A Transient Classification System Implementation on an Open Source Distributed Power Quality Network

Charles Dickens
Department of Electrical and Computer Engineering
University of Hawaii Manoa
Honolulu, Hawaii 96822
Email: dickensc@hawaii.edu

Anthony Christe
Department of Information and Computer Sciences
University of Hawaii Manoa
Honolulu, Hawaii 96822
Email: achriste@hawaii.edu

Philip Johnson
Department of Information and Computer Sciences
University of Hawaii Manoa
Honolulu, Hawaii 96822
Email: johnson@hawaii.edu

***Abstract*—Capturing and classifying power quality phenomena is important for the smooth functioning of electrical grids. This paper presents methods for classifying the four types of transients (impulsive, arcing, oscillatory, and periodic notching) specified in the IEEE 1159 Power Quality standard. Our methods implement a tractable algorithm, which applies well understood signal processing methods and statistical inference for feature extraction and decision making. We tested our methods on simulated power quality disturbances in order to demonstrate the capabilities of the system. The results of this research include an operational implementation of a transient classifier for Open Power Quality, an open source distributed power quality network. Additional functionality can be easily incorporated into the system to extend the utility of our methods, such as a meta-analysis to capture higher level network wide events.**

Keywords–Power quality; power transients; open source; renewable energy

I. INTRODUCTION

Introducing renewable energy generation to existing electrical grid infrastructures has proven itself to be an engineering challenge. The transition to cleaner energy generation methods such as wind and solar, which are inherently unpredictable, has increased the severity and frequency of problems related to power quality [1]. For example, sensitive instruments connected to an unstable grid can be potentially de-calibrated or damaged.

A first step to correcting power quality problems is understanding the problem from top to bottom. Electricity supplied by the grid should be continuously monitored to detect and log power quality events. Classification of power quality phenomena can reveal problematic patterns in the system and provide potential explanations for failures that can be understood and resolved.

There is considerable research on classification of power quality [2], [3], [4], [5], [6]. Current state of the art techniques commonly utilize wavelet transforms for feature extraction and then run the data through a trained neural network or decision tree algorithm. Another approach by Manikandan, Samantaray, and Kamwa [3] decomposes the signal using sparse signal decomposition on an overcomplete hybrid dictionary matrix and then extracts the power disturbance features of the decomposed signal and classifies the transient waveforms using a decision tree algorithm.

In this paper, we present a tractable implementation of a transient classification system for our open source distributed power quality network called Open Power Quality (OPQ). By including this transient detection system in OPQ, we can gather information on both local transients and global transients (i.e., transients from a single source that were detected on multiple, distributed sensors). This information can be used to determine how transients and other power quality (PQ) signals propagate throughout a power grid. Further, data metrics generated from intermittent renewable sources, weather reports, and user reports can be fused by OPQ with the transient detection results to provide insights on how intermittent renewable energy sources affect the quality of power on the grid.

This paper is structured as follows. Section II explains and justifies the proposed methodology for classifying transients. Section III describes the implementation of the methodology on the OPQ system. Section IV reports the simulated results of the transient detection system. Finally, Section V provides with conclusions.

II. METHODOLOGY

The transients classified with the methodologies discussed in this paper are defined in the IEEE 1159 Draft Recommended Practice for Monitoring Electric Power Quality [7]. Table I summarizes the definition and characteristics of each transient.

TABLE I. TRANSIENT CLASSES

Class	*Description*
Impulsive	Unidirectional change from the nominal waveform.
Arcing	Bipolar random frequency noise.
Oscillatory	Decaying oscillatory wave.
Periodic Notching	Periodic and strictly negative in power.

We use a decision tree algorithm to classify signals with potential transients. The benefit of this approach is that it minimizes necessary computation. As PQ features are extracted from the signal, the potential classes that it could fall into are narrowed. Computationally expensive analysis can be bypassed if simple features can rule out a class early in the process. Leveraging this idea, the potential transients are checked to see if they fit the classes in the same order as listed in Table I. Once the signal is classified, then additional meta data can be computed that appropriately details the transient.

