Combined predictions for prognostics and predictive control of transportation PEMFC ⋆

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Abstract: To help a transition of prognostics approaches toward industries, it is necessary to show that they can be adapted in every situation. Nowadays, a lot of prognostics applications focus on energy sources, among them Proton Exchange Membrane Fuel Cells (PEMFC) can be cited. Due to their wide range of applications, different prognostics adaptations should be considered. Issues coming with PEMFC used for transportation are considered in this paper. Different time scales are involved, requiring a modification of the existing approaches. This paper proposes a solution to perform short-term and long-term predictions on a PEMFC stack used in a transportation application based on particle filters. After proposing different data reductions, the adapted particle filters configuration for this use case is determined. Accurate State of Health (SoH) estimations and predictions, with high coefficient of determination, are obtained. Behavior predictions are also performed and show promising results.

Keywords: Prognostics, Proton Exchange Membrane Fuel Cell, Transportation profile, Predictive control

1. INTRODUCTION

To help the slow transition of prognostics approaches from academic research toward industries, it is necessary to provide evidences that these approaches can be adapted to each situation. It is even crucial for energy sources, such as Proton Exchange Membrane Fuel Cells (PEMFC), that are encountered in a great variety of applications: transportation, portable devices' powering, combined heat and power (μ-CHP) applications, etc. In a previous work, Jouin (2015) proposed a roadmap to perform prognostics of PEMFC based on particle filters. It provides guidelines on the data processing and the particle filter configuration to get convincing predictions. However, only two cases were considered: constant mission profiles and variable profiles with variations in hours. Transportation applications are still to be investigated. The aim of this paper is thereby to complete previous work, by considering this case of PEMFC use.

Performing prognostics on PEMFC used for transportation creates new issues. Different time scales are involved: seconds for profile variations and hours for degradations. This was not the case for μ-CHP or constant profiles where the profile variations happened within a few hours. As a consequence, a shorter sampling period is required with transportation profile increasing dramatically the amount of data necessary to follow the profile variations. This has an impact both on the computation time to obtain prognostics results and the memory needed to store both data and results. Nevertheless, it is important to predict the future State of Health (SoH) to adapt the maintenance strategies and mission profiles, and also to predict the future behavior within a few seconds to adapt the control strategies. Once a solution is found to deal with the different time scales, it is important to find the optimal configuration of the particle filter. Based on the methodology developed in Jouin (2015), different likelihood formulations and resampling procedures should be tested.

This paper proposes a new solution to predict both the future SoH and behavior of the PEMFC stack in transportation applications and complete the roadmap from Jouin (2015). In this goal, first, the modeling of the PEMFC's SoH and the functioning of particle filters are introduced in Section 2. Section 3 focuses on the different possible configurations for the particle filter while Section 4 explains the methodology developed to tackle the specific issues of prognostics in transportation applications. Finally, Section 5 proposes and discusses SoH and behavior predictions before concluding.

2. HYBRID PROGNOSTICS - BACKGROUND

To perform prognostics of a transportation PEMFC, the methodology developed in Jouin (2015) is followed. In Jouin (2015), different types of particle filter settings are

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tested to define the best configuration in each case of use of the PEMFC stack. Before detailing the different settings, the modeling of the PEMFC SoH and the functioning of the particle filter should be reminded.

2.1 SoH modeling

Observing inside a PEMFC stack to know exactly the degradation's state of its inner component without disassemble it, is not a trivial task. Consequently, most of PHM applications tend to use "easy to access" measurements to estimate the SoH such as voltage or power measurements (Jouin et al. (2016b); Bressel et al. (2016)), polarization curves (Bezmalinovic et al. (2015)) or electrochemical impedance spectroscopy (EIS) (Kim et al. (2014)). Among these measurement means, only power measurements can be achieved without interrupting the mission profile. So, it becomes a natural health indicator. Moreover, it can be shown that a majority of the stack degradations has a direct impact on the output power, Franco (2012). When using the power signal, the SoH is defined with respect to the loss of power observed since the beginning of life of the PEMFC. The definition of SoH indicators for PEMFC is extensively discussed in Jouin et al. (2016a).
To follow the evolution of the power in time according to the mission profile $I(t)$ and the stack's degradation, the model proposed in Jouin et al. (2016b, 2015) is used:

