SAND2014-18449C

Arc Fault Signal Detection - Fourier Transformation vs. Wavelet Decomposition Techniques using Synthesized Data

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***Abstract* — Arc faults are a significant reliability and safety concern for photovoltaic (PV) systems and can cause intermittent operation, system failure, electrical shock hazard, and even fire. Further, arc faults in deployed systems are seemingly random and challenging to faithfully create experimentally in the laboratory, which makes the study of arc fault signature detection difficult. While it may seem trivial to simply record arcing signatures from real-world system, an obstacle in capturing these arc signals is that arc faults in the PV systems do not happen predictably, and depending on the location of the sensors relative to the arc location, may contribute a negligible portion to the magnitude of the sensed current or voltage waveform. The high-frequency content of the arc requires fast sampling, long memory, and fast processing to acquire, store, and analyze the waveforms; this adds substantial balance-of-system cost when considering widespread deployment of arc fault detectors in PV applications.**

In this paper, we study the performance of the fast Fourier transform arc detection method compared to the wavelet decomposition method by using synthetic waveforms. These waveforms are created by combining measured waveforms of normal background noise from inverters in DC PV arrays along with waveforms of arcing events. Using this technique allows the ratio of amplitudes are varied. Combining these separate waveforms in various amplitude proportions enables creation of test signals for the study of detection algorithm efficacy. It will be shown that the wavelet transformation technique produce more easily recognized detection results and can perform this detection using a much lower sampling rate than what is required for the fast Fourier transform

***Index Terms* — arc fault detection, inverter noise, Fourier transform, wavelet transform, filter banks.**

I. INTRODUCTION

Arc faults have become a major concern for photovoltaic (PV) systems since a large number of electrical connectors and exposed long cables are need in the system. The combination of high voltage DC and deteriorated insulation can lead to arcing over time. Electrical insulation can degrade due to aging effect; chaffing against the mounting hardware, trees and other building materials after installation; abrasion from the conduit during installation, or other circumstances such as rodent bites. Arc faults can result in electrical shock hazard and system failure. While the arc creates high temperature plasma that can ignite surrounding materials, such as in the example shown in Fig. 1 [1], the impedance of the arc may not draw sufficiently high current to activate over-current protection devices. Thus the arc can be sustained undetected for hours or longer. Arc faults in PV systems not only threaten property loss but can also pose significant threats to human safety [2-5].

Thus arc fault detection is extremely important for reliable and safe system operation and is a prerequisite for widespread adoption of PV generation systems [6-8]. Electrical arcs in PV systems can arise from series or parallel faults, as illustrated in Fig. 2 [9]. Series faults can occur due to loose electrical connections such as a crimp-connection not adequately fastened or terminal strips not properly torqued both of which can cause the electrical wires to pull apart. Parallel faults can be caused by abrasion of wire insulation allowing a shunt-path for current such as to earth ground or pole-to-pole in the DC wiring.

While reports of prior research into arc fault detection algorithms exist in the literature [10-16], there has been little

Fig. 1: Damage to a PV system attributed to an arc fault.

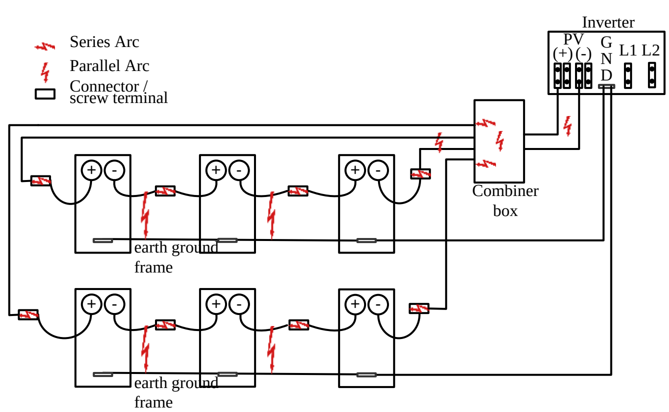


Fig. 2: Example of locations where arcing may occur in a PV array.

discussion of experimental acquisition of the data, which is non-trivial, for evaluation of the detection algorithm validation. Designing an experiment to create scientifically repeatable results is difficult because of the unpredictability, and lack of control over the arc characteristics including ignition, duration, and stability. Sustained arc faults possess chaotic electrical characteristics, which makes it impossible to scientifically repeat the experiment with consistent test data.