A. Signal Decomposition

The first task is to decompose the raw signal into the fundamental waveform and the potential transient waveform. In the context of this application, the fundamental waveform is expected to have little to no variation from the standard, which is 60 Hz and 120 Vrms in the U.S. [8]. There is the potential for simultaneous waveform distortion and transient PQ phenomena. However, waveform distortions for frequency phenomena are typically found to only vary by ± 0.1 Hz and for voltage phenomena by $0.11.8$ pu [7], whereas the transients that the system is capturing typically have a spectral content between 1 kHz5 MHz.

Thus, a simple digital implementation of a 4^{th} order low pass Butterworth filter with a cutoff frequency at 500 Hz is justifiable and practical for this application to extract the fundamental waveform from the raw digital signal. A different filter could be used to achieve similar results. We decided to use a Butterworth filter with these order and cutoff frequencies due to the desirable property that the filter is monotonic in both the passband and stopband, which results in a clean decomposition. Once the fundamental waveform is retrieved, the transient waveform is then obtained by subtracting out the fundamental waveform from the raw signal.

B. Classifying Impulsive Transients

The first step in the decision tree algorithm is to determine whether the transient could be impulsive. We test for impulsive transients first since as it is computationally the cheapest to verify. As defined by the IEEE 1159 standard, an impulsive transient is a unidirectional change from the nominal condition of the voltage [7]. Therefore, a simple check which ensures that the excitation in the transient waveform is unipolar will qualify the transient to be in the broad category of impulsive transients.

If the transient is impulsive, then arcing and oscillatory transients can be ruled out. Additional cases do need to be accounted for since there is a chance that the transient could also be periodic notching. If the impulsive transient is positive in power, then periodic notching can be ruled out, otherwise it needs to be tested. At this point meta-data detailing the rise and decay time, the peak amplitude, and whether or not the transient causes additional zero crossings in the raw signal can be calculated and recorded with the classification.

C. Classifying Arcing Transients

An arcing transient is a burst of relatively higher frequency noise that is random in frequency content. The arcing transient should have more than ten zero crossings and should not have more than two cycles with same period [7].

Thus, the test for arcing transients can be a verification of more than ten zero crossings and a threshold for randomness in the frequency content. The defined threshold for randomness is whether more than two zero crossings have the same period.

D. Classifying Oscillatory Transients

An oscillatory transient is a bipolar change that typically lasts between a few milliseconds to a quarter cycle of the nominal waveform. It is characterized by its frequency content and decay rate [7].

To determine whether the potential transient fits the oscillatory classification, the system implements an incremental F-test. The F-test gives a numerical value of the significance of additional variables added to the regression function. The null hypothesis of the test is $H_0 : \beta_3 = \beta_4 = \beta_5 = 0$.

We implement this by first computing a least squares curve fitting of the potential transient waveform and an exponentially decaying sinusoid using gradient descent. The complete model is shown in (1).

$$\hat{y} = \beta_0 + \beta_1 e^{-\beta_2 t} cos(\beta_3 \cdot 2\pi t + \beta_4) \quad (1)$$

Then, a reduced model is fit using the same least square fitting methods. The reduced model equation is shown in (2).

$$\hat{y} = \beta_0 + \beta_1 e^{-\beta_2 t} \quad (2)$$

Large values of F result in rejection of the null hypothesis and the classification of the transient as oscillatory. The threshold value that F must pass is a design decision and will determine the expected type 1 and type 2 errors of the classification.

We record additional meta-data upon this classification including the decay rate, frequency content, dc offset, and peak amplitude, all of which follow from the results of the curve fitting.

E. Classifying Periodic Notching Transients

A periodic notching transient is a periodic and strictly negative power disruption of the nominal waveform. Therefore, the signal is first verified to be strictly negative in power before further analysis is made. If so, the system moves on to determine whether the potential transient waveform is periodic.

