Data-driven Prognostics of Proton Exchange Membrane Fuel Cell Stack with constraint based Summation-Wavelet Extreme Learning Machine

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ABSTRACT

Aging of a fuel cell (FC) is an unavoidable process, nevertheless managing operating conditions and performing timely maintenance or control can prolong its life span. More precisely, the prognostics of FC is major area of focus nowadays. This paper presents a data-driven approach for prognostics of Proton Exchange Membrane Fuel Cell (PEMFC) stack using constraint based Summation-Wavelet Extreme Learning Machine (SW-ELM). The proposition aims at improving the robustness and the applicability of data-driven prognostics of aging PEMFC stack and estimating the RUL with limited data. The proposed method is applied to run-to-failure data of PEMFC stack from PHM challenge 2014, which had the life span of 1155 hours. Performances of the approach are judged to encounter parsimony problems. Results show the adaptability of constraint based SW-ELM with limited learning data and its suitability for prognostics of PEMFC stack at frequent intervals.

1. INTRODUCTION

Fuel cell (FC) technology is an alternate source of renewable energy that has the power to change the world with a clean energy for the future. A FC can generate electricity as long as fuel is supplied. Among different types of Fuel Cells, the Proton Exchange Membrane Fuel Cell (PEMFC) is a promising technology for the use of mobile, stationary and transportation applications. Mainly, due to the advantages like: high power density, rapid startup, light weight, low temperature [1]. However, the main barriers in commercialization of PEMFCs technology are long-term performances, durability, and high production and maintenance costs [2]. PEMFC suffers from a limited life span [3], and there is a need to increase its durability for large scale industrial deployment. In other words, opimization of FC service and minimization of its life cycle costs/ risks require continuous monitoring of aging process and accurate prediction of life time at which it will be unable to perform the desired functionality. In this context, Prognostics and Health Management (PHM) of FC is an emering discipline that has the potential for improving the use, support and life management of a FC system that consist of a stack and several supporting components. However, repairing the FC stack requires spealist attention. The parts of FC are generally manufactured with expensive and in some cases scarce materials. Ensuring that FC stack is in service for as long as possible is of vital importance [4], which highlights the requirement prognostics. Therefore, leaving aside ancillary systems, the dicussions in this paper are limited to prognostics of FC stack particularly with a data-driven approach.

Basically, the primary objective of prognostics is to build an effective model that is capable of predicting the evolution of degrading indicators and estimating the Remaining Useful Life (RUL) of the FC stack. Knowing that FCs are highly multiphysics and multiscale systems and it is not easy to access their internal parameters to fully understand the aging process. The data-driven prognostics modeling can performed without detailed understanding about the stack aging phenomena.

According to literature, we can classify data-driven RUL estimation strategies into two basic groups. In brief: 1) univariate degradation based modeling that rely on the prediction of continuous degrading state followed by a failure criteria, and RUL estimate is obtained when the degrading signal intersects a pre-defined failure threshold (FT). 2) direct RUL prediction modeling which learns from the data directly, the relation between observed trends and equipment end of life (EOL) time to obtain RUL (by finding similarity). This method does not require FT, but is dependant on sufficient knowledge on

RULs from large training data. According to author’s knowledge, only two data-driven approaches have been applied so far for the prognostics of PEMFC stack namely, Adaptive Neuro-Fuzzy Inference System (ANFIS) [5] and Echo state network (ESN) [6]. The developments in both publications are based on univariate degradation based modeling. Because, due to lack of data availability, direct RUL prediction modeling is not possible for FC application. However, even the univariate degradation based approach cannot guarantee accurate prognostics. This is mainly due to the complex aging phenomena of FC stack, where several factors can impact its degradation behavior. Consequently, the acquired condition monitoring (CM) data are quiet uncertain. As for data-driven approach the model is within data, the uncertainty of measures due to sensor noise, unknown environmental and operating conditions, and engineering variations, etc., prevent prognostics model to capture dynamics of degrading equipment. Therefore, in order to predict the unknown future the model is not enough robust to adapt the degrading behavior over inputs that deviate from learned experience. In addition, lack of data availability requires models with high complexity like ESN, for which uncertainty of parameter intialization can be an added factor for decreasing the accuracy prognostics. Moreover, methods like ANFIS are based on slow iterative tuning and computationally costly and their computational time increases with size of learning data. Also, the choice of model inputs like: voltage, current, etc., and assumptions limit the applicability of a data-driven approach. Therefore, in the presence of such issues the data-driven prognostics can be quiet challenging.

