

Predicting the Remaining Useful Lifetime of a Proton Exchange Membrane Fuel Cell using an Echo State Network

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ABSTRACT:

One remaining technological bottleneck to develop industrial Fuel Cell (FC) application resides in the system limited useful lifetime. Consequently, it's important to develop failure diagnostics and prognostics tools enabling the optimization of FC. The Prognostic and Health Management (PHM) is a discipline involved in the process of industrial maintenance. The objective in PHM is to estimate the Remaining Useful Life (RUL) of a system by predicting its future behavior. The RUL enables to predict the moment when a fault could occur on a system. It also allows identifying the relevant part of the system where a fault could happen. Then, a preventive maintenance could be performed to avoid non-reversible degradations. Three main prognosis approaches can be distinguished: model-based, data-based and hybrid methods. Data-based methods such as Artificial Neural Network (ANN), aims to estimate the ageing behavior of the process without specific knowledges related to the physical system phenomenon. Nevertheless, the deployment of such an approach can be a tedious work, mainly due to the trial and error algorithm method, which represents a real problem for industrial applications where real-time complying algorithms must be developed. Among the various methods of this area, the tool chosen here is called Echo State Network (ESN). An ESN consists in the use of a dynamical neurons reservoir where the training step consists in performing a linear regression. The computation time of this algorithm is thus shorter while keeping the same modeling capability of a Recurrent Neural Network (RNN). Created in 2001 by H. Jaeger, an ESN proposes a better human brain paradigm than traditional ANN, and are based on a reservoir of neurons randomly connected to each other. The aim of this paper is to study the application of ESN as a prognostics system enabling the estimation of the Remaining Useful Life of a Proton Exchange Membrane Fuel Cell using an iterative predictive structure, which is the most common approach performing a one-step prediction. This estimation output value is used in the next step as one of the input regressor and these operations can be repeated until the desired prediction horizon. The results obtained thanks to this method exhibits good prediction and they will be detailed in this paper.

KEYWORDS: Fuel Cell, Ageing, Prognostic and Health Management, Data-based, Echo State Network

I. INTRODUCTION

The current energetic system is based on the use of fossil resources consequently an increase of energy request will make this kind of resources rare and expensive. In order to keep the same energetic comfort, scientists have to explore different way to produce energy. The exploitation of hydrogen energy vector is a promising solution. Nevertheless the use of hydrogen energy implies several technological bottlenecks. The main bottlenecks are:

- The use of fuel cell in cold conditions
- The limited lifetime of the FC systems

This paper is focused on the second technological bottleneck: the limited lifetime of fuel cell systems. Typically, in order to develop automotive applications, fuel cells lifetime have to be at least as long as thermal engine life duration, that's means near to 8000 hours. Two ways can be used to increase the life duration of fuel cells: the materials approach and the use of a discipline called PHM. In this discipline, the aim is to obtain the Remaining Useful Lifetime (RUL) of a system by predicting the evolution of ageing indicators. Then, this RUL make it possible to optimize the functioning condition of the system. To obtain this RUL, three different ways to make a prediction exist [1,2]: the model based forecasting [3], the forecast based on the data [4] and using "black box" models and finally the forecast based on an analytical model

combined with a "black box", the hybrid forecast. This paper is focused on data-based prognostic where a tool called Echo State Network is used. The Echo state network is a new kind of neural networks introduced in the beginning of the 2000's [5]. The main novelty is the use of a reservoir of neurons instead of a succession of hidden layers. Moreover, the other particularity of ESN is that only the output weight matrix is optimized consequently the learning algorithm is quicker than traditional neural networks approaches. Nevertheless, the problem of parameter definition is more important for ESN, mainly due to the important number of parameter to design the ESN. One of the main parameter is the topology of the reservoir, that is why this paper presents a study of different reservoir structure confronted with a case of fuel cell ageing. This article is divided in three main parts. Firstly the PHM data-approach is described with a short background of PHM and a mathematical formulation of a "black-box" problem. Secondly, the ESN are introduced with a short state of art and the learning scheme. Then, the results of the reservoir study are presented.

