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Extended Kalman Filter for prognostic of Proton Exchange Membrane Fuel Cell

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The Proton Exchange Membrane Fuel Cell is a promising energy converter for various fields of application: stationary, portable and mobile. However durability avoids its widespread deployment. Deterioration mechanisms are not all fully understood and that is the reason why the prognostic of such device is gaining attention. This helps determine the present and future state of health of Fuel Cell, to deduce the remaining life in order to take corrective actions. The work presented in this paper attempts to address this issue by proposing a method based on a degradation model. An observer, based on an Extended Kalman Filter, estimates the state of health and the dynamic of the degradations. This result is extrapolated until a threshold is reached and the residual life is deduced. This method allows estimating the lifespan with a single model, robust to uncertainties, whatever the operating conditions are. Simulations are conducted to validate the method. Finally, this framework is used on a set of experimental data from long term test on a 5-cell stack operated under a constant current solicitation.

1. Introduction

In a context of declining fossil energy resources and global warming, it is imperative to begin an energy transition. This transition involves the use of renewable energy, highly intermittent in most cases. The storage of this energy is complex and most of the storage device does not meet the requirement of efficiency, lifespan, power density and cost [1]. The use of hydrogen as an energy vector and the Proton Exchange Membrane Fuel Cell (PEMFC) to convert it into electricity seems to be a promising alternative to fossil energy [2]. Besides the transportation domain, PEMFC showed also their interest to supply energy to systems of small size such as mobile electronic devices [3] and also for micro-CHP

(Combined Heat and Power) applications [4]. However, PEMFC systems suffer from multiple impairments that lower their lifespan and prevent their widespread deployment. These degradation mechanisms are irreversible and are not all fully understood. They include the deterioration of the carbon support, the dehydration of the membrane, or a catalytic degradation [5]. The voltage drops associated to these phenomena are difficult to predict because they depend also on the operating conditions [6].

This is the reason why the Prognostic and Health Management (PHM) of PEMFC is gaining attention. This allows monitoring, diagnosis, prognostic, and help determine corrective action to extend the life of the power converter [7]. Using relevant data from the system to monitor, one can build indicators of the state of health as well as their trends. It allows to plan preventive maintenance at the right time, and so reducing costs. Moreover, knowing the state of health and remaining life of a fleet of energy sources (e.g. batteries and PEMFC), one can estimate the power that can

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be delivered individually by these sources and decides to adapt the energy distribution. It allows to increase the service time of the system or to ensure that the mission is completed successfully. Although papers concerning prognostic of fuel cell begin to appear, the range of application of the methods developed is limited to a single operating condition. One of the major objective of this paper is to tackle this limitation by proposing an algorithm able to perform prognostic for different operating conditions, static or dynamic.

In this context, this paper contributes to observer-based prognostic of PEMFC. It deals with the estimation of the State of Health (SoH) and its evolution in future time using a degradation model and an Extended Kalman Filter (EKF). The determination of the Remaining Useful Life (RUL) of a PEM fuel cell is therefore deduced. This novel method has the advantage of working for different operating condition (current, temperature etc.) without extra training or reconfiguration of the model. In Section 2, some generalities about prognostic and a state of the art of prognostic applied to PEM fuel cell are introduced. A description of the experimental setup and the performed test can be found in Section 3. Section 4 presents a model of degradation of PEMFC, a damage tracking and a damage prediction algorithm based on an Extended Kalman Filter to estimate the RUL. The parameterization of this algorithm and its robustness to model errors are also discussed. An application of this method to a 5-cell stack is then shown. Finally, a conclusion is provided in Section 5.

2. Prognostics of PEM fuel cell

2.1. Background

PHM is an advanced system maintenance strategy which aims to improve the safety, reliability while reducing maintenance costs. It combines different tools that can be separated into seven layers (Fig. 1) [8,9].

- Data acquisition.
- Data processing (signal processing, features selection).
- Condition assessment.
- Diagnostic.
- Prognostic.
- Decision support.
- Human Machine Interface.