In this paper, a test signal is synthesized using time-domain inverter noise signal data measured from a PV array and time-domain arc signals obtained from an arc generator. We define a metric called the arc-signal-to-noise ratio (ASNR) which determines the proportion of power from each source in the composite signal. Adjusting this user-specified parameter in the synthesizing process enables the synthesis of a family of test signals for validation, sensitivity, and efficacy studies of the detection algorithm based upon real-world signals and scenarios.

Once these synthetic signals are created with specified ASNR levels, discrete Fourier transform and discrete wavelet transform are comparatively studied. The influence of sampling frequency on the two analysis approaches is examined. The wavelet transform analysis with distinct types of wavelet are also evaluated and compared.

II. Wavelet Filters

A. Discrete wavelet transform

Wavelet transform (WT) is a linear transformation like the Fourier transform. Unlike FFT, it allows precise time localization of different frequency components of a given signal [17]. Due to the wide variety of signals and problems encountered in power engineering, there are various applications of wavelet transform, such as fault detection, load forecasting, and power system measurement. In addition, information about power disturbance signals is often a combination of features that are well localized temporally or spatially such as power system transients. This requires use of versatile analysis methods in order to handle signals in terms of their time-frequency localization, which is an excellent area to apply the special property of wavelets [18].

The wavelet analysis procedure is based on a pair of wavelet prototype functions, called the wavelet function (mother wavelet) and scaling function (father wavelet) – together they provide a localized signal processing method to decompose the differential signal into a series of wavelet components, each of which is a time-domain signal that covers a specific frequency band [19, 20]. Wavelets are particularly effective in approximating functions with discontinuous or sharp changes like power system fault signals [21]. With proper choice of the mother wavelet, wavelet transformation is an effective tool for fault detection and feature distraction.

There are many types of wavelets. One can choose among them depending on the particular application. While wavelet transform is a continuous-time function, it has a discrete-time counterpart, the discrete wavelet transform (DWT), similar to the discrete Fourier transform (DFT) implementation of the continuous-signal Fourier transform. The DWT is defined as

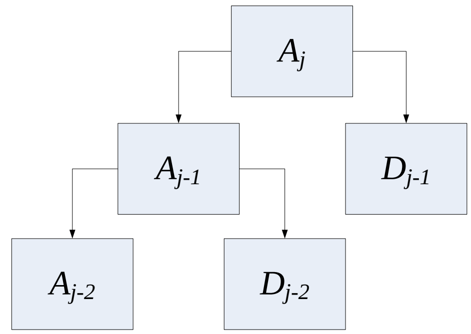


Fig. 3: Wavelet decomposition tree.

$$C(j,k) = \sum_{n \in Z} s(n) g_{j,k}(n) \quad (1)$$
$$j \in N, k \in Z$$

where $C(j,k)$ is the corresponding wavelet coefficient, n is the sample number, $s(n)$ is the signal to be analyzed and $g_{j,k}(n)$ is the discrete scaling function, which for dyadic-orthonormal wavelet transform is defined by

$$g_{j,k}(n) = 2^{-j/2} g(2^{-j} n - k) \quad (2)$$

The auxiliary function to this is the wavelet function.

With this initial setting, there exists an elegant algorithm, the multi-resolution signal decomposition (MSD) technique, which can decompose a signal into levels with different time and frequency resolution. At each level j, approximation signal A_j (represented by linear combinations of father wavelets at jth level) and detail signal D_j (represented by linear combinations of mother wavelets at jth level) can be created. The words "approximation" and "detail" are due to the fact that A_{j-1} is an approximation of A_j taking into account the “low frequency" of A_j, whereas the detail D_{j-1} corresponds to the "high frequency" correction.

