PHOTOVOLTAIC ARC-FAULT DETECTION

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

Photovoltaic Arc-Fault Detection. (May 2014)

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Electric arcs cause fires. The ability to detect an electric arc successfully, reliably, and quickly enables mitigation of arc-induced fires before they start. Within photovoltaic systems, in particular, the detection of an arc poses a significant engineering challenge. To date, arc detecting technologies frequently encounter trouble distinguishing between actual arc-fault scenarios and electrical noise from opening contactors, or power electronics such as the solar inverter or DC/DC optimizer. This paper seeks to investigate the efficacy of a new method for arc-fault detection.

ACKNOWLEDGEMENTS

I would like to acknowledge Sandia National Laboratories for providing data that allowed much of the experimental work to take place. Also, I would like to thank Dr. Robert Balog and Zhan Wang for their continued guidance and assistance throughout this project.

NOMENCLATURE

AC	Alternating Current
DC	Direct Current
DSP	Digital Signal Processing/Processor
DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transform
IFFT	Inverse Fast Fourier Transform
PV	Photovoltaic(s)
SNR	Signal-to-Noise Ratio

CHAPTER I

INTRODUCTION

The need for arc-fault detection

Recent changes in the *National Electrical Code*® (2011) and the UL 1699B safety standard call for the ubiquitous use of arc-fault detectors in photovoltaic arrays. Without these devices, solar arrays remain vulnerable to the risk of fire hazard, which can hamper the widespread adoption of renewable energy resources. The industry has developed methods of detecting arcs, but current technologies are plagued by false positives or *nuisance detection* and false negatives or *non-detection* which ultimately stem from the inability of the incumbent technologies to clearly identify and characterize the arc signatures in comparison with background and normal system noise from other electronics such as the PV inverter.

Direction of approach

Work done by Wang and Balog establishes a theoretical framework for characterizing arc signatures using wavelet analysis which reaches beyond the mainstream approach of Fourier analysis methods [1]. The discrete wavelet transformation (DWT) is a linear transformation that can extract structural information from a signal with no loss of detail from the original signal [2]. As a discrete transformation that executes in real time, the DWT can be implemented in a straightforward and efficient manner by modern computing devices including digital signal processors (DSPs). The DWT enjoys greater computational advantages over the Fast Fourier Transform (FFT), achieving respectively $O(n)$ versus $O(n * \log_2 n)$ speeds [3].

Prototypes for arc-fault detectors employing only Fourier analysis have previously shown to lack true arc-fault detecting capability [1]. For example, they cannot properly predict and distinguish between arc signatures that vary by power level and array geometry or show how those factors are influenced, changed, or masked by other power electronics including the solar inverter.

This paper details experimental validation of the wavelet analysis algorithm in effort to develop and put into practice a robust method for consistent and accurate detection of arc faults.

CHAPTER II

METHODS

Data source

The scope of the research includes both the analysis of data from synthetic arcing scenarios as well as data collected from arcing in real PV arrays. The synthetic arcs come from an arc-fault generator as described by Wang and Balog [1]. Sandia National Labs (SNL) supplied the author with data representing actual noise signatures from a variety of PV inverters. This data is largely comprised of current waveforms captured at different insolation levels.

Gathering empirical evidence

To experimentally verify the wavelet analysis detection method, these short time-domain waveforms must be lengthened and fed through the arc-fault detection algorithm. In a successful trial, the wavelet analysis algorithm will distinguish between the random inverter noise and the superimposed synthetic arc waveform. An unsuccessful trial will result in either a false positive with only the inverter noise present as input, or non-detection with the inclusion of the fabricated arc signature. Through the course of many experimental trial runs, we will build evidence that the wavelet based arc-fault detection algorithm works either absolutely or within a quantifiable margin of error. This approach also allows for repeated future testing which may expand the dataset with benchmarks of actual recorded arc-fault scenarios.

