Prognostics of PEM fuel cell in a particle filtering framework.

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Abstract

Proton Exchange Membrane Fuel Cells (PEMFC) suffer from a limited lifespan, which impedes their uses at a large scale. From this point of view, prognostics appears to be a promising activity since the estimation of the Remaining Useful Life (RUL) before a failure occurs allows deciding from mitigation actions at the right time when needed. Prognostics is however not a trivial task: 1) underlying degradation mechanisms cannot be easily measured and modeled, 2) health prediction must be performed with a long enough time horizon to allow reaction. The aim of this paper is to face these problems by proposing a prognostics framework that enables avoiding assumptions on the PEMFC behavior, while ensuring good accuracy on RUL estimates. Developments are based on a particle filtering approach that enables including non-observable states (degradation through time) into physical models. RUL estimates are obtained by considering successive probability distributions of degrading states. The method is applied on 2 data sets, where 3 models of the voltage drop are tested to compare predictions. Results are obtained with an accuracy of 90 hours around the real RUL value (for a 1000 hours lifespan), clearly showing the significance of the proposed approach.

Keywords: Proton exchange membrane (PEM) fuel cell, Prognostics, Remaining useful life, PHM, Particle filter

1. Introduction

Energetic transition is one of the major challenges for the future. Fuel cell systems might be good candidates to help facing these challenges and are benefiting from a growing interest. Indeed their perspectives of applications are numerous [1]. They are presented as a good alternative to internal combustion engines for transportation, but also as a clean and efficient portable power source for low power electronic devices (μFC). On a biggest scale, fuel cell seems to be a great solution for combined heat and power systems (μCHP), providing both heat and electricity for homes and buildings. Fuel cell stacks have the advantage of having no moving part, offering them a great reliability. However, as all systems, they are prone to material degradations and these phenomena are still far from being all understood. That is why fuel cells suffers from a too short life duration impeding large deployment of this technology.

Prognostics and Health Management (PHM), and particularly prognostics, represents a great opportunity to to contribute to extend fuel cell lifetime, and more precisely PEMFC in this case. PHM appears to be an enabling discipline ranging from data collection to decision making via health assessment, diagnostic and prognostics. It aims at using real monitoring data to propose relevant indicators and trends that depict the health of the system. Also, it enables deciding adequate actions at the right time in order to extend the system's life. It is mainly achieved thanks to prognostics. Indeed, in the case of PEMFC, with the knowledge of the remaining useful life, one can decide to adapt the power demanded to the stack to make it last longer. Another example can be the managing of an entire fleet of PEMFC. Knowing how much power and for how long each PEMFC can provide, the asked power profiles can be individually adapted to complete a defined mission with success. Consequently, PHM benefits from a growing interest in the FC community and some papers dealing with this subject begin to appear [2]. Although one paper dealing with prognostics performed at a single cell level [3] can be found in the literature, no paper performing it at the stack level exists until now.

In this logic, this paper aims at developing a prognostics model for estimating the remaining useful life of a PEMFC stack. The approach is based on a particle filtering framework. It allows predicting the future behavior of the system thanks to a degradation model. This behavior is constructed by successively drawing the probability distributions of the possible degradation states. These probabilities give both the state estimation and the uncertainty related to this estimation.

The core of the paper is organized in three main

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sections. First, section 2 describes Prognostics and Health Management with an emphasis on prognostics . This part enables understanding the aim of remaining useful life estimates and how to perform them. Then, a novel approach for PEMFC prognostics based on particle filter is presented in section 3.3. It presents the hypotheses, the mathematical background and the adaptation of the problem to the fuel cell case. The whole proposition is applied in section 4 and illustrated by performing long duration tests on two PEMFC stacks. Finally, in section 5 the remaining useful life is calculated on the basis of three different models and prognostics results are evaluated and discussed.

2. Toward prognostics of PEMFC

2.1. Prognostics and Health Management

The growth of reliability, availability or safety demand are determining factors to ensure all new industrial system spreading. To meet these requirements while reducing the cost of the useful life of a system, maintenance policies have evolved with the increasing in demands, moving from breakdown maintenance to preventive maintenance, and then to Condition-Based Maintenance (CBM). This evolution gives up a “fail to fix” strategy to switch to a “predict to prevent” one. Therefore, the objective of CBM is to maintain a system at the correct time taking into account the current and future health state of the system [4]. CBM uses real-time monitoring data to estimate the actual health state and thereby optimize, on the one hand the use of the system, and on the other hand, maintenance policies. Consequently, the complete aspects of failure analysis and prediction must be viewed as a set of activities that must be performed jointly. Indeed, various stages ranging from data collection to the recommendation of mitigation actions including detecting and identifying faults and failures, must be carried out to perform predictive control and maintenance. This leads to improved performance of the well-monitored and well-controlled system. Prognostics and Health Management (PHM) derived directly from that [5].
PHM can be defined as a technology to enhance the effective reliability and availability of a system in its life-cycle conditions by detecting upcoming failures. It aims at predicting and protecting the integrity of equipment and complex systems, but also at avoiding unanticipated operational problems leading to mission performance deficiencies, degradations or adverse effects on mission safety. To achieve this goal, PHM technology is seen as an architecture integrating seven layers (Fig 1) described hereafter.

- *Layer 1: Data Acquisition*
  It provides the PHM application with digitized sensor or transducer data.
- *Layer 2: Data Processing*
  It receives data from the sensors (or transducers or signal processors), and performs signal transformations and features extraction, reduction and selection.
- *Layer 3: Condition Assessment*
  It helps determining the system current state-of-health by detecting and localizing a system fault. It compares on-line data with expected values of system’s parameters. It should also be able to generate alerts based on preset operational limits.
- *Layer 4: Diagnostic*
  It determines if the condition of the system has degraded. The module also generates a diagnostic record and suggests fault possibilities. It permits to isolate and to identify the component that has ceased to operate (past propagation: from effects to causes).
- *Layer 5: Prognostics*
  It predicts the future condition of the monitored system, subsystem or component. The module should be able to acquire data from all previous modules (propagation from causes to effects).
- *Layer 6: Decision Support*
  Its primary function is to provide recommended maintenance actions or alternatives on how to run the system until the mission is completed. It should be done automatically.
- *Layer 7: Human-Machine Interface (HMI)*
  This module receives data from all previous modules. This module could be built into a regular human-machine interface.

