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Djedjiga Benouioua, Denis Candusso, Fabien Harel, P Picard, Xavier Francois. On the issue of the pemfc operating fault identification: generic analysis tool based on voltage pointwise singularity strengths. ICEREGA'17, 5th International Conference on emerging and renewable energy : generation and automation, Jul 2017, BELFORT, France. hal-01784367

HAL Id: hal-01784367

<https://hal.science/hal-01784367>

Submitted on 3 May 2018

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ON THE ISSUE OF THE PEMFC OPERATING FAULT IDENTIFICATION: GENERIC ANALYSIS TOOL BASED ON VOLTAGE POINTWISE SINGULARITY STRENGTHS

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Abstract. *The purpose of this article is to study the portability of a non-intrusive and free of any external / internal disturbance diagnosis tool devoted to the monitoring of the State of Health (SoH) of PEM Fuel Cell (PEMFC) stack. The tool is based on a thorough analysis of the stack voltage signal using a multifractal formalism and wavelet leaders. It offers well-suited signatures indicators on the SoH of the Fuel Cell. Some relevant descriptors extracted from these patterns (singularity features) are used in the frame of Machine Learning approaches to allow the PEMFC fault identification. The proposed diagnosis strategy is evaluated with two different PEMFC stacks. The first one is designed for automotive applications and the second one is dedicated to stationary use (micro combined heat and power - μ CHP application).*

1. Introduction

Fuel cells (FC) are considered as a promising alternative way for energy conversion [1]. To ensure their durability, reliability and safety, many fault diagnosis and fault tolerant control methods have been proposed. These methods can be classified into two groups: model-based methods [2-5] and data-driven methods [6-8]. The methods of the first group are very cumbersome and complex because they require an in-depth knowledge of the multi-physical mechanisms (thermal, electrical, electrochemical, and fluidic ones) which can occur in FC systems. They are based on numerous parameters governing its operation, and their values are difficult to estimate. Some model-based methods allows a deeper understanding of the FC physics but they might be not suitable to provide an accurate / quantitative description of the FC performances. Hence, the data-driven techniques attract more and more attention because of their simplicity regarding the implementation and the good performances obtained without profound system structure knowledge. They are supported by efficient signal processing methods as: Fourier transform [9], multi-resolution analysis [10, 11], singularity analysis [12, 13]. For fault identification and isolation tasks, some works use Electrochemical Impedance Spectra (EIS) as normal or faulty operation signatures to supply artificial intelligence algorithms (based for instance on fuzzy logic [14] or neural networks [15]) or conventional pattern recognition approaches (based on

Support Vector Machines (SVM) [16], k-nearest neighbors (knn) [13] methods).

This work aims at studying the portability of an innovative data driven approach dedicated to PEMFC diagnosis, named singularity analysis. This method consists in analyzing the pointwise singularities stamped in the stack voltage signal for various FC operating conditions. The singularity features are then summarized in the form of concave arcs estimated thanks to a set of mathematical equations, baptized multifractal formalism [17-19]. The advanced analysis tool, named Voltage Singularity Spectrum (VSS) is then obtained using a non-intrusive manner and without affecting in any way the FC operation. Indeed, no external additional AC-solicitation has to be superimposed to the existing DC load current as it is the case in the usual EIS operation mode.

This paper is organized as follow. Section 2 deals with the experimental work and environment conducted with two PEMFC stacks. In section 3, a brief mathematical foundation of the singularity measurement is given. In section 4, we show how it is possible to make the singularity spectrum combined with Machine Learning techniques as a PEMFC diagnosis tool. Then, the portability of the proposed tool is discussed. Main conclusions are given in Section 5.

	Auto	μ CHP	Auto	μ CHP	Auto	μ CHP	Auto	μ CHP	Auto	μ CHP	Auto	μ CHP	Auto	μ CHP
FSC	2	2	<u>1.3</u>	<u>2.6</u> <u>1.6</u>	2	2	2	2	2	2	2	2	2	2
FSA	1.5	1.3	1.5	1.3	<u>1.3</u>	<u>1.5</u> <u>1.2</u>	1.5	1.3	1.5	1.3	1.5	1.3	1.5	1.3
P (bar abs)	1.5	0.1	1.5	0.1	1.5	0.1	<u>1.3</u>	<u>ND</u>	1.5	0.1	1.5	0.1	1.5	0.1
T (°C)	80	70	80	70	80	70	80	70	<u>75</u>	<u>72</u> <u>65</u>	80	70	80	70
RH (%)	50	50	50	50	50	50	50	50	50	50	<u>ND</u>	<u>46</u> <u>54</u>	50	50
Presence of CO (ppm)	0	0	0	0	0	0	0	0	0	0	0	0	<u>10</u>	<u>ND</u>

