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# Signal-Based Diagnostics by Wavelet Transform for Proton Exchange Membrane Fuel Cell

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**Abstract**

In order to exploit all the benefits from the Proton Exchange Membrane Fuel Cell (PEMFC) technology and to gain a deeper understanding of operating faults during fuel cell operations, Investigation of the origins of faults is necessary.
In this work, a diagnosis approach consisting of a method using signal-based pattern recognition is proposed. It is aimed at a minimization of efforts and costs in acquisition and evaluation of data for diagnostic purposes. All information needed to locate the faults is drawn from the recorded fuel cell output voltage, since certain phenomena leave characteristic patterns in the voltage signal. A signal analysis tool, namely the Wavelet Transform (WT), is employed to identify different patterns or faults signatures.
The approach has been applied to voltage data recorded on a PEMFC suffering from dysfunctions related to inappropriate humidity levels inside the cell (two different faults are simulated : flooding and drying out). Characteristic features in the output voltage signals were outlined, so a distinction of several states of health was accomplished.
The results show the efficiency of the proposed approach, and the WT can be considered as a reliable method to localize the dysfunctions. A comparison between the Discrete Wavelet Transform (DWT) and the Continuous Wavelet Transform (DWT) has shown that the DWT is more efficient in detecting and localizing faults in fuel cells.

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*Keywords:* Fuel cell; diagnosis; signal processing; Fault signature; discrete wavelet transform; continuous wavelet transform.

## 1. Introduction

The physical and chemical processes forming the functional base of a fuel cell require appropriate operating conditions to run in an optimal way. Unfavorable conditions hinder optimal operation and performances and lead to dysfunctions. As a consequence, the performance of the device is reduced - it generates less power than expected. Some faults can even leave irreversible damage, especially if they last for a long time. In that case, the fuel cell cannot recover its optimal performance, it will constantly generate less power and its lifetime will be seriously shortened.

This work aims at providing a signal-based method for the detection and the identification of faults during fuel cell operation. Knowledge of occurrence and type of those disturbances would allow implementing measures remedying or even totally avoid them (not treated in this work). By doing so (irreversible) damage to the fuel cell could be alleviated or avoided; the reliability of the fuel cell would increase and extended fuel cell lifetime could be assured. This would be a considerable step on the path towards implementation of fuel cells on the mass market.

A crucial step of diagnosis is the collection of data describing the processes inside the fuel cell. The current State of Health (SoH) of the fuel cell has to be determined, in order to allow a distinction between normal and faulty states of operation. Once the faulty state is recognized, its nature and circumstances of occurrence can be examined in more detail.

For several decades, effort is being made to create tools which allow the monitoring of the SoH and thus better understanding the processes going on inside the devices. Various approaches were presented, each of them holding particular advantages and/or possible drawbacks. Benefit of the signal-based method is the simplicity of the data acquisition. This approach was applied for example in [1]. The authors in this paper succeeded in predicting the lifetime of a PEM fuel cell by extracting features from EIS (Electrochemical Impedance Spectroscopy) data.

In [2] and [3], Artificial Neural Networks (ANNs) are used for fault detection diagnosis of PEM fuel cell systems. In [3], the flooding and drying out failures modes are detected and classified.

An analysis of fluidic voltage is done in [4] with a statistical method, namely, statistical correlation.

Wavelet Transform (WT), combined with multi-fractal formalism is proposed in [5] to diagnose a fuel cell stack using the voltage signal.

The single object of investigation in [6] is the stack output voltage: by analyzing this voltage signal with Wavelet Packet Transform algorithm, discrimination between two SoHs of a PEM fuel cell (“flooding” and “non flooding”) was achieved.

Indeed the voltage signal reflects the activities inside the fuel cell. But fuel cells are highly complex systems, since the generation of the voltage is predicated on an interaction of various phenomena [7]. Consequently the amount of voltage generated at a certain instant and thus the shape of the voltage signal is influenced by multiple factors. Put differently, information about diverse processes running inside the fuel cell is merged in the transient voltage signal [6]. As the processes differ in their dynamics, a certain phenomenon should leave characteristic patterns in the time dependent voltage signal. This can be used to unscramble the information.

Now, a tool is needed to tell different influences in the signal apart. Therefore a signal analysis method is engaged, namely the Discrete Wavelet Transform (DWT). With its help, the signal is broken down. The evolution in time of different signal components, sorted by contained dynamics, can be shown in a map. In other words, the signal is “sliced”; each “slice” can be investigated separately, which facilitates a distinction of features.