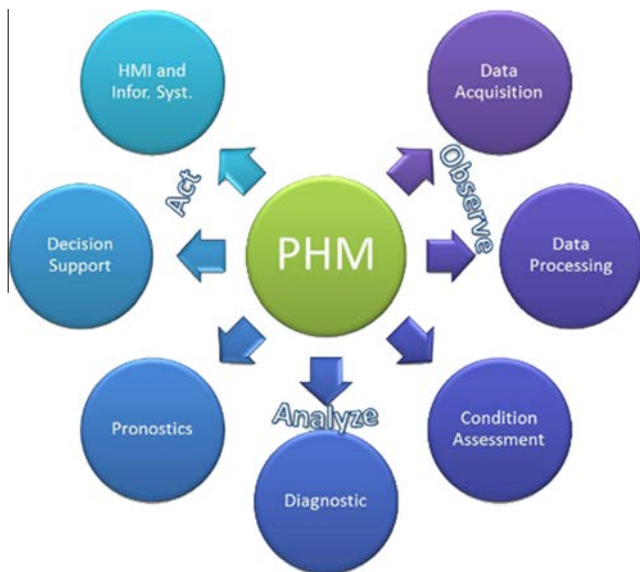


Fig. 1. PHM scheme [9].

- Decision support.
- Human Machine Interface.

This paper mainly focuses on the prognostic layer. It is defined by the International Organization for Standardization as "the estimation of time to failure and risk for one or more existing and future failure modes" [10]. In other words, it is the prediction of the remaining time of a system before a failure occurs. The failure is defined as the inability of a system to perform a given task. In the case of a PEMFC, the US Department of Energy (DoE) considers that the power converter no longer fulfilled its function when it lost 10% of its nominal power [11] (for transportation applications). The prognostic activity is therefore divided into two sub-activities; the first is to estimate the current state of health of the system and to predict its evolution until the chosen failure criterion is reached. The time difference between the predicted end of life $t_{failure}$ and the time when the prediction is made t_{pred} provides the RUL at time t_{pred}

$$RUL(t_{pred}) = t_{failure} - t_{pred} \quad (1)$$

Prognostic can be categorized into three approaches:

- Model-based: use an empirical or physical model of degradation. This method does not require a lot of data. However, building such a model is not a trivial task. Indeed, the degradation phenomenons might not be fully understood and require investigations. It is this approach that has been implemented later in this paper.
- Data-based: This method does not require a *priori* knowledge of the system and captures strong non-linearity. However this approach requires a large amount of data.
- Hybrid: is a combination of the two previous methods. This approach improves the training, although, it remains computationally expensive.

Model-based methods have been used for prognostic in different fields:

- Mechanical systems [12,13].
- Electronic systems [14].
- Turbines [15,16].
- Electrochemical devices [17–20].

Such a success in various areas has motivated the work presented in this paper.

2.2. Literature review

Despite the advantages PHM tool offers, there are still few applications of RUL estimation of PEMFC in the literature. Indeed, only three papers were identified.

Zhang and Pisu [21] proposes a physics-based degradation model of the Electro-Chemical Active Surface Area (ECSA) which is used as an indicator of the fuel cell aging process. The estimated degradation of this surface is linked to the measured voltage, and the algorithm is able to predict its evolution. When the predicted surface becomes too small, the estimated voltage reaches a threshold, the End of Life (EoL) is declared and the RUL is given. The damage tracking and damage prediction algorithm are based on an Unscented Kalman Filter (UKF). This method was successfully applied in simulation with a dynamical load. However, as explain above the ECSA is not the only indicator of the aging of the fuel cell. Therefore research has to be carried out to overtake this limit.

Jouin et al. [7,22] proposes an adaptation of Particle Filtering (PF) based on a Monte Carlo method for PEMFC prognostics. Three

empirical voltage degradation models are tested: a linear, an exponential and a log-linear model. The model also includes the characterization disturbances as described in the next section. The PF allows estimating recursively the probability density function (pdf) of the state of the model during the learning phase. Once no measurements are available, only the future state is predicted using the parameters obtained during the learning phase. When the estimated voltage reaches a threshold at $t_{failure}$ the RUL is given. This algorithm has been applied to two sets of data (constant load with and without current ripples on a 5-cell PEMFC stack) with the three models above. The paper states that the log-linear model gives the best results in both sets of data. Indeed, this method is able to estimate the remaining useful life with 95% of accuracy after 500 h of operation. However, the model does not take into account of the operating condition (load, temperature) and need to be further investigated.

In Chen et al. [23], a rapid lifetime prediction formula is developed. It aims at estimating the voltage drop rate on a bus driving cycle using experimental voltage degradation rate during start-stop, idling, load change and high power load measured on a PEM fuel cell in the lab. The authors noted that environmental factors affect the rate of degradation (including air quality). This is the reason why a correction factor is estimated online every week. It is equal to the ratio between the voltage drop rate of the tested driving cycle in the lab and measured on the bus. This method is tested on two fuel cell buses and gives accurate prediction of the voltage degradation rate. Nevertheless, the authors consider a linear degradation of the voltage which do not reflect the real aging of a PEM fuel cell especially at the end of life.