$$\begin{aligned} P(I,t) = {} & nI(t)[E_{rev} \\ & - \frac{RT}{2\alpha_a F} ln(\frac{i_{loss,0}e^{b_{loss}t} + \frac{I(t)}{A_0 e^{b_{A1}t} + A_1 e^{b_{A2}t}}}{i_{0,a}}) \\ & - \frac{RT}{4\alpha_c F} ln(\frac{i_{loss,0}e^{b_{loss}t} + \frac{I(t)}{A_0 e^{b_{A1}t} + A_1 e^{b_{A2}t}}}{i_{0,c}}) \\ & - \frac{I(t)}{A_0 e^{b_{A1}t} + A_1 e^{b_{A2}t}} (R_{ion,0}e^{b_{ion}t} + R_0 + b_R t) \\ & + (B_{c,j} + b_B t) ln(1 - \frac{\frac{I(t)}{A_0 e^{b_{A1}t} + A_1 e^{b_{A2}t}}}{\frac{4F}{RT}\left(\frac{D_{O_2,j} + b_D t}{L_{GDL}}\right) P_{O_2}})] - p \end{aligned} \quad (1)$$

The mission profile of a PEMFC is very often expressed as a current in Ampere. Indeed, it is the input of a majority of PEMFC model. It is nevertheless important to note, that this current is deduced from the speed of the vehicle in real applications. Regarding the degradation, lots of degradation mechanisms occur within the PEMFC (loss of active area, resistances' increasing, etc.) and integrated in some of the model parameters. Please refer to Jouin et al. (2016b) for the explanation of these degradation mechanisms and the different parameters in the model.
This model shows great capabilities for SoH estimations and predictions if used in a proper framework. Indeed, some parameters (b_{loss}, b_{A1}, b_{A2}, b_{ion}, b_R, b_B, b_D, p) are evolving with time and need to be continuously adjusted. This motivates the use of a particle filter-based framework for SoH estimations and prognostics.

2.2 Particle filter-based prognostics

Performing prognostics with particle filters consists in two stages, Jouin et al. (2016c):

(1) a current state estimation based on a model identification by the particle filter and the data available;
(2) a prediction of the future state based on the last known state and the identified models.

Particle filters are commonly used to solve Bayesian tracking problems. They allow estimating states for nonlinear, non-stationary and non-exact processes. The following explanations focus on the practical use of particle filters, for theoretical considerations please refer to Chen (2003).
Two types of model appear in the Bayesian formulation of the problem:

(1) a state model, representing the health of the system;

$$x_t = f(x_{t-1}, \Theta_{t-1}, u_t, \omega_t) \quad (2)$$

where $\{x_t, t \in \mathbb{N}\}$ is the state evolving with time modeled as a Markov process of initial distribution $p(x_0)$; f is the transition function between two states; Θ_{t-1} is a vector of parameters to identify; u_t is the input of the system and ω_t is a process noise.
(2) an observation model linking the state model to the measurements available.

$$y_t = h(x_t, v_t) \quad (3)$$

where $\{y_t, t \in \mathbb{N}^*\}$ are measurements assumed conditionally independent given the process $\{x_t, t \in \mathbb{N}\}$, h is the measurement function linking y to x and v_t is a measurement noise.

Particle filters work with a set of samples called particles. They allow giving, at each time instant, the probable states of the system in the form of an approximated probability density function (pdf). Each particle of the pdf written x_t^i has a weight w_t^i. So at each time step, the state is given by:

$$x_t = \sum_{i=1}^{N} w_t^i x_t^i \quad (4)$$

The confidence interval is given by the bounds of the particle distribution. The use of distributions allows including naturally some uncertainties from measurements, from the ignorance of the precise state of the system, etc. Sankararaman (2015). This asset makes particle filters more and more popular among PHM applications.
In practice, once initialized, the filtering process has three main steps:

(1) *Prediction:* the state x_{t+1} is estimated by propagating the particles obtained at time step t thanks to the state model;
(2) *Update:* a new measurement is available, the likelihood is calculated according to the degree of matching between the particles and the last measurement, the particles are now weighted;
(3) *Resampling:* the particles with low weights are eliminated and the other duplicated.