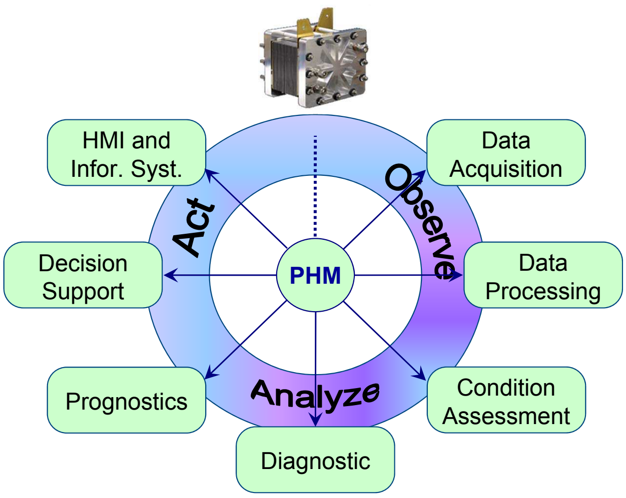

Figure 1: PHM architecture

From this PHM description, the great interest offered by prognostics can be easily guessed. Let’s now focus on this key process.

2.2. *Prognostics as a determining factor*

2.2.1. *Definition and approaches*

Capability to anticipate degradation phenomena and failures have become unavoidable for industrials to meet nowadays global performance requirements. This leads to adopt new maintenance strategies in which waiting for a failure to occur is unacceptable. It can mainly be achieved thanks to prognostics, that appears to be a key process to move from a "fail to fix" to a "predict to prevent" strategy, enabling the improvement of reliability, availability and safety of systems, while reducing costs and down times.
Although there are some divergences in literature, prognostics can be defined as proposed by the International Organization for Standardization: "prognostics is the estimation of time to failure and risk for one or more existing and future failure modes" [6]. In this acceptation, prognostics is also called the "prediction of a system's lifetime" as it is a process whose objective is to predict the Remaining Useful Life (RUL) before a failure occurs, given the current machine condition and its past and future operation profile. Various approaches exist to perform prognostics, and it does not exist a unique classification.
One of them consists in distinguishing three main approaches [7, 8, 9].

- *Model-based approaches* These approaches use analytical models based on the occurring non linear phenomena. They do not require a lot of data. However, it is computationally expensive, system and defect specific, and constructing models can be very complicated.

- *Data-driven approaches* Here raw data is used to construct relevant behavioral models. No *a priori* model of the degradation is needed and it has a good capability to catch the non linearities. Their main drawback is the huge amount of data required to perform prognostics.

- *Hybrid approaches* This category combines model-based and data-driven approaches to take benefits from their advantages. It allows improving the learning of the models and better managing uncertainties. Nevertheless, it can be complex to develop and still computationally expensive. The approach used later in this paper is a hybrid approach, a behavioral model is constructed and updated thanks to the data available.

More details about these approaches and the tools used in each case can be found in [7, 8, 9, 10].

2.2.2. *Performing prognostics*

Whatever the approach used, prognostics is divided into two stages : learning and prediction. During the learning phase, the prognostics tool learns the behavior of the system and updates some of the parameters of the model. This stage lasts until the prediction time chosen is reached, let's call it t_p. At that time, one enters in the prediction phase. The prognostics tool gives the estimated evolution of the system and determines at which time a critical threshold is going to be reached. The duration between the predicted time of failure $t_{failure}$ and the starting point of prognostics t_p gives the RUL. This process is illustrated in Fig 2.
It can be noticed that both a critical threshold and a failure threshold are defined. The failure threshold indicates the End of Life (EoL) of the system. In order to plan mitigation actions (control and/or maintenance), it is more interesting to have a safety time interval. That's why a critical threshold, a little higher than the failure threshold, is defined. It also protects the system in case of late predictions given by the prognostics.
As explained earlier, the main goal of prognostics is to

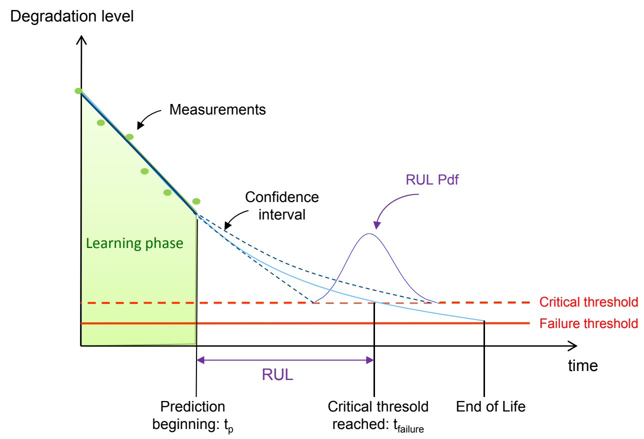

Figure 2: Performing prognostics

predict the RUL. What can be interesting is to know the RUL at each time of the system's life. To achieve this goal, predictions described above are repeated but with a different starting point t_p. The curve obtained can be compared to the actual RUL if the data is available and evaluated thanks to different kind of prognostics performance metrics [11, 12], (Fig 3). A prediction can be considered as a good prediction when the predicted curve enters and stays in the confidence interval. Metrics are more explained and used further in section 4.3.3.
Last, but not least, regarding prognostics is the problem of uncertainty coming with the predictions [9, 13]. This is a major issue in prognostics applications. This uncertainty may come from:

1. the system;
2. the way the system is used;
3. the sensors;
4. the prognostics approach chosen.