II. THE DATA-BASED APPROACH IN PHM

a. BACKGROUND

The industrial maintenance corresponds at all the actions to prevent or correct the damages of a system in order to maintain it in good condition. It is divided into two types, the preventive maintenance and the corrective maintenance. Whereas a corrective maintenance is done after the system failed, that means after the fault appeared, the preventive maintenance as for aim to correct the system before the failure appearance. This last approach is planned in advance and consists in acting exactly on a part of the system to prevent the appearance of the dysfunction. Consequently, this operation will require a shorter interruption of the system and will imply less loss of production for the company. Furthermore, the life duration of the system will increase thus it will avoid the expenses relative to the change of one or several elements of the system, or the whole system in the worst case.

The operating safety of equipment became a main stake of the industries. The industries and the academics have a growing interest for a discipline called CBM (for Condition Based Maintenance), as mentioned in recent papers [6,7,8] about this subject. In the literature, Jardine and al. [8] defines the CBM as being " a program of maintenance which recommends maintenance actions by taking into account information collected during the system supervision" whereas Lebold and Thurston [9] defines it as "a technique of maintenance which justifies the choice of the maintenance action to be made by the evaluation of the current and planned condition of the system ".

The objective in CBM consists in using deterioration or failure indicators of the system to predict the Remaining Useful Lifetime. By using the real time data of the system, the CBM will allow a hierarchical organization of the priorities and an optimization of the operations of maintenances. The observation of the system health, called "Condition Monitoring ", make it possible to plan a maintenance action only when it is necessary. The CBM implies two main notions: the diagnosis (current state) and the forecast (future state). Whereas the diagnosis will consist in detect, isolate and in identify the fault, the forecast's aim is to anticipate this failure and will estimate the moment of its appearance.

As indicated in the introduction, this article will concern exclusively the prognostic and we shall be interested only in the natural ageing of the PEMFC.

b. DATA-DRIVEN PROGNOSTIC

Data-driven prognostics rely on the uses of an approximation tool from artificial intelligence. 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 $[\theta]$ [10], 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):

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

III. ECHO STATE NETWORK AS A PREDICTING TOOL

a. BACKGROUND

The data-based approach is based on the direct use of the supervision data, or by the indirect use of indicators. The whole does not require a physical model of the system behavior. These indicators are observable or calculated facts identifying in a quantitative or qualitative way the system state of degradation. The inputs of these models are the current and previous supervision data and the output is the prediction or the trend of the system degradation. The data-based forecasting is based on the use of a tool coming from the domain of the Artificial Intelligence allowing the approximation of function. It is typically a black-box model where the learning phase consists in the optimization of the parameters of this black box to obtain the best possible approximation of the real function linking between the inputs and the outputs.

Among the Dated-based methods, the Recurrent Neural Network (RNN afterward) are in theory more suited to obtain the RUL of a complex system [11], the neural networks are in fact parsimonious universal approximators [12]. This method was already confronted with the challenge PHM of 2008 by Felix O. Heimes and obtained the second place [11]. It can also being specified that Jie Liu and Abhinav Saxena proposed an improvement of this method called ARNN (for Adaptive Recurrent Neural Network) used for the prediction of dynamic systems health [13]. In this article, the neural network used is inspired by the classic architecture of the RNN except that the weights are optimized by using the method of Levenberg-Marquardt. The neural network created by this way is then confronted with the problem of the lithium-ion batteries lifetime estimation.

In theory, the RNN are able to approximate any dynamic function, but some practical difficulties limit their use [14]. So the main drawbacks of RNN are:

- (1) The definition of the topology including the number of neurons in the hidden layer, in the input layer and in the output layer
- (2) All the weights have to be optimized
- (3) The use of the gradient back-propagation algorithms can lead in a local optimum and not global optimum

In 2001 and 2002, two publications lead in the birth of the Reservoir Computing. The technical report "The 'echo state' approach to analysing and recurring training neural networks" by Jaeger and the letter of Neural Computation "Real-time stable computing without states: In new framework for neural based calculation one disturbances" by Maass and al.. These publications introduce a new way to train and use complex neural networks. The network created by Jaeger, the Echo States Network, have the following particularities [15]:

- (1) The hidden layers are replaced by a neurons reservoir [16] as unit of data processing
- (2) The input weight matrix, the feedback weight matrix and the reservoir are created randomly
- (3) Only the output weight matrix is optimised by a multi-linear regression (for example by using the generalized matrix inversion Moore-Penrose, simplifying the training processus of the network and allowing finding the global optimum of the weight optimization problem.

b. BASIC STRUCTURE OF AN ESN

According to [17], an ESN can be divided in three main parts: the first part is the input layer, where the neurons receive the information coming from the environment. The second one is the neurons reservoir. This reservoir, with recurrence inside, provides a kind of input « projection » into a larger space and a memory effect. This input projection via the reservoir improves the data linear separation.

