Fuel Cells Impedance Estimation Using Regression Analysis

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***Abstract* — This paper describes the application of the PHM concept to assess the State of Health (SoH) of a Proton Exchange Membrane Fuel Cell (PEMFC) as part of the IEEE PHM 2014 Data Challenge. A linear regression approach is used as health monitoring algorithm to estimate the impedance of the PEMFC. So that, the linear regression curves were estimated using least-square equations. After that, linear regression is deployed to find future values for impendance for four different frequencies: 50mHz, 789mHz, 5.18mHz and 505Hz.**

Keywords—Regression Analysis, Prognostics, Health Monitoring, Fuel Cells.

I. Introduction

Prognostics and Health Management (PHM) can be defined as the ability of assessing the health state, predicting impending failures and forecasting the expected Remaining Useful Life (RUL) of a component or system based on a set of measurements collected [1].

In order to accomplish this task, it is necessary to collect a set of data from the component. This dataset is defined on the basis of the type of equipment to be monitored (hydraulic, electronic, mechanic, etc.) and the failure modes that are intended to be covered by the PHM system.

After that, a health monitoring algorithm must be developed for each monitored equipment or failure mode. Each algorithm processes the relevant data and generates a degradation index that indicates how degraded the monitored equipment is.

This paper describes the application of PHM concept to assess the state of health (SoH) of a Proton Exchange Membrane Fuel Cell (PEMFC) as part of IEEE PHM 2014 Data Challenge.

PEMFC are electrochemical systems that convert directly hydrogen energy into electrical energy with high efficiency, and no CO_2 emission.

SoH is addressed by considering frequential domain. So that, EIS (Electrochemical Impedance Spectroscopy) measurements made at separate frequency ranges may be used to diagnose important PEMFC failures, as flooding and dehydration, tackled in [2].

PEMFC relevant physical processes (electron transfer, reactant diffusion, etc.) are controlled by the bulk properties of the different materials and, more importantly, by the interfacial characteristics between materials or phases. At each interface, the material properties change discontinuously and abruptly, and can become the limiting performance factors. EIS is a technique especially suited to characterize interfaces, and it can be used to characterize fuel cell performance non-invasively and in situ [2].

A linear regression approach is used as health monitoring algorithm to estimate the impedance of the PEMFC. This algorithm was developed over data provided by FCLAB Research Federation (FR CNRS 3539, France, http://eng.fclab.fr/) as part of the IEEE PHM 2014 Data Challenge.

Relating to the data, two datasets were provided: 1) fuel cell operated in stationary regime and 2) fuel cell operated under dynamic current. The first one corresponded to 1,155 hours of experimental data of the entire life of the fuel cell and the second one corresponded to 550 hours, without the failure information. Both datasets contained polarization, electrochemical impedance spectroscopy (EIS) and ageing parameters.

The rest of this paper is organized as follows: Section II presents the problem of assessing the State of Health (SoH) of a PEMFC; Section III describes the approach adopted to tackle that problem; followed by results in Section IV and concluding remarks in Section V.

II. Problem Description

The problem addressed in the IEEE PHM 2014 Data Challenge is focused on a PEMPF (Proton Exchange Membrane Fuel Cell) and can be divided into two parts.

- Part 1: Assess the State of Health of a PEMFC
- Part 2: Predict its Remaining Useful Life

In part 1, the dynamic behavior of a fuel cell stack must be assessed based on information regarding its internal physical parameters. The State of Health estimation is addressed by considering frequency domain. The objective is to predict both the real and the imaginary parts of the impedance of a fuel cell stack.

In part 2, the objective is to predict the Remaining Useful Life of a fuel cell. The RUL is defined as the time before a fuel cell stack looses its ability to provide sufficient power. Various power drops are considered in this part of the challenge: 3.5%; 4.0%; 4.5%; 5.0% and 5.5% of the initial power.

In this paper, the authors present the approach used to solve the part 1 of the challenge.

A. Polarization Curves

Polarization curves, which describe the relationship between the cell voltage and the current density, provide information about the static behavior of the fuel cells. These curves have been used in many applications such as fuel cell characterization, ageing studies and diagnosis. In order to perform a polarization test, the fuel cells must be operating in stable conditions (temperature, pressure, humidity, etc.). In this work, before each polarization test, the fuel cells operated under the same operating conditions during 30 minutes.