This paper presents a performance test of the DWT in depicting different phenomena in the fuel cell.

It is organized as follows: section 2 presents a short introduction to the Discrete Wavelet Transform; the working methods of fault diagnosis by wavelet transform and results are detailed in section 3. Section 4 provides a conclusion to this work and draws an outlook for the research in this field.

**Nomenclature**

| | |
|---|---|
| PEM | Polymer Electrolyte Membrane |
| SoH | State of Health |
| DWT | Discrete Wavelet Transform |
| CWT | Continuous Wavelet Transform |

## 2. Wavelet Transform

### *2.1 Wavelet and Wavelet transform*

"Wavelet Analysis" is the generic term for a set of mathematical tools used for signal processing. Contributions from different fields of research led to its establishment, among them mathematics, physics and engineering. Reference [8] offers a compilation of applications in various domains.

The "wavelet" ϕ is an oscillatory function, used as "filer" to excerpt certain information from the signal to be examined. In the courses of the analysis the wavelet is modified, it is stretched and squeezed as well as shifted, creating thus a "wavelet basis". By this means, minuscule and large oscillations in the signal can be investigated even-handedly. Because of this ability for examination on different orders of magnitude, the method is often called "mathematical microscope" or"multi-resolution analysis" in the literature.

The Wavelet Transform (WT) of a signal $x(t)$ is defined by

$$Wx(t) = x(t) * \phi_s(t) = \frac{1}{s}\int_{-\infty}^{+\infty} S(t)\phi(\frac{t-u}{s})du \tag{1}$$

where s is the scale factor, $\phi_s(t) = \frac{1}{s}\phi_s(\frac{t}{s})$ is the dilatation of the basic wavelet $\phi(t)$ by the scale factor s. Let $s = 2^j, j \in \mathrm{Z}$ then the WT is called dyadic WT.

According to the formula (1), the convolution of the signal with the wavelet gives information about how much the signal is similar to the wavelet.

### *2.2 Continuous and discrete wavelet transform*

The Continuous Wavelet Transforms (CWT) permits to represents signal of 1-D into 2-D space (position-scale).

The Discrete Wavelet Transform (DWT) of a digital signal $x(n)$ can be calculated with the Mallat algorithm [9] as follows:

$$S_{2^j}x(n) = \sum_{k\in \mathrm{Z}} h_k S_{2^{j-1}}x(n-2^{j-1}k) \tag{2}$$

$$W_{2^j}x(n) = \sum_{k\in \mathrm{Z}} h_k S_{2^{j-1}}x(n-2^{j-1}k) \tag{3}$$

Where $S_{2^{j-1}}$ is a smoothing operator and $S_0x(n) = x(n)$ . $W_{2^j}x(n)$ is the WT of the digital signal $x(n)$ , and $h_k$ and $g_k$ are the coefficients of low pass filter $H(\omega)$ and high pass filter $G(\omega)$ respectively, where:

$$H(\omega) = \sum_{k \in Z} h_k e^{-ik\omega} \tag{4}$$

And

$$H(\omega) = \sum_{k \in Z} g_k e^{-ik\omega} \tag{5}$$

Practically, the DWT is similar to a filtering operation of a digital signal that is composed in two phases: the decomposition and the reconstruction.

In the first phase, the signal $x(n)$ enters in a system composed by (i) a sub-sampling (consisting of a system such that the input is $x(t)$ and the output $y(n) = x(2n)$ ), followed by (ii) a convolution operation, producing thus the approximation and detail coefficients, underlying the following equations:

$$cA_1(k) = \sum_n h_0(n-2k)cA_0(n) \tag{6}$$

$$cD_1(k) = \sum_n h_1(n-2k)cA_0(n) \tag{7}$$

And the signal $x$ is expressed as:

$$\begin{aligned} x(t) &= \sum_k cA_0\phi_{j,k}(t) \\ &= \sum_k cA_1\phi_{j-1,k}(t) + \sum_k cD_1\phi_{j-1},_k(t) \\ &= A_1(t) + D_1(t) \end{aligned} \tag{8}$$