This paper contributes a univariate degradation based prognostics of PEMFC stack using constraint based Summation-Wavelet Extreme Learning Machine. The constraints are included in the modeling phase to reflect stack degradation using trends that properly decrease with respect to time and intersect with the failure threshold. The development focuses on improving robustness and applicability of data-driven prognostics of aging PEMFC stack and estimating the RUL at frequent intervals.

The paper is organized as follows. Section 2 presents the framework of data-driven prognostics, where each step is briefly discussed according to FC application. The choice of health indicators (variables) and the constraint based SW-ELM are described in section 3. Discussions on the prognostics results on PEMFC stack are given in section 4. Finally, section 5 concludes this work.

2. DATA-DRIVEN PROGNOSTICS FRAMEWORK

A data-driven appraoch can learn system behavior directly from CM data e.g. temperature, current, voltage, etc., and use that knowledge to infer its current state and predict future progression of failure. Therefore, when focusing on prognostics process, one can underline a flow that goes from multidimensional data through the RUL of equipment. The frame of data-driven prognostics is based on the following necessary steps: acquiring CM data, data-processing, learn model (off-line), test model (on-line) and estimate RUL, as presented in Figure 1. The main aspects of each step are discussed including the issues and requirements for PEMFC application as follows.

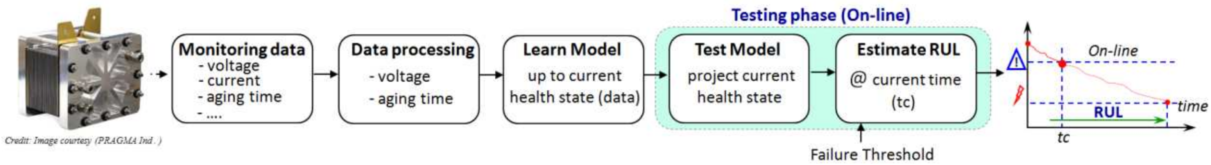

Figure 1. From stack monitoring data to RUL

- **Acquiring CM data**: to gather useful CM data from the FC stack, those are economically possible and easier to be used for prognostics. This will enable identifying the changes in aging stack which can develop faults or can even lead to failure. The measurements that are economically possible from PEMFC stack are: aging time, current, voltage, air compressor speed, cooling water temperature, Air/ H2 temperatures & Electrical Impedance Spectroscopy.
- **Data-processing:** to extract or select features/ health indicators from CM data, those are sensitive to stack degradation and clearly indicate fault growth. The effectiveness of a prognostics model is closely related to the quality of health indicators, which can impact uncertainty of prognostics. Therefore, useful health indicators are those which reflect overall behavior of aging stack with irreversible degradation. In brief, feature extraction can be performed by applying signal processing techniques e.g. discrete wavelet transform, etc. The

selection can be performed by drawing health indicators (or variables) in a new space by techniques like: Self-organizing map or clustering, etc., or by selecting variables that have highest information content, preferably monotonic and trendable ones. For example Figure 2 shows hourly mean voltage signal (U_{tot}) and the filtered trend by applying **rloess** filter (see section 4.1 for details). The large variations (peaks) in U_{tot} are due to characterization phases, however, after filtering a monotonic and trendable health indicator is achieved. Obviously, the filtered signal is can be learned more accurately as compared to the actual U_{tot}.