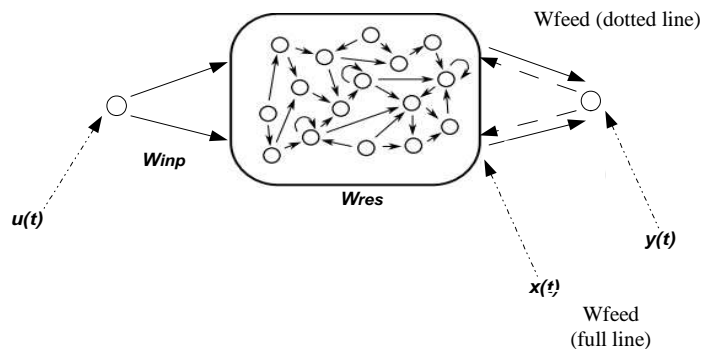


Figure 1: ESN basic structure [18]

With:

- N_{res} the number of neurons inside the reservoir

- K the number of input(s),
- L the number of output(s),
- W_{inp} the weight matrix making the link between the input layer and the reservoir (N rows, K columns),
- W_{res} the weight matrix representing the reservoir (N rows, N columns),
- W_{out} the weight matrix representing the link between the reservoir and the ESN output (L rows and (N+K) columns),
- W_{feed} the weight matrix representing the output feedback (N rows and L columns).

c. LEARNING SCHEME

The learning algorithm is divided in two main steps. Firstly, the ESN is simulated with data previously choosed for the learning step in order to find the W_{out} matrix providing the lowest MSE value. The reservoir output is calculated as following. In a first time, the reservoir update $\tilde{x}(n)$ is computed [19]:

$$\tilde{x}(n) = f(W_{inp} \cdot u(n) + W_{res} \cdot x(n - 1)) \quad (5)$$

With $\tilde{x}(n)$ the reservoir update, $u(n)$ the ESN input and $x(n - 1)$ the reservoir value corresponding to the previous sample. This reservoir update calculation make it possible to compute the ESN output by using α .

$$x(n) = (1 - \alpha) \cdot x(n - 1) + \alpha \cdot \tilde{x}(n) \quad (6)$$

The ESN output is calculated with the equation (6) previous result:

$$y(n) = W_{out} \cdot x(n) + W_{feed} \cdot y(n - 1) \quad (7)$$

However, the W_{feed} weight matrix is optimal thus the ESN output calculation given in equation (7) can be simplified by the equation (8):

$$y(n) = f(W_{out} \cdot x(n)) \quad (8)$$

With the equation (6) and (8), it is possible to obtain the W_{out} matrix thanks to a multilinear regression.

d. THE DIFFERENT KIND OF RESERVOIRS

In this part the studied reservoir are described. The first reservoir is the original reservoir used by Jaeger in 2001 and the others are introduced by [5-15]. The following figure represents the random reservoir used by Jaeger in 2001. The reservoir matrix is created randomly according to a connectivity coefficient c . This coefficient represents the percentage of non-zeroes values in the reservoir weight matrix and can take values between 0 and 1. For example, the following matrix in Table 1, with a connectivity $c= 0.25$ (i.e. $\frac{1}{4}$ 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.