In order to pass to the next level coefficients, the same operation is realized using the approximation coefficients, up to some level N, called decomposition level, the resulting equations are:

$$\begin{aligned} x(t) &= A_1(t) + D_1(t) \\ &= A_2(t) + D_2(t) + D_1(t) \\ &\vdots \\ &= A_N(t) + D_N(t) + D_{N-1}(t) + \ldots + D_1(t) \end{aligned} \tag{9}$$

As for the second phase (reconstruction), the operation is inverted. The signal is reconstructed using its detail and approximation coefficients, by convoluting them with a reconstruction filter ( $h_1$ for approximation and $g_1$ for details), followed by an over-sampling operation, that consists of a system whose input is the signal $x(n)$ and the output is $y(n) = x(n/2)$ , if n is even, and $y(n)$=0, if is n is odd.

Multiple wavelets are available to be used for DWT. The one chosen in this study is the Haar wavelet, having the shortest filter among other wavelets [8]. (see Fig.1 ).

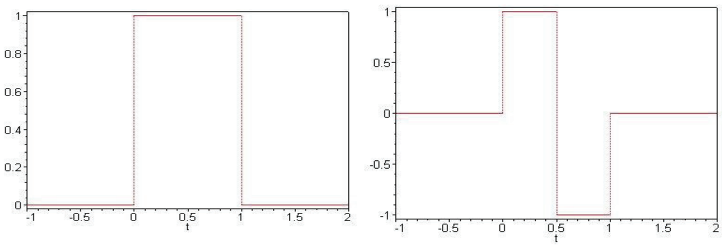

Fig. 1. Haar mother wavelet (left) and Haar father wavelet (right).

The low pass and high pass filters are associated to the mother and the father wavelets respectively (the smooth and the dynamic version of the analysis wavelet) see Fig.1. This filtering operation gives information of the similarity of the signal with the mother and father wavelets. Indeed, the larger the detail coefficients are, the more the signal is similar to the considered wavelet: small coefficients indicate high similarity with the smooth wavelet (mother) enabling thus to detect low dynamics in the signal, and large coefficients indicate high similarity with the oscillated wavelet (father), enabling thus to detect high dynamics in the signal.

## 3. Results and discussion

### *3.1. Working method and results*

The performance of the DWT in the above presented signal-based approach was tested. Object of investigation for these tests were voltage signals recorded in the laboratory on PEM fuel cells which were operated at unfavorable conditions on purpose. The recorded voltage signals presented in the following originate from a PEM fuel cell suffering from dysfunctions related to inappropriate humidity levels inside the fuel cell, which can have a severe impact on fuel cell performance [7]. In detail, these are the flooding dysfunction (liquid water in the cell blocking the pores of the electrode and hindering the H+ ions from moving through it) and the drying out disturbance (membrane too dry which restrains the H+ ions transfer in this area). The humidity related dysfunctions were created in the laboratory through inadequate humidifying of the gas that feed the fuel cell. The laboratory setup was similar to the one described in [6]. The signals were recorded with an acquisition frequency $f_{aq}$ of 1 Hz. For the DWT performance tests, signal sections showing the evolution of the voltage during a period of 5 minutes were employed. The tests were conducted and the maps created using the computing language MATLAB [10], which provides a set of commands for the Wavelet Analysis. Fig.2 shows the voltage signal including 3 SoHs, namely normal operation, drying out and flooding, accompanied by the corresponding DWT. After testing multiple levels, 5 levels are chosen to perform the DWT, and the detail signal of level 5 shows the best localization of dysfunctions.

In Fig.3, the flooding is well localized and the wavelet coefficients have high values. It means that in this region between 495 s (second) and 2430 s, the dynamics change very quickly (high similarity between the Haar wavelet and the oscillations in the voltage signal).

In the region between 2430 s and 3500 s, these coefficients start to decrease and to become near to zero, showing thus that the signal is recovering the normal functioning. Between 3500 s and 4450 s, the detail coefficients increase again, but remains still smaller than the coefficients in the period of flooding (the dynamics change less), indicating thus a period of drying is occurring, and finally from 4450s up to end, a period of recovery and stabilization is occurring, indicated by the stabilization of the detail coefficients.

Consequently, the wavelet coefficients picture varied pattern in different locations on the map.

Accordingly the signals contain dynamics-related features that allow distinguishing them. By the help of the DWT it is possible to describe those differences.