3. Experimental setup

The considered PEMFC is a commercially available five cells stack with an area of 100 cm^2 and with a nominal current of 60 A. A 10 kW test bench (Fig. 2) supplies the fuel cell in humidified air to the cathode and humidified hydrogen to the anode. Moreover the temperature, pressures and flows are regulated. The operating conditions are summarized in Table 1.

This stack is operated under a constant load (60A) for 1500 h which corresponds to the nominal current given by the manufacturer. Fig. 3 shows the evolution of the stack voltage during the long time test. Moreover, characterizations are performed periodically on the stack during the test period. It involves measuring the static response (with a polarization curve, see Fig. 4) and the dynamic ones (with an Electrochemical-Impedance Spectroscopy) throughout the life of the PEM. These characterizations provoke voltage perturbations (see Fig. 3).

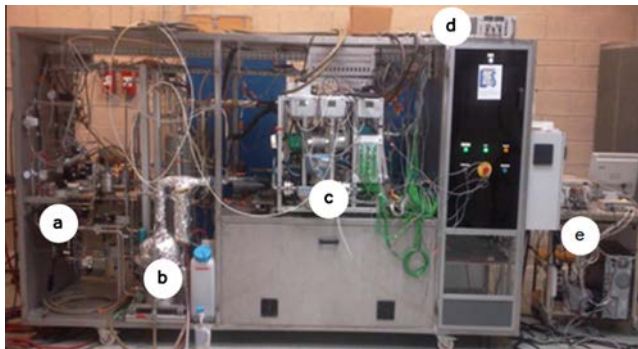


Fig. 2. 10 kW in-lab test bench, (a) air and hydrogen supplies, (b) humidifiers, (c) cooling system (the PEMFC is located behind), (d) electrical load, (e) control and acquisition unit.

Table 1
Operating conditions.

Parameter	Value
Anode and cathode stoichiometry ratios	1.5–2
Relative humidity anode/cathode	50%
Temperature	60 °C
Absolute pressure anode/cathode	1.5 bar
Nominal current	60 A

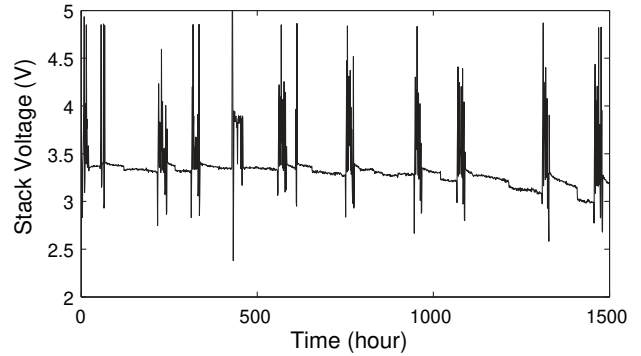


Fig. 3. Stack voltage degradation.

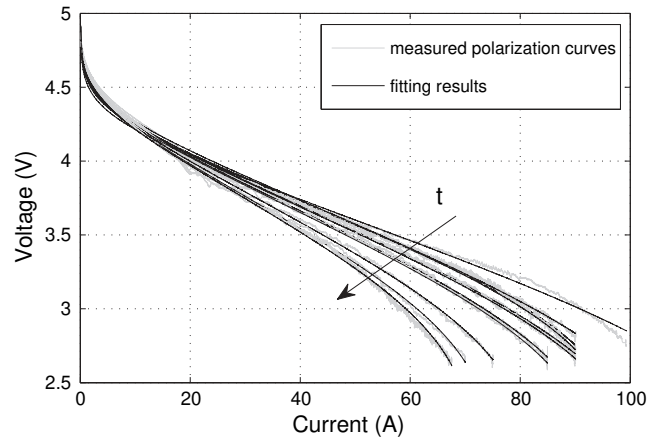


Fig. 4. Polarization curves during aging.

4. PEMFC prognostic in a Kalman filter framework

In this paper, the methodology used for the prognostic is inspired by the work of Celaya et al. [24] adapted for PEM fuel cell. This procedure is presented in Fig. 5.

A nonlinear Levenberg–Marquardt optimization method is applied on the characterization data (see Fig. 4) to identify the parameters of a static model and to determine the representative aging factors as presented in Section 4.1. The evolution of the selected parameters is afterward used to develop an empirical model of degradation. At each sample time, an Extended Kalman Filter estimates the SoH and its variation. Based on these information, the RUL is deduced. The robustness of the method to modeling errors is presented in Section 4.4 and results on experimental data have been detailed in Section 4.5.

