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RESEARCH ARTICLE

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APPLICATION OF TRAINED NAÏVE BAYES CLASSIFIER FOR DETECTION OF POWER QUALITY EVENTS

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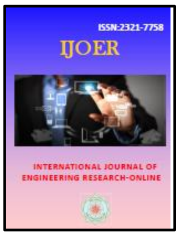

ABSTRACT

The effects of power quality events can be devastating if not properly managed. Effective detection and classification techniques played a key role in the management of power quality disturbances. This paper employed trained Naïve Bayes classifier for the detection and classification of PQ events. PQ events of interest in this paper are voltage swell, voltage dip and voltage interruption. The Naïve Bayes classifier was sufficiently trained using generated synthesized parameters. The results of the analysis showed that the prediction and the actual PQ event using the proposed approach tallies for all the PQ and for the 50 samples carried for each event of interest, the trained Naïve Bayes classifier gives 100% accuracy. The proposed approach is therefore a good tool for detection and classification of PQ events in power system engineering.

Keywords: Naïve Bayes classifier, Power Quality Events, Short Time Fourier transform, Voltage Dip, Voltage Interruption, Voltage Swell.

1.0 Introduction

Researches intoquality of power delivered are emerging field of interest in the area of power system engineering aimed at curtailing revenue lost associated with poor power quality [1]. It is not a gainsaying that proliferation and continuous use of non-linear loads has inherent ability to deteriorate the quality of power supplied to the end-users[2]. The need for efficient, cost-effective, real time power quality detection, classification and preferably power quality monitoring system will always be the heart centre of researchers, if the dream of clean, safe and steady power supply will be realised [3]. Ideally, electrical power system is expected to deliver undistorted sinusoidal voltage and current continuously at rated frequency to the consumers [4], this is far behind what is obtainable in many third world countries including Nigeria.

Power Quality (PQ) problem can be viewed as any power problem expressed in voltage, current, or frequency deviation which is potentially capable of resulting in partial/ total failure or malfunction of customer connected equipment [5, 6].PQ is an issue of interest which the utility companies, the electrical/ electronic equipment manufacturers, and the end users has to deal with; the utility companies viewed PQas the quality of service delivered in reliability manner, the end users measured it from the perspective of being able to use the delivered energy in the desired manner while equipment manufacturer perceived PQ as the level of supply that ensure efficient running of their equipment [7, 8].

One of the visible sign of power quality problem is a distortion in the waveform of the voltage of the power sine wave or from the

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amplitude established reference level or a complete interruption.In a nutshell,power quality problem can be seen as any deviation from the normal standard sinusoidal wave.The duration of this disruption may ranges from a fraction of a cycle (milliseconds) to seconds or hours in the supplied voltage and it could originate from either the power plants,the transmission lines, the distribution substations, the service equipment or building wiringsystem [9, 10]. The detailed classification of power quality problems was reported as in [4] and is as given Table 1.

Table 1: Categorization, Duration and Voltage Magnitude of Different Power Quality Events.

S/N	Categories	Duration	Voltage Magnitude
I.	**Short Duration Variation (SDV)**		
a).	Sag; Instantaneous	0.5-30 cycle.	0.1-0.9 p u.
	Momentary	30cycles-3sec.	0.1-0.9 p u.
	Temporary	3sec-1min	0.1-0.9 p u.
b).	Swell; Instantaneous	0.5-30 cycle.	1.1-1.8 p u.
	Momentary	30cycles-3 sec	1.1-1.4 p u.
	Temporary	3sec-1min.	1.1-1.2 p u.
c).	Interruption; Momentary	0.5cycles-3sec.	< 0.1 p u.
	Temporary	3sec-1min	< 0.1 pu.
II.	**Long Duration Variation (LDV)**		
a).	Interruption,	>1min	0.0 pu.
b).	Sustained Under-voltage	>1min	0.8-0.9 p u.
c).	Sustained Overvoltage	>1min	1.1-1.2 p u
III.	**Transients**		
a).	Impulsive; Nanosecond	<50nsec	
	Microsecond	50-1msec.	
	Millisecond	>1msec.	
b).	Oscillatory; Low frequency	0.3-50msec	0-4 p u.
	Medium frequency	20µsec.	0-8 p u.
	High frequency	5µsec.	0-4 p u
IV	**Voltage Imbalance**	Steady state	0.5-2%
V.	**Waveform Distortion**		
a).	Harmonics	Steady state	
b).	Notching	Steady state	
c).	Noise	Steady state	