CHAPTER III

TESTING

Signal reconstruction

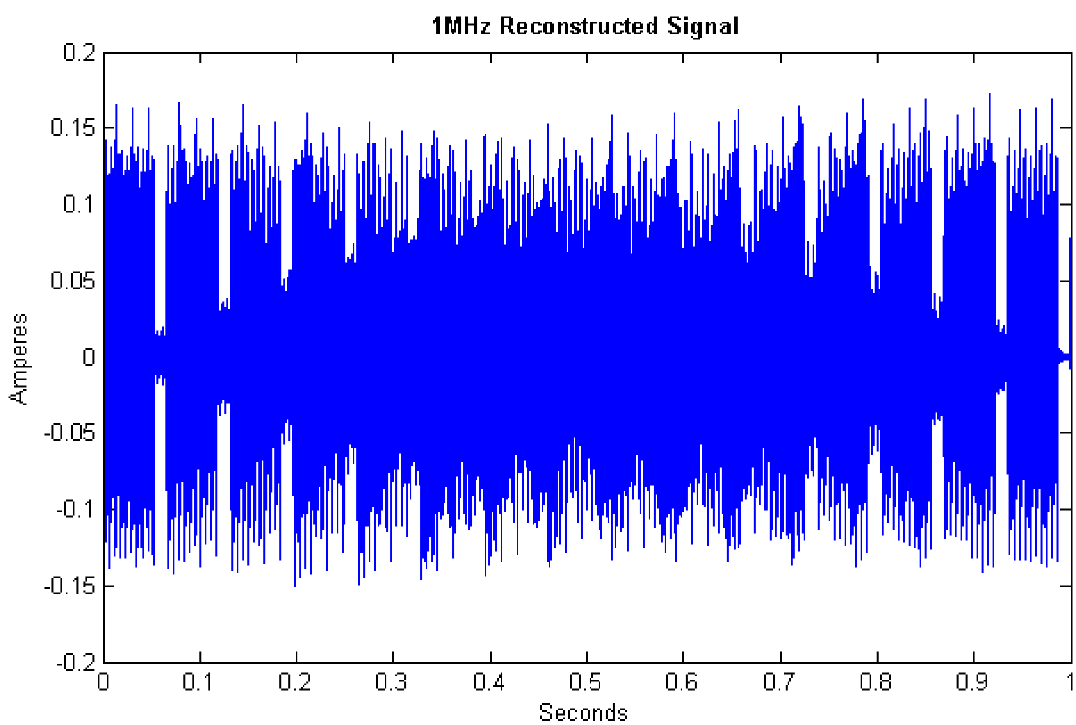
The data supplied by SNL includes short time-domain recordings of PV inverter current noise in length approximately five one-hundredths of a second. Brevity presents the first challenge in incorporating such data. In order to show the ability of wavelet analysis to pinpoint the exact time location of an arc in real time, we desire a signal 1-10 seconds in duration. The longer the test lasts, the greater the proof that the new method of detection does not misfire and haphazardly return false positives.

The Fourier transform provides a way to quantify the periodic frequency components of a signal. By identifying the relative magnitude and phase of each component, exceedingly close approximations of even aperiodic signals can be formed. After computing the efficient FFT of a signal, the Inverse Fast Fourier Transform (IFFT) provides a means of rapid reconstruction. However, with the object of lengthening a signal in mind, the IFFT fails to accomplish this purpose because it requires a point-to-point reconstruction from the original signal. IFFT's parameter of signal length, N, only provides a way to manipulate the sampling rate of the output signal rather than extending its time duration.

Instead, the author chose to reconstruct and extend signal length in an iterative manner though the addition of sinusoidal frequency components at the specified magnitude and phase provided by the FFT. Though computationally more expensive, this method allows the user to reconstruct an arbitrarily long time-domain signal from the representative periodic frequency spectrum.

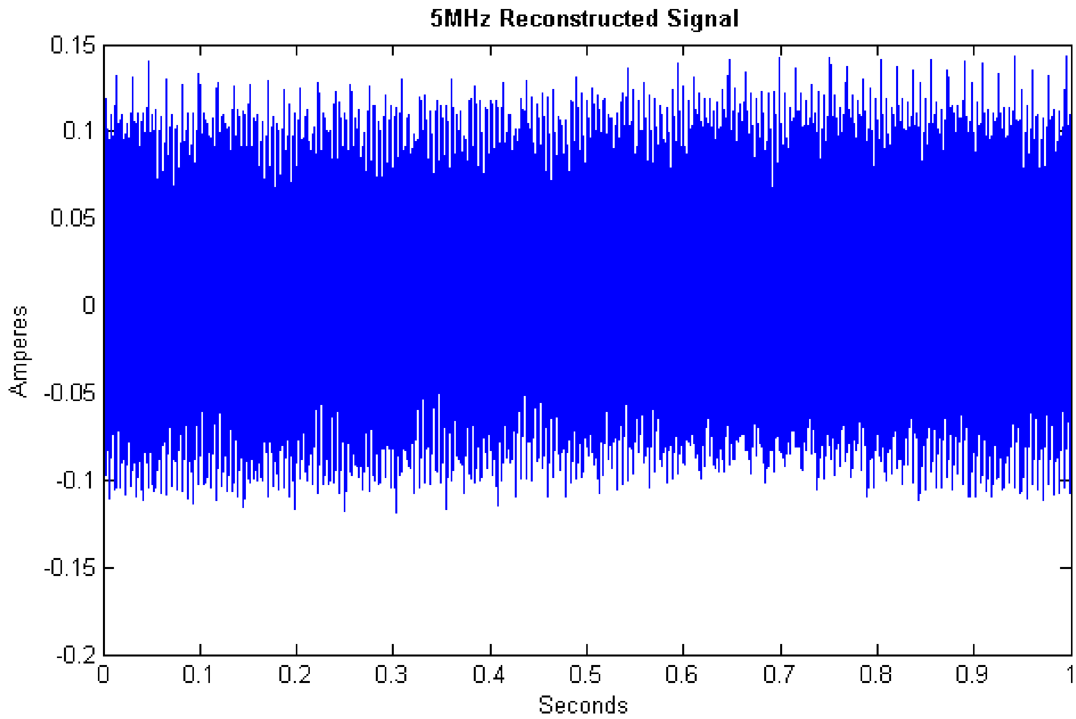
Preliminary results showed strikingly close resemblance to the original waveform, but these were perpetually accompanied by unanticipated periodic bands of noise throughout the reconstructed signal. Further analysis of the result proved that these unexpected streaks stemmed directly from the resolution of the FFT. At 1 MHz, this periodic event obscured the reconstructed signal at a rate of 15.26 Hz, corresponding exactly to the FFT resolution. Increasing the sampling frequency by five-fold, the resolution of the reconstruction improved enough to make the signal usable.

