Evaluating windowing based continuous ST with deep learning for detection and classifying PQDs

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Abstract. This paper discusses the performance of evaluating a windowing based continuous S-Transform (ST) with deep learning classifier for the detection and classifying of interrupt and transient disturbances. The primary purpose is to analyze the detection and classification of voltage interrupt and transient using ST as a signal processing technique. The detection technique is divided into half-cycle and one-cycle windowing techniques (WT with both cycles used for the purpose of comparison. The disturbances signal was create using MATLAB programming language and set in the form of m-file. ST was used to extract the significant feature in a form of scattering data from the disturbances signal. Then, the scattering data was used to build the detection interface inside the disturbances signal. The scattering data is an input for neural network (NN) to classify the percentage accuracy of the disturbances signal. This analysis presents the suitable windowing technique that can provide smooth detection and suitable characteristics to produce high accuracy percentages in the classification of power quality disturbances (PQDs).

1. Introduction

In all technological aspects of the world today, the growth of power distribution system has been rising drastically every year without much concern about the effects caused by it. Hence, the usage of sensitive electronic equipment, solid-state switching systems, non-linear loads, digital energy converters, relaying devices, and protective devices is increasing to facilitate daily activities [1]. The new equipment produces unwanted voltages, current and frequency signal interferences, but at the same time they are very essential for the consumer. Each difference in the normal values that is shown in data signals is classified as a power quality PQD [2]. The problems of PDQ can result in electrical or electronic protection systems malfunctions, machine file disruptions or sympathetic charging errors, and unpredictable actions in an automated device [3]. The power distribution system is an expensive asset that require proper protection and maintenance systems and therefore very critical to constantly track these disturbances [4].

Interruption is a type of disturbance in power quality (PQ). Short duration interrupt (SDI) can be described as the decrease in voltage amplitude between 90% to 100% from its normal voltage up to a 60-seconds duration. SDI can be subdivided into three forms of data which are instantaneous (0 - 0.5 seconds), momentary (0.5 - 3 seconds), and temporary (3 - 60 seconds). If the voltage amplitude is between 90% to 100% for more than 60 seconds, it can be expressed as sustained interrupt (SI) which
means power failure [5]. SI is the type of weakness in PQ phenomena because it occurs for a long period of time in voltage drop variation. Voltage transient is one of the PQDs which can quickly generate tremendous high voltage and current or both at same time occasionally. This disturbance usually occurs in low voltage systems that produce thousands of volts and amps in a certain period of time. The transient effects often exist within a very short period of 50 nanoseconds or 50 milliseconds [6]. This is the least of the concerns when it comes to PQ problems. Transients usually come with an abnormal frequency that can reach a high frequency spike around 5 MHz and above caused mostly by lightning strikes. To minimize power and water usage, moisture content sensors were used to detect the amount of water already present in the soil so as to determine the amount to be supplied.

This problem will become critical if PQD sources are not detected and classified correctly. Improvements can be made by establishing the needs to detect the unwanted disturbances that exist inside the power signal. Then, the process of identifying disturbances characteristics and designing an interface to counter the problem can take place to display all unnecessary signals. In past researches and studies, the researchers commonly used many types of approaches to detect and classify the PQD events. Among approaches used in past studies are Stockwell Transform (ST), Wavelet Transform (WT), Neural Network (NN), Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), and Support Vector Machine (SVM), or the combination of any of them and others [7]. Many solutions have been made in past analyses involving PQ issues where the difference in data is constantly being created from one domain to another to achieve much detailed information regarding the defects in power signals. In this research, an Atmega 328 microcontroller on Arduino board will be interfaced with a solar system providing power for a smart irrigation system in order to determine the amount of power generated at the solar PV and the battery at any instance in order to optimize power usage by the irrigation system for the purpose of system efficiency and quality service delivery. The rest of this paper is arranged as follows. Section 2 presents the methodology followed by section 3 which is the result. Section 4 presents the discussion while section 5 concludes this paper.