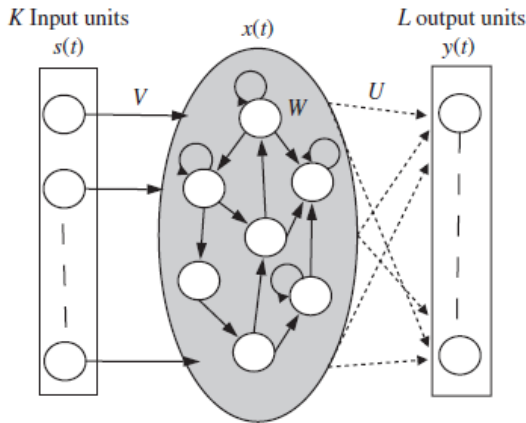


Figure 2: Random reservoir

Table 1: Example of a random reservoir matrix

	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

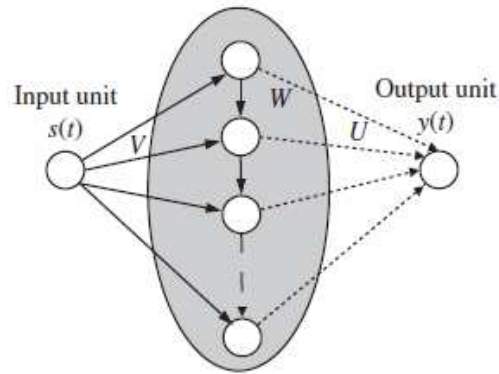


Figure 3: Delay Line Reservoir [20]

Table 2: Example of a delay line reservoir

	1	2	3	4
1	0	0	0	0
2	0.45	0	0	0
3	0	0.72	0	0
4	0	0	0.61	0

The Figure 3 and the table 2 below show a delay-line reservoir introduced by [20]. In this kind of reservoir, the output of each N^{th} neurons is connected with the $N^{\text{th}+1}$ neurons. It involves a non-zero weight value for the inferior diagonal of the reservoir matrix. Another variant is presented in Figure 4 and Table 3, where the delay-line reservoir has feedback on each neuron, adding another memory effect on the reservoir, and can be represents by the same matrix as previously but with a non-zero memory weight effect on the diagonal of the reservoir matrix. It's important to notice than for no-random reservoir, the connectivity c is fixed by the reservoir structure, and especially the number of neurons inside the reservoir N .

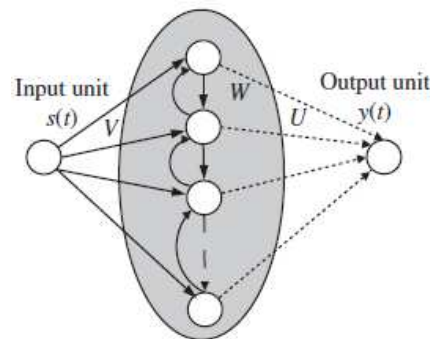


Figure 4: Delay Line Reservoir with feedback [20]

Table 3: Example of delay line reservoir with feedback

	1	2	3	4
1	0.36	0	0	0
2	0.45	0.42	0	0
3	0	0.72	0.27	0
4	0	0	0.61	0.85

The last reservoir presented in Figure 5 and Table 4 is the Simple Cycle Reservoir and adds a weight between the last neuron output and the first neuron input. The matrix can be done with the DLR reservoir to which a weight value is added in the superior right corner.

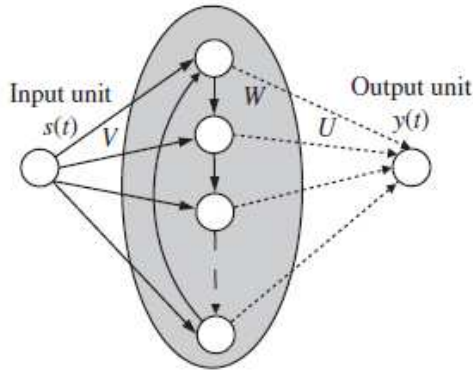


Figure 5: Simple cycle reservoir [20]

Table 4: Example of Simple Cycle Reservoir

	1	2	3	4
1	0	0	0	0.12
2	0.45	0	0	0
3	0	0.72	0	0
4	0	0	0.61	0

The last reservoir consist in the combination of a DLR reservoir with feedback and a SCR reservoir, that results in a reservoir weight matrix presented in Table 5. The diagonal and the lower diagonal have non-zeroes values while a weight value is added in the superior right corner.