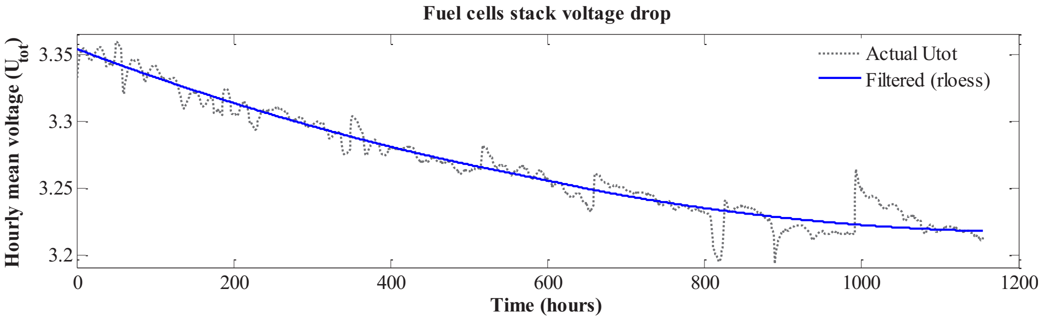

Figure 2. Filtering stack voltage signal

- **Learn model (off-line):** to fit changing observations. In other words, the learning problem is to estimate the target data from the given multidimensional input data. For example for PEMFC stack the prognostic model inputs can be current, cell/ stack voltage, aging time and the target can be stack power drop. Therefore, the off-line phase requires flexible methods that learn and infer complex relation among data. However, the accuracy of prognostics is strongly dependant on the learning. For instance, incomplete coverage data can impact model learning and can result poor predictions. In addition, model complexity, parameter initialization, computational time and assumptions are factors, which should be properly addressed.
- **Test model (on-line)**: to project the current state of FC stack (at time **t**current) up to defined failure threshold (FT), i.e., the failure time (**t**fail). With univariate degradation modeling this step is achieved with "iterative approach" for performing long-term multi-step ahead prediction (*msp*). In brief, the *msp* is achieved by a single model that is tuned (during learning phase) to perform a one-step ahead prediction $\hat{x}_{t+1}$. This estimated value is used as the regressors of the model to estimate the following ones and the process is repeated until the estimation of $\hat{x}_{t+H}$, where *H* represents the prediction horizon (see details in [7]). However, due presence of issues like: measurement uncertainties, lack of data, modeling errors. The predictions obtained in recursive manner result error accumulation with increasing *H*, as shown in Figure 3a. Such poor predictions are useless for prognostics, because they do not intersect with FT and thus, the RUL estimation is impossible. This requires including constraints in the prognostics modeling phase to select those models which can project current state of FC stack up to FT, as shown Figure 3b. Indeed, good predictions can enable managing the uncertainty of prognostics and will improve the accuracy of RUL estimates.

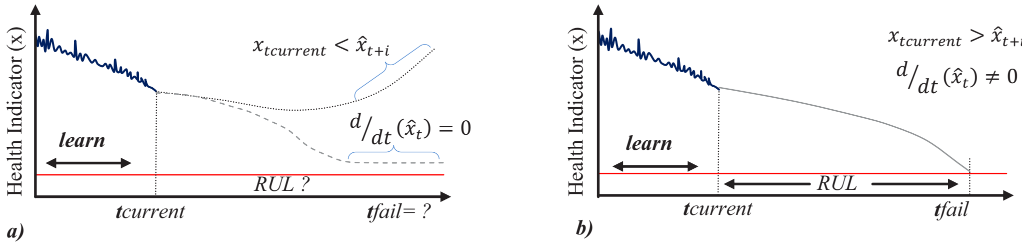

Figure 3. a) Poor predictions vs. b) Good prediction

- **Estimate RUL:** to determine the life span of aging PEMFC stack. RUL is expressed by considering units corresponding to the primary measurement. For FC application the RUL is expressed in hours. The RUL is estimated as the time between the hour of prediction at **t**current and the time at which the predicted value intersect the FT at **t**fail, as shown in Figure.

3b & given in Eq.1. According to US department of energy, the FT for FC is defined on the basis of its power drop, which states that the degradation should not exceed 10% of initial power on a 2500 hours life span [8]. Note that, it is nesseccary to update RUL at appropriate intervals, when new data arrive. It means that the frequency of RUL updation should be synchronized with preceding steps, i.e., acquisition, processing, model learning with new data.

$$RUL = \boldsymbol{t}fail - \boldsymbol{t}current \tag{1}$$

Finally, the complete data-driven prognostics enables decisions for managing operating conditions on-line and performing timely maintenance off-line or control to prolong the life span of the FC stack.

3. PROPOSED APPROACH

According to the discussions on data-driven framework, this section higlights the choice of useful health indicators for PEMFC prognostics and also introduces a new health indicator. Following that, the constraint based Summation Wavelet- Extreme Learning Machine (SW-ELM) algorithm is presented. The proposed data-driven approach is based on following hypothesis.

- Stack voltage drop is a useful prognostics indicator.
- Stack aging process is irreversible degradation.