To test for periodicity the auto-correlation of the signal is computed. Auto-correlation highlights the similarity between the signal and its previous values. Our method convolves the first half the transient signal with the original transient. The convolution is only calculated for points where the signals completely overlap. If the potential transient is indeed periodic, then the resulting signal from the convolution will have the same periodicity with peaks that highlight where the signal had the highest correlation.

Our method determines the peaks of the auto-correlation signal by setting a height threshold. Then, it finds the standard deviation of the distance between the peaks, and if this value is less than a defined threshold, the signal is classified as periodic. If so, the period is easily calculated from the auto-correlation signal along with additional meta-data to characterize the transient.

III. Implementation

We implemented and tested these methods using our OPQ system. The OPQ project began in 2012 with the goal of developing and evaluating PQ technology to support improvements to electrical grids, in particular the incorporation of distributed intermittent renewable energy sources.

In general, the OPQ system architecture consists of OPQ Boxes, which are plugged into standard residential outlets to monitor PQ as it is experienced at the point of consumption. These results are communicated over the Internet to OPQ

Cloud, a set of cloud-based services that provide end-to-end support for the capture, triggering, analysis, and reporting of local and global level PQ phenomena. A major design goal of OPQ is to not just report PQ locally for each device, but to look at PQ in an aggregate manner. This is possible because the OPQ cloud services provide a global view of all PQ sensors (OPQ Boxes). Thus, OPQ is able to detect distributed PQ incidents (where multiple distributed sensors sense the same incident) and also observe how PQ incidents propagate through the electrical grid.

The two principle cloud services in OPQ are called Makai and Mauka. The Makai service is responsible for aggregating and processing the measurements generated by the OPQ boxes. Inside Makai, a triggering broker creates a PQ event when it detects a deviation from the nominal waveform in a low fidelity data stream and sends a message to the Mauka system to analyze the event further. The Mauka service performs analysis of high fidelity data and is thus where our transient detection system is located.

Our implementation proceeds as follows.

First, the raw signal is decomposed into its fundamental and potential transient waveform. The fundamental waveform is extracted using a digital implementation of a 4^{th} order low pass Butterworth filter with a cutoff frequency of 500 Hz. The digital filter used is an implementation in the scientific Python library SciPy [9]. The transient waveform is then the raw waveform minus the fundamental waveform.

Our method does not assume that only a single transient exists in a PQ event triggered by the Mauka system. Therefore, before classification, the complete transient waveform is separated into potential windows with individual transients. This is achieved through a sliding window technique with a predefined threshold for a maximum lull. The maximum lull between transients is a design decision that is made with domain knowledge. The transients that are being classified with the system are expected to have a duration on the order of milliseconds.

The sliding window method works by first scanning the transient waveform and finding the first measurement which is above the configuration noise floor. It is common practice to account for potential instrumentation error by defining a noise floor. Measurement deviating from the nominal waveform more than the defined noise floor are considered to be significant and can reasonably be considered to be PQ phenomena and not a faulty measurement. The noise floor in the implementation is defined to be 5% of the nominal voltage.

The first measurement above the noise floor is considered to be the starting point of the transient. Then, the scanning continues until there is a lull in measurements above the noise floor longer than the defined maximum, or the scanning has reached the end of the transient signal. At which point the last significant measurement is defined to be the endpoint of the potential transient. This process is repeated until the end of the transient signal is reached.

Once the start and end points of all of the potential transients are determined, then the classification analysis can begin. Feature extraction and the decision tree structure is described in detail in Section II. Only important implementation notes will be mentioned in the rest of this section.

The multiple non-linear least squares regression required for classification of the oscillatory transient is provided in the SciPy library [9]. The solution to the regression is an approximation obtained by a gradient descent method. Since the expected characteristics of oscillatory transients are known, the gradient descent method can be seeded to increase the rate at which a local optimum is found.