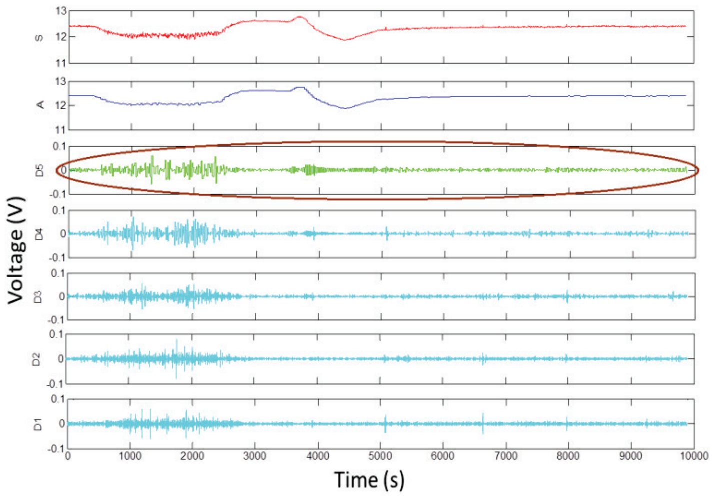


Fig. 2. Five levels DWT for voltage signal (in red) S: voltage signal, A: approximation signal, D5… D1 are the detail signals.

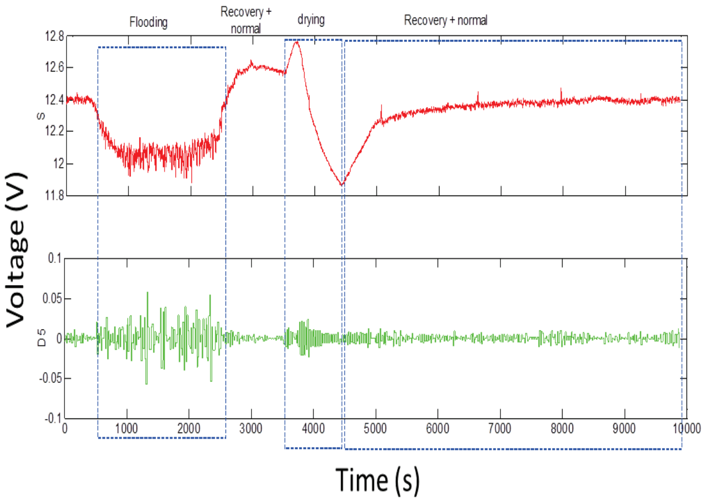


Fig. 3. Localization of the flooding and drying regions by DWT

*3.2. Comparison with the CWT*

In order to compare the performance of the DWT and the CWT in the domain of diagnosis, a CWT for the same voltage signal is performed in Fig.4. The CWT can also provide information about the different dynamics presented in the signal.

The main drawback of the CWT is that a large number of scales is needed to show the signal components (in Fig. 4, 200 scales are used), which can be considered as time coasting, and useless for online application.

A comparison between DWT and CWT can be summarized as follows: the CWT provide regions where the faults occur, while the DWT can localize them much better (the time of beginning and end of mal-functioning are set), and with few number of decomposition level, which make the DWT more desired for algorithm that need fast execution, for instance, in the present work, the performance of 5 level DWT is achieved in less than 0.8 second.

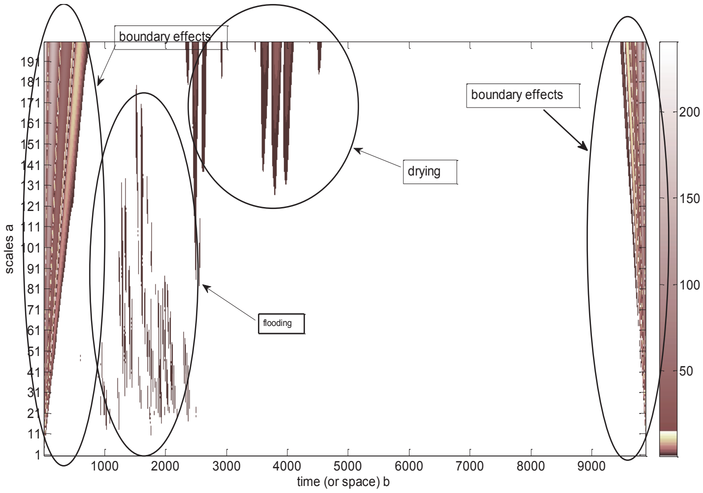


Fig. 4. CWT for localization of faults

Another advantage for the DWT is the elimination of boundary effects, which are presented in the CWT. The presence of boundary effects can impact negatively the origin of the faults, leading to false alarms.