3.1 CHOICE OF HEALTH INDICATORS FOR FC PROGNOSTICS

The FC stack degrades due to different factors like: material degradation, design and assembly, etc., and the performance decay induced is strongly associated to the operating conditions (for e.g. operating temperature, current, etc.,) [9]. Also the performance of the FC stack is constrained by the worst performing cell [4]. Whatever the cause of stack degradation, it will result a voltage drop. Therefore, the stack voltage is considered useful for FC health assessment and prognostics.

Based on this assumption and considering the importance of FT for prognostics a new health indicator is proposed, which is obtained by computing the difference between the stack voltage drop and the FT ($D_{U\theta}$), Eq. 2. The final set of variables for data-driven prognostics are aging time (T_{age}),$D_{U\theta}$ and U_{tot}.

$$D_{U\theta} = U_{tot} - FT \tag{2}$$

3.2 CHOICE OF SW-ELM ALGORITHM & CONSTRAINTS

To account for robustness and applicability challenges of prognostics modeling (i.e., learning phase and the testing phase), the choice of a data-driven approach is crucial for achieving accurate RUL estimates. Recent advances show that data-driven approaches mainly based on machine learning methods are increasingly applied for fault prognostics. Among those methods, artificial neural networks (ANN) are most commonly used in PHM domain [10]. In this paper we present relatively a new data-driven algorithm, called as Summation Wavelet- Extreme Learning Machine [11].

Basically, the SW-ELM is one-pass batch learning algorithm for single layer feed forward network (SLFN), as depicted in Figure 4. SW-ELM is the combination of ANN and wavelet theory, and appears to be an effective prediction approach [11]. It benefits from an improved parameter initialization to minimize the impact of random weights and bias (of input-hidden layer), and an improved structure with dual activation functions for each hidden node, that work on actual scales of data. This enhances dealing with non-linearity in an efficient manner and improves robustness of algorithm. In comparison to recent data-driven approaches for FC prognostics, i.e., ANFIS and ESN, SW- ELM has better applicability due to major advantages like: rapid learning, good generalization ability, not prone to local minima and require only two parameters to be set by the user.

Let note n and m the numbers of inputs and outputs, N the number of learning data samples (x_i, t_i), where $i \in [1, \dots, N]$, $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in \Re^n$, $t_i = [t_{i1}, t_{i2}, \dots, t_{im}]^T \in \Re^m$, and $\widetilde{N}$ is the number of hidden nodes, each having activation functions (f1 & f2). To minimize the difference between output o_j and target t_j , there exist β_k, w_k and b_k such that:

$$\sum_{k=1}^{\widetilde{N}} \beta_k \bar{f}\left[(\theta, \psi)(w_k . x_j + b_k)\right] = t_j , \qquad j = 1,2, \dots, N \tag{3}$$

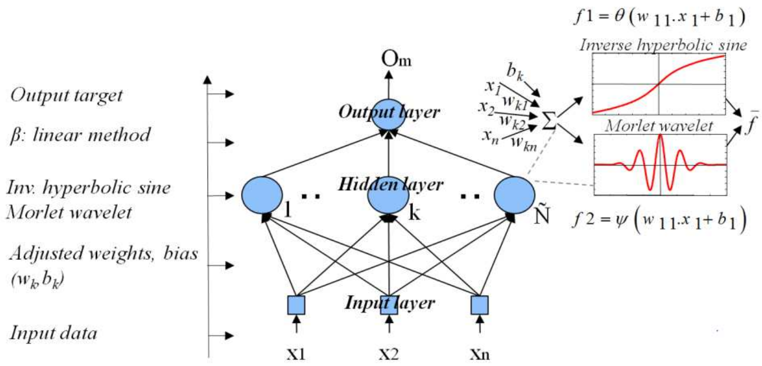

Figure 4. Machine learning view of SW-ELM for SLFN

where $\bar{f}$ is the average output from two different activation functions θ and ψ, $w_k = [w_{k1}, w_{k2}, \dots, w_{kn}]^T \in \Re^n$ is an input weight vector connecting the k^{th} hidden to input layer neurons, $(w_k . x_j)$ is the inner product of weights and inputs, and $b_k \in \Re$ is the bias of k^{th} hidden neuron. $\beta_k = [\beta_{k1}, \beta_{k2}, \dots, \beta_{km}]^T \in \Re^m$ is the weight vector to connect k^{th} hidden neuron to the output neuron. In matrix form Eq. 3 can be written as $H_{avg}\beta = T$, where T is target matrix and H_{avg} is hidden layer output matrix expressed as:

$$H_{avg}\left(w_1, \dots, w_{\tilde{N}}, x_1, \dots, x_{\tilde{N}}, b_{1,\dots,}, b_{\tilde{N}}\right) = \bar{f}(\theta, \psi)\begin{bmatrix} (w_1 . x_1 + b_1) & \dots & (w_{\tilde{N}} . x_1 + b_{\tilde{N}}) \\ \vdots & \dots & \vdots \\ (w_1 . x_N + b_1) & \dots & (w_{\tilde{N}} . x_N + b_{\tilde{N}}) \end{bmatrix} \tag{4}$$

$$\beta = [\beta_1^T \dots \beta_{\tilde{N}}^T]_{\tilde{N}\times m} \ \ and \ \ T = [t_1^T \dots t_N^T]_{N\times m} \tag{5}$$

The least square solution of the linear system $H_{avg}\beta = T$, with minimum norm of output weights β is:

$$\hat{\beta} = H_{avg}^{\dagger}\, T = (H_{avg}^T\, H_{avg})^{-1}\, H_{avg}^T\, T \tag{6}$$

where $H_{avg}^{\dagger}$ shows the Moore-Penrose generalized inverse for the hidden layer output matrix H_{avg}. The SW-ELM algorithm can be synthesized as follows (see detailed algorithm in [11]).

Algorithm 1 Brief learning scheme of SW-ELM

Require

- N learning samples (x_i, t_i), n inputs, $\tilde{N}$ hidden nodes
- Arcsinh and Morlet activation functions (θ and ψ)

1: Initialization of wavelet parameters (i.e., dilatation & translation) using heuristic approach.
2: Initialize hidden nodes parameters (w_k, b_k) randomly & adjust with Nguyen widrow procedure.
3: Obtain hidden layer output matrix H_{avg} using Eq. 4.
4: Find the output weight matrix $\hat{\beta}$ in Eq. 6.

Although, SW-ELM appears to be a suitable data-driven method, however, due to lack data model learning it is sensitive to initialization of w_k, b_k. As a result, with each run the learning performances are changed, which can lead to poor predictions in the test phase, i.e., with recusrsive prediction the error accumulates with increasing horizon (see Figure. 3a). To overcome this problem and to improve robustness of SW-ELM, constraints are included in the prognostics modeling phase to ensure that in test phase *msp* decay properly to reflect stack degradation and intersect with FTs. In other words, models with poor learning are rejected in the test phase, which fail to satisfy following constraints.

$$d/_{dt}\,(\hat{x}_t) \neq 0 \tag{7}$$

$$x_{tcurrent} > \hat{x}_{t+i}\ ,\ i \in \mathbb{Z}_+ \tag{8}$$

$$\hat{x}_{t+h} \leq FT \tag{9}$$

The constraints given in Eq. 7 and Eq. 8 are based on the assumption that FC stack degradation is irreversible (i.e., decreasing trend). Thus, the slope of *msp* at any step cannot be zero and predicted value ($\hat{x}_{t+i}$) at each step i should be less than current state of stack at time **t**current from which prediction is initiated. The constraint given in Eq. 9 ensures that predicted trends intersect FT.

4. EXPERIMENT AND RESULTS DISCUSSIONS

To validate the effectiveness of our proposition, real data PEMFC stack are used from PHM challenge 2014 [12]. The considered data are from 5-cell PEMFC stack with an active area of 100 cm². The FC stack was operated under constant current of 70 A, and it had the life span of 1155 hours. The health indicators used for the prognostics task are aging time and hourly mean voltage of the stack (see [12]).

4.1 Simultion settings and Performance evaluation

Prior to prognostics modeling task, the stack voltage signal is filtered by applying **rloess** filter with span value 0.9, Figure1. Basically, **rloess** is a robust local regression filter that allocates lower weight to outliers, see [13]. The filtered signal clearly shows voltage drop with a monotonic trend which will reduce the uncertainty of SW-ELM, when few data are used in the learning phase.

Note that, two groups of health indicators are used for prognostics: 1) T_{age}, U_{tot} and 2) T_{age}, $D_{U\theta}$, U_{tot} (section 3.1). For the first group of variables, the structure of SW-ELM model is set to 4 inputs nodes which represent 3 regressors of U_{tot} and T_{age}, hidden layer complexity is set to 20 nodes, and 1 output $U_{tot\ t+1}$. For second group of variables, there is an additional input in the structure, i.e., $D_{U\theta}$ (see Eq. 2). For both structures the parameter initialization constant C=0.01 for w_k, b_k (see [11]). The FT is set to EOL. Assuming that a single SW-ELM model cannot guarantee accurate prediction, whatever the input set used for learning, a group of 100 SW-ELM models is learned, and the best model with minimum learning error is selected for testing. However, the selected model must satisfy the constraints (Eq. 7-9) in the test phase, otherwise the learning phase is repeated.