As shown in Fig. 3, for a reference level J, there are two categories of details: 1) those details associated with indices $j \geq J$ correspond to the scales $2^{-j/2} \leq 2^{-J/2}$, which are the fine details; and 2) the other details correspond to $j < J$ and are the coarse details, which define an approximation of the signals

$$s = A_J + \sum_{j \geq J} D_j \quad (3)$$

which signify that s is the sum of its approximation A_J improved by the fine details [22].

B. Wavelet and filter banks

Multi-resolution signal analysis using discrete wavelet transform (DWT) can be implemented by filter bank theory, where a wavelet and a scaling function is associated with a highpass and a lowpass filter respectively. As shown in Fig. 4, on each level of decomposition, the input signal is split into a

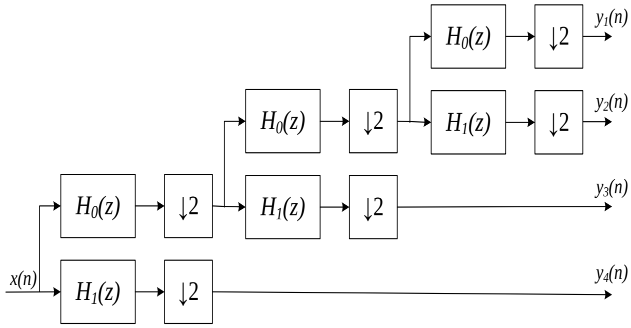


Fig. 4: Dyadic tree wavelet analysis bank.

low-frequency component and a high-frequency component. With dyadic wavelet filters (wavelet transform), only the low-frequency part is further decomposed. In comparison, binary-tree wavelet filters (wavelet packets), which splits both low- and high-frequency component on each level, leads to decomposed signals with an equal bandwidth [23]. In this paper, only dyadic wavelet filter implementation is discussed.

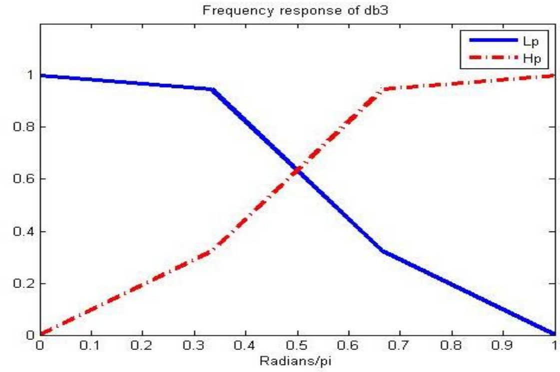
C. Selection of mother wavelet

The criteria for selecting the mother wavelet adopted in this paper is summarized in [24, 25]:

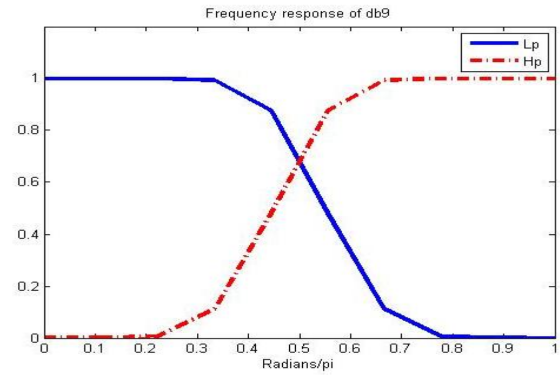
1) The wavelet function should have a sufficient number of vanishing moments to represent the salient features of the disturbances.
2) The wavelet should provide sharp cutoff frequencies to reduce the amount of leakage energy into the adjacent resolution levels.
3) The wavelet basis should be orthonormal.
4) For applications where the information lasts for a very short instant, wavelets with less number of coefficients are better choices; on the other hand, for signal signature spread over a longer period of time, wavelets with a larger number of coefficients tend to show smoother results.

There are several well-known families of orthogonal wavelets. An incomplete list includes Harr, Meyer family, Daubechies family, Coiflet family, and Symmlet family [26]. Daubechies wavelets are chosen in this paper due to their outstanding performance in detecting waveform discontinuities [24, 27].