4.1. Model of PEMFC including degradation

To identify the parameters of the system at each characterization time, a Levenberg–Marquardt optimization algorithm in its

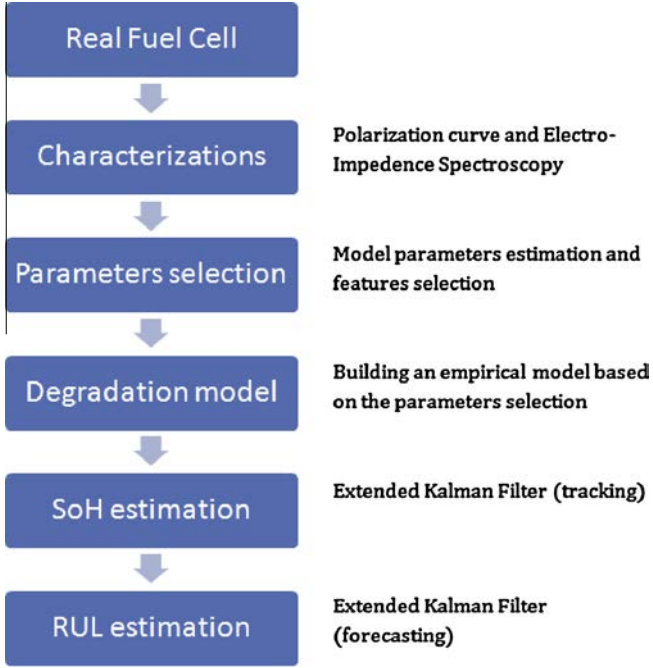


Fig. 5. Model-based prognostics methodology for PEMFC.

non-linear version is used. This algorithm is only capable of minimizing the error locally. To overcome this limit, standard values available in the literature [25,26] have been used to initialize the parameters. To describe the polarization curve this model is used for identifying [25]:

$$V_{st} = n \left(E_0 - Ri - AT \ln \left(\frac{i}{i_0} \right) - BT \ln \left(1 - \frac{i}{i_L} \right) \right) \quad (2)$$

V_{st} the stack voltage i the current, n is the number of cells, T the temperature, A the Tafel constant, and B a concentration constant. The parameters identified for this static model are:

- The Open Circuit Voltage E_0 (OCV) for a given temperature and pressure
- The total resistance R (membranes, end plates, connectors, etc.)
- The exchange current i_0
- The limiting current i_L

Fig. 4 shows the polarization curves measured during the life of the PEMFC and the fitting of the model. The evolution of the identified parameters through time is represented in Fig. 6.

From the four identified parameters during aging, only two are evolving significantly versus time. The overall resistance increases by more than 50%. This loss of conductivity may result in degradation of the polymer membrane, the corrosion of the plates (increase in contact resistance), the dehydration of the membrane, or the corrosion of the catalyst support [27]. The decrease in the limit current (i_L) of 45% reflects the apparent reduction in the mass transfer that may be due to the ripening of the platinum particles, compression of Gas Diffusion Layer (GDL), and change on the surfaces that make evacuation of water more difficult. The exchange current i_0 and also the OCV are considered as constant later in this paper.

Moreover, it seems that the evolution of the parameters follows a linear equation; this has motivated the creation of an empirical model of parametric degradation. For a given current, it is impossible to estimate separately the influence of parameters on the stack voltage. It was therefore chosen to link the change in the

resistivity and the current limit by a single parameter $\alpha(t)$ that reflects their time deviation.

$$R(t) = R_0(1 + \alpha(t)) \quad (3)$$

$$i_L(t) = i_{L0}(1 - \alpha(t)) \quad (4)$$

$$\alpha(t) = \beta t \text{ with } \beta \text{ nearly constant.} \quad (5)$$

4.2. State of health estimation

4.2.1. Problem formulation

In this context of a joint estimation of state and parameters, the system is described by the non-linear system:

$$x_{k+1} = Ax_{k|k} + w_k \quad (6)$$

$$y_k = g(x_k, u_k) + v_k \quad (7)$$

where x_k represents the state of the system, u_k the inputs (current and temperature), y_k the output (stack voltage), w_k and v_k process and observation noises supposed Gaussian with zero mean and with variances Q and R respectively. Since aging phenomena have time constants much higher than the other dynamics of the PEMFC (temperature, electrical and hydraulic phenomenon), the latter are ignored. The equations of state are therefore summarized by the dynamics of aging α_k which is the State of Health indicator and its derivative β_k .