This study focuses on the step to diagnose PQDs to detect the disturbances using the S-Transform (ST) mathematical equation to fully understand the control PQ and neural network namely extreme learning machine neural network (ELMNN) that were used as a method to classify, and analyze the PQDs performance within power signal. The detection of PQDs have been experimented and analyzed based on two difference approaches namely one cycle windowing technique (OCWT) and half cycle windowing technique (HCWT) [5]. A mathematical model of PQDs was constructed using the MATLAB software to find the initial period, the final period, the magnitude and duration of the PQDs [8]. This paper will also provide a summary of the analysis of the PQDs for the detection and classification based on the continuous Stockwell transform (CST) for the faulty electrical distribution system using OCWT and HCWT with ELMNN approaches [9].

2. Methodology

Figure 1 shows the flowchart of the method used to conducted both the detection and classification analyses for PQD. This section consists of the signal processing, detecting, and classifying techniques. MATLAB programming language was used to construct the PQD data. Firstly, the PQD signal was generated using the mathematical equation, then saved in the form of m-file. Secondly, the disturbances signal generated will be used as input and the ST signal processing technique was conducted. The ST will produce an output in the form of s-matrix [10]. Then, the data in s-matrix will be extracted into significant data which are variance, standard deviation and mean value [11]. The windowing technique programming language was created for the detection line in the disturbances signal. Finally, deep learning algorithm which is ELMNN will take part for further processing in the classification step. ELMNN consist of input, hidden, and output layers will be filled with variance, standard deviation, and mean value for training testing data. ELMNN produced an accurate percentage of training testing data. The output accuracy was then being compared whether it was acceptable or unacceptable. The higher an accuracy percentage, the higher the accuracy will be to the existing result.
2.1 Disturbances Signal Generation

MATLAB programming language was used to create a mathematical module to form the disturbances signal [12]. The data required to generate the disturbance signals are real time from the signal duration and magnitude of signal voltage [6]. There are two types of disturbances which are interrupt and transient. Based on the explanation above, the equation of PQDs are shown in Table 1.

2.2 Stockwell Transform (ST)

ST was an extension of STFT and WT. It is very common and has been extensively applied in the signal processing of PQD because of its effectiveness [13]. The advantage of using ST is that it can recognize the disturbances perfectly in even noisy conditions. The ST performed multiresolution analysis (MRA) on a time varying signal as its window width varied inversely with frequency [14]. The following equations below show the mathematical model of ST.

The continuous Wavelet Transform (CWT), of a function $h(t)$ is defined as [9]:

$$W(\tau, d) = \int_{-\infty}^{\infty} h(t)w(t - \tau, d)dt$$  \hspace{1cm} (1)

Equation (1) determines the expansion factor of $d$ which is inverse from frequency $f$. The expansion determines the width of the wavelet.

ST is obtained by multiplying CWT with a phase factor as defined by [9]:

$$S(\tau, f) = e^{i2\pi ft}W(\tau, d)$$  \hspace{1cm} (2)
Where the mother wavelet is defined as

$$w(t,f) = \frac{f}{\sqrt{\pi}} e^{-\frac{t^2}{2}} e^{-i2\pi ft}$$

(3)

Thus, the final form of the continuous ST is obtained as

$$S(t,f) = \int_{-\infty}^{\infty} h(t) \frac{f}{\sqrt{\pi}} e^{-\frac{(t-t')^2}{2}} e^{-i2\pi ft'} dt$$

(4)

And the width of the Gaussian window is

$$\sigma(f) = T = 1/f$$

(5)