1
2 **3. Singularity measurement**

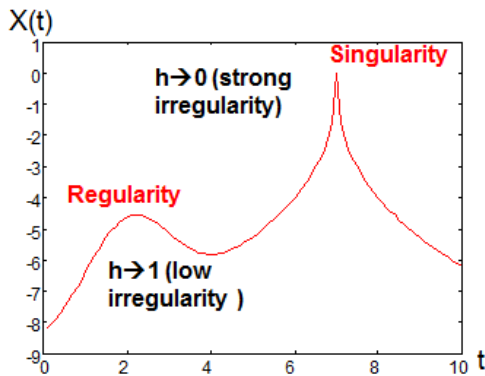
3 Multifractals are the distribution of singularities, all lying on
4 interwoven sets of varying fractal dimensions [20].
5 Multifractals arise in a variety of physical signals in the forms
6 of self-similar sub-sets of samples, such as Multifractal
7 Brownian Motion (MBM) signal [21], signals in turbulence
8 [22], and temporal series in finance [23].

9 The singularity analysis, also named “multifractal analysis”,
10 allows the characterization of data by describing globally and
11 geometrically the fluctuations of local regularity, usually
12 measured by means of the Hölder exponent h .

13 It describes the time (t) based fluctuations of the signal given
14 by a function $X(t)$. This is achieved by comparing the local
15 variations of $X(t)$ around fixed time position t_0 , against a local
16 power law behavior: $X(t_0)$ is said to belong to $C^\alpha(t_0)$ with
17 $\alpha \geq 0$ if there are a positive constant C and a polynomial P ,
18 satisfying $\deg(P) < \alpha$, such that $|X(t) - P_{t_0}(t)| \leq C|t -$
19 $t_0|^\alpha$.

20 The Hölder exponent is defined as the largest α such as:
21 $h(t_0) = \sup\{\alpha: X \in C^\alpha(t_0)\}$.

22 In practice, when $h(t_0)$ takes a value which tends to zero, the
23 signal exhibits a strong singularity at t_0 (Fig. 2).
24

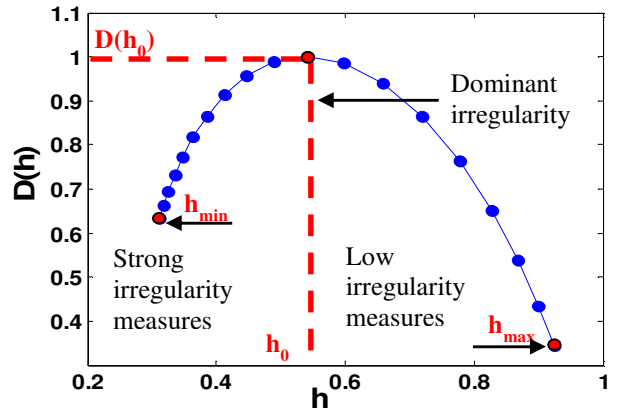


26 Fig. 2. Illustration of two pointwise regularity measures in the
27 signal $X(t)$ quantified by the Hölder exponent h .

28 The singularity strength regarding the variability of the
29 regularity of $X(t)$ vs. t is usually described through the so-
30 called singularity spectrum. Building a singularity spectrum
31 consists in associating to each Hölder exponent h the
32 Hausdorff dimension $D(h)$ of the sets of points which exhibit
33 the same value of h :
34

$$h \mapsto D(h)$$

35 An example of singularity spectrum is given in Fig. 3.



39 Fig. 3. Example of a singularity spectrum $D(h)$.
40

41 The numerical implementation of the mathematical formula
42 can be achieved using the wavelet leaders multifractal
43 formalism. Detailed descriptions of the theoretical and
44 practical relevance, and benefits of the use of wavelet leaders
45 for singularity analysis are depicted in [17-19].
46

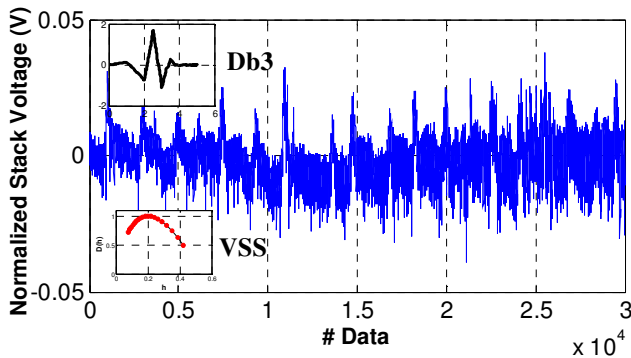
1 4. Voltage Singularity Spectrum as diagnosis tool 31