In figure 5 ((a) and (b)), a comparison between CWT using haar wavelet (short support), and Daubechie's 5 (large support). It can be noticed that, with a wavelet of large support, the faults can be detected better, but more boundary effects are presented.

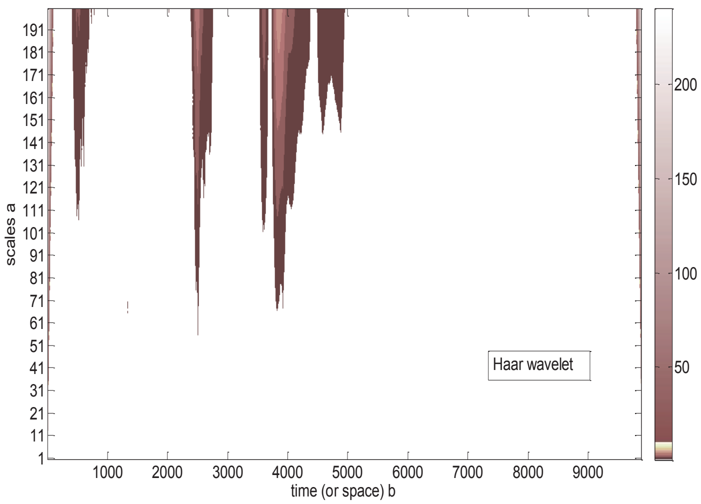


Fig. 5. (a) CWT using Haar wavelet

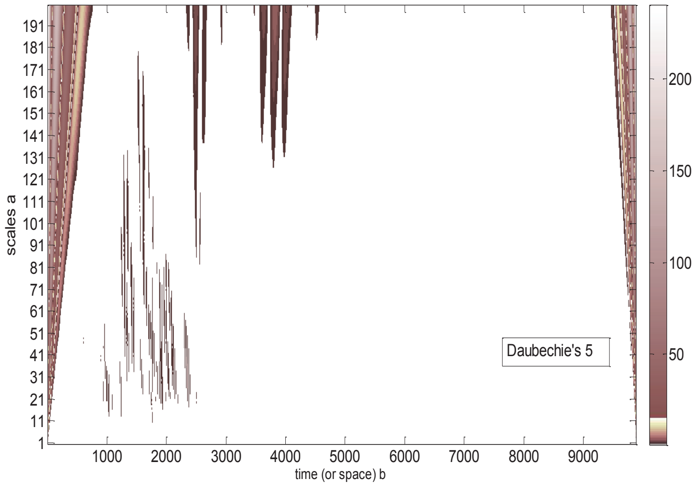


Fig. 5. (b) CWT using Daubechie's wavelet

## 4. Conclusion

This study proved that discrimination between different SoHs based on the analysis of dynamics-related signatures is possible; furthermore the DWT is qualified to specify these signatures. The method is cost-saving and possibly applicable to a wide range of dysfunctions.

As a sophisticated "Mathematical Microscope" the DWT offers a variety of settings and adjustments to optimize the analysis. On several steps of the analysis a selection has to be done, each of these decisions contributes to the accentuation of certain characteristics, but possibly eclipses others.

Already the selection of the wavelet function or the range of scales at the very beginning of the analysis is a relevant action giving direction to the whole analysis. Depending on the choice, features of a certain shape and size in the signal will be detected or omitted.

The detection of faults in the fuel cell, namely: flooding and drying out can be recognized according to the details coefficients: the larger coefficients indicate the occurrence of these faults. The localization (the beginning and the end of the malfunctioning) can also be stated using the DWT.

To obtain a totally robust algorithm, further tests have to be conducted, both with already investigated dysfunctions as well as with other kinds.

A comparison between DWT and CWT for diagnosis has also been studied, and the DWT showed more advantages as for the localization and the execution time.

Another interesting work that could be done is to adapt the DWT for real time investigation of faults, this could have significant impact of the lifetime of the fuel cell, the earlier the SoHs are detected, the better the fuel cell can be protected, and thus, a longer useful remaining lifetime can be obtained.

## 5. Acknowledgments

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