Consequently, prognostics framework must take into account this uncertainty at all stages of the process. This uncertainty is illustrated on Fig 2 by the presence of a confidence interval. It means that at each time, the prognostics in fact gives a probability distribution of the possible states of the system. The estimated state evolution is constructed by taking the maximum value of each distribution calculated. Consequently, at the end of the process, the RUL is given with a probability density function (pdf) that will help managing uncertainty.

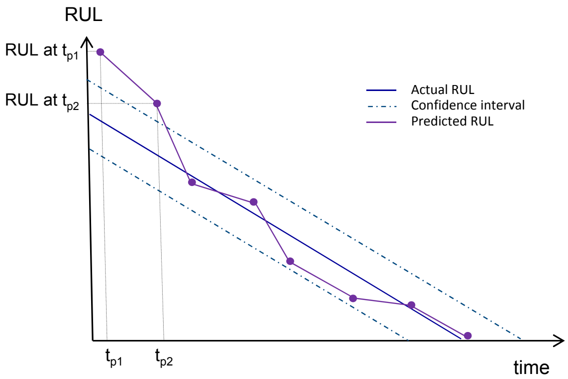

Figure 3: RUL estimates through time

2.3. Application to PEMFC

2.3.1. Motivations

Over the past decade, many successful applications of prognostics have been presented in the literature, that for very different kinds of systems.

- mechanical systems [14, 15];
- machining tool [16, 17];
- cutting tool [18, 19, 20]
- air cooling systems [21];
- space avionics [22];
- electrochemical devices [23, 24, 25].

Hundreds of papers in PHM and prognostics (both theoretical and applied) appear every year in academic journals, conference proceedings and technical reports. By taking a closer look to electrochemical devices, and more precisely to batteries, one can see that applying prognostics and more generally PHM can give very good results. Indeed in [26, 27], on line prognostics performed, thanks to a particle filtering framework, on a UAV (unmanned aerial vehicle) powered by batteries allows adapting fly plans according to the predicted RUL and so land the UAV before the batteries are fully discharged. Another successful application can be found in [28], where an association of Dempster-Shafer theory and particle filter proves to offer good results. For more informations on prognostics methods for RUL calculation in batteries, the readers is invited to refer to [23, 29, 30]. These papers show the applicability on prognostics, and more precisely particle filtering framework, to electrochemical devices; but due to the differences in functioning, behavior or aging between fuel cells and batteries, these examples cannot be directly transposed to fuel cells.
According to such successful applications, prognostics appears to be a very interesting tool for monitoring the state-of-health (SOH) and estimating the RUL of PEMFC with the aim of extending its durability, managing its use or even organizing a PEMFC fleet. Let's now look at what is already existing regarding prognostics applied to PEMFC.

2.3.2. Literature review

Despite the great interest of applying prognostics to PEMFC, only one paper estimating the RUL has already been published until now [3]. It proposes a damage tracking and a RUL prediction by using an unscented Kalman filter framework. A physics-based prognostic-oriented model is implemented in order to link the operating conditions to the degradation rate of the electrochemical active surface area. The main idea is to use the size evolution of this area as an aging criterion. By linking this degradation to the measured output voltage, RUL predictions are performed. The EoL criterion is fixed regarding the size of this area. EoL is declared when it becomes too small to give an acceptable performance in terms of output voltage. The prognostics method performed in this paper shows good results. Yet, the prognostic is performed on a single cell, not on the whole stack and covers a short period of time (300 h). Furthermore, the decrease of the electrochemical active area is not an indicator of all the possible degradations. In an industrial perspective, research has to be reinforced to face those limits.
The rest of the paper is dedicated to PEMFC prognostics using a new approach based on a particle filtering framework.

3. PEMFC prognostics: particle filtering framework

This section intends to set the context and the hypotheses in which the prognostics is performed. But it also sets the bases to construct the prognostic framework and then to use it to perform RUL predictions.

3.1. Context and hypotheses

Before going further, it should be specified that the following work is limited to the stack level, interactions with ancillaries are left aside.

3.1.1. Aging processes in the stack

To be able to study the SOH and the aging of the stack, and consequently performed prognostics, at least one good indicator representing the evolution of the system is needed. A good indicator, in a system as a PEMFC stack, is an irreversible degradation with a slow evolution in time (large time constant). Several candidates can be pointed out, namely the degradation of the catalyst area [31] or the hydrogen rate crossing the membrane [32]. However these parameters are not easily accessible, their measurement strongly disturb the behavior of the stack and accelerate aging processes. Therefore, their evolution, or at least their consequences, must be deduced from other parameters easier of access.

Even if a global and simple enough model does not exist yet, various experiments show that most of the degradation processes, reversible or irreversible, have an impact on the output voltage which is always monitored for control purpose. Consequently, the aging of the stack will be observed and determined by using voltage measurements and predictions.

3.1.2. Operating conditions

There are two ways of soliciting a stack: under dynamic and static conditions. Dynamic conditions are more representative of load profiles that can be found in practical applications. Indeed, when embedded in a vehicle for example, the stack has to deal with start and stop, changing load profiles, changing temperature and weather conditions, etc. However, for first prognostics tests and stack aging experiments, it is more reasonable to consider only a constant or quasi constant current solicitation with environmental conditions remaining unchanged all along the experiments. This hypothesis allows to validate a simple prognostics model that can be little by little completed with new parameters taking into account conditions and phenomena described above.

3.1.3. Model framework

As previously said, an hybrid approach for prognostics is to be set. To ensure the widest application limits while avoiding creating constraints, the model representing the state evolution of the fuel cell should follow these criteria:

- non-exact: it can contain unknown coefficients;
- non-stationary: it can evolve with time;
- nonlinear: even if in fuel cell studies voltage drop is almost always represented by a straight line, there is no reason to restraint it to a linear model;
- non-Gaussian noise: noise distribution might be unknown.

These conditions are characteristics of a nonlinear Bayesian tracking problem [33, 34].

3.1.4. Hypotheses summary

Here the last statements are summarized. The hypotheses considered to construct the prognostics model are the following.