$$x_k = [\alpha_k \ \beta_k]^T \quad (8)$$

$$A = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} \quad (9)$$

$$g(x_k, u_k) = n \left(E_0 - R_0(1 + \alpha_k)i_k - AT_k \ln \left(\frac{i_k}{i_0} \right) - BT_k \ln \left(1 - \frac{i_k}{i_{L0}(1 - \alpha_k)} \right) \right) \quad (10)$$

with T_s the sampling period. The stack voltage V_{st} (which includes the degradation model) given in the previous section is used as measurement as seen in Eq. (10). The algorithm of the discrete Extended Kalman Filter is:

initialization

$$x_{0|0} = E[x(t_0)]$$

$$P_{0|0} = \text{Var}[x(t_0)]$$

prediction

$$x_{k|k-1} = Ax_{k-1|k-1}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q$$

correction

$$K_k = P_{k|k-1}H_k^T(H_kP_{k|k-1}H_k^T + R)^{-1}$$

$$\text{with } H_k = \frac{\partial g(x_k, u_k)}{\partial x_k}$$

$$P_{k|k} = (I - K_kH_k)P_{k|k-1}$$

$$x_{k|k} = x_{k|k-1} + K_k(V_{stk} - g(x_k, u_k))$$

Since the Kalman filter is a linear algorithm, it can only guarantee a local convergence of the estimates. However, the EKF is able to give satisfactory results and this is the reason why it is wide used in estimation problems [28]. Moreover, with this formulation, it is possible to estimate the SoH for different operating conditions.

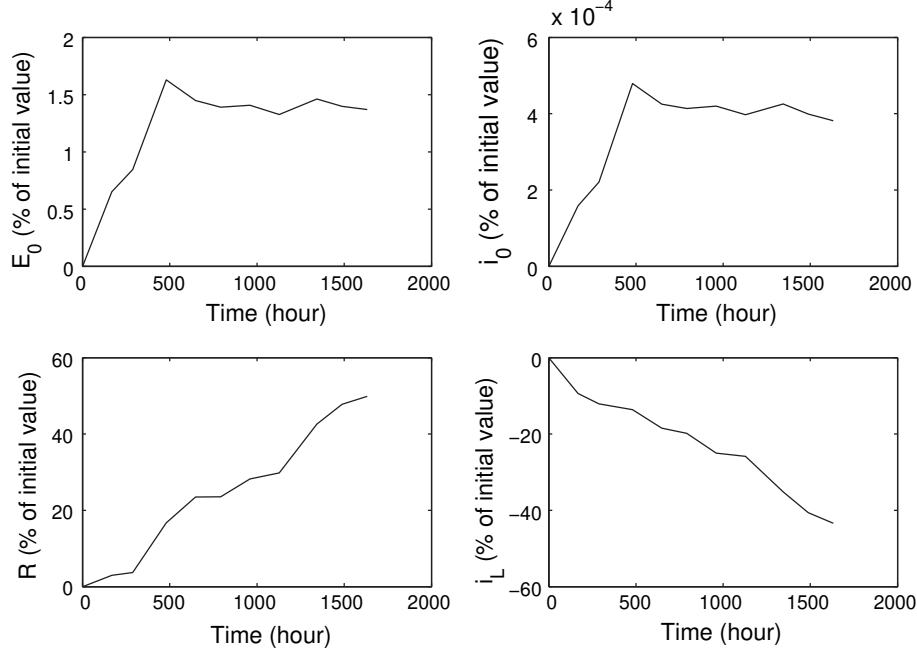


Fig. 6. Parameters deviation during aging.

4.2.2. Setting of the EKF

In practice, process and measurement noises Q and R are difficult to obtain. Therefore, they are often used as tuning parameters. Laroche et al. [29] proposes a methodology for the tuning of Q for parameters tracking. The component of the diagonal is chosen as the square of the typical variation of parameter on a sampling interval. To ensure the convergence in less than 500 h and without being too sensible to the noises, Q and R are chosen:

$$Q = \begin{bmatrix} 0 & 0 \\ 0 & (10^{-6})^2 \end{bmatrix} \text{ and } R = 1 \quad (11)$$

Moreover, the Kalman filter requires an initialization of $x_{0|0}$ and $P_{0|0}$. The degradation rate is assumed unknown and so $x_{0|0} = [0 \ 0]^T$. $P_{0|0}$ is set by running the EKF at a smaller sampling time for about a thousand iterations, which is equivalent to solve the algebraic Riccati equation in steady state.

$$AP_{k|k}A^T - P_{k|k} - AP_{k|k}H_k^T M H_k P_{k|k} A^T + Q = 0 \quad (12)$$

with $M = (H_k P_{k|k} H_k^T + R)^{-1}$

where H_k is the observation matrix with $\alpha_k = \alpha_{max}$ the maximal parameter deviation allowed.