The detection and appropriate classification of power quality disturbances is a fundamental stepin the adequate control of power quality events. Feature extraction played a key role in PQ events detection and classification and several techniques reported in literatures ranging from Wavelet Transform (WT) [11], Fourier Transform (FT) [12], Hilbert Hung Transform (HHT) [13], to S-Transform[14]among others. The desired extracted feature(s) need to be classified based on the interest of researchers, some of feature classification techniques reported in literatures include Artificial Neutral Network (ANN)[15], Fuzzy Logic based classifier [16], Support Vector Machine (SVM)[17], Adaptive Neuro-fuzzy system (ANFS)[18] and Bayesian classifier[19] among others.

NaïveBayes is a simple generative probabilistic classifier which assumes independence between features of the objects to be classified [20]. The fundamental concept of this classifier is rooted in Bayes theorem with the assumption that the

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presence or absence of each feature is unrelated to other features [21].

Generally, Naïve Bayes Classifier is a supervised learning algorithm which means it needs to be trained before being able to do classification; henceit must have a training set and the training set usually comprises a number of observations and the classes in which they are categorized [22].One of the major merits of Naïve Bayes classifier is that it requires only a small amount of training data to estimate the parameters necessary for classification and this attribute makes it appropriate for PQ events classification[23].

2.0 Materials and Method

Short Time Fourier Transform (STFT) is a form of the Fourier Transform (FT) known as the sliding window version of the Fast Fourier Transform was employed to extract features from generated synthetic signals required to train Naïve Bayes classifier used in this analysis. The essence of synthetic signal is to determine the feature extraction points of the PQ events waveform required in the training of the Naive ayes classifier. The following input parameters were used in the generation of the synthetic signals and is as given in the Table 2.

Table 2: Input Parameters Used to Generate the Synthetic Signals Required for Training of Naïve Bayes Classifier

S/N	Input parameters	Value Used
1.0	RMS Nominal Voltage (V)	220 Volts
2.0	Fundamental Frequency (f_o)	50Hz
3.0	Sampling rate (f_S) in samples per second	6.4×10^3 (kHz)
4.0	Samples per 50Hz cycle (N cycle)	f_s/f_o
5.0	Window Width	1500 – 3000

The cosine sinusoidal signal with the nominal voltage used as amplitude was generated and the PQ events was introduced between the signal waveform samples at the window width. The PQ events introduced in this research was limited to voltage dip, voltage swell, and voltage interruption. Each of the PQ event waveform signal was passed through the STFT. The maximum frequency which are the points of the fundamental magnitudes(triggering point) are located and the waveform was segmented based on this triggering points. The signal energy was computed using the Parseval's theorem and the Total Harmonic Distortion (THD) was also computed. Also, to generate various signal energy and THD, the PQ events were introduced at different percentages. Lastly, the data obtained from the signal energy and the THD was used to train the NaïveBayes implemented in MATLAB/SIMULINK and run on a portable computer with an Intel Core2 Duo (1.8GHz) processor, 2GB RAM memory and MS Windows 7 as an operating system.

3.0 Results and Discussion

The generated normal waveform without any PQ events is as shown in the Figure 1,PQ events were later introduced with a view to be detected and classified accordingly with the trained STFT-Bayes classifier. The maximum and the minimum voltage amplitude of the generated signal waveform ranges from 200 to -200 volts, the time in seconds for the completed cycle ranges from 0 to 0.5 seconds and the corresponding samples times also range from 0 to 3250 samples.

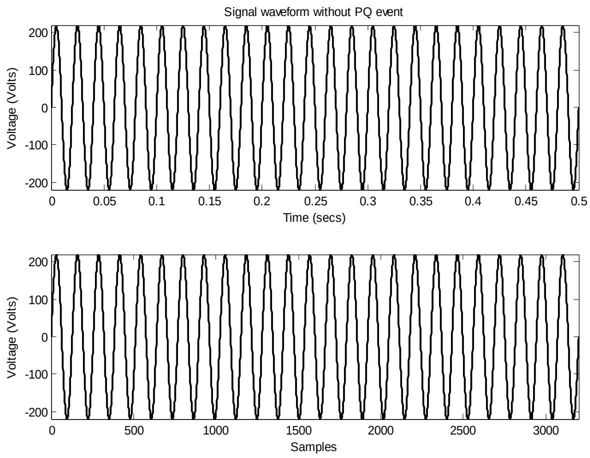

Figure 1: Signal Waveform without Any PQ Events

The PQ events of interest in this research are voltage dip, voltage swell and interruption, these are used to train the STFT-Naïve Bayes Classifier, the results of train and corresponding classification using the proposed approach is as presented in Table 3.