1. Aging processes are irreversible degradations;
2. Voltage drop is an aging indicator;
3. The stack is solicited under constant current in stable environmental conditions;
4. Solicitation is realized at the nominal operating point;
5. Modeling and estimates match a Bayesian tracking problem.

These five hypotheses are used hereafter to construct the prognostics framework.

3.2. Mathematical background - Non-linear Bayesian tracking

A problem of tracking is defined by two equations [33, 34]. The first one, the state model, considers the evolution of the system state. In the case of the fuel cell, the state is the degradation and as the degradation is not directly measurable, it is called a hidden state. The state noted $\{ x_k, k \in \mathbb{N} \}$ is going to evolve following

$$x_k = f(x_{k-1}, \vartheta_k, \nu_k) \tag{1}$$

where f is the transition function from the state x_{k-1} to next state x_k, possibly nonlinear; ϑ_k is the vector of unknown parameters in the model and ν_k an independent identically distributed (i.i.d.) noise. The objective of the tracking is to recursively estimate x_k from measurements introduced by the second equation, the observation model $\{ z_k, k \in \mathbb{N} \}$

$$z_k = h(x_k, \mu_k) \tag{2}$$

where h is the observation function and μ_k an i.i.d. noise. The aim of the tracking problem is to recursively estimate, not directly the state of the system, but the probability distribution of the state at time k by constructing the probability density function (pdf) $p(x_k|z_{1:k})$. It is assumed that the initial pdf $p(x_0|z_0) \equiv p(x_0)$ of the state is available. $p(x_k|z_{1:k})$ can be obtained recursively in two stages:

- prediction:

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1}) p(x_{k-1}|z_{k-1}) dx_{k-1} \tag{3}$$

- update:

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k) p(x_k|z_{1:k})}{p(z_k|z_{1:k-1})} \tag{4}$$

This gives the optimal solution but in many cases it cannot be solved analytically. An approximate solution can be encountered by using filtering framework such as Kalman filter or particle filter depending on the hypotheses of the problem. A review of these filters can be found in [34].

To solve the problem, a particle filtering framework is chosen. This choice is motivated by several reasons. First, it was guided by the classification of the Bayesian methods given in [10]. This leads to consider particle filters.

But there are still many options. The choice is refined by a small literature review regarding particle filter applications in the prognostics field [24, 35, 36, 37]. It shows that the sequential importance sampling (SIS) one gives good prediction if well-used. So a particle filter of the SIS type is chosen for this application.

3.3. Resolution by particle filter

NB: For all that follows, it is important not to confuse the prediction phase in prognostics and the prediction step in the filtering framework.

3.3.1. Principle of particle filtering

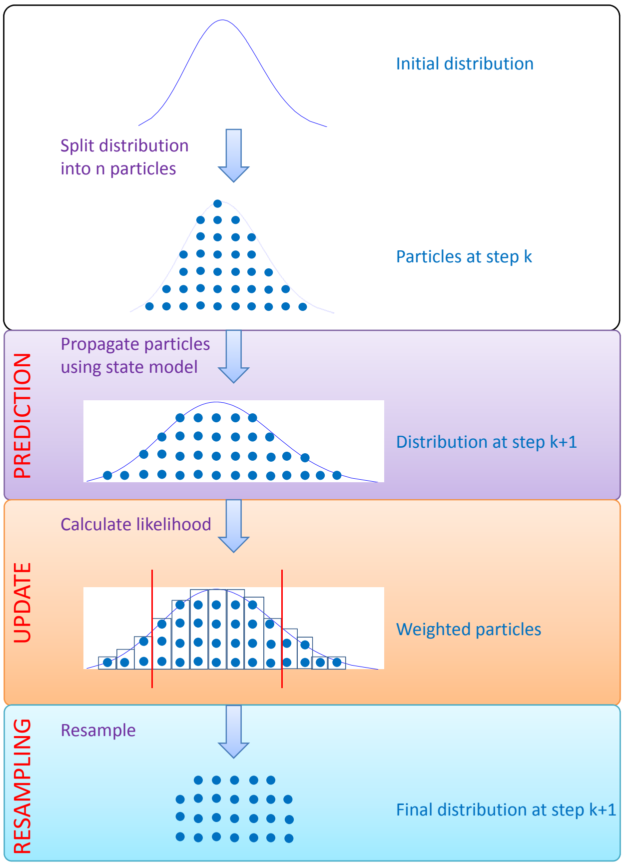

Figure 4: Principle of particle filtering

Particle filter is a Monte Carlo-based tool based on the Bayes' theorem. At the first stage ($k = 1$), the initial distribution $p(x_0)$ is split into n samples, called particles. Then, the following steps are repeated until the end of the process (Fig 4).

1. *Prediction* Particles are propagated from state $k-1$ to state k using the state model. A new pdf is obtained.
2. *Update* The coming of a new measurement z_k allows to calculate the likelihood $p(z_k|x_k)$. This probability shows the degree of matching between the prediction and the measurement. Its calculation allows attributing weights at each particle according to the likelihood. Particles with higher weights represent the most probable states.
3. *Re-sampling* This stage appears to avoid a degeneracy of the filter. Indeed after several iterations, the particle with low weights become too numerous altering the prediction step. Their are different kind of re-sampling strategies but the principle remains the same. Particles with the lower weights (compared to a chosen limit weight) are eliminated whereas the ones with higher weights are duplicated.

3.3.2. Adapting particle filter for prognostics purpose

One filter is used for the learning and prediction phases of the prognostics process. During the learning phase, it works as described above. The behavior of the system is learned and the unknown coefficients in the state model are adjusted consequently. But at the end of this phase no measurement is available anymore, only the state x_k is propagated from stage to another and the likelihood is no longer calculated. The different computed steps are represented on Figure 5.