According to previous research, polarization curves may provide three different internal behaviors of fuel cells, depending on the current density level, as described below [3].

- In low current density levels, polarization curves illustrate charge transfer kinetics.
- In medium current density levels, the form of the polarization curves is influenced by ohmic resistances.
- In high current density levels, polarization curves are influenced by the mass transfer.

Fig. 1 shows the variation of both the form and the slope of a polarization curve during an ageing experiment. The parameterization of polarization curves is helpful in order to provide indications about the evolution of the ageing process.

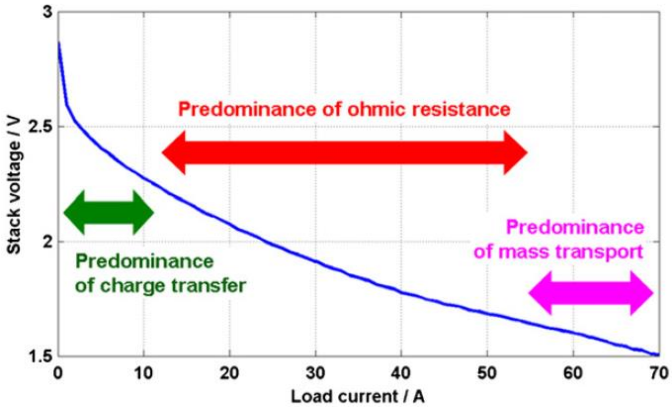

Figure 1. Example of a polarization curve. Source: Ref [4]

B. Electrochemical Impedance Spectrum

The Electrochemical Impedance Spectroscopy (EIS) test, which measures the dielectric properties of a medium as a function of frequency, provides relevant information about the dynamical behavior of the fuel cells during the ageing process [4]. This test has been used in diagnostics and prognostics applications for batteries [5] and fuel cells [3]. EIS allows the characterization of the dynamic processes at different timescales. In this work, fuel cell characterization was obtained by separating the impedance spectrum into two curves that represent the evolution of the real and the imaginary parts of the impedance as functions of the frequency.

Previous research focused on defining some characterization points in the impedance spectrum that could be used for fuel cells diagnosis purposes. The following parameters were chosen as features:

- The polarization resistance value.
- The minimum value of the imaginary part of the impedance, its corresponding real part value and its corresponding frequency.
- The internal resistance and its corresponding frequency.

Fig. 2 shows an example of the identification of the characterization points in the impedance spectrum.

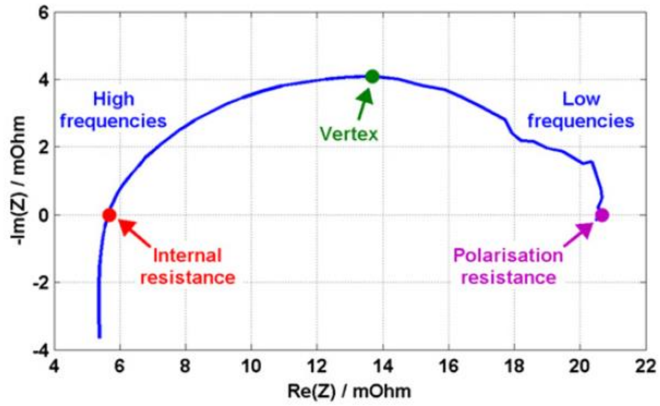

Figure 2. Example of an impedance spectrum curve. Source: Ref [4]

III. Proposed Solutions

Polynomial regression analysis consists of one of the common approaches [6] to model historical data for the purpose of prognostics. Its implementation is simpler compared to other data-driven method requiring less computational resources and fewer setting parameters. In spite of that, the polynomial order must be chosen and often its definition influences on the quality of results. In the present work, a linear regression, which is a 1st order polynomial regression was chosen. That proposal is described on the following topic.

A. Linear Regression

Linear regression has been widely used and compared to other methods. Examples include [7] and [8] which compares linear regression to non-linear methods such as Neural Networks. Although this method does not consider non-linear characteristics of the data, it can provide satisfactory results when the non-linear effects are less relevant compared to the linear ones [9].

The proposed solution consists in finding the coefficients a_{Re}, b_{Re}, a_{Im}, b_{Im} of the following linear equations:

$$Re_Z = a_{Re} t + b_{Re} \tag{1}$$

$$Im_Z = a_{Im} t + b_{Im} \tag{2}$$

Where:

Re_Z is the real part of the impedance in Ohms for a given time and frequency;

Im_Z is the imaginary part of the impedance in Ohms for a given time and frequency;

t is the time.