4.2.3. Estimation result from simulation

The aging of a PEMFC under a constant load is simulated using the data from Fig. 6 and the voltage model from Eq. (2). Figs. 7–9 show the output voltage V_{st} , the aging factor $\alpha(t)$ and the parameter $\beta(t)$ of the model as well as their estimates by the SoH estimation algorithm.

It is noted that the algorithm converges in 500 h (with a hourly sampling period). The state of health $\alpha(t)$ and the degradation rate beta are well estimated despite a zero initialization of the initial state $x_{0|0}$. To help the Kalman filter, one can give an *a priori* value of the rate of degradation $\beta(t_0)$.

To verify the effectiveness of the method under other operating conditions, a change in the current load at $t = 800$ h is simulated. One can notice in Fig. 10 that the estimated voltage tracks accurately the measurement voltage. A variable load profile reflects

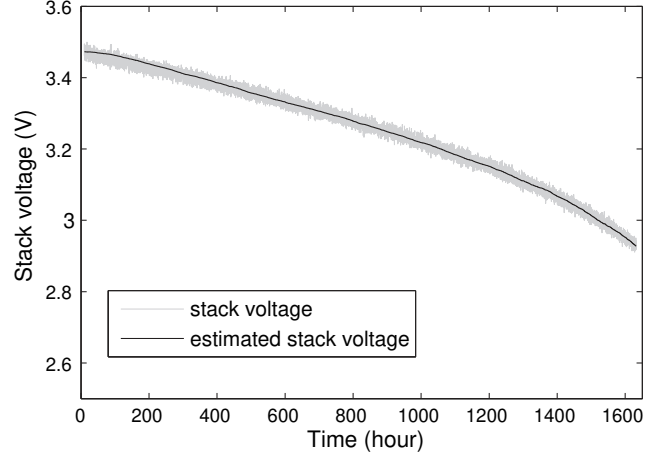


Fig. 7. Voltage degradation and its estimation.

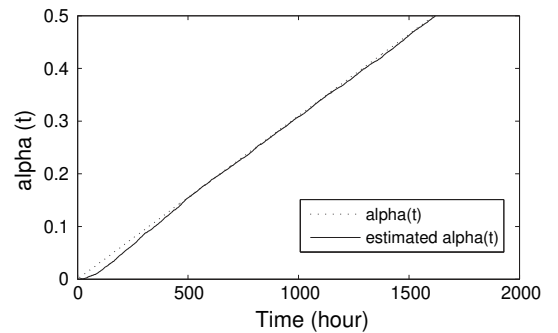


Fig. 8. $\alpha(t)$ estimation.

better the real application of the PEMFC and this is the reason why the algorithm should be able to estimate correctly when a change in the operating conditions is performed (not experimentally tested in this paper). The estimation of the State of Health under a variable load profile will be the subject of future work.

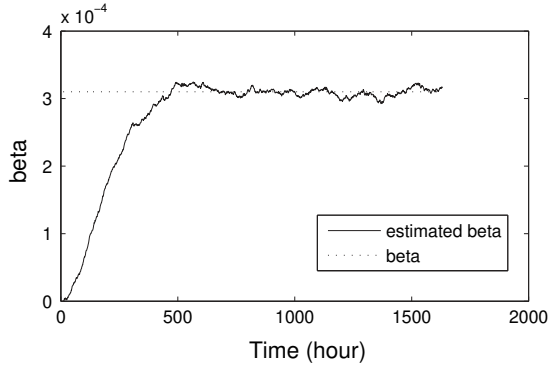


Fig. 9. $\beta(t)$ estimation.

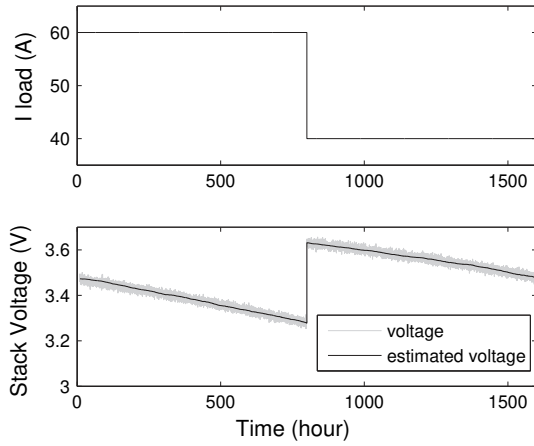


Fig. 10. Voltage degradation estimation under different constant load currents.