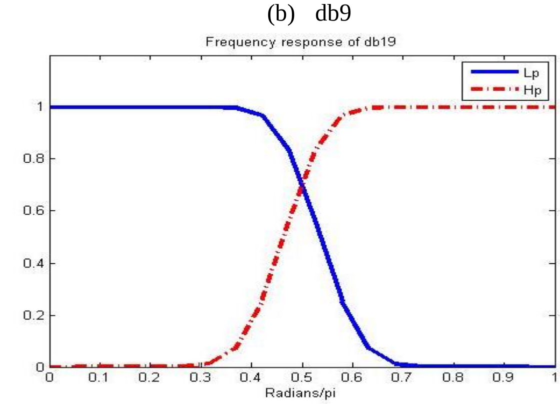
Frequency response of filter banks of Daubechies 3 (db3), Daubechies 9 (db9), and Daubechies 19 (db19) are shown in Fig. 5. It can been seen that, the frequency response of db9 filters have a significantly sharper cutoff frequency in comparison with that of db3 filters. But db19 does not provide equally significant improvement over db9. Considering the extra computation load brought by wavelets with more coefficient, db9 is a good compromise.



(a) db3



(b) db9



(c) db19

Fig. 5: Frequency response of filter banks using db3, db9, and db19.

III. Comparison of the Two Analysis Approaches

Although it is widely used, the conventional Fourier transform has a significant limitation in that it works best for periodic signals. However, the nature of arc faults in power systems is not periodic [6]. Further, the conventional Fourier transform gives only frequency information [28]; it does not provide time-domain information to determine exactly when an event occurs. Such temporal localization could help correlate the arc signature with other events (internal or external to the PV system) such as lighting or electrically fast transients that couple from other system components.

The short-time Fourier transform (STFT) is a time/frequency analysis technique which retains the time index of the frequency spectrum and seems to overcome the temporal localization problem. However, it still has a fundamental drawback in that the length of the window used in the STFT is the same for all frequencies. In order to obtain good frequency resolution, a large number of data points is required which in turn causes any short time variation within the window to be obscured on the resulting spectrum and minimizes the ability to temporally localize high frequency signals. If one wishes to have different resolutions in different parts of the frequency spectrum, the discrete STFT will have to be repeated for a number of window sizes. Thus, the problem is really that of time and frequency resolution tradeoff. As a result, good frequency resolution prevents accurate time localization of the high frequency signals. But in order to provide time localization for the finite duration events, if the window length is made sufficiently small, it will not be able to concurrently provide the required frequency resolution for low frequency content [23, 29].

It is worth pointing out that, to prevent the spectral leakage, window size usually has to be chosen carefully to meet the coherent sampling requirement. However, the arc fault signature can be distributed in a wide frequency band [30, 31]. Thus it is impossible to choose a perfect window to extract all relevant accurate information using Fourier transform based approaches.

In conclusion, Discrete STFT might be more suitable than wavelet transform for time-frequency domain analysis of harmonic related disturbances, but not for discovering short abrupt changes like arc faults. In comparison, owing to the distinguishing capability of signal discontinuity detection, wavelet transform excels in extracting sharp changes throughout the entirety of the signal.

IV. Results of Signal Analysis

A. Composite signal with high-rate data (F_s=1MHz)

A composite signal with a duration of one second is synthesized by combining inverter noise and arc fault signals at a sampling rate of 1MHz to achieve an ASNR of 0.1. FFT analysis, shown in Fig. 6, is first performed on the entire one-second sample (second from top), the non-arcing portion (third from top) and then the arcing portion (bottom) of the waveform. The strong presence of the inverter switching frequency and harmonics appears to overshadow the arc noise, making detection difficult.

By contrast, the 7^{th} decomposed signal (covers the frequency band of 3.9kHz – 7.8kHz) from the wavelet transform is selected. Different decomposition results using db3, db9, and db19 are shown in Fig. 7. The temporal waveforms for the selected frequency band clearly indicate the causality and timing synchronization of the initiation and extinction of the arc.

B. Composite signal with downsampled data (F_s=100kHz)

The composite signal from part *A* is downsampled by a factor of 10 to produce a composite signal with a sampling rate of 100kHz and a total of 100k sample points for the one-second signal. The FFT and wavelet analysis results are shown in Fig. 8 and Fig. 9 respectively. The decomposed signals cover the band of 3.125kHz – 6.25kHz are selected.