Once all the measurements available are used, only the state model is used to propagate the particles until the state reaches a failure threshold, Fig. 1. For this stage, it is assumed that the future mission profile is completely known.

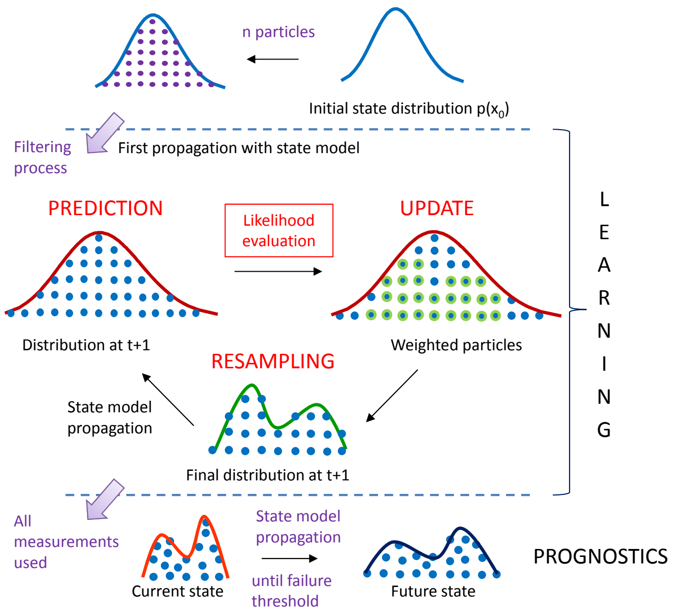

Fig. 1. Particle-filter based prognostics

3. PARTICLE FILTER SELECTION

3.1 Different configurations

To provide the best state estimations as possible, it is important to select a good filter configuration. According to the methodology and the results proposed in Jouin (2015), for variable mission profiles, two stages of the filtering process should be studied:

(1) the choice of the likelihood function that allows weighting the particles;
(2) and the choice of the resampling algorithms.

Regarding the likelihood choice, Jouin (2015) shows that with variable mission profiles, the classic Gaussian formulation does not give any results. Indeed, even if the state estimation is close enough to the last measurement, the Gaussian likelihood remains equal to 0 and prevent the filtering process to reach its end. Consequently, the new forms proposed in this paper should be tested:

$$L1(T,i) = \frac{1}{abs(y_T - x_T^i + \sigma_T^i)} \tag{5}$$

$$L2(T,i) = \frac{1}{\frac{1}{T}\sum_{t=1}^{T}.abs(y_t - x_t^i + \sigma_t^i)} \tag{6}$$

$$L3(T,i) = L1(T,i) + L2(T,i) \tag{7}$$

$$L4(T,i) = 0.25 \times L1(T,i) + 0.75 \times L2(T,i) \tag{8}$$

$L1$ is called the absolute error-based likelihood and $L2$ is the trajectory based-likelihood. For the record, the idea behind these expressions is to use the literal definition of the likelihood (measuring the degree of matching between a particle and a measurement) instead of defining it with the observation noise as indicated by the theory.
As far as resampling algorithms are concerned, different procedures are tested. Five procedures working with a constant number of particles n that can work with any likelihood function:

1) systematic resampling;
2) multinomial resampling;
3) stratified resampling;
4) residual resampling;
5) partial resampling.

and four procedures that automatically adapt the number of particles at each time step:

6) the reallocation;
7) the branching;
8) the rounding;
9) and the residual systematic (RSR).

However, due to implementation issues at this stage of the work, these last four can only work with $L1$. The reader is invited to read Jouin (2015) for a justification and discussion on the choice of these procedure and Li et al. (2014) for the algorithms explanations.
Consequently, there are 24 combinations likelihood / resampling to try before selecting the right particle filter. Each combination is launched 50 times to assess the repeatability of the results.