Table 5: Example of a DLR and SCR combination reservoir weight matrix

	1	2	3	4
1	0.36	0	0	0.12
2	0.45	0.42	0	0
3	0	0.72	0.27	0
4	0	0	0.61	0.85

IV. EXPERIMENTS: FC VOLTAGE PREDICTION IN AN AGEING PROCESS USING DIFFERENT KIND OF RESERVOIR

a. SIMULATIONS

The study is about the reservoir influence on the direct prediction results [10-21]. Firstly, the Direct prediction structure has to be defined. For the Direct approach, one model provides results for one forecasting horizon. 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 6 and in equation (9).

$$\begin{aligned}
 \hat{x}_{t+1} &= f^1(x_t, x_{t-1}, \dots, x_{t+1-p}, [\theta^1]) \\
 \dots \\
 \hat{x}_{t+h} &= f^h(x_t, x_{t-1}, \dots, x_{t+1-p}, [\theta^h]) \\
 \dots \\
 \hat{x}_{t+H} &= f^H(x_t, x_{t-1}, \dots, x_{t+1-p}, [\theta^H])
 \end{aligned} \tag{9}$$

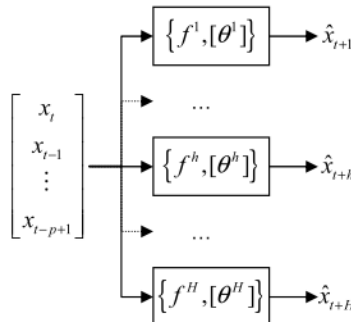


Figure 6: Direct structure scheme

Then, each result corresponds of the mean of 100 simulations where each reservoir is simulated with the same signal and the same parameters definition, that means a reservoir of N=50 neurons, an echo coefficient of 0.5 and a spectral radius of 0.5. These parameters are designed from the article [21]. The purpose is to use mean voltage cells $U_{moy}(t)$ to create three regressors as input of ESN in order to predict $U_{moy}(t+1)$. The data (after the above mentioned pre-treatment) are used as input of an ESN. The first 30% values are used to train the network and the remaining values to test it. The data provide a Franche-Comté region project (after a pre-treatment with a wavelet filter).

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.

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (y_t - \hat{y}_t)^2}{n}} \quad (10)$$

-The simulation duration (in seconds). That is an important parameter for 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.

b. RESULTS

The Figure 7 give information about the results obtained during this study. It corresponds to a 4 hour direct prediction with a random reservoir (N=50 neurons, an echo coefficient of 0.5 and a spectral radius of 0.5).

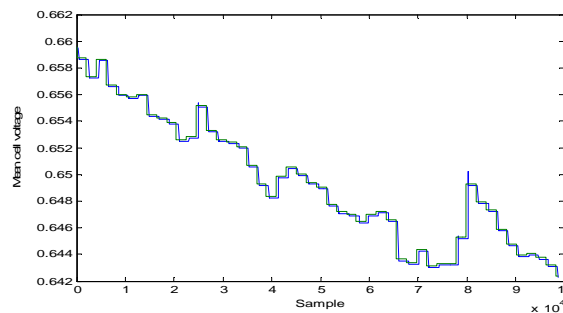


Figure 7: Example of a Direct prediction result with h=4 hours

As described in Table 5, all the results are interesting (a RMSE value under $1e^{-3}$ for a signal near to 0.6 is an interesting result). The time consumption is quicker with the random reservoir which time duration is near to the half of the other reservoirs values. In term of performance, the second reservoir, corresponding to the Delay Line reservoir, and the fourth reservoir, the simple cycle reservoir, have the best performances values; nevertheless there are not a lot of differences between all the reservoir results. In this case, compromises between time consumption and precision have to be done.