Figure 1



The time-lengthening reconstruction technique using FFT produces 15.26 Hz bands at a sampling rate of 1 MHz.

Figure 2



The same reconstruction technique at a sampling rate of 5 MHz diminishes the effect of frequency resolution.

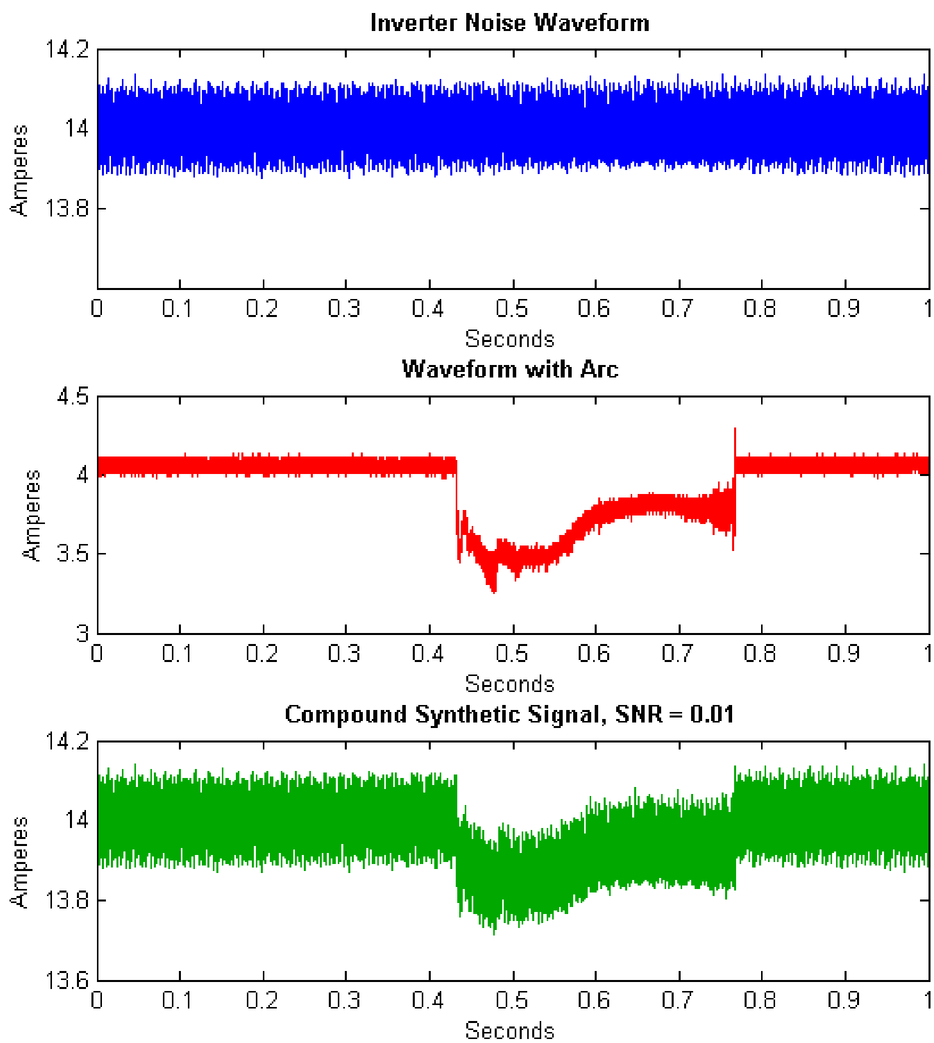
Synthesizing test signals

After obtaining a satisfactory signal from the SNL data, we combined the new waveform with a synthetic arc produced by the arc-fault generator. Such a combination could be accomplished through simple wave superposition, but it strikes as more interesting and revealing to define an arc-signal to noise ratio describing the relative power magnitudes of the two signals, such as the following:

$$SNR = P_{arc}/P_{noise} \qquad (1)$$

This implementation by superposition at different relative power magnitudes allows more thorough and critical testing of the strength of the wavelet detection algorithm. Taking SNR as 0.01, we synthesized a signal containing both the arc signature and background noise.

Figure 3



(Top) 5 MHz-reconstructed, 1-second inverter noise signal. (Middle) Arc signature from synthetic arc generator. (Bottom) Combined signal with arc superimposed at SNR = 0.01.

Similarly, arcs at higher signal to noise ratios—namely 0.1 and 1—were also synthesized.