3.2 Selection criteria

The filter selection is based on two criteria. First, the estimated state should be as close as possible to the available data on the whole PEMFC's lifetime. As the error may evolve with time, a global measure is used: the coefficient of determination R2 defined as:

$$R2 = 1 - \frac{\text{sum of (errors from t=T1 to T2)}^2}{\text{sum of (difference to mean error)}^2} \tag{9}$$

For the current state estimation T1 equals 0 and T2 is length of the learning, while for the prognostics T1 = length of the learning + 1 and T2 = End-of-Life (EoL). The R2 is equal to 0 when the estimation has no concordance with the data and equal to 1 if the estimation is perfect. In this work, the estimations are considered as precise if R2 $\geq$ 0.9.
The second criterion is the uncertainty on the estimates. It is proposed in Jouin et al. (2016a), based on worldwide electrical norms, that the uncertainty for good SoH or RUL estimates should be constrained in a $\pm$5% interval. Also, a confidence interval of $\pm$10% allows to assert that the predictions are quite satisfying but can be improved.
Finally, the dispersion of the R2 on the 50 tries is also considered. Like for the uncertainty, it should be as small as possible and the same intervals of $\pm$5% and $\pm$10% are used as performance criteria.

4. ADAPTATION TO TIME SCALE ISSUES

4.1 State and measurement models

Equation (1) provides a degradation model expressing the power as a function of current and time $P(I,t)$. The aim now is to deduce a state equation from this model. As the health state of the system can be obtained from the power, it is possible to write $x \sim P$. There is now an equation of x as a function of t and I that should be transformed to have $x(t_k, I_k) = f(x(t_{k-1}, I_{k-1}), \Theta_{k-1}, I_k)$.

$$P(t_k, I_k) = P(t_{k-1}, I_{k-1}) + \frac{\Delta I}{I_{k-1}}(P(t_{k-1}, I_{k-1}) + p) + n.(I_{k-1} + \Delta I).(residual.terms) \tag{10}$$

As the recursive expression is very long, for more clarity, all the terms that don't contain the state $P(t_{k-1}, I_{k-1})$ are gathered in the expression $residual.terms$. For the whole demonstration, please refer to Jouin (2015). No process noise is added to this model.
The observation model has also to be defined. As the power is both measured and used as a health indicator, the observation model is:

$$y_t = x_t + v_t \qquad (11)$$

with v_t the observation noise.
Different parameters in the state model have to be continously adjusted. As recommended by the literature, the update of these parameters is made thanks to a random Gaussian walk. Consequently, for each parameter, an equation is defined as follows:

$$\Theta_k = \Theta_{k-1} + N(0, \sigma_\Theta) \qquad (12)$$

4.2 Transportation data

Only one dataset is available. It comes from a 8-cell PEMFC stack with an active area of 220cm^2 following a mission profile simulating a transportation application. The stack and test-bench characteristics are the same as in Pahon et al. (2016). The data are recorded during 342 hours, representing 822 165 data points.

4.3 State estimation using the whole dataset

To highlight the issues coming with SoH estimation in transportation application, this paragraph comments on the results of the combination $L1$ / systematic resampling performed only once. 100 hours are used to learn the current SoH before predicting it from t=101 h to t=342 h. The state estimation is quite satisfying, as a R2 greater than 0.9 is obtained. However, the model diverge relatively quickly during the prediction. The main reason seems to be the overfitting that appears when using too many points to identify the model (100 h = 240 012 data points). However, this is not the only issue.
Learning so many points takes around 8 hours and requires 4 GB to store the results (state + identified parameters + particle weights at each step). This would not be acceptable in industrial applications. Two solutions can be considered:

(1) starting the state estimation since the start-up of the system and use the recursive functioning of the particle filter;
(2) reducing the amount of data to the minimum according to a specific goal.

Estimating since the start-up of the system may be a good solution but it may unnecessarily requisition computing and memory resources. Indeed, SoH estimations and predictions might be useless as long as the system has not started degrading yet. So the second option is explored.