### Table 1. Equation of Interrupt and Transient

| Disturbances | Equation |
|--------------|----------|
| **Interrupt** | $y=(1-\alpha*((\text{Heaviside}(t-0.05)-\text{Heaviside}(t-0.15)))). \sin(314*t);$  
$\alpha=\text{reduction level of rms voltage in p.u.};$  
$0.9 \leq \alpha \leq 1.0$  
$t=\text{time};$  
$0:0.001:0.2$  
$t1=\text{interrupt initiation}$  
$t2=\text{interrupt recovery or clearance}$ |
| **Transient** | $y=\sin(2\pi*50*t)+\text{amp}*((\text{Heaviside}(t-t2)-\text{Heaviside}(t-t1)))*\exp(-t/\text{ty})*\sin(2*3.14*\text{fn}*t);$  
$\text{amp}=\text{amplitude 1 to 5.};$  
$\text{fn}=\text{rise of frequency}$  
$t=\text{time};$  
$0:0.001:0.2$  
$t1=\text{transient initiation}$  
$t2=\text{transient recovery or clearance}$ |

2.3 Detection Technique

The windowing technique required both disturbances signals data, interrupt and transient to be loaded into the detection programming language in MATLAB for the detection technique process. The half cycle (HCWT) and one cycle (OCWT) windowing technique was constructed using the output data of the s-matrix from the signal processing technique [15]. The s-matrix was able to produce the feature needed to detect and classify PQ disturbances. Once the detection line programming language was being construct, the OCWT and HCWT of the line height were adjusted to match the amplitude of the disturbances signal. The detection line of HCWT was in the form of sinusoidal shape while OCWT was in form of a straight line that flowed on top of the disturbances signal.

2.4 Classification Technique

Extreme Learning Machine Neural Network (ELMNN) was selected for the classification technique because of its ability for training, validation, and testing data. The structure of ELMNN consists of an input layer, hidden layers, and output layers. This technique is also called the feed forward neural network. ELMNN used the output data from the detection technique to act as the input for NN initial layer [16]. The output data of the detection technique initially has to be arranged using Microsoft Excel which consists of the standard deviation, variance, and mean columns before passing to the NN for classification. Standard deviation, variance, and mean were used as input data while selected binary value as the target data. The 3 input data consist of 1800 absolute values of PQD. NN will process the input data by comparing with the target data in order to produce the percentage accuracy of the correct data. The percentage accuracy was display using the confusion matrix where green box is for correct
classification while red box for misclassification. The binary ‘0’ represents interrupt and binary ‘1’ represents transient disturbances [5].

3. Result and Discussion

Figure 2 shows Sample 1 of an absolute value interrupt disturbance signal and its half cycle windowing technique detection line. An absolute value of interrupt disturbance signal is shown in the form of red line while detection line was represented in the form of a blue line. Based on this result, the point where disturbance initially started at 501ms and finally ended at 1001ms. The duration of interrupt disturbances was around 500ms with the magnitude of 0.0783 per unit. The detection line of the half cycle was in a sinusoidal wave signal. This technique was not suitable because it was unable to accurately detect the amplitude of the absolute value due to the sinusoidal detection line.

![Figure 2. Detection of Half Cycle Windowing Technique for Interrupt](image)

Figure 2. Detection of Half Cycle Windowing Technique for Interrupt

Figure 3 shows one cycle windowing technique for detection of the interrupt disturbance Sample 1. The blue line represents the detection signal whereas the red line is the absolute value of interrupt disturbance. It can be observed from the result that 498ms was the time where an interrupt disturbance initially occurred until the final end time which was 1003ms. The duration of interrupt disturbances was 505ms with the magnitude of 0.1 per unit. One cycle windowing technique was the most accurate in detecting the interrupt disturbance because of the detection shape which was in a straight line. The detection line was able to locate the amplitude of the absolute disturbance value.