2
3 In this work, we propose to study the portability of the new
4 diagnosis tool based on the investigation of singularity
5 measurements stamped in FC stack voltage signals. Indeed,
6 measuring local singularities on voltage signals provides
7 suitable information about the evolving dynamics of non-
8 stationary and non-linear processes involved in FC systems.
9 We assess the generalization and the usefulness of the
10 proposed VSS by establishing the diagnosis on two databases
11 issued from the two investigated PEMFC stacks.

12
13 For the stack PEMFC_{Auto}, 10 scenarios are analyzed (normal
14 and abnormal conditions including one fault or more complex
15 situations with 2 or 3 faults occurred simultaneously).
16 For the stack PEMFC _{μ CHP}, 9 operating conditions (normal and
17 abnormal conditions) are studied.

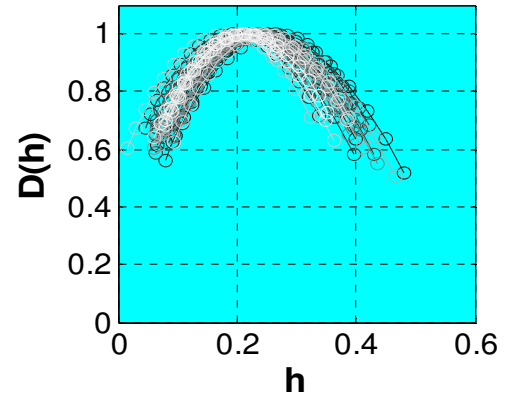
18
19 In this aim, we use 30 voltage profiles for each FC operating
20 condition; each voltage profile covers 1000 voltage samples
21 acquired at a frequency $f_a = 1$ Hz (Fig. 4) using the monitoring
22 data system of the FC experimental test bench.

23
24 To perform the VSS, the analyzing wavelet is selected as
25 Daubechies 3 ('Db3') function (with 3 vanishing moments,
26 Fig. 4).



28
29 Fig. 4. Stack voltage signal scanned by Daubechies wavelet
30 (Db3) for VSS computing.

32 An example of a set of 30 VSS is shown in Fig. 5.



33
34 Fig. 5. Typical VSS computed on 30 profiles covering 1000
35 stack voltage samples.

36 Singularity features are then used to supply the Machine
37 Learning approach, named k Nearest Neighbors (kNN). To
38 improve the performance of the fault classification method, the
39 Minimum Redundancy - Maximum Relevance (MRMR)
40 technique [24] is used to select some relevance features
41 offering the best classification rates.

42 Actually, 20 VSS / class are used to generate the learning
43 database and the 10 others serve as test data to evaluate the
44 performances of the classifier. Each VSS contains 38 features
45 (19 h data and 19 $D(h)$ data). So, by applying the MRMR
46 method on the full feature set (38 features) of the VSS, the good
47 classification rate obtained using the top 6 selected features is
48 about 89.4 % for the stack PEMFC_{Auto}, separating 10 classes
49 (10 FC operating conditions).

50 For the second stack PEMFC _{μ CHP}, 9 classes are discriminated
51 with a success of 95.5 %.

52
53 The best results of the classification rates of the different
54 operating conditions studied are embedded in confusion
55 matrixes given by Tables 4 and 5, for the stacks PEMFC_{Auto}
56 and PEMFC _{μ CHP} respectively.

57

Table 4. Confusion matrix of the good classification rates obtained with MRMR and kNN from the VSS computed with the stack voltage signals of the PEMFC_{Auto}. The studied FC operating conditions are: **Ref**: normal conditions - **DFSC**: cathode flow fault (slight air starvation) - **DFSA**: anode flow fault (slight H₂ starvation) - **DP**: gas pressure fault (lower gas pressure) - **DT**: cooling circuit temperature fault (lower stack temperature) - **DCO**: carbon monoxide poisoning (H₂+CO).