CHAPTER IV

RESULTS

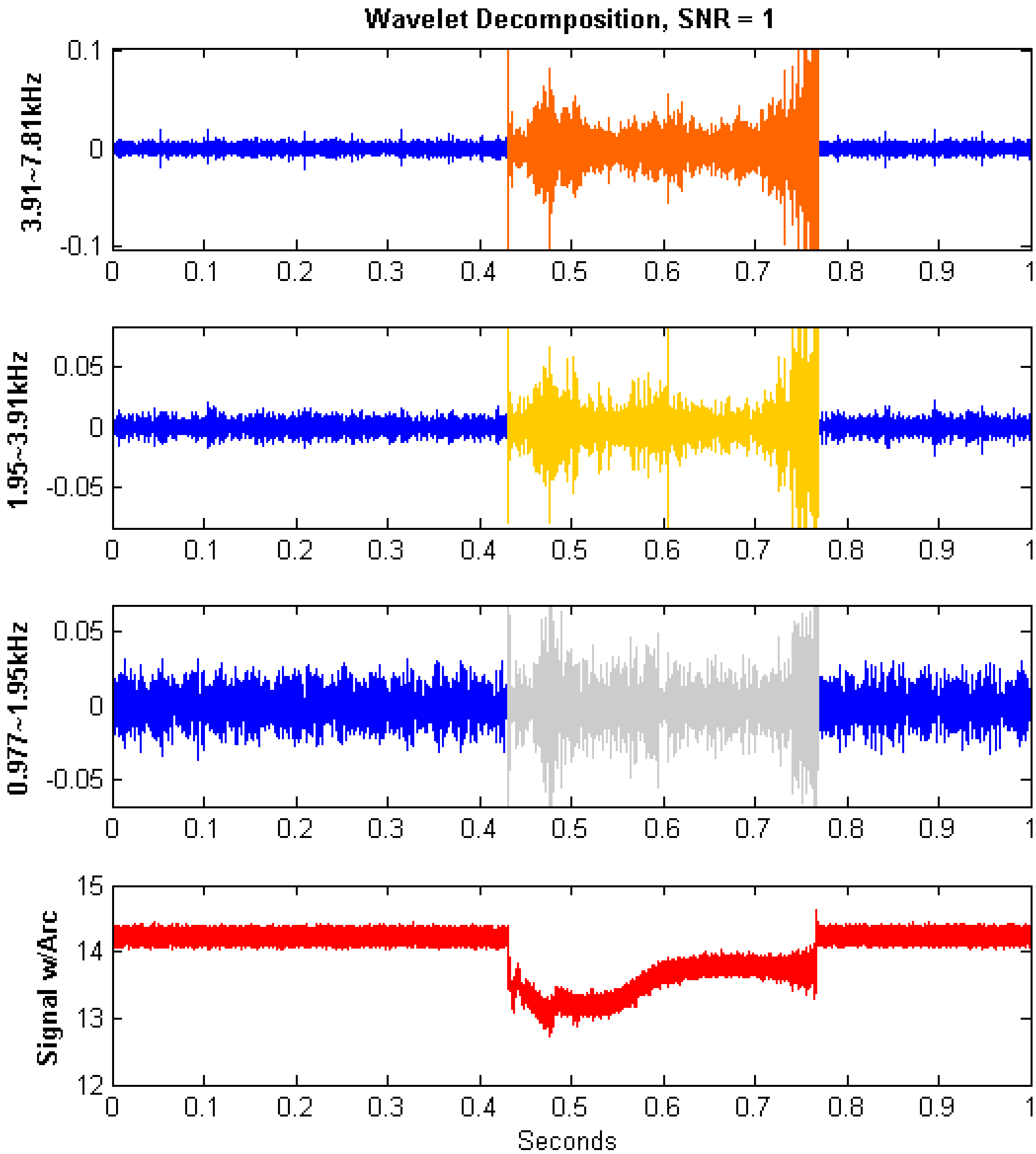
Wavelet decomposition results

After combining the arc with the PV background noise, the newly created synthetic signal passed through the wavelet decomposition algorithm developed by Wang [1]. The underlying spectral range used finds support in work done by other authors [4], [5]. At an SNR of unity, the arcing portion of the signal is detected on three different frequency bands (detection regions shown in orange, gold and gray in Figure 4) which come to light as a result of the wavelet decomposition.

Of utmost importance is the consistent behavior of the background noise during the non-arcing portion of the signal. An arc may start and stop again on a microsecond timescale. However, these results show no erratic deviations of nuisance tripping during a full 400,000 microseconds before the arc begins. Similarly after the conclusion of the arcing portion of the signal, the frequency bands show no nuisance detection for another 200,000 microseconds.

The immediate nature of the detection embodies another key feature of the result. Fourier analysis always involves some finite time window over which to conduct spectral analysis. This often arbitrarily-wide window represents a fundamental delay in the detection processing of methods relying on the Fourier transform. Because wavelet decomposition takes place in real time and manifests abrupt changes in high frequency content rapidly, we can observe a measurable spike in frequency content the moment the arc begins in our experiment in each of the three frequency bands of interest.