4. Adaptation of the prognostic framework

4.1. Available data presentation

Only two data sets are available to conduct this prognostics study. They come from two 5-cell PEMFC stacks (quoted FC1 and FC2) with an active area of 100 cm^2. The aging under a constant current of 70A for FC2 and under small variations at high frequency (5kHz) around 70A for FC1 are observed during 1000 hours. More details about the stacks and the experiments can be found in [38, 39]. Eight characterizations are carried out throughout the aging (polarization curve and electrochemical impedance spectroscopy) leading to voltage disturbances, peaks are visible (Fig 6). The voltage signal is filtered to remove the different peaks (Fig 6 and Fig 7).

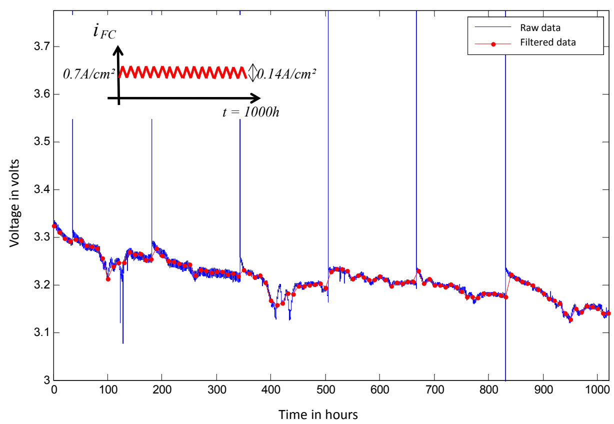

Figure 6: Data used for prognostics - Fuel cell 1

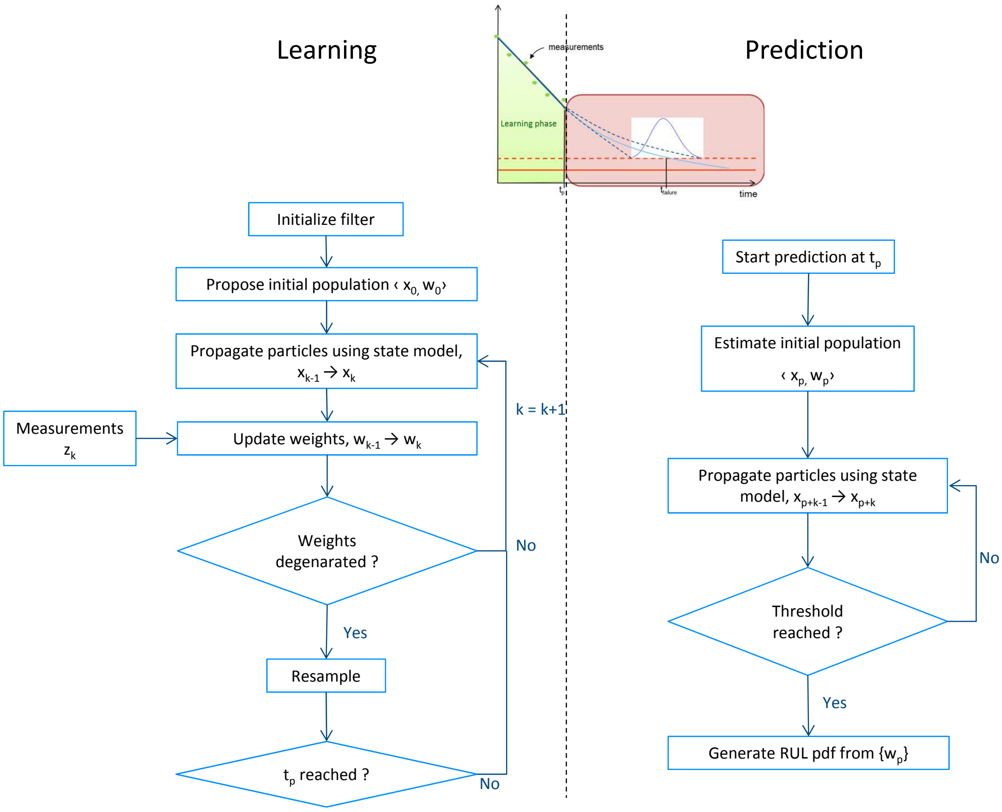

Figure 5: Particle filter framework for prognostics

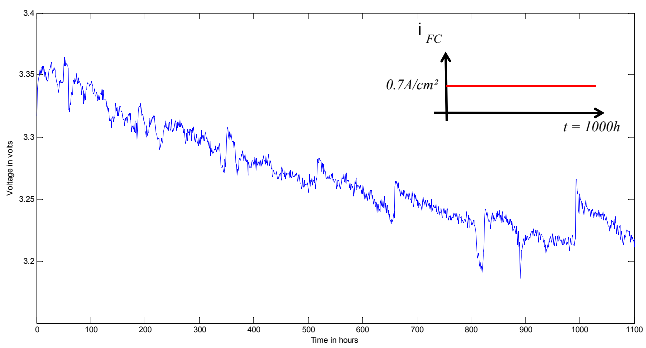

Figure 7: Data used for prognostics - Fuel cell 2

4.2. Formulation for the PEMFC problem

As stated before, in our particular case, the voltage drop is chosen as an indicator of degrading states. Consequently, the state model represents the voltage evolution through time. Moreover, as voltage noisy measurements are available, there is no need to construct a particular observation function.
Given the data available and the problem framework, the following formulation is adopted.

- state model: three models are tested:

$$x_{k+1} = exp(-\beta.(t_{k+1} - t_k)).x_k \tag{5}$$

$$x_{k+1} = -\alpha.ln(t_{k+1}/t_k) - \beta.(t_{k+1} - t_k) + x_k \tag{6}$$

$$x_{k+1} = -\beta.(t_{k+1} - t_k) + x_k \tag{7}$$

  The linear model is commonly used in the literature to represent voltage drop or the degradation rate under constant current and constant operating condition during aging through time [40, 41, 42], but it does not take into account what happens at the very beginning and end of life. This can be modeled either by an exponential or a logarithmic function. However the logarithm would not fit to the voltage drop all along the time, that's why a linear part is added.