![Figure 3. Detection of One Cycle Windowing Technique for Interrupt](image)

Figure 3. Detection of One Cycle Windowing Technique for Interrupt

Figure 4 shows an absolute value of the transient disturbance for sample 1. The red line indicates the absolute value which means only the positive data will be shown and the blue line shows the detection signal. This result explains that the transient disturbance was detected at 780ms to 801ms. The total time taken for transient disturbance occurrence was around 21ms. The magnitude of transient signal was 2.083 per unit while the detection line magnitude was 1.005 per unit. HCWT was unable to detect properly because the transient disturbances generated was in a short amount of time. Even the detection line could not reach the transient amplitude. The shape of detection line was the main factor on how to recognize the transient disturbances.

![Figure 4. Detection of Half Cycle Windowing Technique for Transient](image)

Figure 4. Detection of Half Cycle Windowing Technique for Transient
Figure 5 shows the one cycle windowing technique used to detect transient disturbance in Sample 1. The red line represents the absolute value of transient disturbance while the blue line represents the detection signal. OCWT were more accurate in detecting because the detection line could correctly locate the amplitude of a signal absolute value. The starting time was 780ms until the final end time at 802ms. The total duration taken by transient disturbances was only 22ms. The magnitude of an absolute disturbance value was 2.079 per unit while the detection line was 1.186 per unit. Although using OCWT was the most accurate detection mechanism, but the detecting line was still unable to follow the transient disturbance until the peak amplitude of 2.079 per unit.

![Figure 5. Detection of One Cycle Windowing Technique for Transient](image)

Table 2 shows the tabulation of data regarding the windowing technique which were HCWT and OCWT using three types of different samples. Based on the results, the shape of detection line was different for both the windowing techniques. HCWT was in the form of sinusoidal line while OCWT in the form of straight line. Sample 2 had the longest disturbances occurrences for both windowing techniques with the total duration of 1000ms and 1001ms due to the earliest initiation time of 502ms and 500ms and delayed final time of 1502ms and 1501ms. Samples 1 and 3 had almost the same total amount of duration time which were 500ms, 505ms, and 498ms respectively but both samples were different in initiation and final times. OCWT was the most accurate in detecting interrupt disturbance because of its ability to provide the highest magnitude in detection line as compared to HCWT.

Table 3 shows the overall tabulation data of detection technique which were HCWT and OCWT using three different samples regarding transient disturbances. The detection technique using one-cycle type was far more accurate and stable because of the ability where the detection line was continuously located at peak amplitude of the signal. Most of the samples had the same amount of duration time which was around 21ms until 22ms. The initiation and final times for each same were similar for both HCWT and OCWT. The magnitude of the detection line was much more accurate for the OCWT with all three types of sample which achieved the value of 1.2 per unit. HCWT is considered as less effective in detecting due to the sinusoidal detection line. For Sample 1 HCWT, the magnitude was below 1 per unit amplitude, 0.9789 while the another both sample was located at 1.048 and 1.065 per unit.

Table 4 explicates an overall accuracy data classification using both the windowing techniques HCWT and OCWT. ELMNN was the mechanism used to classify all the three samples of interrupt disturbances. Based on the table, true classification was most likely the highest with the classified of above 90% while false classification was below than 10%. OCWT was the most accurate in detecting disturbance thus, the classification data for this technique could provide a high percentage accuracy compared to HCWT. An average percentage of classification clearly showed that the HCWT with 95.23 % was less accurate in classification compared to OCWT with 98.17 %. Furthermore, HCWT for interrupt disturbance had the most misclassification with an average percentage of 4.77 % while OCWT recorded less misclassification with an average percentage of 1.83 %. The data size of classification for all three samples’ interrupt disturbance was 1800. In a nutshell, by using 1800 as overall data size, the best classification can be achieved because the classifying process will cover all time and magnitude.

| Sample | Windowing Technique | Initiation Time (ms) | Final Time (ms) | Duration (ms) | Magnitude (pu) | Shape of Detection Line |
|--------|---------------------|----------------------|----------------|--------------|----------------|------------------------|
| Sample 1 | OCWT | 780 | 802 | 22 | 2.079 | Sinusoidal |
| Sample 2 | HCWT | 502 | 1502 | 1000 | 1.048 | Straight |
| Sample 3 | OCWT | 500 | 1501 | 1001 | 1.065 | Sinusoidal |

