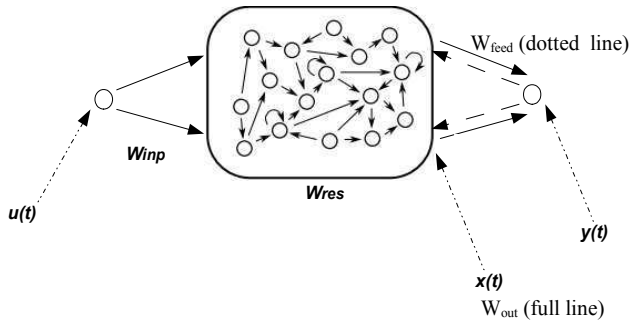


Figure 3: Basic Structure of an Echo State Network [20]

- The leaking rate α:
This parameter is also called ESP. It is an important notion of ESN and it corresponds to the previous reservoir output importance, as shown in equation 8. Its value has to be determined in the range [0;1], and the more important this value is, the less important becomes the reservoir echo.

IV. Experiments: FC voltage prediction considering an ageing process

A. Data set

The data set used for simulations comes from a 1 000 hours PEMFC duration test realized at the FCLAB research institute [21], [22]. Figure 4 represents the evolution of the experimental cells mean voltage (one sample represent 30 seconds). The data were perturbed by the Electrochemical Impedance Spectrometry (EIS) characterization at different times as shown in Figure 4a at the sample 110 000 for example.
In order to predict some values, the data have to be processed (for example it can be judicious to delete the perturbations due to the EIS characterizations). The method considered here is to delete the abnormal points manually and then use a moving average filter in order to reduce the signal noise (Figure 4b).

B. Simulation settings

This paper uses the Direct and Parallel forecast approach [12], consequently the purpose is to use the mean voltage cells U_{moy} (n) to create three regressors (in equation 5) as input of ESN in order to predict $U_{moy}(n+500)$, $U_{moy}(n+1000)$ and $U_{moy}(n+2500)$.
The data (after the above mentioned pre-treatment) are used as input of an ESN. The 10000 first values are used to train the network and the remaining values to test it. The metrics used to check the network performance are the following.
-Root Mean Square Error (RMSE), sometimes called Root Mean Square Deviation (RMSD), is commonly used to quantify the difference between a forecasted signal and its real target.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \quad (13)$$

-Mean Average Percentage Error (MAPE) is also a quantification measurement between two signals. The main difference is the result of this calculation which is a percentage.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{y}_t - y_t}{\hat{y}_t}\right| \quad (14)$$

-The Coefficient of determination (R^2) is a value between 0 and 1 letting a quick evaluation of a prognostics performance. The more nearest to 1 this value is, the better is the prediction.

$$R^2 = 1 - \frac{(\sum \hat{y}_t - y_t)^2}{(\sum y_t - y_{moy})^2} \quad (15)$$

-The simulation duration (in seconds). That is an important parameter for real time industrial applications. These simulations have been realized with a computer equipped with a Intel®-Core™ i5-3210M CPU of 2.5 Ghz and 6 Go of RAM memory.

Each simulation corresponds to a couple of parameters: α (taking the values 0,2/0,5/0,7) and N_{res} (equal to 50 and 250 neurons) .

C. Results and discussion

As shown in Table 2, the results have low error (RMSE and MAPE) for every tested couple of α and N_{res}. However, best results are observed for 50 neurons and $\alpha < 0.5$. That means than the *(t-1)* reservoir output value is important for the calculation of the reservoir at the moment (*t*). That can be explained by the global shape of the studied characteristic (mean voltage of the fuel cell stack), where just one sharp variation near sample 125 000 can be seen.