- observation model: voltage measurements. Indeed, as real measurements of the voltage are available, there is no need to define a measurement function. The last measurement available is used for the update stage in the particle filter.

It can be seen that there is no adding noise in both model. The process noise is ignored because it can be handled by the uncertainty in model parameters. And regarding the measurement noise, noisy measurements are used, so there is no need to add more noise.

4.3. Simulation settings

4.3.1. Parameters initialization

Before getting good results, the optimized parameters for initializing the filter should be found. In this case, the first series of results and a sensitivity analysis were used to define the initialization.
First, the initial distributions have to be defined. For the initial state x_0, one can guess that the distribution is centered on the initial measured value. If the noise induced by the sensors is known, it becomes easy to construct the initial pdf $p(x_0)$. Else, it is possible to give a uniform distribution, centered on the initial measurement but it might introduce more uncertainties. In this application, a uniform distribution is used, centered on the initial voltage with a range of ± 0.1V around this value.
To guide the filter for the first iterations, the unknown parameters in the state model are also initialized with distributions. It is possible to find a range of values by fitting the models to data. This allows to find the interval in which parameters initial values are located, uniform distributions are defined for each of them. As the two fuel cells have the same characteristics, the initialization remains the same for the different RUL predictions.

4.3.2. Experimental setting

Then the number of particle has to be chosen. The higher it is, the better the predictions are. However, it can lead to huge calculation times. By refining the parameters initialization, the number of particles can be diminished. In [43], a methodology to choose the optimal number of particles in each application is proposed but it implies to launch numerous times the filter to make statistics and choose the number of particles. For the results presented in this paper, 2000 particles are used. This value was defined thanks to a sensitivity analysis, which also shows that only one measurement each fifteen hours is enough to help learning the model and then giving good predictions. As these parameters just rely on the particle filter computation, only one sensitivity analysis was conducted.

4.3.3. Evaluating the results with prognostics metrics

To construct the RUL evolution in time, a prediction is made each 50 hours, starting from 100 hours to 950 hours. Each prediction is calculated 100 times in order to evaluate the dispersion of the results given by the particle filter. As a first step, the predictions are evaluated with a classical prognostics metrics: the α-performance metrics. It evaluates the probability of the RUL falling in the time windows $[(1-\alpha).t_{failure} \quad (1+\alpha).t_{failure}]$. That means the prediction can be considered as a good prediction if it enters in an interval of $\pm\alpha$ around the real RUL. A prediction located under this interval is called an early prediction, one located above is a late prediction. Here $\alpha = 5\%$ is chosen.
Finally, a failure threshold has to be defined. Considering that the two stacks aged differently, one threshold is defined for each test. Regarding the length of the experiment, the threshold is fixed to 94% of the initial power performance for FC1 and to 96% for FC2 , namely 3.127 V and 3.212 V speaking in terms of voltage. Working on complete data sets allows first, checking that the defined failure thresholds are not located on particular voltage peaks that would be located out of the aging trend and so would not reflect the behavior of the stack. And then it will help verifying the prognostics results.

4.3.4. Illustration

The previously defined experimental setting and the failure threshold are used to perform behavior predictions and RUL calculations. An example is given on figure 8. It represents one prediction among the 100 for a training with 400 hours applied to FC1 and using the exponential model. The estimated behavior is represented with a confidence interval, the real behavior is also drawn for visual comparison. Indeed, when the particles are propagated at each time step a new distribution of particles is created representing the last predicted state (see section 3.3). All these distributions can not be represented, the figure would be unreadable. So the curve called estimated voltage is drawn thanks to the successive positions of the top of the particles distribution, while upper and lower bounds are its edges. The RUL distribution is in fact the final particles distribution obtained when the failure threshold is reached.

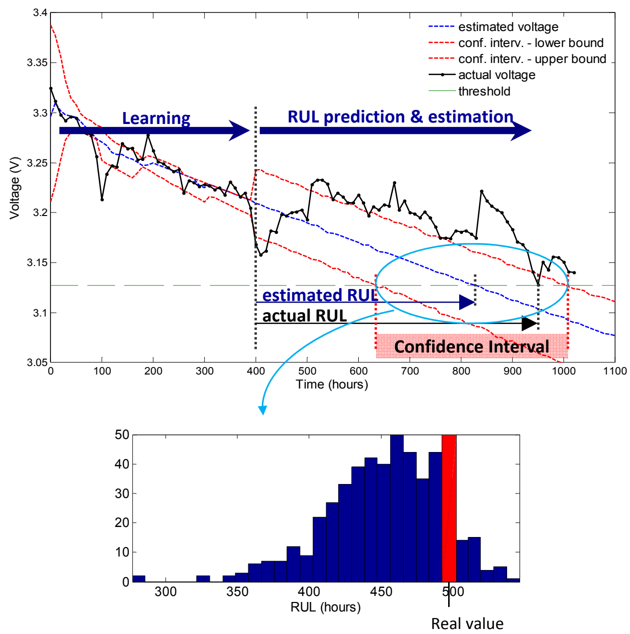

Figure 8: Behavior prediction and RUL construction for a 400 hours long training for fuel cell 1

5. Results and discussion

5.1. RUL estimates vs time - comparison of the models

The three RUL evolutions corresponding to the different models are represented for both stacks (Fig 9 and Table 1). Eighteen points are used to construct these evolutions. It means the initial learning phase is 100 hours long and after new calculations are launch adding 50 hours to the learning phase. The last prediction is made with 950 hours long learning phase which already very close to the failure time. The points drawn are the median of the 100 predictions. First we compare the three models for each stack and then stack between them.

- *Stack 1.* Considering the upper part of figure 9, it can be seen that the exponential model underestimates the RUL, even if it is not so far from the 2α interval. And by leaving two points from the middle part aside, it seems to have a constant bias on the prediction. The linear model shows predictions always in the interval when the starting point for prediction is higher than 150 hours. Nevertheless, these predictions are very often upper the real RUL indicating late predictions. Then regarding the logarithmic model, it needs at least a length of learning data of 200 hours. It goes once out of the 2α interval. But looking at the voltage, it can be seen that there is a disturbance between 300 and 500 hours, and the voltage drop trend is deviated. In fact, this affects the three models predictions.

