Detection and Classification of Power Quality Event using Discrete Wavelet Transform and Support Vector Machine

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***Abstract*—The quality of supplied power which reaches the consumers has been greatly reduced. This is as a result of continuous use of non-linear loads and the faults that occur on the power system. The power quality disturbances that often occur include voltage sag, voltage swell, harmonics, transients, flicker and interruption. To detect power quality disturbances, discrete wavelet transform was adopted in the feature extraction process. For the classification of the power disturbances support vector machine was used. Synthetic power quality signals were used in this paper. The synthetic signal was generated using synthetic parametric equations; the signal was filtered to remove unwanted noise. Events such as dip, swell and interruption were introduced to the signal. Discrete Wavelet Transform is then used for the detection of the events and change points, the signals of each event were trained using Support Vector Machine. The results obtained from the developed system show a high degree of classification rate.**

Keywords-- Power quality, events, discrete wavelet transform, support vector machine

I. INTRODUCTION

The Power Quality (PQ) analysis was introduced at the end of 19th century; it was found that rotating machinery and transformers were the major sources of the waveform disturbance. It is required of an electrical power system to deliver normal sinusoidal rated voltage and current at the rated frequency to the consumers. But due to the large introduction of power electronic devices as well as a modification of the electric power industry and an advent of distributed generation have put more serious demand on the quality of power supplied to the consumers. The utility providers, the equipment manufactures, and the consumers view PQ in different ways. Utility providers are concerned with the reliability of PQ. Equipment manufacturers view PQ as the level of supply that ensure efficient running of their equipment; however, consumers view good PQ as that which ensures uninterrupted running of processes, operations and businesses. Generally PQ problem can be defined as any disturbance in voltage, current and frequency that results in failure of customers' equipment [1].

For electric power providers to remain competitive in the emerging power market, they have to ensure a high quality of their service. This is because the electric power consumers can shift to new service providers if PQ is not good. The consumers can also demand for improved power Quality [1].

When non-linear loads are used from time to time, the power quality of the system is drastically reduced; this reduction in PQ can also be as a result of the fault occurring on the system. For efficient power quality improvement, it is very essential to detect and identify the occurring PQ problems. This has resulted in significant advances in PQ monitoring equipment. This necessitates the development of automatic recognition system to classify the disturbance waveform. This paper utilizes the application of Discrete Wavelet Transform (DWT) and support vector machine (SVM) for power quality disturbance recognition.

The quality of the power is with increasing importance due to the great damage caused by power quality (PQ) disturbances. The damage is clearly noticeable at great public or industrial facilities where the PQ disturbances cause a malfunction in the equipment. To improve the power quality, the PQ events detection is very necessary. The detected disturbances are subsequently classified, and information describing localization, duration and type of the disturbance is reported. The Manual approach of analyzing and identifying PQ disturbances such as visual inspection of disturbance waveforms is laborious. The usual method for analysing these PQ problems is too simple and sacrosanct to capture all the relevant disturbance structure. An automated system for PQ problem detection and classification which is reliable has many merits over the conventional one. These merits include the processing speed, amount of data that can be processed, the convenience in the collection of data and its storage, cost and reliability [2].

DWT is a major tool for analysing PQ signals. It gives both time and frequency representations of the PQ signal. In PQ detection and classification, other properties apart from stationarily thatFourier analysis are well adapted for are required. Hence, the need for DWT [3].Fourier Transform FT only allows the study of fixed interval of disturbance, the location cannot be detected. To preserve the resolution both in time and frequency domain, i.e. the location and width, then a dynamic scheme is necessary which is in a form of DWT [4].

The DWT has been applied with success to detect and classify PQ problems[2],[4], [5],[6],[7].In [2],[8] and [9],a wavelet-based method for PQ problem detection was presented. Wavelet feature extraction technique based on an energy of detail and approximation coefficient was used for automatic PQ problem detection and classification. [2] used two DWT, one with short filter and the other with a long filter to carry out the detection process. This was to reduce the influence of the choice of the wavelet.

[4] describedthe mathematical concept of DWT. Daubechies 4 wavelet function was used as a base function to detect and identify due to its frequency response and time localization information properties.