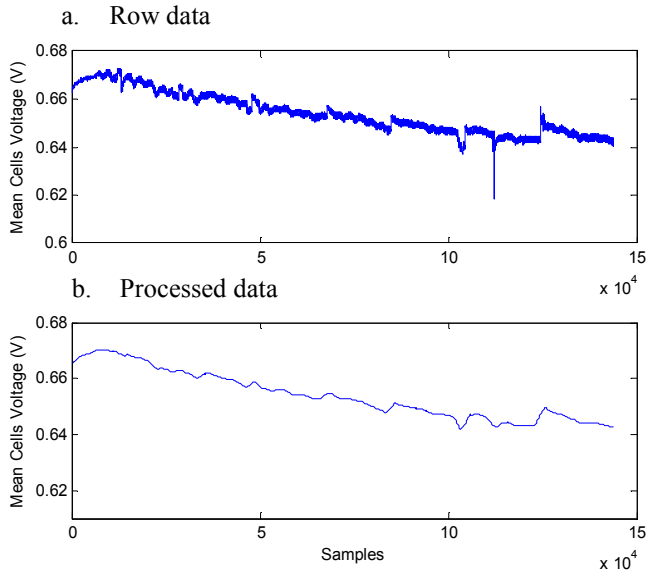


Figure 4: Mean cells voltage time evolution before (a) and after data processing (b)

Table 2: Performance summary of ESN using a Direct structure

	Alpha = 0,2					
	N=50			N=250		
	h=500	h=1000	h=2500	h=500	h=1000	h=2500
RMSE	0,0002	0,0006	0,0018	0,0002	0,0006	0,0018
MAPE	0,0205	0,068	0,2263	0,0204	0,068	0,2273
R^2	0,9968	0,9756	0,7674	0,9968	0,9756	0,7658
	Alpha = 0,5					
	N=50			N=250		
	h=500	h=1000	h=2500	h=500	h=1000	h=2500
RMSE	0,0002	0,0006	0,002	0,0002	0,0006	0,0021
MAPE	0,0195	0,068	0,2412	0,0204	0,068	0,2494
R^2	0,9969	0,9748	0,7111	0,9966	0,9747	0,6796
	Alpha = 0,7					
	N=50			N=250		
	h=500	h=1000	h=2500	h=500	h=1000	h=2500
RMSE	0,0002	0,0006	0,0021	0,0002	0,0006	0,0021
MAPE	0,0202	0,068	0,2501	0,0202	0,068	0,2514
R^2	0,9967	0,9748	0,6772	0,9966	0,9746	0,6733

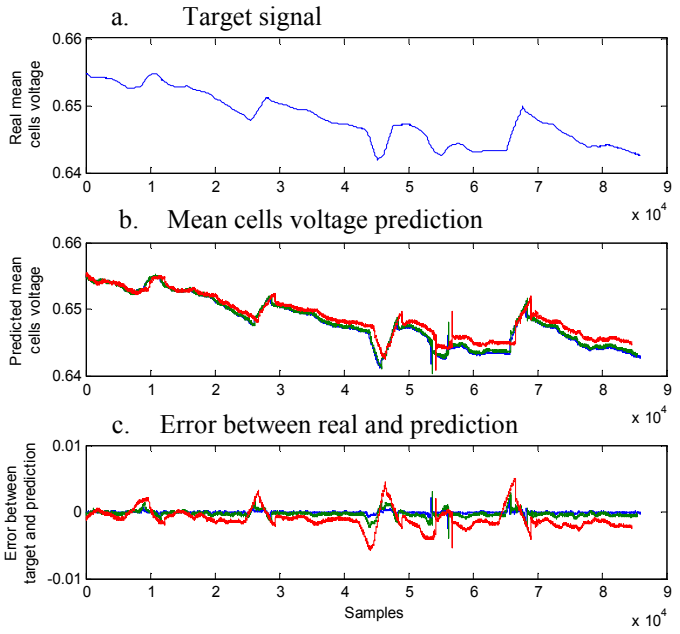


Figure 5: Test Target (a) and Direct predicted mean cells voltage (b) in blue for h=500, in green for h=1000 and in red for h=2500 samples and Error between real and prediction (c)

Figure 5 represents the target (in a) and the predicted output of the ESN (in b) for $\alpha = 0.5$ and N_{res}=50. It is also important to underline the fact than the first 100 points were forgotten. These points are not precise due to the initialization phase of the reservoir. Once the reservoir is set, the prediction becomes really good. Figure 5c shows the error between the target and the predicted signal, where the maximal error corresponds in the more sharp variation of the mean cells voltages (generally after an EIS characterisation). However, these results cannot be dissociated from the simulation duration. In Table 3, the evolution of time simulation is not a linear function dependant on the number of neurons. Generally, the more neurons there are in the reservoir, the better are the results but longer is the simulation time. Nevertheless, in any application, the number of neurons has to be previously designed to really correspond to the desired application.

