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Multi-Reservoir Echo State Network for Proton Exchange Membrane Fuel Cell Remaining Useful Life prediction

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Abstract— In this paper, a Multi-Reservoir Echo State Network is used to estimate the Fuel Cell degradation, and its remaining useful lifespan. It proposes a methodology for predicting the fuel cell output voltage evolution with time. Echo State Network is a powerful Artificial Intelligence tool for time series predicting which main characteristics is the use of a reservoir of neurons, randomly created, instead of hidden layers such as for Artificial Neural Networks. Only the output layer is optimized by a multi-linear regression, resulting in a time reduced training phase. This leads to a possible increase of the reservoir size to preserve, even improve, its accuracy. However, the bottleneck linked to the use of this tool lies in its architecture optimization. This paper proposes a way to overcome the echo state network parameters optimization process by using a Multi-Reservoir Echo State Network. Then a comparison between an Echo State Network optimized algorithm and a Multi-Reservoir Echo State Network for fuel cell RUL prediction is proposed. In order to have a good prediction of the FC lifetime, an innovative approach based on the Multi-Reservoir Echo State Network is developed and validated using experimental data.

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

I. INTRODUCTION

The Proton Exchange Membrane Fuel Cell (PEMFC) technology is a clean way for electricity production with high efficiency. Unfortunately, the fuel cell limited lifetime, high cost and low reliability hinder its deployment at large scale. This work is realized in the context of optimizing the operating conditions (temperature, stoichiometry, relative humidity) in order to reduce the fuel cell degradation rate and thus to extend its lifetime.

To show the effectiveness of our approach, an important issue is to be able to predict the fuel cell Remaining Useful Lifetime (RUL). Prognostics is a suitable technic for RUL prediction. It can help anticipating the degradations by accurate prediction of the future FCs' performance loss and subsequently provides information to the reconfiguration control module. Several FC

prognostics approaches have been proposed in the literature during the last four years. They can be divided into model, hybrid and data driven approaches. Among hybrid approaches, filtering methods are widely used such as Unscented Kalman Filter (UKF) and a physical model of the catalyst degradation as shown in [1]. Only the Electro-chemical surface area degradation is considered in this model. An empirical degradation model and an Extended Kalman Filter (EKF) have been used in [2] to estimate the State of Health (SoH), the dynamics of the degradations and the RUL. The proposed algorithm depends strongly on the initial conditions that are set by the user. In [3] the authors also used a degradation model of the fuel cell with a particle filter to predict the future behavior of the stack and therefore its RUL, assuming semi-empirical laws for the evolution of the model parameters.

Data-driven approaches proposed in the literature doesn't need any a prior knowledge of the inside physics. Regarding Echo State Networks (ESNs), they have shown their effectiveness on representing the degradation evolution dynamics [4]. They have been applied to the RUL prediction of different systems such as turbofan engine [5], [6], [7], Lithium-Ion battery [8] and fuel cells [9].

The main advantage of this tool is that only the output layer is optimized by a multi-linear regression [10], resulting in a time reduced training phase. However, the authors in [11] highlight the sensitivity to the reservoir parameters choice to obtain good results for a given application.

Optimization algorithms such as Genetic Algorithm [12], [13], Particle Swarm Optimization [14], Bee Colony [7], Differential Evolution [6] have been studied to optimize the reservoir architecture. In [13], authors have developed a relation between the signal Hurst coefficient and the spectral radius, one of the reservoir parameters. Several parameters could be optimized, among them: the reservoir size, the spectral radius, the input and output scale and the input and output shift. Generally speaking, the algorithm performance is measured by evaluating the error and subsequently the

accuracy. However, computational time is not taken into account. According to [15], the spectral radius has the most important influence on the ESN performance and a suitable setting of this parameter still has to be found. There are no rules for the optimal setting of the spectral radius. In [16], authors highlight the link between the spectral radius and the echo state property (the effect of initial conditions should vanish as time passes) which is mandatory for employing ESN. Besides, the fuel cell voltage is a signal with a rich content of frequency and the spectral radius is an important parameter that controls the reservoir dynamics [11]. Therefore, a key requisite for obtaining good prediction results using the ESN is the availability of different reservoirs with different spectral radius and therefore dynamics. The main contribution in this paper is to propose a Multi-Reservoir Echo State Network (MR-ESN) for fuel cell lifetime prediction. Each reservoir has a different spectral radius. The developed approach allows predicting the fuel cell lifetime without the limitation shown in other works of filtering the input signals and choosing the adequate optimization algorithm for the best values of the reservoir parameters. The evaluation criteria of the proposed approach will not only be the accuracy criterion but also the robustness.