C. Comparison of the results

From the FFT analysis results shown in Fig. 6 and Fig. 8, it is difficult to find any significant detectible arc fault features by comparing the FFT result of the non-arcing part and the

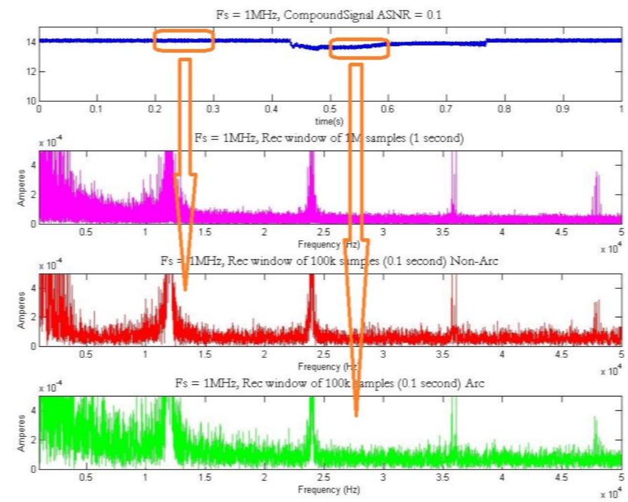


Fig. 6: Composite signal (Fs = 1MHz); FFT analysis of the entire composite signal (red); FFT of the non-arcing part of the signal (red); FFT of the arcing part of the signal (green).

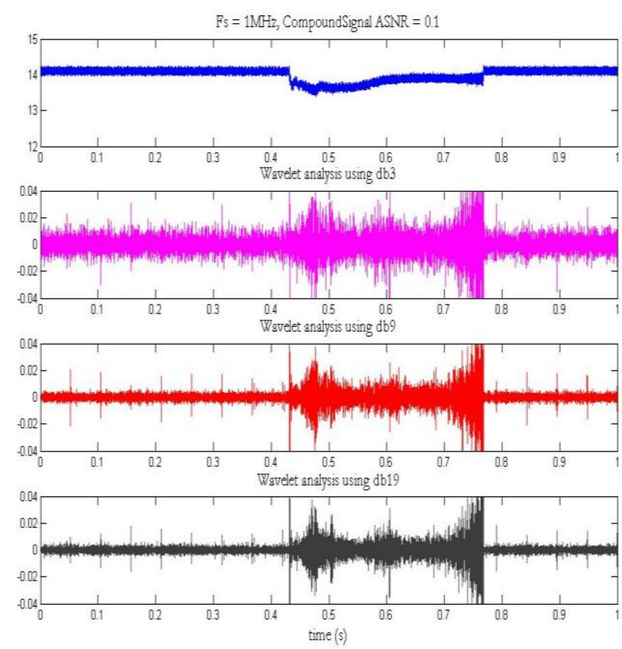


Fig. 7: Wavelet analysis (db3 – magenta, db9 – red, db19 - grey) of the composite signal (Fs = 1MHz).

arcing part of the signal, especially when the sampling rate is decreased (Fig. 8). Slight differences do exist between the two spectral analysis graphs, but the fault detection threshold can be very difficult to select, particularly if a detection technique using limit-lines is used. Detection threshold setting involves consideration of the signal-to-noise ratio, which may change from application-to-application. Selecting a threshold without delicate calculation and thorough understanding of the system behavior would lead to not triggering or false triggering of the protection mechanism.

However, from the wavelet analysis plots, not only arc features can be easily distinguished from the non-arcing signal, but the exact moments when the arc fault ignites and extinguishes can also be observed. This facilitates selection of a detection threshold for an embedded microcontroller for real-time arc fault detection. It also enables characterization of the arc event.

By comparing the analysis result using 3 different Daubechies wavelets, we can conclude that decomposition results using db9 and db19 are significantly better than using db3. But db19 doesn't provide much improvement to the result of db9. This is consistent with our frequency response analysis of the filter banks. By taking the DSP computational load into consideration, db9 is a good compromise between calculation speed and decomposition quality.