The performances of the proposed approach are judged based on following criteria:

- Model complexity
- Prognostics accuracy over increasing perdition horizon (H) by:
  - Correlation of determination (R2), which should be close to 1.
  - PHM challenge 2014 scoring metric, which should be close to 1 (see [12] for details).
- Time to learn and test model for maximum prediction *H* and for minimum prediction *H*.

4.2 Prognostics results

4.2.1 Impact of constraints on predictions

To validate the enhancements with proposed constraint based SW-ELM. In the first step, a group of 100 models is trained in batch mode using same data set of 400 hours (from health indicators T_{age}, U_{tot}). For the test phase, the best model with minimum learning error is selected to perform long-term *msp* with iterative approach. The prediction initiated at 400 hours for RUL estimation is shown in Figure 5. In comparison to actual U_{tot}, the predicted U_{tot} decreases properly up to 1100 hours, however, it stays constant beyond that and fails to intersect FT to stop *msp*. In the second step, the learning data are increased to 500 hours from same health indicators T_{age}, U_{tot}, and model training and selection are performed like the previous step. The prediction initiated at 500 hours diverges from the actual U_{tot} approximately around 700 hours as shown in Figure 5.

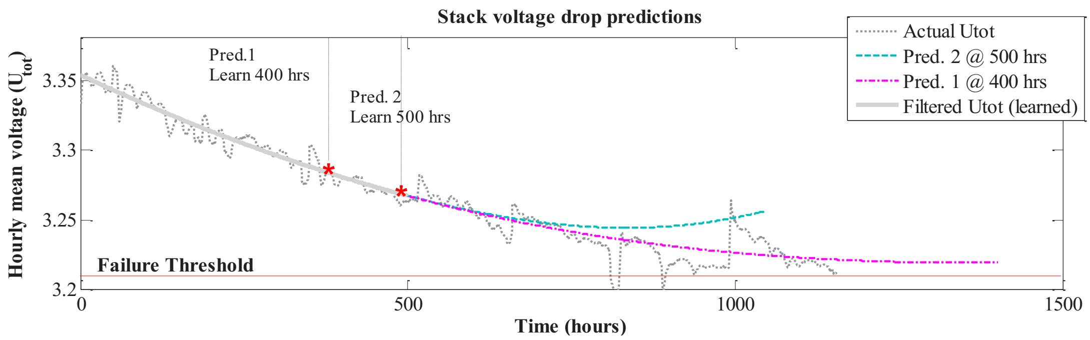

Figure 5. Long-term *msp* results without constraints

Both models fail to estimate RUL. The prediction performances are poor because, the learning phase cannot guarantee good models due to lack of training data and parameter initialization issues. However, the constraints introduced in the prognostics modeling phase (i.e., to learn and test model) enable choosing those models from the learning phase which fulfill the given conditions in Eq. 7-9. The long-term *msp* results in Figure 6, validate the enhancements due to constraints. Prognostics is performed at different hours, and for all cases *msp* properly show the degradation and intersect FT.