II. RESEARCH CONTEXT

A. Fuel cell system

A Fuel cell is an electrochemical converter. It produces electricity, water and heat from hydrogen and oxygen according to (1).

A fuel cell is composed of several cells, each one composed of two electrodes and an electrolyte membrane. The whole is called Membrane Electrode Assembly MEA. The hydrogen is fed at the anode side, where it splits into protons H^+ and electrons e^- according to (2). The electrons are driven through an external circuit to the cathode side and H^+ protons pass through the membrane. They react with the oxygen fed at the cathode side and produce water according to (3).

Operating conditions such as temperature, flow rates of reactant gases, pressure, relative humidity, and various combinations of these parameters have a large impact on both fuel cell performance and durability. The control of these operating conditions is ensured by several systems called ancillaries (cooling and heating systems, humidifiers, gas flow controller, converter ...).

The fuel cell system (fuel cell stack + ancillaries) is one of the most promising power technologies. It can be used in transportation, stationary and portable applications. Nevertheless, many degradations can affect its lifespan and lead to high maintenance cost. The main phenomena that impact the fuel cell durability are water and heating management, gas starvation (if a too low amount of reactant feeds the electrodes compared to the required power) and operating electric load cycles. These degradations have

different dynamics; their constant time can vary from several seconds to several hours. To monitor the system degradation, we need to deal with accessible parameters. As the stack voltage is a good indicator of the FC SoH [17] and is easily monitored, this work proposes to predict the output voltage decrease vs time using a MR-ESN.

B. Fuel cell prognostics

Prognostics is crucial to help taking actions for extending fuel cell lifetime. The choice of the prognostic algorithm depends strongly on the application. Fuel cell system is highly nonlinear, multi scale and multi physics and it is thus difficult to use a model-based approach for prognostics. In our case, a data-based approach has been chosen to face the lack for a complete fuel cell degradation model in the literature. Before listing the different steps leading to the RUL estimation, the two different prognostic structures are presented.

1) The direct structure

Initially, this approach is the combination of H prediction tools, with H is the maximum of the desired predictive horizon h , and $h \in [1, H]$. Each tool is optimized to predict its own predictive horizon. All predictors use the same input set. As each tool is dedicated to its own predictive horizon h , the temporal dependencies between variables are lost.

2) The iterative structure

This approach is the most commonly used, and consists of a direct structure optimized to predict a signal $x(t+h)$ with $h=1$. Then, the estimated value is used as a new input of the prognostic tool to estimate the next step forecasting, and so on. The main problem with this method is that the iterative process propagates the errors. Both direct and iterative structures are presented in Fig. 1.

Fig. 1. From a direct to an iterative structure

To obtain the RUL, [18] shows that it is more accurate to use the iterative tool for high prediction horizons. Therefore, the structure used in this paper is the iterative one. The first step is to optimize the prognostic tool used for a direct prediction from n to $n+1$, and then create the feedback of the estimation as a new input to obtain the iterative method.

III. ECHO STATE NETWORK

The data-driven methods are increasingly used for PEMFC prognostics. In [18], the authors proposed a method based on the use of an Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to predict the FC voltage degradation. This approach is very dependent on the quality and quantity of the available data, besides the voltage signal should be pre-processed in order to eliminate abrupt perturbations. The Wavelet-Extreme Learning Machine (SW-ELM) has been proposed in [19] for

predicting the fuel cell voltage losses. This method was compared to Extreme Learning Machine and Leaky-Echo State Network and according to the authors SW-ELM gives better results than the other two approaches. ESN is one of the most interesting approaches used for systems prognostics thanks to its ability to represent the degradation evolution dynamics, it has been used by authors in [5], [6] and [9] for system prognostic and the results are quite satisfying thanks to its fast and easy training procedure.