In this work, the degradation speed is supposed quasi-constant between two sample times. In practice, the operating conditions are affecting the durability of the fuel cell [30].

4.3. Remaining useful life estimation

The previous algorithm estimates at every sampling step the state of health α_k and its evolution β_k . This information is provided to a prediction algorithm as detailed in Fig. 11. At each sample time k , a prediction of the future SoH is computed until it exceeds a threshold that is defined as α_{max} , the RUL is given as the output data of the algorithm. This process is repeated each time a new estimate of the SoH is available.

Using our simulation case with a maximum parametric deviation $\alpha_{max} = 50\%$, the stack has a life of about 1550 h. This value is used as an indicator of good prediction. To obtain satisfactory results, our estimated RUL should be within the bounds $\pm 10\%$ of the real RUL. Fig. 12 shows the results of the estimation algorithm RUL.

One can notice that in the first 200 h, the RUL is over-estimated. Indeed, the EKF gives an under-estimation of the rate evolution β . Once the SoH estimation algorithm converges, the computed RUL is always within the bounds.

4.4. Robustness

From the degradation model, one can notice that the method results depend strongly on the initialization of the parameters R_0 and I_{L0} . Indeed, if at least one of the parameter is initialized

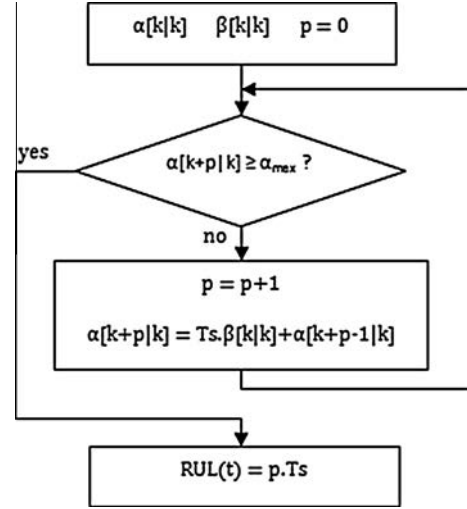


Fig. 11. RUL algorithm.

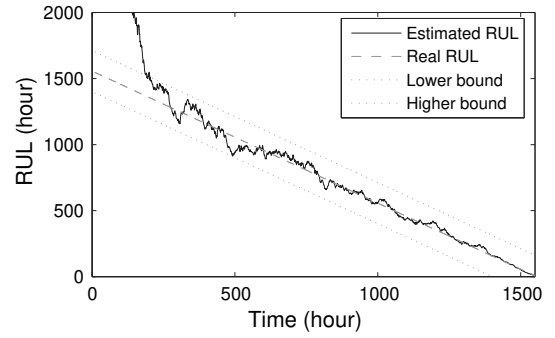


Fig. 12. RUL estimation.

incorrectly, the algorithm compensates this error with its degrees of freedom (α_k, β_k) leading to a wrong estimation of the RUL.

To check the robustness of the method, several simulations are performed with different value of the initial parameters (in a range of $\pm 20\%$ of the nominal value). Fig. 13 shows the area of validity of the algorithm where the estimated RUL is within the defined bounds (i.e. $\pm 10\%$).

One can notice that the errors in R_0 and I_{L0} with the same sign get compensated. This is due to the formulation of parametric degradation as detailed in Section 3.1. However, the algorithm is

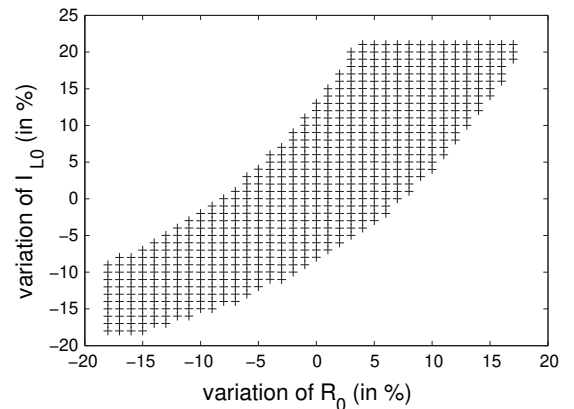


Fig. 13. Robustness of RUL estimation.

able to successfully evaluate the RUL when the parametric error is limited in a $\pm 6\%$ range.