4.4 Proposed solution

To reduce the amount of data, two types of reductions are proposed (Fig 2):

- initial dataset: 822165 data points;

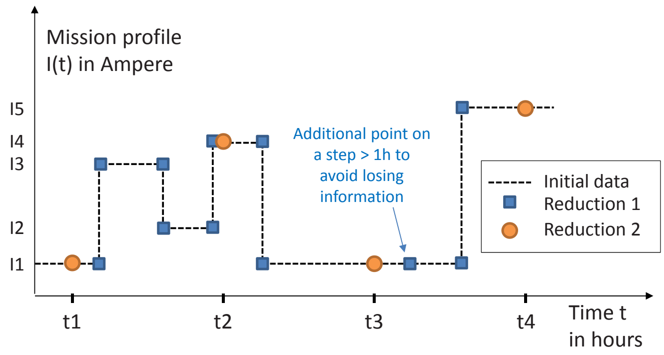

Fig. 2. Initial mission profile vs reductions - the mission profile in this figure is designed for illustration purpose and does not reflect the actual one from Fig. 3

- Reduction 1: reduction with respect to changes in the mission profile, from a value I1 to I3 in Fig 2 for instance or I2 to I4: 53365 data points;
- Reduction 2: reduction at one point per hour: 342 data points.

The power data obtained after each reduction are depicted in Fig 3.
By reducing with respect to changes in the mission profile, all the useless points saved during transitional regimes or on constant steps are removed. Nevertheless, when a constant step lasts during a few hours (for instance between t=48 and 65 hours), a point per hour is kept to avoid losing information.
The reduction at one point per hour relies on the fact that all the degradations occurring within the PEMFC stack and taken into account by the modeling having time constants greater than the hour, Jouin et al. (2016b).
This is a major hypothesis for the remaining of this work. Indeed, as the degradation does almost not progress during an hour, it means that the parameters of the state can remain constant during that period. Consequently, the idea is to use the data reduced at one point per hour to learn the SoH of the system. At the end of the learning, two types of predictions are done:

(1) SoH predictions using the mission profile reduced at one point per hour, that can be used to assess the EoL of the system;
(2) behavior predictions using the mission profile reduced according to changes in the input, that can be used for predictive control purposes.

This principle is summarized in Fig 4.
It is important to note that in this paper, the future mission profile is supposed to be known. In a more complete prediction framework, the mission profile would also be predicted.

5. RESULTS AND DISCUSSION

5.1 SoH estimates

Particle filter setting Whatever the particle filter's configuration, before the resampling of the particle, an additional step is added. It allows taking into account that the parameters in the model, as they represent physical phenomena and must have realistic values, are in a con-