In recent years, SVM have shown excellent performance in patterns recognition and classification[4]. Support Vector Machines are set of related supervised learning methods that are recently introduced and are used for pattern recognition and regression. SVM is a prediction tool that uses the theory of machine learning to increase the accuracy of prediction and it avoids over-fit to the data automatically. SVM have solid theoretical background which is based on statistical learning theory. They minimize misclassification probability of unknown patterns with an unknown probability data distribution. Most of the real world problems cannot be solved using hypothesis spaces with linear discriminants. For linearly non-separable classes, SVM is able to find non-linear boundaries. SVM has better generalization performance; hence it performs better than neural networks in this respect [1].

SVM have been used for many applications within power system as reported in [1]. In [4], 4 classification techniques were implemented in order to automatically classify disturbances by using their patterns. The techniques used are Multilayer Perceptron (MLP), Kohnen ANNs, Bayes and SVM. In the SVM classification, the linear SVM look for a hyper-plane in a manner that the greatest number of points of the same group are located at the same hyperplane side, whereas the distance of such groups to the hyper plane is the greatest. For easy classification of the patterns, a Radial Base Function, RBF was used as the kernel. It was proved that out of the 4 classification strategies that were employed, SVM has the best accuracy. In[2], a binary decision tree was constructed where for every node a linear SVM model is created. Seven signals were analysed. The signals were grouped into 2 at the root node,the first group belongs to signals without harmonics while the other group belongs to signal with harmonics. The results obtained with the use of the decision tree were similar with the results using one against one or one against all technique. But decision tree approach was faster.

II. METHODOLOGY

This research work is mainly to classify electrical signals consisting of voltage sag, voltage swell and interruption. But before these signals can be classified, it would be necessary to detect the various types of power quality events. The power quality signals used as input to Discrete Wavelet Transform are synthetic signals.

Synthetic power quality signals are generated using Matlab. For the synthetic signals to represent real-time signal accurately, mathematical parametric equations are used to generate the PQ signals. The synthetic signals are generated from signal wave equations that are given below;

Table I. Power Quality synthetic equations.

Disturbance	Model	Parameters
normal	$x(t) = \sin(\omega t)$	
swell	$x(t) = A\Big(1 + \alpha\big(u(t-t_1) - u(t-t_2)\big)\Big)\sin(\omega t)$	$0.1\leq \alpha \leq 0.8\,, T \leq t_2 - t_1 \leq 9T,$
sag	$x(t) = A\Big(1 - \alpha\big(u(t-t_1) - u(t-t_2)\big)\Big)\sin(\omega t)$	$0.1\leq \alpha \leq 0.9\,, T \leq t_2 - t_1 \leq 9T$
Interruption	$x(t) = A\Big(1 - \alpha\big(u(t-t_1) - u(t-t_2)\big)\Big)\sin(\omega t)$	$0.9\leq \alpha \leq 1\,, T \leq t_2 - t_1 \leq 9T$

Discrete Wavelet Transform technique was employed for the feature extraction. Discrete wavelet transform is better used as compared to Discrete Fourier Transform (DFT) because it provides information on both frequency and location of the components.

The discrete wavelet transform is given by;

$$\text{DWT}\,[m,n] = \frac{1}{\sqrt{a_0^m}} \sum_{k=-\infty}^{\infty} f[k]\psi\,[\frac{[k - nb_0 a_0]}{a_0^m} \qquad (1)$$

The signal that is being tested for power quality disturbance was first decomposed into 5-levels using DWT. The feature vectors are taken as the energy of the detail and approximation coefficients at each level of decomposition from 1 to 5. These feature vectors are calculated with the equations below;

$$\text{ED}_{i} = \sum_{k=1}^{N} c^2{}_{jk}\,, \quad j = 1\,.\,.\,.\,, 5 \qquad (2)$$

$$\text{EA}_{m} = \sum_{k=1}^{N} b^2{}_{jk}\,, \qquad (3)$$

where $d_{jk}j = 1\ .\ .\ .\ , 5$is the detail coefficient of the wavelet in the wavelet decomposition from level 1 to level $5$and $a_{jk}$is the approximation coefficient of wavelet in the wavelet decomposition at level 5. N is the total number of wavelet coefficients at each level of decomposition from 1 to 5, $\text{ED}_j$is the detail coefficients energy at the decomposition level $j$and $\text{EA}_m$is the approximate wavelet coefficients energy at decomposition level 5.

For classification, the training sets are of three categories;

1. Normal and swell
2. Normal and dip
3. Normal and interruption

This is because SVM could only classify between 2 classes.