Table 3:Classification Results Using the Proposed Approach

PQ Events	Swell	Dip	Interruption	Classification Rate
Swell	50	0	0	100%
Dip	0	50	0	100%
Interruption	0	0	50	100%

In the training of the Naïve Bayes classifier, it was noticed that the prediction and the actual PQ event tallies for all the PQ and for the 50 samples carried for each event the trained classifier gives 100% accuracy.

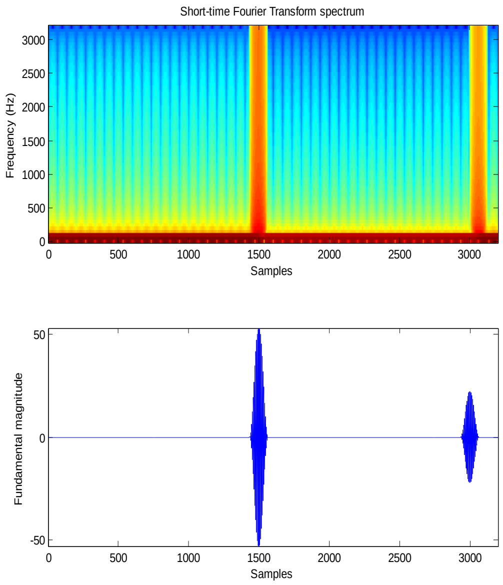

Figure 2a: Signal Waveform with Voltage Dip; Fundamental Magnitude

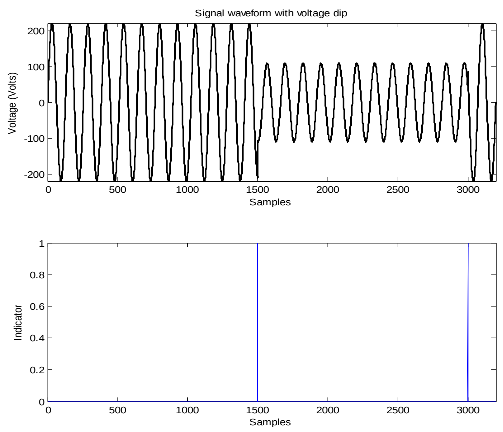

Figure 2b: Signal Waveform with Voltage Dip; Indicator

In Figure 2 voltage dip was introduced in the signal at window width of 1500 – 3000 samples as the PQ event,the trained STFT-Naïve Bayes classifier was able to detect itby showing the fundamental magnitude of triggering point which allows it to be successfully located on the indicator as showed in Figure 2b.The signal waveform reduced in magnitude and ranges from 100 to -100 volts where voltage dip occurred.

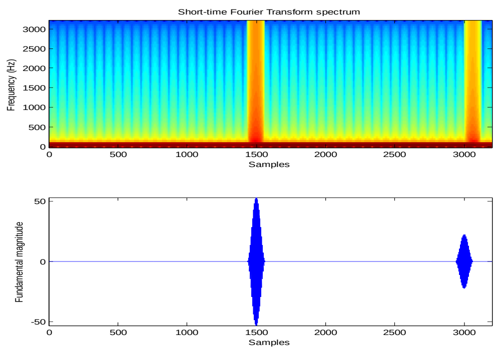

Figure 3a:Signal Waveform with Voltage Swell; Fundamental Magnitude

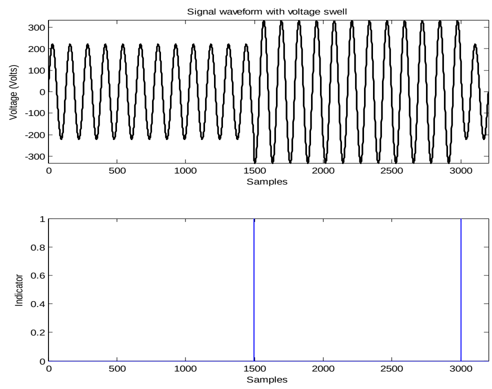

Figure 3b: Signal Waveform with Swell; Indicator

In Figure 3,voltage swell was introduced in the signal at window width of 1500 – 3000 samples; the STFT-Naïve Bayes classifier was able to detect it reflecting the fundamental magnitude of triggering point allowing it to be successfully located on the indicator as shown in Figure3b. Voltage swell was detected between 1500 to 3000 samples with conspicuous swell in voltage magnitude ranging from 300 to -300 volts.