To classify periodic notching transients, a convolution operation is necessary. The code used to implement this calculation is found in the NumPy library [10].

IV. RESULTS

To test the performance of the proposed methodology, simulated transients were constructed and run through the system. The configuration of the system at the time of these reported results has the sampling rate at 12000 Hz.

First, we created a simulated waveform with an impulsive transient by superimposing an exponentially decaying excitation onto a portion of 6 cycles of a fundamental waveform. This simulated transient has a peak amplitude of 18 volts and decays to the noise floor in $\frac{1}{32}$ cycles. The raw signal is shown in Figure 1.

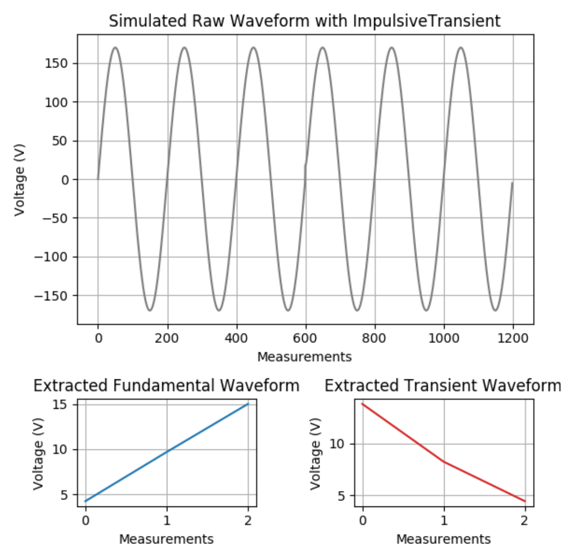

Figure 1. Simulated 60 Hz 120 Vrms sine wave with an impulsive transient. The decomposed fundamental and transient signal are shown in the bottom left and right subfigures, respectively.

Second, we created a simulated waveform with an oscillatory transient by superimposing an exponentially decaying sinusoidal wave with 960 Hz frequency with starting amplitude of 72 volts onto a portion of 6 cycles of a fundamental waveform. The raw signal is shown in Figure 2.

Third, we created a simulated arcing transient by drawing 7 random samples from a uniform random distribution over the support $(61, 2401)$. We then used the random samples to define the frequencies for single cycles of an arcing transient wave. The raw signal is shown in Figure 3.

We simulated a multiple zero crossing transient by superimposing three single sawtooth cycles in positions of the

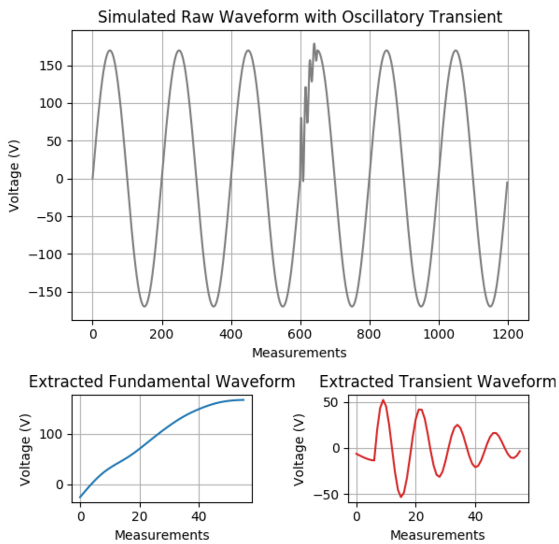

Figure 2. Simulated 60 Hz 120 Vrms sine wave with an oscillatory transient. The decomposed fundamental and transient signal are shown in the bottom left and right subfigures, respectively.