The challenge consists in finding future values for the impedance for four different frequencies: 50mHz, 789mHz, 5.18Hz and 505Hz. For each of them the coefficients in (1) and (2) are estimated with historical data using the least-squares equation given by (3).

$$B = (X^T X)^{-1} X^T Y \tag{3}$$

Where:

X are the past time historical data

Y are the past time values of impedance

B are the coefficients estimations

Given the results of (3) the future estimations of impedance are given by (4).

$$\hat{Y} = X_f B \tag{4}$$

Where:

$\hat{Y}$ are the future estimations of impedance

X_f are the estimation times

IV. Results

In order to evaluate the method, the score was estimated for times 685h, 823h and 991h using FC1 data. The estimation of both real and imaginary impedance components for frequencies 50mHz, 789mHz, 5.18Hz and 505Hz for the linear regression are shown in Fig. 3 to Fig. 10.

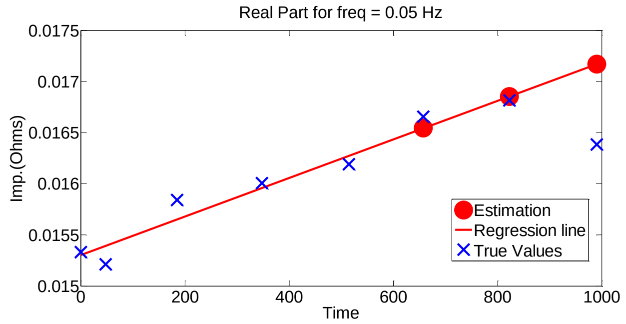

Figure 3. Real part linear regression estimations for FC1 at 50mHz

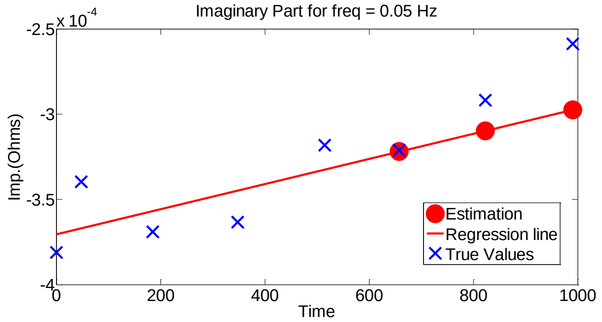

Figure 4. Imaginary part linear regression estimations for FC1 at 50mHz

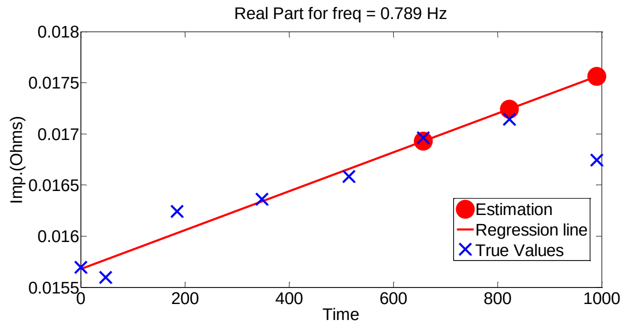

Figure 5. Real part linear regression estimations for FC1 at 789mHz

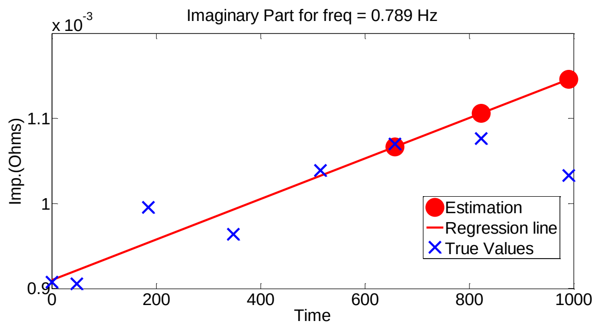

Figure 6. Imaginary part linear regression estimations for FC1 at 789mHz

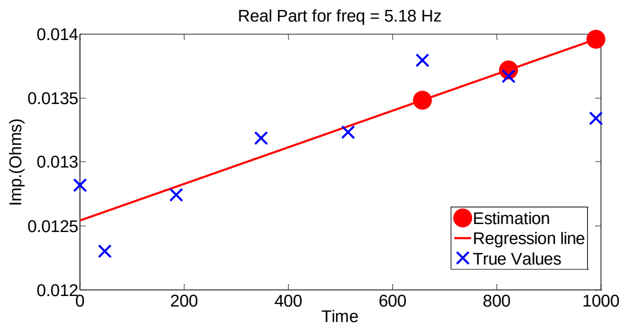

Figure 7. Real part linear regression estimations for FC1 at 5.18Hz

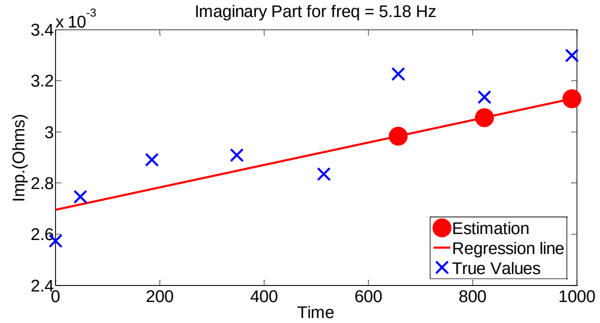

Figure 8. Imaginary part linear regression estimations for FC1 at 5.18Hz

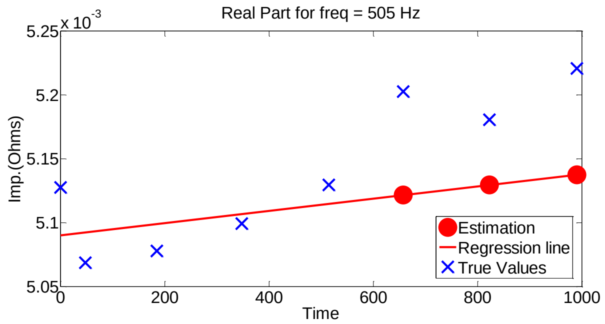

Figure 9. Real part linear regression estimations for FC1 at 505Hz