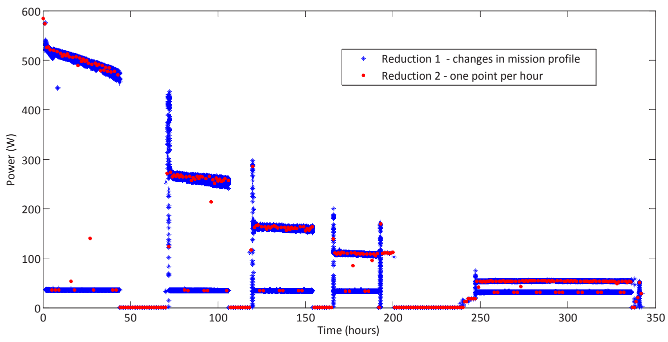

Fig. 3. Reduced power data from a transportation PEMFC

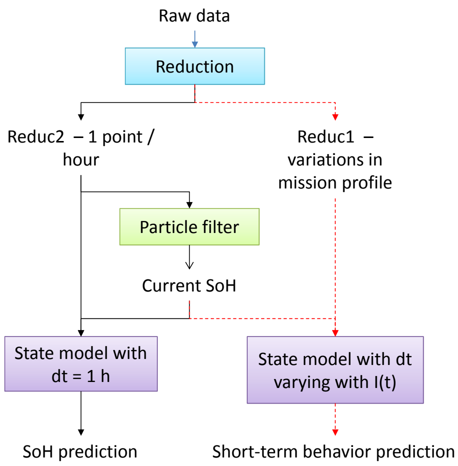

Fig. 4. Principle of the prognostics framework

strained state. So, when a particle contains at least one parameter value out of its defined range, this particle is eliminated before resampling. Without this step, good SoH estimations can lead to poor predictions.
For all configurations, the initial number of particles is n=200. Different lengths of learning are tested from 50 to 300 hours with a step of 50 hours for SoH estimations. Predictions are made only for learning lengths smaller or equal to 200 hours.

Filters' selection To select the particle filters that could be used in transportation applications, the R2 on the SoH estimations is computed. For the sake of brevity, Table 1 proposes results averaged on the six lengths of learning.
According to the criterion R2>0.9, only 9 configurations can be selected (mean in bold in Table 1). However, by looking at the relative gap between the mean R2 and the lower and upper bounds, the results are less convincing (Table 2). Indeed, the dispersion of the R2 on 50 tries is greater than expected and only one configuration enters the ±10% bounds (*L3* / residual).
Finally, the uncertainty on the estimated has to be evaluated. Whatever the learning length with the combination *L3* / residual, the dispersion of the particle never exceed ±3% all along the trajectory. Consequently, it validates this combination for the SoH estimation and it can be tested for predictions. Fig. 5-a) shows an example of SoH estimation for a learning of 50 hours with this configuration *L3* / residual.

Table 1. R2 for SoH estimation - mean on the 6 learning length

n constant		$L1$	$L2$	$L3$	$L4$
syst	min	0,82	0,43	-0,02	0,37
	mean	**0,98**	0,45	0,05	0,41
	max	1,00	0,97	0,99	0,99
mult	min	0,75	0,58	0,73	0,47
	mean	**0,98**	0,61	0,78	0,51
	max	1,00	0,99	1,00	0,98
str	min	0,88	0,67	0,41	0,56
	mean	**0,99**	0,69	0,46	0,58
	max	1,00	0,98	1,00	0,99
res	min	0,70	0,55	0,91	0,05
	mean	**0,98**	0,58	**0,92**	0,11
	max	1,00	0,99	0,99	0,99
part	min	0,17	-0,34	-0,22	0,43
	mean	0,87	0,23	0,02	0,66
	max	1,00	0,98	0,97	0,93

n variable + $L1$					
rea	min	0,81	rou	min	0,74
	mean	**0,99**		mean	**0,98**
	max	1,00		max	1,00
br	min	0,83	RSR	min	0,74
	mean	**0,99**		mean	**0,98**
	max	1,00		max	1,00

Table 2. Relative error to mean R2 in %

Config.	gap (%)		Config.	gap (%)	
L1 / syst	min	17%	*L1* / mult	min	23%
	max	2%		max	2%
L1 / str	min	11%	*L1* / res	min	29%
	max	1%		max	2%
L1 / rea	min	18%	*L1* / br	min	16%
	max	1%		max	1%
L1 / rou	min	24%	*L1* / RSR	min	25%
	max	2%		max	2%
L3 / res	min	1%			
	max	8%			

5.2 SoH and behavior predictions

Based on a good current SoH estimation, the future SoH and behavior can be predicted. The SoH is estimated until the end of the dataset, 342 hours, whereas the behavior is predicted only for the 50 hours as it seems far enough for predictive control. Reduction 2 is used to predict the SoH while Reduction 1 serves for the behavior predictions. Fig. 5-b) and c) depict these predictions, still with the learning of 50 hours. In both cases, it can be seen that even if the predictions are not perfect yet, they are very close to reality. The R2 is once again computed (Table 3). Surprisingly, no good behavior predictions can be obtained for learning length of 150 and 200 hours. No explanation can be found as very good SoH predictions are available and further tests and analysis are required.
A point that should be highlighted is that behavior predictions for the next 50 hours are performed in around 35 seconds. This is clearly more convincing that the numerous hours required when using the full dataset.