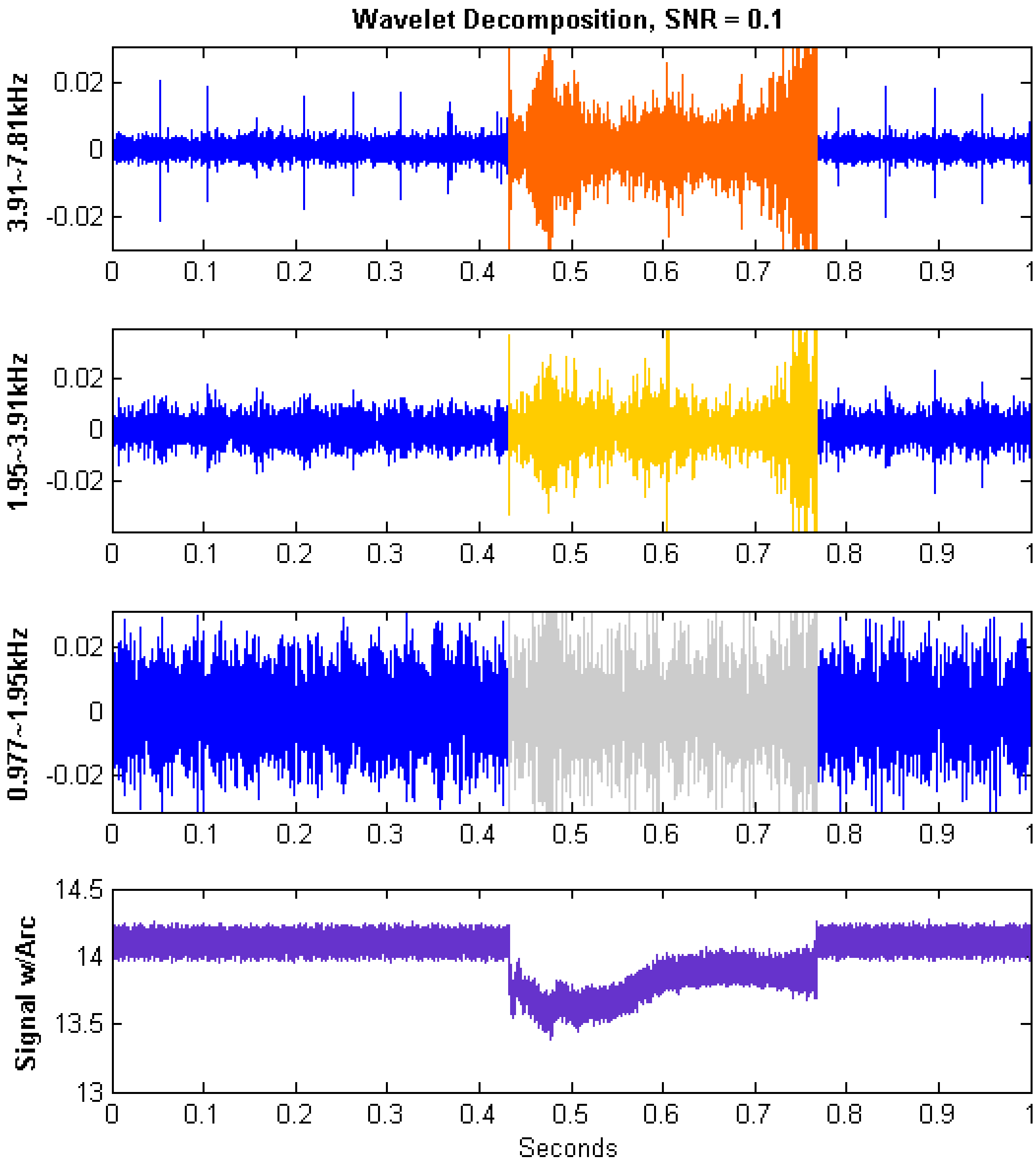
Figure 4



At SNR = 1, the wavelet analysis algorithm decomposes the signal into 3 different frequency bands (top) which each indicate the presence of the arc in the red synthetic signal (bottom).

With the relative power magnitude of the arc at one tenth of the background noise, wavelet decomposition detects the arc in at least two frequency bands. The orange and gold regions of