4.5. Experimental results and discussion

4.5.1. Results

The methodology described in the previous section was applied to a 5-cell stack using the voltage presented in Fig. 3. At the beginning of the experiment, we perform a polarization curve. From this initial characterization, the initial set of parameters: E_0, I_0, R_0 and I_{L0} are extracted by the Levenberg–Marquardt optimization method, as described in Section 4.1. The Kalman filter estimates the state of health and its evolution hourly. The result of the estimation is shown in Fig. 14.

It is found that disturbances due to the Electrochemical-Impedance Spectroscopy distort the estimate. Indeed, when the characterizations are performed, there is a recovery effect on the stack voltage. This can be explained by the re-initialization of local conditions of temperature and water content in the PEMFC [31]. The algorithm takes into account the performance improvement and re-evaluates the state of health. This effect leads to an overestimation of the remaining life by the prediction algorithm (which runs every 50 h). The estimate of the RUL is shown in Fig. 15.

The chosen criterion for end of life is a maximum parameter deviation $\alpha_{max} = 40\%$, which corresponds to the end of life of the fuel cell stack after 1450 h of operation. After the convergence phase of the EKF of about 400 h, the algorithm is able to estimate the remaining life properly until the end of the experiment.

4.5.2. Discussion

The result of the prognostic algorithm is highly dependent on the initial setting of the algorithm. This paper provides some elements for easy tuning. However, setting the initial state $x_{0|0}$ remains the responsibility of the user. We can still give any *a priori* on the degradation rate which is of the order of $10^{-2}\%$ per hour. The method gives promising results despite the voltage recovery phenomenon. Indeed, in real situations (transport application for example) characterization like polarization curves might not be made periodically.

The Extended Kalman Filter is able to provide information on the uncertainty of the estimate through the covariance matrix P. However it was chosen not to exploit this information. In addition, Celaya et al. [32] states that if the variance of the state of health and its prediction is estimated by Kalman filtering, it is impossible to know the distribution of the RUL. Uncertainty about the present and forecast SoH will be the subject of further research.

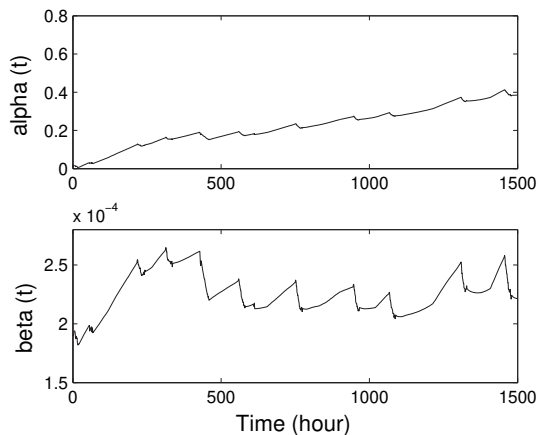


Fig. 14. $\alpha(t)$ and $\beta(t)$ estimation.

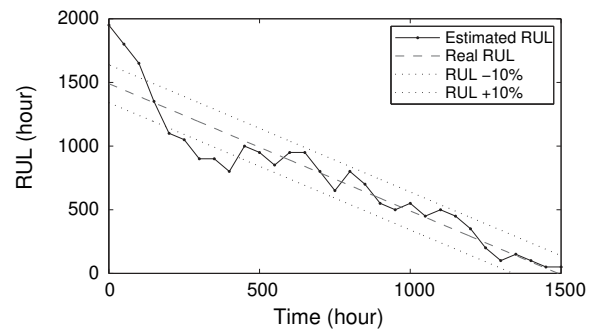


Fig. 15. RUL estimation.

5. Conclusion

A new model-based prognostic algorithm for PEMFC is presented. It is able to estimate the state of health and to predict the remaining useful life while being robust to model error. This methodology uses an Extend Kalman Filter to estimate a time varying parameter and its derivative which are both representative of the aging of the fuel cell. For this, an empirical model of degradation is developed based on a parameter analysis on experimental data. The EKF offers good results in the estimation of the SoH and its tendency leading to a fast and accurate estimation of the RUL.

The developed methodology allows giving prognostic results for variable operating conditions which would reflect better the mission profile of a real fuel cell stack. Estimating the RUL of a PEMFC under a variable load and quantifying the uncertainty of the SoH estimation and prediction is the following step of this work. In practice, the speed of degradation depends on the operational condition, so one major issue is that the algorithm has to be able to converge quickly when a change in the load is performed.

Acknowledgments

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