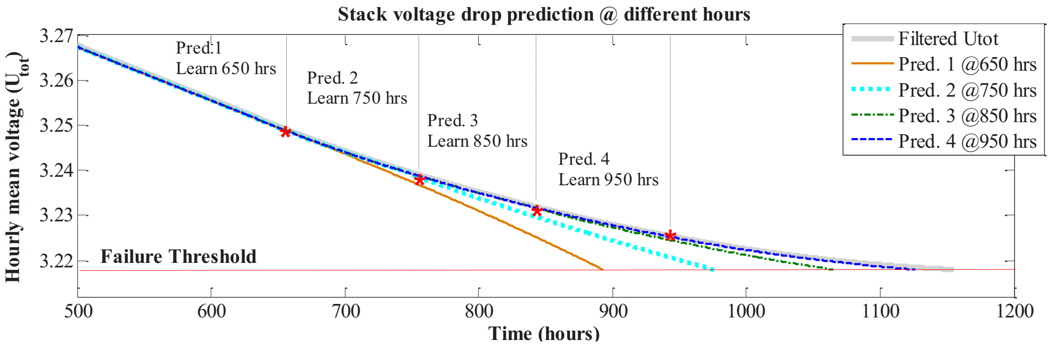

Figure 6. Long-term *msp* results with constraint

4.2.2 RUL estimation

The RUL estimation performances with constraint based SW-ELM are investigated with two groups of health indicators: 1) T_{age}, U_{tot} and 2) T_{age}, $D_{U\theta}$, U_{tot}. The prognostics task is initiated at 650 hours and the RUL is updated after 10 hours interval. That is, the predictions are performed when new data arrives. To achieve the repeatability of prognostics results, RUL is estimated from the mean value from the RULs obtained from 20 trials, at a given time interval. A comparison on the quality of RUL estimation with both groups of health indicators is given in Figure 7.

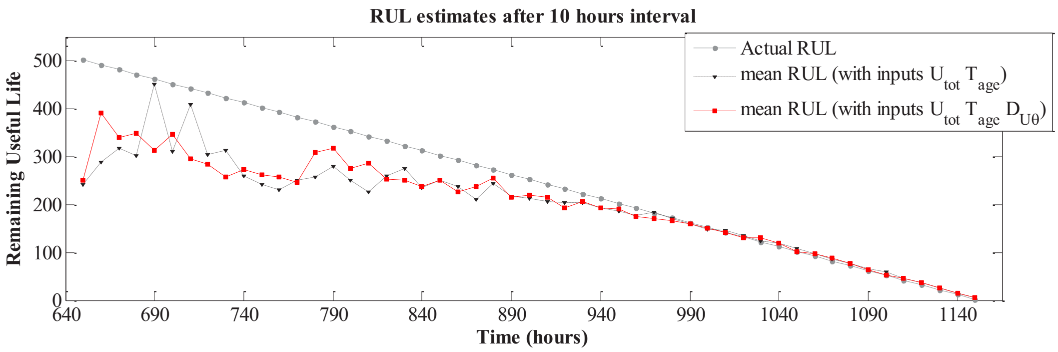

Figure 7. RUL estimation with different sets of inputs for prognostics

It can be judged from the qualitative analysis, that better RUL estimates are achieved by including proposed health indicator $D_{U\theta}$, as an input to constraint based SW-ELM. However, it is important to evaluate over all prognostics performances with both set of health indicators. Table 1 summarizes prognostics performances using different criteria given in section 4.1. The results show that with the same complexity of 20 hidden nodes SW-ELM model for inputs U_{tot}, T_{age} and $D_{U\theta}$, has higher accuracy with R=0.69 and Score=0.51. However, due to additional input $D_{U\theta}$ its learning time is slightly higher than the SW-ELM model with input indicators U_{tot}, T_{age}. Note that, the timings can vary due to decrease in the length of prediction horizon; even the learning data are increased, as given in Table 1. The SW-ELM model with 3 input indicators requires only 48.22 sec for a prediction 2 hours. Also, the overall accuracy can also vary by changing the frequency of prediction intervals.

Table 1. Comparison of overall prognostics performances

SW-ELM model Inputs	Hidden layer complexity	R2	Score	Time learn & test (max H=502 hours)	Time learn & test (min H=2 hours)
U_{tot} T_{age}	20 nodes	0.65	0.49	**84.49 sec**	48.51 sec
U_{tot} T_{age} $D_{U\theta}$	20 nodes	**0.69**	**0.51**	105.88 sec	**48.22 sec**

5. CONCLUSION

This paper presents data-driven prognostics of PEMFC stack with constraint based SW-ELM. The development focuses on improving the robustness and applicability of data-driven prognostics of FC. The constraints in the prognostics modeling phase ensure that predictions decrease properly to depict the FC aging behavior and intersect failure threshold (FT). This enables performing data-driven prognostics with limited data. This proposition of constraints can also be useful for other random projection methods as well (like Echo State Network). Moreover, a new health indicator is also proposed to infer the changing behavior of stack voltage with respect to FT, which further increases accuracy of RUL estimates. Overall results show that the performances with proposed approach are quite satisfactory to encounter parsimony problem, i.e., to look for a compromise between the prognostics model complexity, computational time and accuracy performances. Finally, RUL estimation with proposed SW-ELM can be performed at frequent intervals.

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