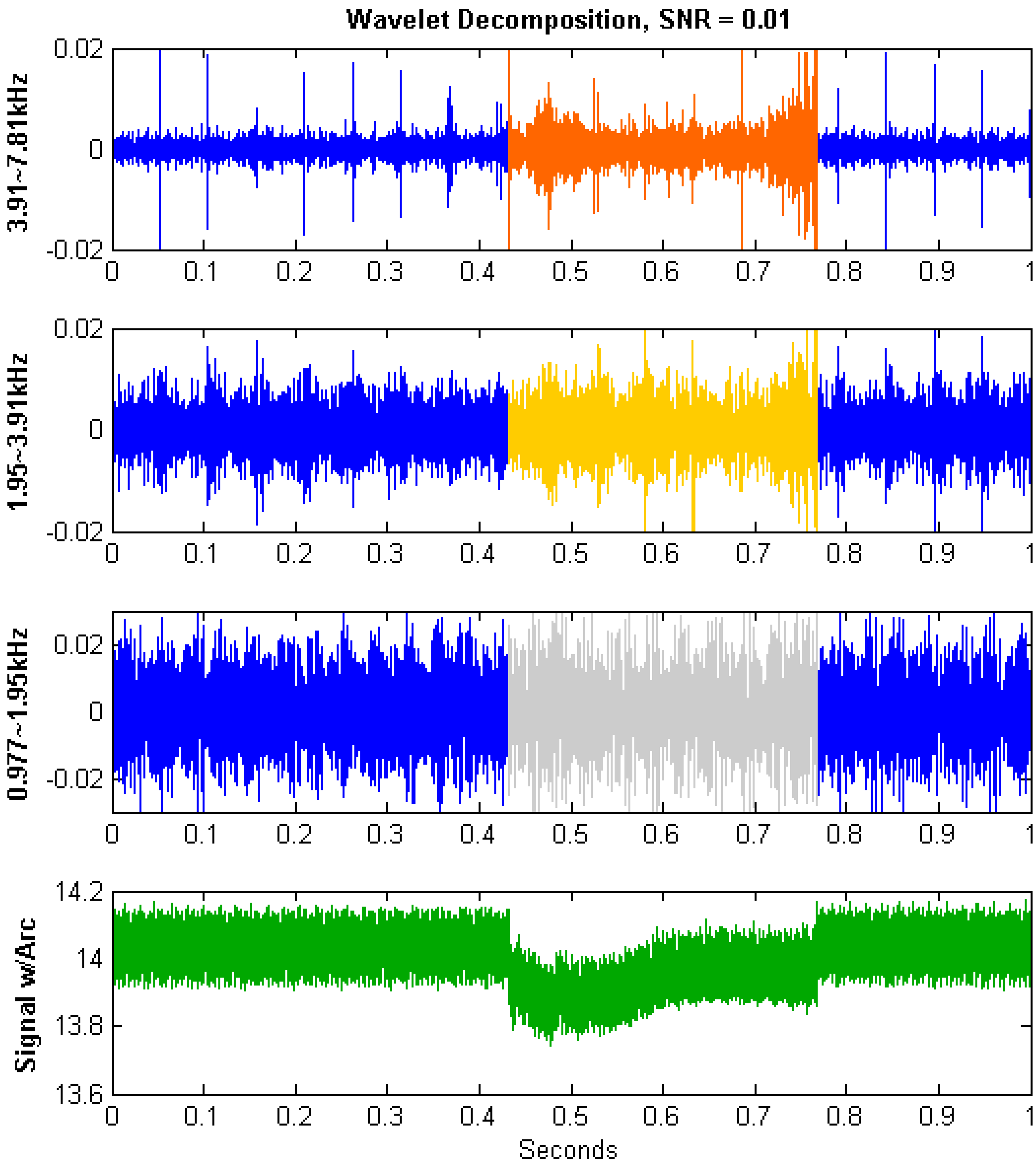
Figure 5



At SNR = 0.1, the wavelet analysis algorithm decomposes the signal into 3 different frequency bands (top). The first two each clearly indicate the presence of the arc in the purple synthetic signal (bottom).

Figure 5 show spikes at exactly the moment the arcing region of the synthetic signal begins. The

Figure 6



At SNR = 0.01, the wavelet analysis algorithm decomposes the signal into 3 different frequency bands (top). The first band indicates the presence of the arc in the green synthetic signal (bottom).

gray region likewise shows these spikes, but the increase in signal magnitude is less dramatic.

Even at SNR = 0.01, with the arc signal at one hundredth of the power level of the PV noise, the wavelet decomposition method detects the presence of the arc at the precise instant the arc begins. In Figure 6 we see the orange spikes signifying the opening and closing of the arcing region embedded within the green synthetic signal.