Figure 6 shows Parallel structure test results, with nearly the same accuracy than the Direct structure even if the Direct structure results remain the bests in term of accuracy. However, in a Direct structure, the information between t and $t+h$ is missing whereas those information are sometimes interesting. For example, to obtain the informations between t and $t+1000$, 1000 ESN have to be created and simulated. As shown in Table 3, one ESN simulation using Direct approach lasts about 19 seconds with N=50 and $\alpha = 0.5$ thus the totallity of the 1000 ESN simulations lasts19 000 seconds whereas for the Parallel structure,with the same values for N and α, the simulation for $t+1000$ lasts only 185 seconds. Consequently the structure choice depends on the system application. In a fuel cell system, even if the results of Direct approach are quite good, a Parallel approach is more interesting due to the need of ageing information between t and $t+h$.

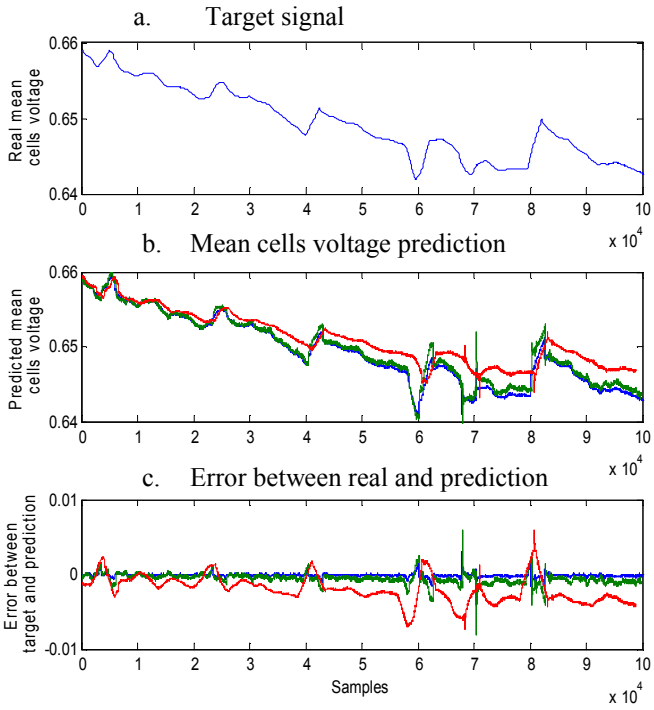


Figure 6: Test Target (a) and Parallel predicted mean cells voltage (b) in blue for h=500, in green for h=1000 and in red for h=2500 samples and Error between real and prediction (c)

Table 3: ESN Direct approach simulations durations (in seconds)

	N=50			N=250		
	h=500	h=1000	h=2500	h=500	h=1000	h=2500
Alpha = 0,2	19	18,95	18,8	27,96	27,4	27,94
Alpha = 0,5	19,31	19	21,49	27,6	27,89	26,94
Alpha = 0,8	19,1	19,53	18,87	27,18	27,35	26,96

V. CONCLUSION

It is important to underline that this article and these simulations do not improve the ESN theory and fuel cells systems; it is just a proposition of a new concept to apply PHM with a data driven method (here with ESN) to a PEMFC system in order to predict the degradation evolution of the stack.

First, this article shows that the ESN is a powerful AI tool that can be used for PHM purpose. The first results are very promising and in the future it would be also interesting to develop full data-driven models using this tool. Nevertheless, the parameters and the design of ESN have to be optimized for each application and other forecasting approaches than Direct and Parallel have to be studied, such as the Iterative approach.

Secondly, the fuel cell systems degradation can be surely forecasted. In this paper, only the mean cell voltage has been used. As perspectives, other parameters coming from measurement on an actual PEMFC system could also been considered, and the health assessment and an estimation of the RUL of the system will be realized.

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