- *Stack 2.* Regarding the exponential model, the same remark can be done, except for the bias, no particular bias appears in this case. The linear model is less good than with the other data and enters the interval only after 700 hours. Finally, the logarithmic model gives clearly the best predictions.

Table 1: RUL estimates evaluation with the α-metrics

		Linear	Exponential	Logarithmic
FC 1	Early Prediction	0	17	4
	On-time	17	1	13
	Late prediction	1	0	1
FC 2	Early Prediction	10	16	4
	On-time	8	2	14
	Late prediction	0	0	0

Taking a closer look at Table 1, the linear and logarithmic models clearly give a great number of predictions on time. However, only the logarithmic one shows some stability with 13 and 14 predictions on time. By stability, we mean it shows a great ability to give on time predictions with different sets of data. By concentrating on late predictions for this model, it can be seen that most of them are located in the first estimates. It is not abnormal that the model fails to catch the behavior of the system when it has a too short training. Here, it can be noticed that data longer than 200 hours is necessary for training. The voltage trend is not enough drawn before. Then, it can be pointed out that for the two last points (t_p=900 and 950 hours), all the models tend to give negative values of the RUL, that's something to correct because a time duration can not be negative. A first conclusion is that the exponential model can not catch the behavior of the stack on 1000 hours. A second one is that the logarithmic model, leaving aside predictions with a learning phase shorter than 200 hours, seems to offer a great stability, better than the linear one.
Let's now refine this second conclusion by considering the dispersion on the 100 simulations for each prediction.

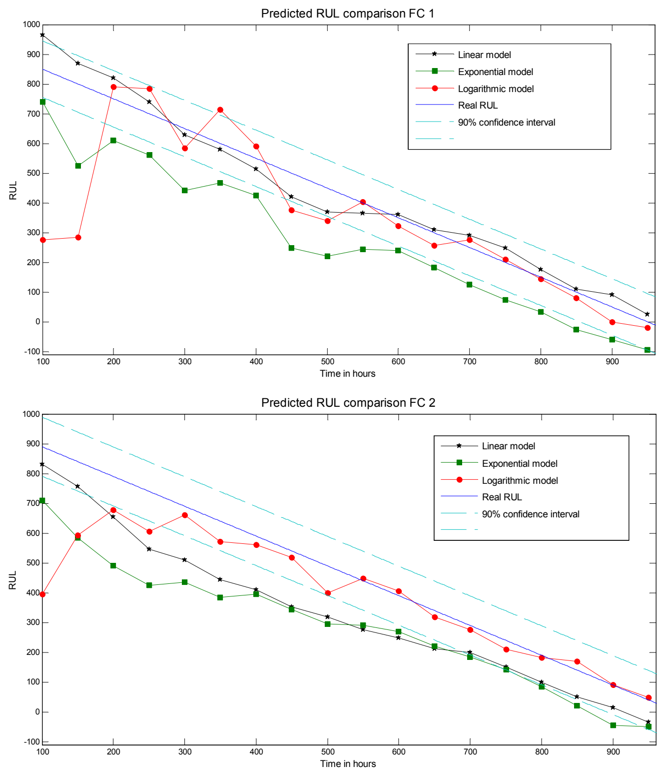

Figure 9: RUL predictions for both stacks

5.2. Linear vs Logarithmic - Dispersion of the estimates

The exponential form can be eliminated for the continuation, but RUL predictions on stack 1 show that both linear and logarithmic models can give interesting results. One way to chose the best one is to compare the distributions of error given by the 100 simulations. Only results with a training longer than 200 hours are compared.
The absolute error for each model and stack can be seen on Figures 10 and 11. On each box, the central red mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data

points not considered outliers, and outliers are plotted individually by red crosses. To help comparing, on the third graph on each figure, the median error with the 25th and 75th percentiles are plotted. The positive and negative signs are kept to highlight the late predictions.
It clearly shows a larger dispersion of the predictions for the logarithmic. Indeed, the average value of the dispersion is 234.3 hours for the logarithmic model against 82.8 for the linear one (Table 2). It means that even if the RUL predictions are better and more stable with the logarithmic model, the uncertainty associated to results is non-negligible. Here comes the issue of choosing between the stability and the reliability of the predictions. It can be dangerous for the system to take decisions based on predictions dealing with uncertainties of 100 hours, especially for systems with an order of magnitude of 1000 hours as the life duration as PEMFC.

Table 2: Error dispersion between 25th and 75th percentiles on RUL predictions

	Linear	Logarithmic
Minimum range	31.5	112.5
Average range	82.8	234.3
Maximum range	150	388

Even if we have to deal with large uncertainties, the logarithmic model offers median predictions in a ± 90 hours interval if we can learn the model with data ranging up to 200 hours for the learning phase. It becomes even better when the model can learn the 500 first hours, with predictions in the interval $[-25 \quad +50]$ around the real RUL value. It also proves that the linear model used most of the time in the literature to represent the voltage drop shows some limits when it comes to precise modeling.
To sum up, this prognostics model demonstrates prediction with an accuracy of 90% for an horizon of 800 hours and at least 95% for an horizon of 500 hours. Nevertheless, some hypotheses limits its applications, particularly in real conditions. Some possible ways for improving this prognostics framework are now discussed.

5.3. Discussion: improving the results

These results are very promising, however they still suffer from too high uncertainties and do not take into account operating condition variations. Indeed characterization measurements introduce disturbances that are not modeled. One can observed a self healing after each characterization campaign that clearly change the behavior tendency. The same remark can be done with reversible degradations like flooding or drying which also temporarily modify the behavior of the stack or the influence of the current ripple [38]. These phenomena creates small voltage drops that make the voltage reach the failure threshold before the EoL and lead basic models to false predictions.