As shown in part A and part B, the sampling frequency has significant impact on both Fourier and wavelet detection approaches. With the signal sampled at 100kHz, it is almost impossible for the Fourier transform to capture any arc fault features. While the sustained presence of the arc is not as obvious as when the sampling frequency is 1MHz for wavelet decomposition, we should still be able to draw enough information to detect the arc fault. Thus, detection approaches based on wavelet can use a lower sampling rate than Fourier transform to accomplish accurate arc fault detection if indeed Fourier methods can accomplish it at all.

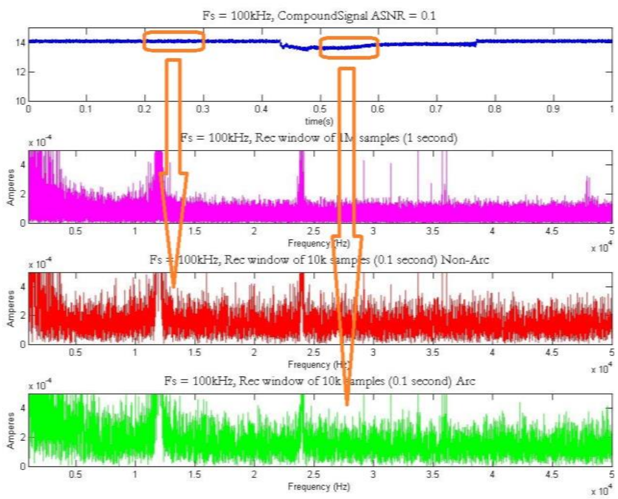


Fig. 8: Composite signal (Fs = 100kHz); FFT analysis of the entire composite signal (magenta); FFT of the non-arcing part of the signal (red); FFT of the arcing part of the signal (green).

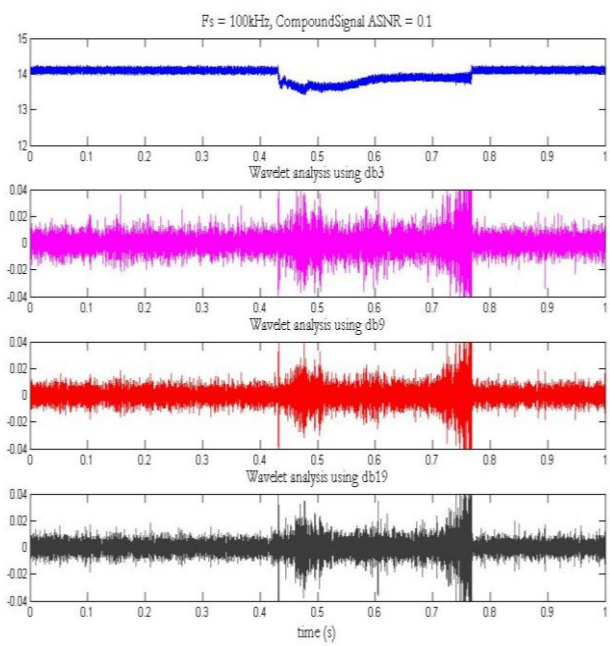


Fig. 9: Wavelet analysis (db3 – magenta, db9 – red, db19 - grey) of the composite signal (Fs = 100kHz).

V. CONCLUSION

This paper proposes a method of studying arc fault detection algorithms by using waveforms synthesized from real-world PV system voltages and current representing arcing and inverter electrical noise with a user-specified arc-signal-to-noise ratio (ASNR). Wavelet analysis using various mother wavelet is studied by analyzing frequency responses of the respective filter banks. The proposed method is then used to compare the results of Fourier and wavelet analysis of the signal. From the test results, wavelet analysis performs much better than the traditional Fourier transform approach. The mother wavelet selection is studied as well by using various orders of Daubechies wavelet. The simulated results using the synthesized test signals coincides with theoretical analysis derived from wavelet filter banks.

VI. ACKNOWLEDGEMENT

This material is based upon work supported in part by the National Science Foundation under Grant No. ECCS-1238412. This research was also partially funded by the Department of Energy's Office of Energy Efficiency and Renewable Energy through a collaboration with Sandia National Laboratories. Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

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