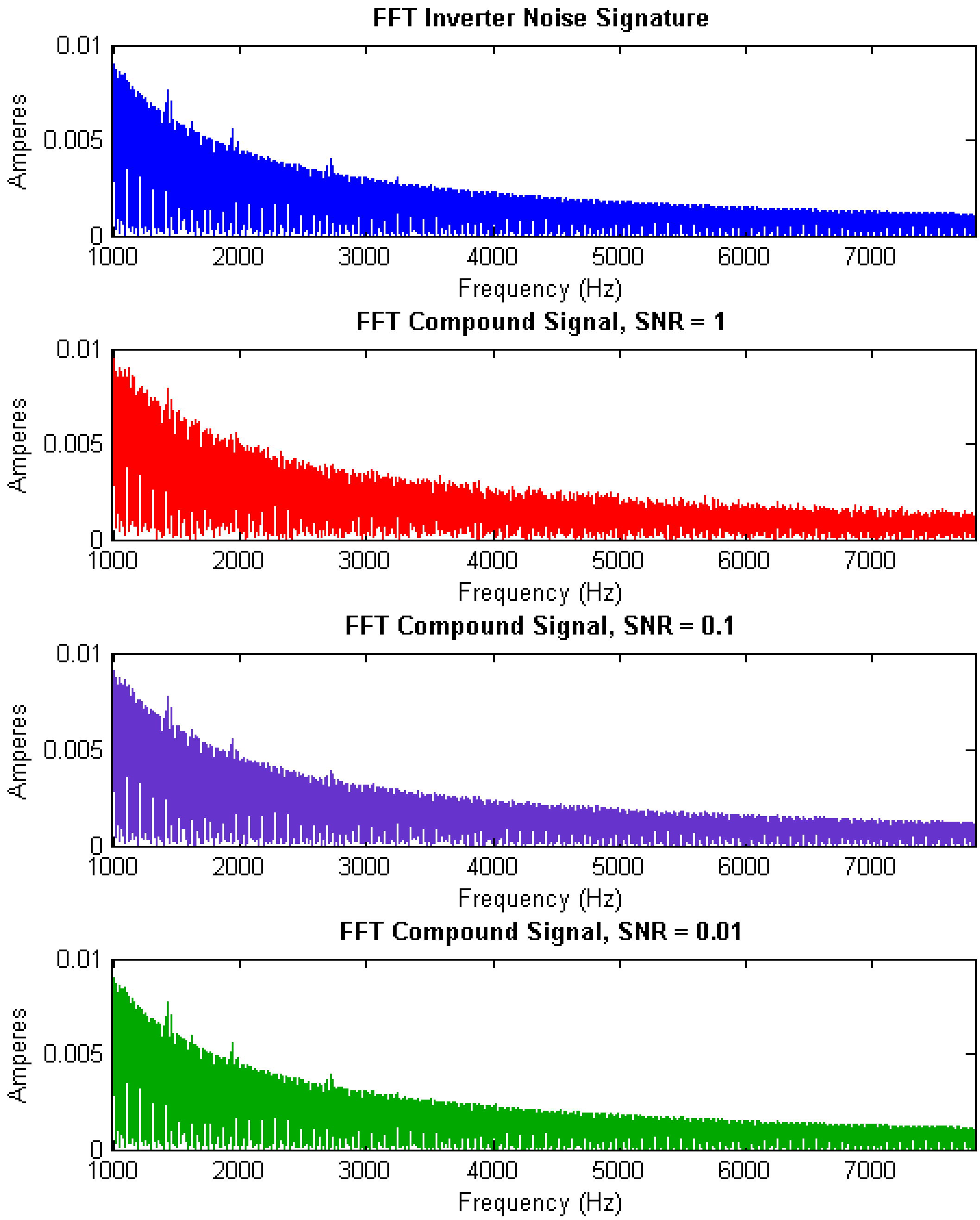
It is interesting to note the presence of other periodic spikes throughout the waveform representing the 3.91-7.81 kHz band. It would appear that these recurring spikes could create problems with nuisance tripping at an SNR of 0.01 if this wavelet decomposition algorithm were implemented into an industrialized arc-fault detector.

Further study, however, reveals that these spikes occur at exactly 19.07 Hz, or at the resolution of the FFT result corresponding to the 5MHz signal used in reconstruction. In other words, these spikes do not come from an arc, but come from the method used to lengthen the background signal for testing. If the data representing PV inverter noise had originally come from SNL at a full 1-second length, there would be no need for reconstruction, and there would be no 19.07 Hz streaks visible in Figure 4, 5, or 6. However, the author's experimental method which incorporated Fourier transform into the reconstruction does shed light on further problems associated with the Fourier analysis, specifically the resolution at which it operates.

Fourier analysis results

While the results from the wavelet decomposition method show promise, these results need to be compared against a simultaneous Fourier-transform approach to justify a preference for one arc-fault detection tool over the other.

Figure 7



FFT of background inverter noise (blue) is shown in comparison with the FFTs of the compound synthetic signals (red, purple, and green) at each specified arc-signal to noise ratio.