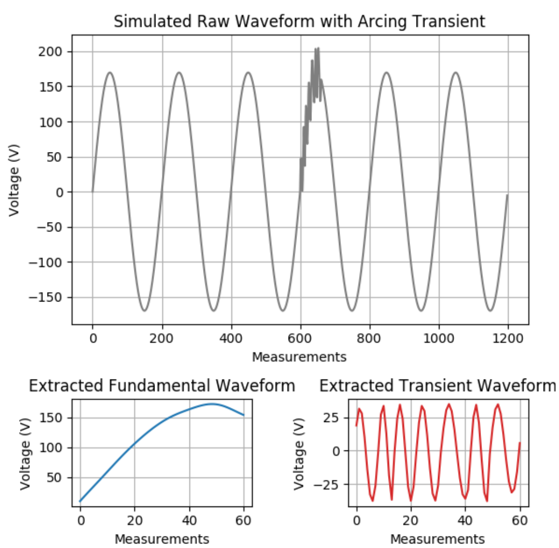

Figure 3. Simulated 60 Hz 120 Vrms sine wave with an arcing transient. The decomposed fundamental and transient signal are shown in the bottom left and right subfigures, respectively.

fundamental waveform near a zero crossing. The single sawtooth cycle has an amplitude of a 72 volts and a period of 10 samples. The raw signal is shown in Figure 4.

Finally, we created a simulated waveform with a periodic notching transient by superimposing a sawtooth waveform with a frequency of 1440 Hz and amplitude of 18 volts for a single fundamental cycle, i.e., 24 notches per cycle for one cycle. We determined the polarity of the notching transient by the fundamental signal since notching is defined to be strictly negative in power. The raw signal is shown in Figure 5

Figures 1, 2, 3, 5 show the raw simulated waveforms with impulsive, oscillatory, arcing, and periodic notching transients,

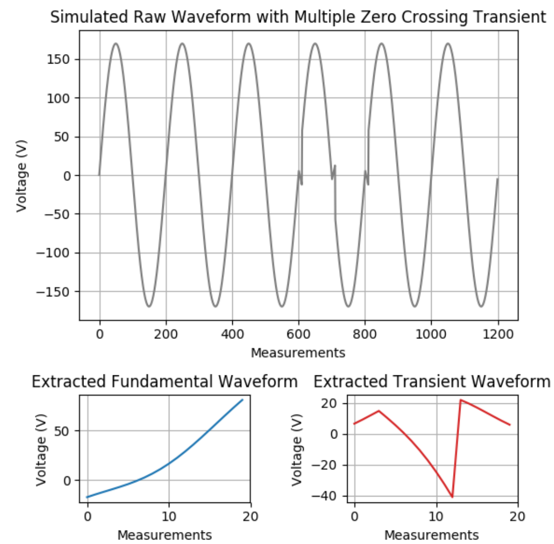

Figure 4. Simulated 60 Hz 120 Vrms sine wave with multiple impulsive transients which cause additional zero crossings in the raw waveform. The first decomposed fundamental and transient signal are shown in the bottom left and right subfigures, respectively.

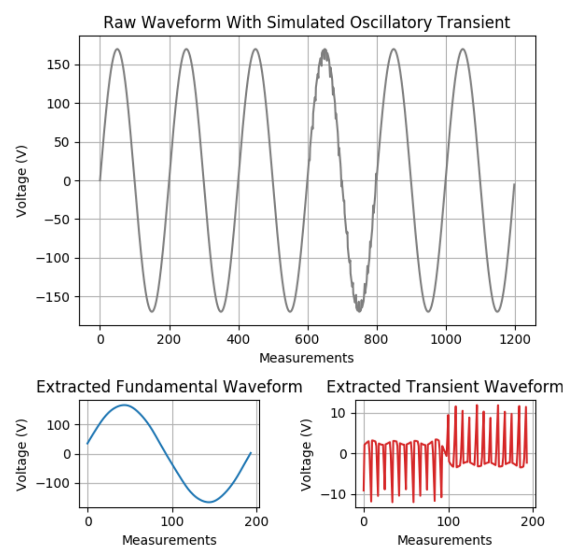

Figure 5. Simulated 60 Hz 120 Vrms sine wave with a periodic notching transient. The decomposed fundamental and transient signal are shown in the bottom left and right subfigures, respectively.

respectively, all starting near the 600^{th} measurement. The two subfigures show the extracted fundamental waveform and transient waveform detected by the system. These simulated waveforms were all correctly classified by the system using our methods.