Fig. 2. Reservoir computing first basic structure [10]

A. Echo State Network generalities

Before explaining the ESN, it is necessary to introduce the Reservoir Computing (RC). Two publications are behind the RC birth. The first one is the technical report "The 'echo state' approach to analyze and train recurrent neural networks" by Jaeger [10], where the ESNs are introduced. The second one is the letter of Neural Computation "Real-time stable computing without states: In new framework for neural based calculation one disturbances" by Maass et al [20] who explained the Liquid State Machine (LSM). These publications introduce a new complex neural networks structure.

According to [10], ESN can be set up in the following way: the neurons of the input layer receive the information coming from the environment and send it to the reservoir. This reservoir aims to expand the input data into a larger dimension space. As a result, the information richness provided by the input data is more easily revealed in this new space, and their linear separation becomes easier, while maintaining in its state a nonlinear transformation of the input (a memory effect). Finally, the desired output signal is obtained from a linear combination of the reservoir's outputs. This linear combination is generated by multi-linear regression in such a way to find the optimum of the output weight matrix using the teacher signal as a target.

The main differences between the ESN and the ANN are defined in [10]:

- (1) The hidden layers are replaced by a reservoir with recurrence inside. This reservoir is created randomly, and acts as a unit of data processing.
- (2) The input, the feedback and the reservoir weight matrices are created randomly.
- (3) The output weight matrix is optimized. This optimization is realized during the training phase by a multi-linear regression. This process simplifies the learning scheme and makes it less time consuming than traditional weights optimization.

Learning scheme

The reservoir structure is shown in Fig. 2; with k inputs $u(n) = (u_1(n), u_2(n), \dots, u_k(n))$; N internal neurons inside the reservoir presented by the reservoir states $x(n) \in \mathbb{R}^N$; and the output vector $y(n) \in \mathbb{R}^L$. At time step n , the activation state of the internal nodes is a non-linear transformation of the current inputs, the previous nodes and outputs states.

The reservoir states are updated according to (4):

$$x(n) = f(W_{res} \cdot x(n-1) + W_{in} \cdot u(n) + W_{fb} \cdot y(n-1)) \quad (4)$$

where $W_{in} \in \mathbb{R}^{N \times K}$ is the input weight matrix making the link between the input layer and the reservoir; $W_{res} \in \mathbb{R}^{N \times N}$ the weight matrix of the interconnected nodes in the reservoir; $W_{fb} \in \mathbb{R}^{L \times N}$ is an optional output feedback weight matrix; and $f(\bullet)$ is the neuron activation function which is usually non-linear.

The readout output is further calculated by a simple linear combination of $x(n)$ as shown in (5).

$$y(n) = f_{out}(W_{out} \cdot (u(n+1), x(n+1))) \quad (5)$$

where $f_{out}(\bullet)$ is a linear output unit activation function and $W_{out} \in \mathbb{R}^{L \times (N+k)}$ is the output weight matrix.

The learning algorithm consists of reducing the Mean Square Error (MSE) between the computed values for the training data set y and the teacher signal y_{target} as in (6).

$$MSE = 1/N \cdot \sum^N (y_{target}(n) - y(n))^2 \quad (6)$$

The goal is now to find the best W_{out} corresponding to the lowest Mean Square Error (MSE) possible result, achieved by a simple linear regression as in (7).

$$W_{out} = (y_{target}^T y_{target})^{-1} y_{target}^T x \quad (7)$$

B. ESN Reservoir

The reservoir is the main part of an ESN, and aims to realize a non-linear expansion of the input signal. The weights of the first reservoir created by Jaeger in 2001 are defined randomly and only the output weights are optimized. Nevertheless, to have "good" performances, the reservoir parameters have to be designed according to the application (processed data). The design of a reservoir consists in the following steps:

1. Define a number of neurons N
2. Random creation of a sparse matrix, with a connectivity c (the connectivity is the parameter which determines the percentage of the non-zero elements of the reservoir matrix)
3. Calculation of the spectral radius, $\rho(W_{res})$ of the reservoir matrix where $\rho(W_{res}) = \max |\lambda(W_{res})|$ and $\lambda(W_{res})$ are the eigenvalues of the W_{res} matrix
4. Then, to create a matrix with the desired $\rho(W_{res})^{desired}$ value, simply divide the W_{res} matrix by $\rho(W_{res})$, thus the

new matrix obtained has a spectral radius of 1. Finally multiply this matrix by $\rho(W_{res})^{desired}$ as in (8).

$$W_{res} = (W_{res} / \rho(W_{res})) \cdot \rho(W_{res})^{desired} \quad (8)$$

All the parameters in bold have to be designed for the application. According to [11] the reservoir's parameters setting have a great effect on its performance. Thus, a good tuning of these parameters is needed, leading to the use of an optimization procedure, such as metaheuristic. However, this kind of methodology is computationally expensive, thus the time saved by using a multilinear regression for weights' optimisation is lost with the use of an optimization procedure. To overcome this problem, a multi-reservoir ESN algorithm is developed.

C. Multi reservoir

To be efficient, reservoir architecture optimization should be realized by optimizing only parameters that have a high impact on the performance. In [15] an ANalysis Of VAriance (ANOVA) has been done and a study of the reservoir parameters' effect on its performance has been proposed. The studied parameters are: the reservoir size, the spectral radius and the connectivity. The result of this study had shown that the most performance-impacting parameter is the spectral radius. The aim of the multi reservoir proposed here agrees with this main idea. The multi reservoir creation consists of a diagonally concatenation of N_{res} small reservoirs, each one with a different $\rho(W_{res})^{desired}$. All the other parameters are defined with the default values recommended in [4]. The creation of N_{res} reservoirs consists in the iteration of the 4 steps described in the previous section N_{res} times. As a result, no optimization process is needed (we avoid the limitations of the optimization algorithms), the architecture design of the reservoir becomes independent of the application so the approach is significantly time saving. The multi-reservoir design is represented in Fig. 3.

Fig. 3. Multi-reservoir creation

The main advantages of this architecture compared to classical ESN are: the multitude of spectral radius and so different reservoir dynamics which allows to explore and encapsulate the teacher signal dynamics and to be able to reproduce them, offering more freedom degrees and computational savings.

IV. SIMULATION RESULTS

The study presented in this section consists of a comparison between a heuristic optimized classic structure ESN and the

multi-reservoir ESN presented in the previous section applied to a PEMFC lifetime forecasting.

A. Experimental data

The data used to validate the proposed approach is generated in the framework of the Region Franche-Comté PHM PAC project, and consists of fuel cell voltage degradation monitoring during 1700 hours under a constant load (60A). This test is performed on a 5-cell PEMFC, with an area of 100 cm². The FC is supplied with dry hydrogen in the anode and humidified oxygen (60-80%) in the cathode and the stack is operated under 60°C.

The used test bench can be divided in three separated parts:

1. Arrival and conditioning of gases: Flow meters, boilers, manometers.
2. PEMFC, cooling system and measurement sensors: pressure, temperature, flow, voltage, current and hygrometry.
3. Control and data acquisition part using National Instruments' Ni-Daq.

The measured fuel cell voltage evolution vs time is presented in Fig. 5.

Fig. 5. Mean cell voltage evolution vs time

These data are used in the next section to compare optimized ESN and MR-ESN algorithms.

B. Algorithm's comparison

Firstly, the two algorithms will be compared at different steps of the forecasting process, meaning:

- on the direct forecasting from $u(t)$ to $u(t+1)$ where 50% of the dataset are used for the training phase,
- on the iterative structure, where 50% of the available dataset are dedicated to the training phase,
- on the RUL forecasting, at different prediction times.