6. CONCLUSION

This paper proposes a solution to perform short-term and long-term predictions on a PEMFC stack used in a transportation application. It completes the missing branch of the roadmap for prognostics of PEMFC based on particle

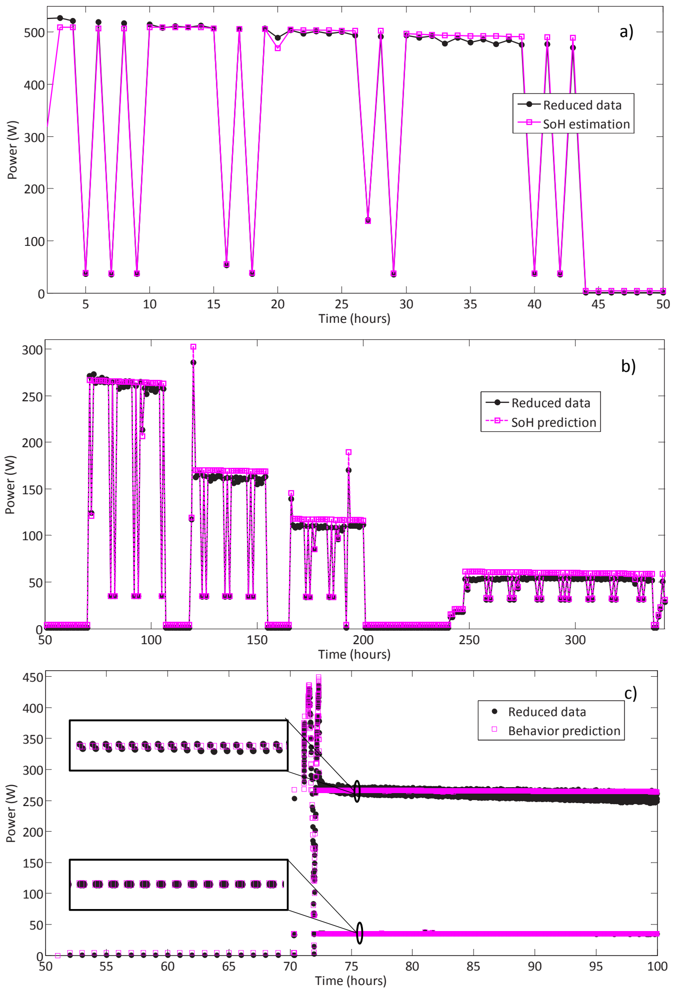

Fig. 5. Reduced power data from a transportation PEMFC

Table 3. R2 on the 50 tries for SoH and behavior predictions

SoH	50	100	150	200	Mean
min	0,94	0,98	0,99	0,95	0,97
mean	0,99	0,99	0,99	0,98	0,99
max	1,00	1,00	1,00	1,00	1,00

Behavior	50	100	150	200	Mean
min	0,92	0,98	≈0	≈0	x
mean	0,98	0,99	≈0	≈0	x
max	0,99	1,00	≈0	≈0	x

filters built in Jouin (2015).

The main issue when performing prognostics on PEMFC with fast variations in the mission profile is the coexistence of different time scales. The degradation phenomena are progressing within hours whereas the mission profile may vary each second. This implies an adaptation of the prognostics framework to provide short and long term accurate predictions fast enough to allow reacting. To meet these requirements, this paper proposes a simple prognostics framework based on particle filters and a two-stage prediction.

This framework allows using raw data reduced with respect of degradation time constant to estimate the future SoH of the system. The prognostics' results are quite convincing as they show a R2 greater than 0.94 with less than 5% of uncertainty. Based on SoH estimations and a data reduction to key points in the mission profiles, behavior predictions for the next 50 hours, useful for predictive control, can be obtained within 35s. Next steps of this work consist first in validating this approach on other PEMFC stacks for transportation applications. Another perspective is to find a correlation between the evolution of the parameters in the model and the mission profile to improve further the quality of the prediction whatever the time horizon considered.

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