Table 6: RMSE and Time consumption for each reservoir

	RMSE mean	Time consumption
Random Reservoir	$7.9e^{-4}$	12.9 seconds
Delay Line Reservoir	$6.1e^{-4}$	21.4 seconds
Delay line Reservoir with feedback	$6.7e^{-4}$	21.0 seconds
Simple Cycle reservoir	$6.0e^{-4}$	22.4 seconds

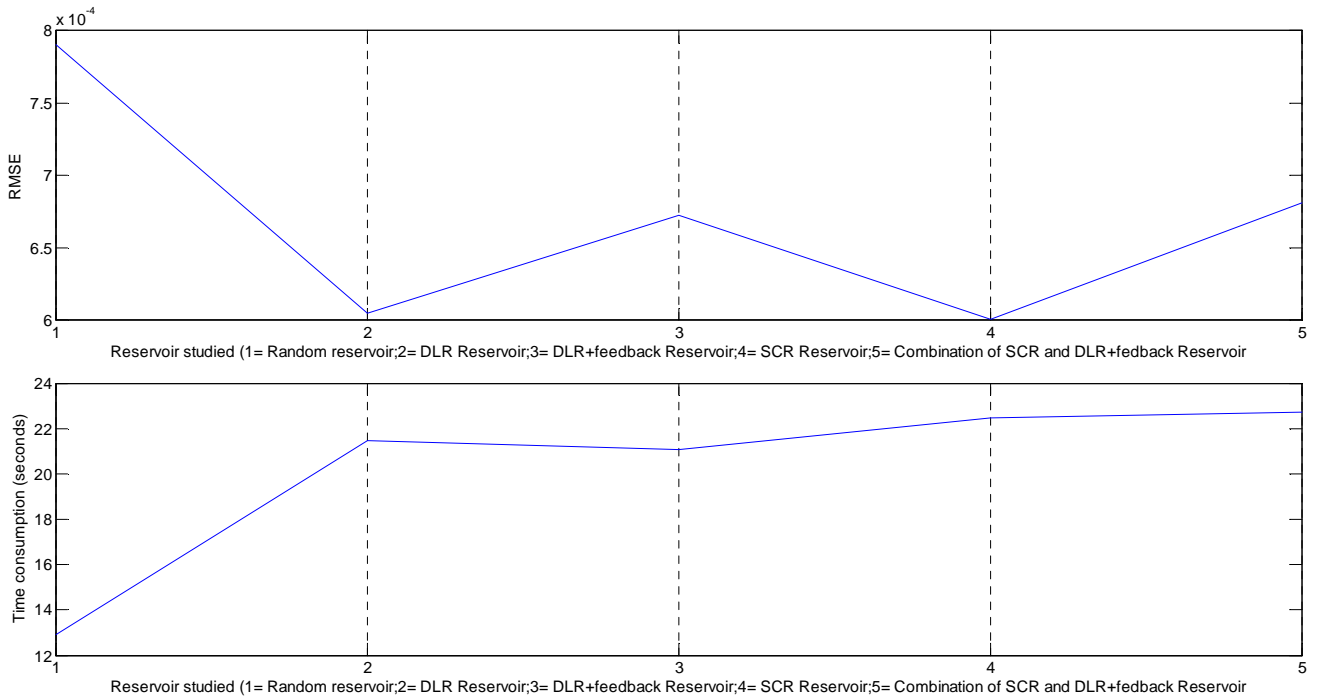


Figure 8: Summary of results

This part can give information about the best reservoir structure to use with ESN. The DLR and the SCR reservoir have the best precision values. It's important to denote that the DLR and the SCR reservoir have feedback inside. That can be explained by the fact that an echo property and a output feedback weight matrix already exists in the ESN structure.

V. CONCLUSION AND PERSPECTIVES

It is important to underline that this article and these simulations do not improve the ESN theory and fuel cells systems. This article is a first step to design an ESN for the ageing of fuel cell systems.

This article shows that the ESN is a powerful AI tool that can be used for PHM purpose. These results can give information about the design of ESN. In the future it would be also interesting to develop full data-driven models using this tool. Nevertheless, the other parameters design of ESN have to be optimized and a general parameter design method for ESN have to be defined.

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.

VI. ACKNOWLEDGEMENT

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VII. REFERENCES

- [1] A. K. S. Jardine, D. Lin, et D. Banjevic, « A review on machinery diagnostics and prognostics implementing condition-based maintenance », *Mechanical Systems and Signal Processing*, vol. 20, no 7, 2006, pp. 1483 -1510.
- [2] G. Vachtsevanos, F.-L. Lewis, M. Roemer, and A. Hess, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*. New Jersey, Hoboken: Wiley & Sons, 2006
- [3] C. S. Byington, M. Watson, M. J. Roemer, T. R. Galic, et J. J. McGroarty, « Prognostic enhancements to gas turbine diagnostic systems », in *2003 IEEE Aerospace Conference*, 2003. Proceedings, vol. 7, 2003, pp. 3247-3255.