Each comparison consists of an accuracy and robustness analysis. The metric chosen for the accuracy is the Mean Average Percentage Error (MAPE), given in (9), due to its interpretability and scale independency [21]. Using MAPE for forecast accuracy measuring is recommended since the signal doesn't contain zero or close to zero values.

$$MAPE = (100/n) \sum |(y_{target} - \hat{y}) / y_{target}| \quad (9)$$

For the robustness, 100 experiences, with different random matrices weights for each of the experiments, are performed

and the MAPE results are analyzed. The min, max, median and mode metrics values are presented in boxplots illustrated by Fig. 6 for the direct structure and Fig. 8 for the iterative one. To perform these experiences, 50 % of the available experimental data is reserved for the MR-ESN training. The remaining data (that is not used for training) is dedicated to the validation of the results.

C. Obtained results

1) On direct structure forecasting

The direct structure forecasting is the first step to estimate the RUL, as explained in the section II.B. Both algorithms input is the cell voltage at time step t , and output is the cell voltage at $t+1$. The classic ESN is optimized using a BB-BC algorithm, as described in [22]. The results obtained are shown in Fig. 6.

Fig. 6. Direct forecasting results boxplot

This boxplot gives information about the 100 obtained results. The median, in red line, tells us about the middle of the series, the widths of the two parts of the box reflect the dispersion of the values located at the center of the series. The box contains 50% (approximately) of all observations: 25% above the median and 25% below.

As we can see, the two approaches give interesting results, with 50% of the MAPE results under 1.5% of MAPE error. This is due to the fact that at each time step iteration, the input is the voltage real value $v(t)$, thus there is no error propagation. The next step is to include the feedback of the estimation to obtain the iterative structure.

2) On iterative structure forecasting

This step is crucial for the RUL estimation. The aim is to replace the current real values used as ESN inputs signal by the ESN estimated values at the previous time step. This method can lead to error propagation as shown in Fig.7.

Fig. 7. Iterative forecasting results boxplot

As expected, the results are not as good as previously, but remain still less than 10% MAPE error for both algorithms, which is a good result given the presence of errors propagation. Nevertheless, the performance difference between the two structures becomes more visible for both accuracy and robustness, with MR-ESNs being about twice more accurate and robust than conventional optimized ESNs.

3) On RUL prediction

The RUL estimation is based on the results of the iterative structure, to find when the voltage is below the threshold of $0.9U_{max}$, threshold defined by the US Department Of Energy DOE [23] under which the PEMFC is considered at the end of its life for a vehicle application. The Fig. 8 and Fig. 9 show results of RUL estimation for ESN and MR-ESN respectively:

Fig. 8. RUL forecasting with classic optimized ESN

Fig. 9. RUL forecasting with MR-ESN

As the aim is to be the closest possible to the real RUL (blue line in Fig. 8 and 9), it is clear that the MR-ESN RUL estimation gives better results than classic ESN. The beginning of the RUL estimation is poor due to the lack of data allowing good forecast of the fuel cell voltage behavior. In the Fig.9, the maximum RUL error between the real RUL and the estimated one is 244 h. Without this poor RUL estimation, the mean RUL error is 30 h. The Fig. 10 shows the robustness of the MR-ESN algorithm for RUL estimation. More than 75 % of the RUL errors are below 170 h which represents 10% of the FC useful total lifetime.

Fig. 10. RUL error dispersion of the MR-ESN algorithm for 100 simulations

V. CONCLUSION

In this paper we have proposed a method for fuel cell prognostics based on the use of MR-ESN. ESNs are promising tools for predicting time series due to their capability of integrating the dynamic temporal behavior of the input signal. An interesting property of the ESNs is their intrinsic memory; it allows them to remember input time history information that is a crucial characteristic when performing prognostics of dynamical systems. The dependency between the outputs and the old inputs is very interesting for having good prediction results of the voltage evolution from the past degradation patterns. Besides, optimizing only the output weights allows having considerable computational timesaving. However, the critical part of the ESN is its architecture. To make the best profit of the ESN abilities, it is interesting to associate many reservoirs with different spectral radius in parallel. One spectral radius might be not enough to encapsulate the dynamic features of complex systems especially that the FC voltage is a signal rich of frequencies. Associating many reservoirs in parallel offers freedom degrees to the prediction model. The developed approach will be evaluated in future works by varying the reservoir structure and activation functions in a MR-ESN. Moreover, the estimated RUL will be used for the FC control strategy reconfiguration.

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