V. Conclusion and Future Work

This paper presents an implementation of a transient detection system using OPQ, an open source distributed PQ network, which can successfully classify four types of transients as defined in the IEEE 1159 standard. Our method shows promise based upon its ability to correctly classify simulated versions of all four transients.

The most immediate future work is to monitor an electrical grid in real-time to determine how well the methods work on real world transients.

We also hope to add functionality to OPQ that would enable us to search our historical data for the occurrence of transients and classify them. From this, a meta-analysis for higher level network wide events could lead to clues regarding the sources of these phenomena. This data could provide new insight into our understanding of how intermittent renewable energy sources affect PQ on the grid, helping us to better modernize our grids with larger amounts of distributed renewable energy.

References

[1] R. Toma and M. Gavrilas, "The impact on voltage stability of the integration of renewable energy sources into the electricity grids," in *Proceedings of the 2014 International Conference and Exposition on Electrical and Power Engineering (EPE) October 16–18, 2014, Iasi, Romania*. IEEE, Oct. 2014, ISBN: 978-1-4799-5849-8.

[2] V. Garrido, J. Rodriquez, and A. Garcia, "Classification of power quality phenomena using intelligent techniques," in *Proceedings of the 2014 IEEE PES Transmission and Distribution Conference and Exposition - Latin America (PES TD-LA) September 10–13, 2014, Medellin, Colombia*. IEEE, 2014, ISBN: 978-1-4799-6251-8.

[3] M. Manikandan, S. Samantaray, and I. Kamwa, "Detection and Classification of Power Quality Disturbances Using Sparse Signal Decomposition on Hybrid Dictionaries," *IEEE Transactions on Instrumentation and Measurement*, vol. 64, pp. 27–38, Jan. 2015, issue: 1, ISSN: 0018-9456.

[4] K. Thirumala, A. Umarikar, and T. Jain, "A generalized emperical wavelet transform for classification of power quality disturbances," in *Proceedings of the 2016 IEEE International Conference on Power System Technology (POWERCON) September 28–1 October, 2016, Wollongong, NSW, Australia*. IEEE, 2014, ISBN: 978-1-4673-8848-1.

[5] M. Valtierra-Rodriguez, R. Romero-Troncoso, R. Osornio-Rios, and A. Perez-Garcia, "Detection and Classification of Single and Combined Power Quality Disturbances Using Neural Networks," *IEEE Transactions on Industrial Electronics*, vol. 61, pp. 2473–2482, May 2014, issue: 5, ISSN: 1557-9948.

[6] N. Tse, J. Chan, W. Lau, and L. Lai, "Hybrid Wavelet and Hilbert Transform With Frequency-Shifting Decomposition for Power Quality Analysis," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, pp. 3225–3233, Dec. 2012, issue: 12, ISSN: 1557-9662.

[7] *P1159/D3 Draft Recommended Practice for Monitoring Electric Power Quality*, IEEE, 2018.

[8] *C84.1-2016, American National Standard for Electric Power Systems and Equipment Voltage Ratings (60 Hz)*, ANSI, 2016.

[9] E. Jones, T. Oliphant, P. Peterson *et al.*, "SciPy 1.1.0: Open source scientific tools for Python," 2001–, [Online; accessed February 2, 2019]. [Online]. Available: http://www.scipy.org/

[10] T. Oliphant, "NumPy 1.14.5: A guide to NumPy," USA: Trelgol Publishing, 2006–, [Online; accessed February 2, 2019]. [Online]. Available: http://www.numpy.org/