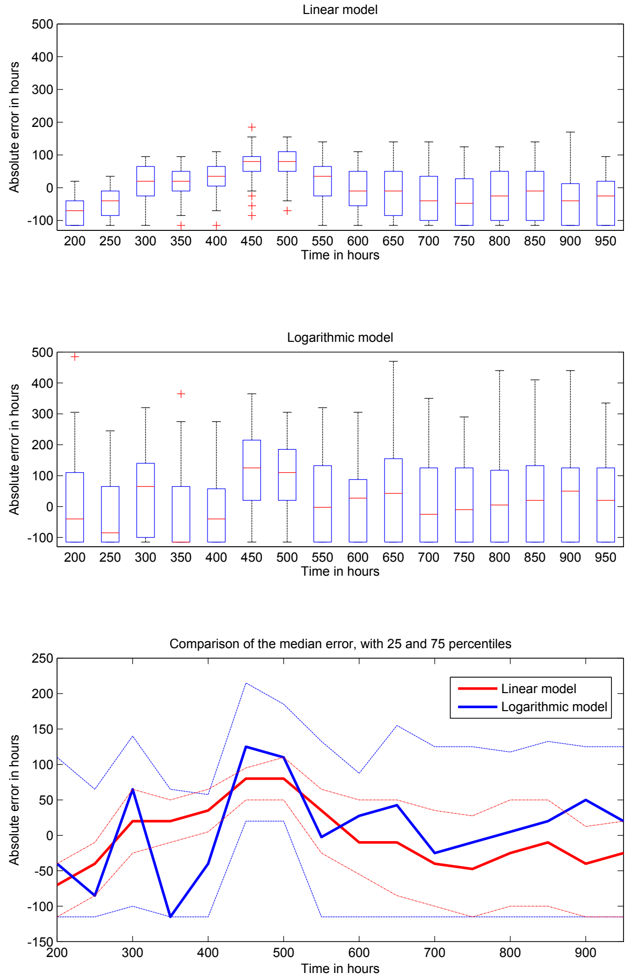

Figure 10: Comparison of absolute error between linear and logarithmic models for FC1

Then, we conclude that the logarithmic model may lead to the best results in the future. This result needs to be further confirmed with data acquired on different stack technologies. It can be interesting to test it on larger stacks as well and to investigate the single cells' signals in case of non-uniform behavior in the stack. It is also important to mention that considering the uncertainties due to the model, some improvements might also be brought to fit better to the behavior. It can be achieved by adding new terms in the model that will catch better small variations in the voltage. Finally, it is necessary to completely eliminate late predictions because they can be disturbing for the decision making process linked to prognostics.

6. Conclusion

Prognostics appears to be of great interest to help extending PEMFC lifetime. This paper presents a prognostics framework allowing remaining useful life predictions with an accuracy of ± 90 hours on a 1000-hours lifetime. It also questions the way voltage drop is modeled when the

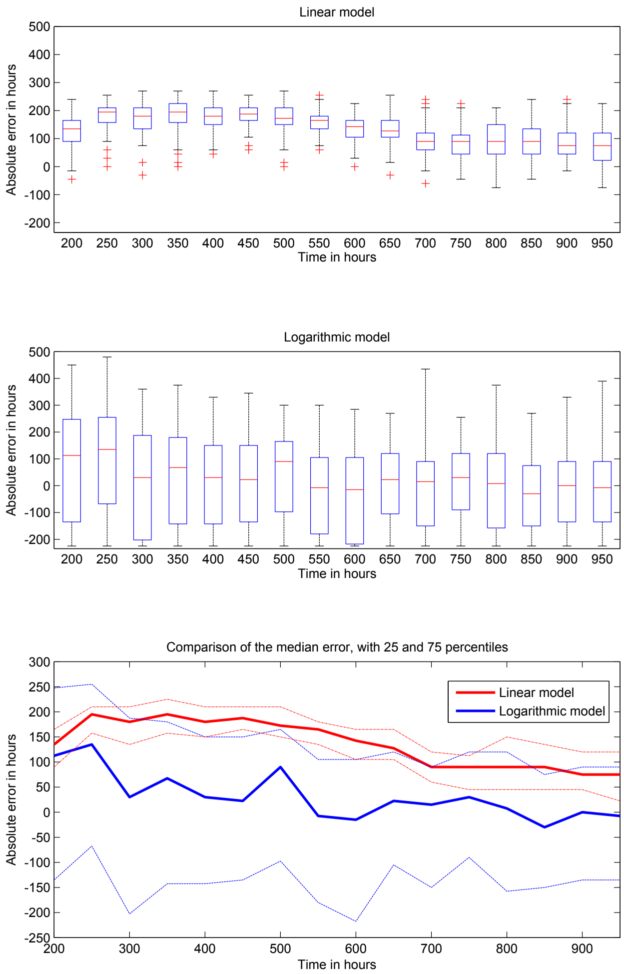

Figure 11: Comparison of absolute error between linear and logarithmic models for FC2

stack is solicited with a constant current, showing that a model combining a logarithmic and a linear part is more efficient that a simple linear model.

The use of a particle filtering framework allows predicting the future behavior and estimating the remaining useful life while taking into account the uncertainties related to the predictions. Repeating 100 times the predictions and taking the median one offers very good results. The error existing in RUL predictions demonstrates the multiplicity of phenomena that should be taken into account in the model such as electrochemical impedance spectroscopy (EIS) or intrusive measurements performed for characterization purposes, or variations in the operational conditions leading to reversible degradations.

The following step in this work will be to integrate them in the prognostics framework as well as mission profiles with variable loading conditions. The case variable loading conditions highlights one major limit of that work: its validity with changing conditions. In the case of a stack used in another value of constant current solicitation, initial values of the parameters just have to be adapted by a new fitting to perform prognostics, but in the case of variable loading conditions, the state model, and consequently the prognostic, will no longer be valid. That's one of the ongoing issues in the PHM community: most of prognostics approaches are valid for the particular problem and hypotheses they were designed for but also the major challenge to pursue this work.

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