Class	C ₀	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉
Ref	87.5	0	0	12.5	0	0	0	0	0	0
DFSC	0	100	0	0	0	0	0	0	0	0
DFSA	0	0	100	0	0	0	0	0	0	0
DP	50	0	0	50	0	0	0	0	0	0
DT	0	0	0	0	100	0	0	0	0	0
DCO	0	0	0	0	0	100	0	0	0	0
DFSC & DP	0	0	0	0	0	0	100	0	0	0
DFSA & DP	0	0	0	0	0	0	0	71.43	28.57	0
DFSC & DFSA	0	0	0	0	0	0	0	0	100	0
DFSC & DFSA & DP	0	0	0	0	0	0	0	0	0	100

With: $C_0 \equiv \widehat{Ref}$, $C_1 \equiv \widehat{DFSC}$, $C_2 \equiv \widehat{DFSA}$, $C_3 \equiv \widehat{DP}$, $C_4 \equiv \widehat{DT}$, $C_5 \equiv \widehat{DCO}$, $C_6 \equiv \widehat{DFSC \& DP}$,
 $C_7 \equiv \widehat{DFSA \& DP}$, $C_8 \equiv \widehat{DFSC \& DFSA}$, $C_9 \equiv \widehat{DFSC \& DFSA \& DP}$.

Table 5. Confusion matrix of the good classification rates obtained with MRMR and kNN from the VSS computed with the stack voltage signals of the PEMFC_{μCHP}. The studied FC operating conditions are: **Ref**: normal conditions - **DFSC'**: cathode flow fault (air over-supply) - **DFSC_v**: cathode flow fault (slight air starvation) - **DFSA'**: anode flow fault (H₂ over-supply) - **DFSA_v**: anode flow fault (H₂ starvation) - **DT'**: cooling circuit temperature fault (higher temperature) - **DT_v**: cooling circuit temperature fault (lower stack temperature) - **DRH'**: dew temperature fault (higher dew temperature) - **DRH_v**: dew temperature fault (lower dew temperature).

Class	C ₀	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈
Ref	100	0	0	0	0	0	0	0	0
DFSC'	0	100	0	0	0	0	0	0	0
DFSC _v	0	0	100	0	0	0	0	0	0
DFSA'	0	0	0	90	0	10	0	0	0
DFSA _v	0	0	0	0	90	0	0	0	10
DT'	0	0	0	20	0	80	0	0	0
DT _v	0	0	0	0	0	0	100	0	0
DRH'	0	0	0	0	0	0	0	100	0
DRH _v	0	0	0	0	0	0	0	0	100

With: $C_0 \equiv \widehat{Ref}$, $C_1 \equiv \widehat{DFSC'}$, $C_2 \equiv \widehat{DFSC_v}$, $C_3 \equiv \widehat{DFSA'}$, $C_4 \equiv \widehat{DFSA_v}$, $C_5 \equiv \widehat{DT'}$, $C_6 \equiv \widehat{DT_v}$, $C_7 \equiv \widehat{DRH'}$,
 $C_8 \equiv \widehat{DRH_v}$.

As we can see, the proposed diagnosis strategy identifies successfully several complex operating faults (i.e. slight deflections from the nominal operating conditions, and even combination of faults) for both PEMFC_{Auto} and PEMFC_{μCHP}.

5. Conclusions

In this study, VSS are computed on voltage signals acquired under different FC operating conditions (normal and abnormal,

i.e. more or less severe, deviations from the normal conditions) with considering situations that combine 2 or 3 faults simultaneously. Two stacks are investigated: a PEMFC_{Auto} stack that is designed for automotive applications and a PEMFC_{μCHP} stack, dedicated to stationary ones.

Singularity features extracted from the estimated VSS are classified using Machine Learning approach, named k-Nearest Neighbors (kNN).

1 The obtained classification results show that the proposed 51
 2 PEMFC diagnosis tool allows identifying simple operating 52
 3 faults and more complicated situations that contain several 53
 4 fault types. The diagnosis are realized on two different test 54
 5 stands, for different stack sizes, powers and technologies, with 55
 6 different targeted environments of power application. 56
 7 In this paper, we demonstrate that the singularity analysis of 59
 8 voltage signal offers a generic diagnosis tool for the PEMFC 60
 9 SoH monitoring. One key-point of the method is that the VSS 61
 10 can be estimated from the “free” evolution of the stack voltage 62
 11 and without affecting in any way the FC operation: no external 63
 12 additional solicitation is required to reveal the SoH patterns. 64

13

14 Acknowledgement 65

15 *The work performed was done thanks to the French ANR 70*
 16 *project “DIAPASON 2” and in the framework of the 71*
 17 *“Decentralized energy production” project, directed by 72*
 18 *EFFICACITY, the French R&D Institute for urban energy 73*
 19 *transition. 74*

20

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