Table 2. Interrupt Detection by using Windowing Technique
Table 3. Transient Detection by using Windowing Technique

| Transient Disturbances | Sample | Windowing Technique | Initiation Time (ms) | Final Time (ms) | Duration (ms) | Magnitude (pu) | Shape of Detection Line |
|------------------------|--------|---------------------|---------------------|----------------|--------------|----------------|------------------------|
|                        | 1      | Half-Cycle          | 501                 | 1001           | 500          | 0.07830        | Sinusoidal Line         |
|                        |        | One-Cycle           | 498                 | 1003           | 505          | 0.10000        | Straight Line           |
|                        | 2      | Half-Cycle          | 502                 | 1502           | 1000         | 0.04184        | Sinusoidal Line         |
|                        |        | One-Cycle           | 500                 | 1501           | 1001         | 0.05002        | Straight Line           |
|                        | 3      | Half-Cycle          | 1002                | 1500           | 498          | 0              | Sinusoidal Line         |
|                        |        | One-Cycle           | 1002                | 1500           | 498          | 0              | Straight Line           |

Table 4. Classification for Interrupt and Transient

| Sample | Data Size | Interrupt and Transient | Half-Cycle | One-Cycle |
|--------|-----------|-------------------------|------------|-----------|
|        |           |                         | Classified | Misclassified | Classified | Misclassified |
| 1      | 1800      | 94.4 99.7 5.6 0.3       | 95.8 99.8 4.9 0.2 |
| 2      | 1800      | 94.9 99.8 5.1 0.2       | 99.1 99.8 0.9 0.2 |
| 3      | 1800      | 96.4 99.6 3.6 0.4       | 99.6 99.8 0.4 0.2 |
|        | Average   | 95.2 99.7 4.8 0.3       | 98.2 99.8 1.8 0.2 |

Table 4 shows the results of classification of transient disturbances for both windowing techniques. Based on the table, Sample 2 had identical classified (99.8 %) and misclassified (0.2 %) data for OCWT and HCWT respectively. However, Samples 1 and 3 produced different data which explains that OCWT was the best in transient disturbances classification compared to HCWT. An average percentage of true and false classifications for OCWT was 99.8% and 0.2% while HCWT had 99.7% and 0.3%. It can be noticed here that almost all the transient classifications were above 99% which allowed ELMNN to be classified perfectly because these disturbances exist in the signal for a short amount of time such as below 25ms. OCWT surely was the most effective in detecting disturbance that exist in signal due to its detection line characteristics located at the amplitude of the signal absolute value. Besides that, the shape of detection line produced by OCWT in the form of straight line was much more stable in detecting the magnitude of PQD. The sinusoidal line produced by HCWT was less accurate to detect the magnitude of PQD. OCWT had the highest average percentage on classifying both disturbances than HCWT. Finally, ST had the ability to verify harmonic that existed within the PQD. The process of detection will not be affected if the interrupt and transient had harmonic combination that existed inside the disturbances.

4. Conclusion
This paper explains the analysis of detection and classification process for interrupt and transient disturbances based on the S-Transform using the half cycle and one cycle windowing techniques with the extreme learning machine as classification technique. The signal processing technique ST was used to extract all significant features available within the PQD. Standard deviation, variances, and mean were the features used to generate the detection line simultaneously with input power supply. Then, the detection line can be different by applying OCWT and HCWT. The process of obtaining the percentage accuracy for both windowing techniques was established using the ELMNN classifier. The ability of pattern recognition available within ELMNN was the source in producing an accurate classification...
technique. Improvements can be made in the future using more types of disturbances with harmonic existent, where more than one disturbance occurring at the same time, and by using another type of classification mechanism.

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