- [4] M. Karpenko et N. Sepehri, « A neural network based fault detection and identification scheme for pneumatic process control valves », in 2001 IEEE International Conference on Systems, Man, and Cybernetics, vol. 1, 2001, pp. 93-98.
- [5] H. Jaeger, "The "echo state" approach to analysing and training recurrent neural networks", Technical Report GMD 148, German National Research Center for Information Technology, 2001.
- [6] Ciarapica FE, Giacchetta G. Managing the condition based maintenance of a combined-cycle power plant:an approach using soft computing techniques.J of Loss Prevention in the Process Industries, vol. 19, 2006, pp. 316-325.
- [7] Heng A,Zhang S,Tan A,Matwew J. Rotating machinery prognostic: State of the art, challenges and opportunities. Mechanical Systems and Signal Processing, vol. 23, pp. 724-739, 2009.
- [8] A. K. S. Jardine, D. Lin, et D. Banjevic, « A review on machinery diagnostics and prognostics implementing condition-based maintenance », Mechanical Systems and Signal Processing, vol. 20, no 7, 2006, pp. 1483 -1510.
- [9] M. Lebold et M. Thurston, « Open standards for Condition-Based Maintenance and Prognostic Systems », presented at the 5th Annual Maintenance and Reliability Conference, 2001.
- [10]R. Gouriveau et N. Zerhouni, « Connexionist-Systems-Based Long Term Prediction Approaches for Prognostics », IEEE Transactions on Reliability, vol. 61, no 4, 2012, pp. 909-920.
- [11]Heimes, F.O. Recurrent Neural Networks for Remaining Useful Life Estimation. Prognostics and Health Management, 2008. PHM 2008. International Conference on.6-9 Oct. 2008.
- [12]Jemeï S., Hissel D., Péra M.-C., Kauffmann J.-M. , "A new Modeling Approach of Embedded fuel cell generators based on Artificial Neural Network", IEEE Transactions on Industrial Electronics 55, 1, pp. 437-447, 2008.
- [13]Jie Liu, Abhinav Saxena, Kai Goebel, Bhaskar Saha, and Wilson Wang. An Adaptive Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-ion Batteries. Annual Conference of the Prognostics and Health Management Society 2010 .September 28, 2010
- [14]Yu Peng, Hong Wang, Jianmin Wang, Datong Liu, Xiyuan Peng "A Modified Echo State Network based Remaining Useful Life Estimation Approach", Proceedings of PHM 2012, Denver CO, July 2012
- [15]H. Jaeger. Tutorial on training recurrent neural networks, covering BPTT, RURL, EKF and the "Echo State Network" Approach. Technical Report GMD Report 159, German National Research Center for Information Technology, 2002
- [16]F. Triefenbach, A. Jalalvand, B. Schrauwen, et J.-P. Martens, « Phoneme recognition with large hierarchical reservoirs », in Advances in Neural Information Processing Systems, vol. 23, 2010, pp. 2307-2316.
- [17]I. B. Yildiz, H. Jaeger, et S. J. Kiebel, « Revisiting the echo state property », Neural Networks, vol. 35, 2012, pp. 1-9.
- [18]S. Basterrech et G. Rubino, « Echo State Queueing Network: A new reservoir computing learning tool », in 2013 IEEE Consumer Communications and Networking Conference (CCNC), 2013, pp. 118-123.
- [19]Lukoševičius, M., "A practical guide to applying echo state networks", Neural Networks: Tricks of the Trade, vol. 7700, 2012, pp. 659-686.
- [20]Rodan, A., et P. Tino. « Minimum Complexity Echo State Network ». IEEE Transactions on Neural Networks 22, n° 1 (2011): 131-144.
- [21]Morando S., Jemei S., Gouriveau R., Zerhouni N., Hissel D., "Fuel Cells prognostics using Echo State Network", In Proceedings of the IECON - 39th Annual Conference of the IEEE Industrial Electronics Society, 2013.