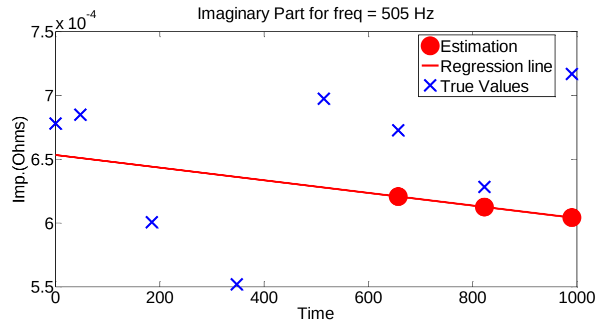

Figure 10. Imaginary part linear regression estimations for FC1 at 505Hz

The points indicated as True Values are the impedances collected for the EIS curves of FC1 data, the Regression curve is the curve estimated from (1) and (2), and the Estimation points are estimations from the linear regression for score estimation. The closest the Estimation points are to the True Values, best is the estimation and consequently the score.

Finally score was estimated for the FC1 data. The linear regression got a score of 4.14.10e-6. The score metrics are detailed on the following web page: http://eng.fclab.fr/ieee-phm-2014-data-challenge/.

The same methods were used to estimate future impedances for the FC2 data. Result is shown in TABLE I.

TABLE I. FC2 LINEAR REGRESSION IMPEDANCE ESTIMATIONS

	50mHz	789mHz	5.18Hz	505Hz
Re/666	0.0178	0.0181	0.0141	0.005
Im/666	-0.0003	0.0013	0.0034	0.0006
Re/830	0.0183	0.0186	0.0145	0.005
Im/830	-0.0002	0.0013	0.0036	0.0005
Re/1016	0.0189	0.0192	0.0149	0.0051
Im/1016	-0.0002	0.0014	0.0038	0.0005

V. CONCLUSIONS

This paper presented a PHM method used to estimate the State of Health of a Proton Exchange Membrane Fuel Cell (PEMFC) as part of the IEEE PHM 2014 Data Challenge.

The linear regression method consisted of linear curves estimated for the real and imaginary impedance components using least-squares equations. These curves were then used to estimate the future fuel cell impedance values.

The impedance for future times was estimated and the score was calculated for the FC1 data.

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