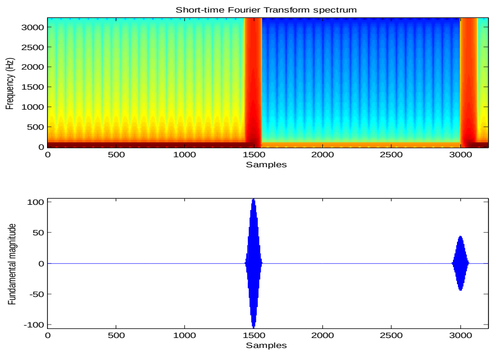

Figure 4a: Signal Waveform with Voltage Interruption; Fundamental Magnitude

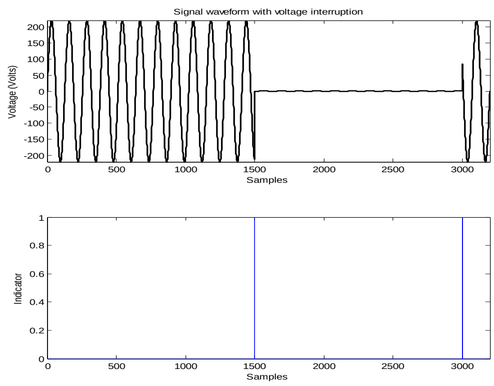

Figure 4b: Signal Waveform with Voltage Interruption; Indicator

In Figure 4voltage interruption was introduced in the signal at window width of 1500 – 3000 samples and it was appropriate detected.The proposed STFT-Naïve Bayes classifier showing the fundamental magnitude ofthe triggering point which allows it to be successfully located on the indicator showed in Figure 4b. A steady interruption exist which reduced the voltage magnitude to zero between 1500 - 3000 samples.

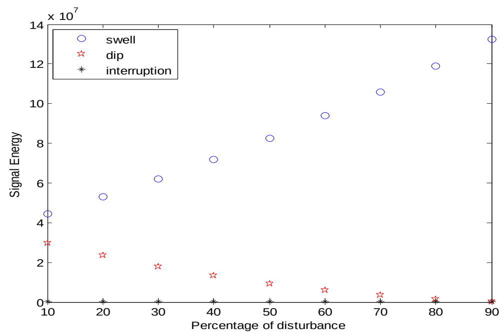

Figure 5a: Distribution of the PQ Events (Swell, Dip, and Interruption) using the Signal Energy

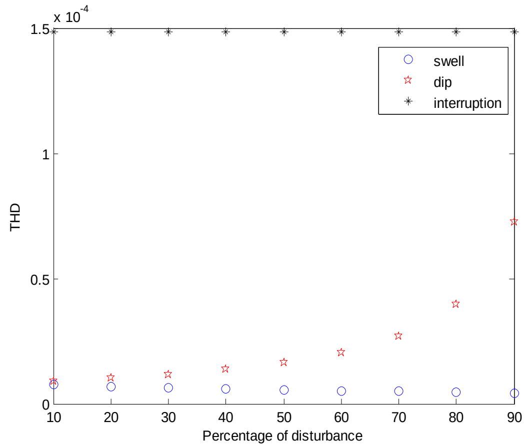

Figure 5b: Distribution of the PQ Events (Swell, Dip, and Interruption) using the THD

Figure5a and 5b showed the relationship between the signal energy and total harmonic distortion with respect to the increase in the percentages of PQ event introduced. It was observed that the signal energy for the voltage swell increases while that of the voltage dip decreases and voltage interruption is constant for increase in the percentage of each PQ event introduced. The THD for the voltage swell slightly decreases while that of the voltage dips increases. It is as well observed that voltage interruption appeared to be fairly constant for increase in the percentage of each PQ event introduced.

4.0 Conclusion

This paper presents training and application of Naïve Bayes classifier for detection of power quality events, the power quality events of interest in this research are voltage swell, voltage dip, and voltage interruption. Naïve Bayes classifier was trained to detect PQ events. The STFT was employed to determine the triggering point which is the point of disturbances to make the Naïve Bayes classifier train itself to classify the PQ events. The classification accuracy of the classifier is excellent as depicted in Table 3. The classifier presented in this research is useful for any classification of the triggering point detected by any of the detection classification model

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