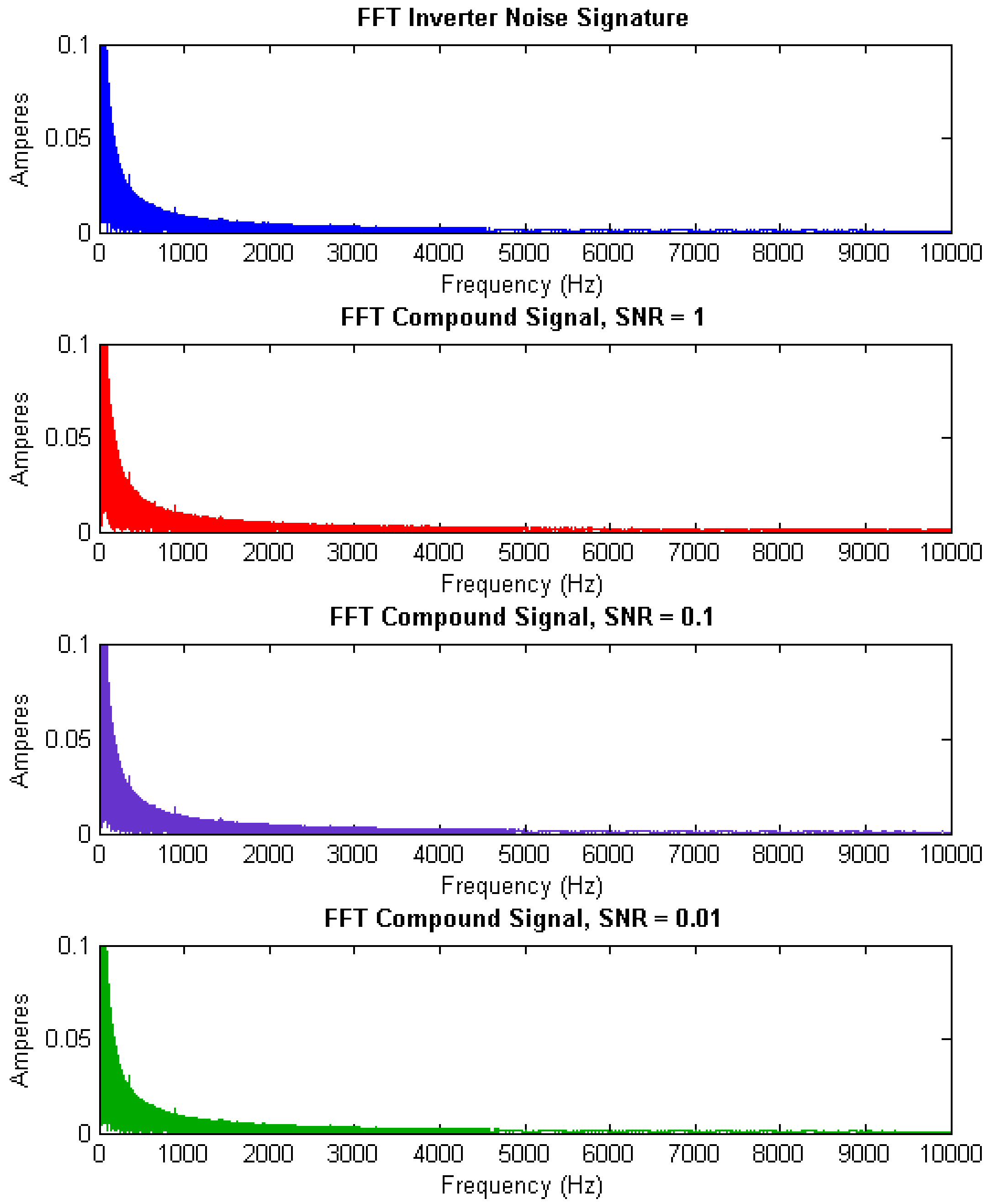
Figure 7 displays the FFT of the background inverter noise together with the FFTs of the compound synthetic signals. The graphs show the magnitude of the contribution of all frequency components in the 0.977-7.81 kHz spectral range at the specified SNRs as measured by the FFT. This spectral range matches the cumulative range of the three frequency bands analyzed by the wavelet decomposition algorithm.

Comparing the background inverter noise with the smaller SNR values of 0.1 and 0.01, virtually no visible difference can be distinguished. At the SNR of unity, however, where the relative power magnitudes of the arc and the background noise are equivalent, a careful observer may perceive some “fuzzy” behavior prevalent throughout the continuous spectrum. While this spectral noise may serve as an indicator of something unusual, this “fuzz” alone is not sufficient to verify the presence of an arc and certainly not adequate to characterize what an arc looks like. When applying Fourier transform, the objective is to see characteristic peaks—a point or band of frequencies which protrude or deviate in magnitude from the surrounding harmonic components. Conversely, these graphs essentially show a gentle, rolling slope, and those small bumps or peaks which do exist are present with or without the arc.

Any further analysis to characterize the somewhat odd behavior displayed at the SNR of unity necessarily requires other mathematical tools which presumably would lie outside the scope of Fourier methods. Even with such a multifaceted approach, real-world situations would not likely bend towards an SNR of unity.

Figure 8 shows an expanded view of the spectral components as computed by the FFT. This

Figure 8



FFT of background inverter noise (blue) is shown in comparison with the FFTs of the compound synthetic signals (red, purple, and green) in the spectral range from 0 to 10 kHz.

broader picture reveals even less regarding any differences between the signals containing an arc and the background inverter noise.

CHAPTER V

CONCLUSION

The results demonstrate the ability of wavelet analysis to detect an arc where Fourier methods fall short considerably. Furthermore, the wavelet decomposition algorithm executes in real time indicating at precisely which moment in the time domain the arc begins.

Due to the chaotic, asynchronous nature of arc faults, wavelet transformation proves better suited to detect the abrupt, high-frequency changes found within arc-fault signatures, particularly in photovoltaic applications. Fourier transform gives rudimentary insight into arc faults because the signal is completely non-periodic and the user has no fore-knowledge of how to select an appropriate window.

Like the Fourier methods, wavelet decomposition is a linear transformation which can be readily incorporated into dedicated electronic circuits such as a DSP. With no computational disadvantages, these findings give evidence that wavelet decomposition is a more effective tool in photovoltaic arc-fault detection.

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