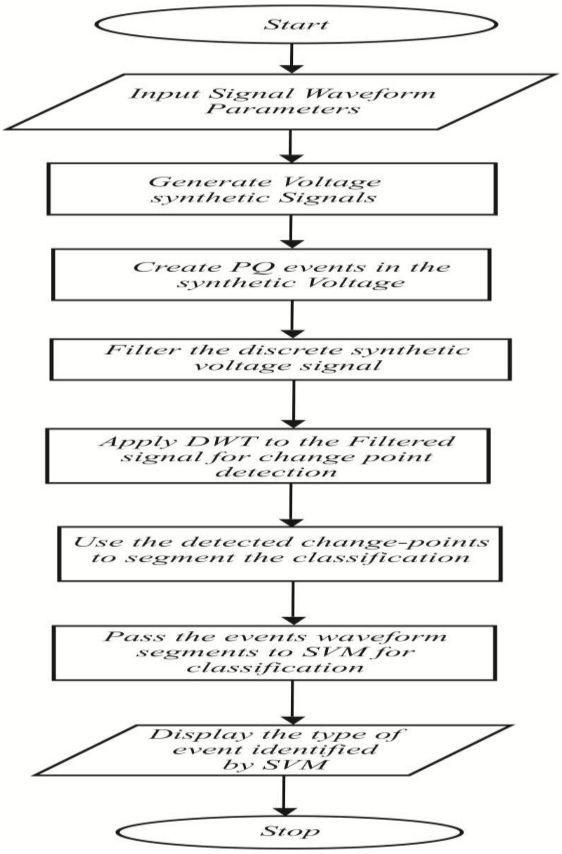

Fig.1.Flow chart for the methodology.

From figure 1, the signal waveform parameters are supplied. Voltage is taken as 230V and the frequency is 50Hz. The synthetic voltage signals are then generated. PQ events which are voltage swell, sag and interruption are then introduced in the normal waveform using their various waveform equations. The generated electrical signals are then filtered to remove the noise. The filtered signals are then passed to DWT for change point detection, and the detected change points are then used to segment the signals before being passed to SVM for classification.

III. RESULTS AND DISCUSSION

The generated synthetic signals for normal waveform, voltage dip, voltage swell and interruptions with their DWT decompositions are shown below;

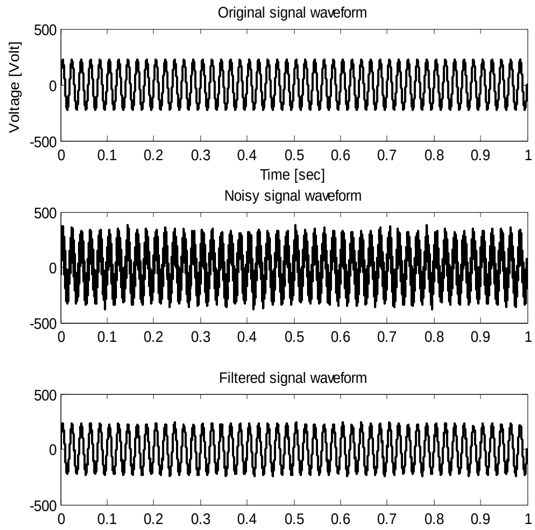

Fig. 2.Normal synthetic signal waveform

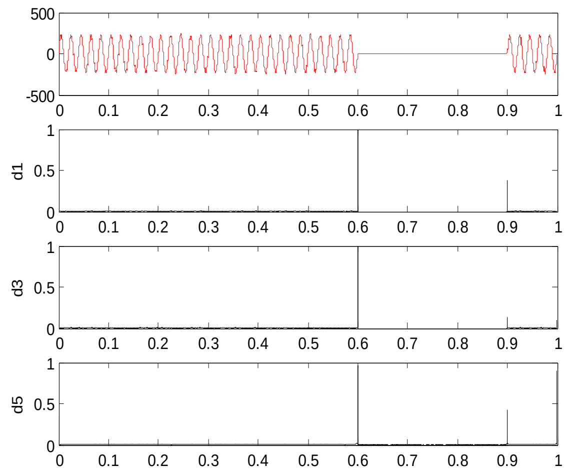

Fig. 3.Signal for voltage interruption event with DWT decomposition

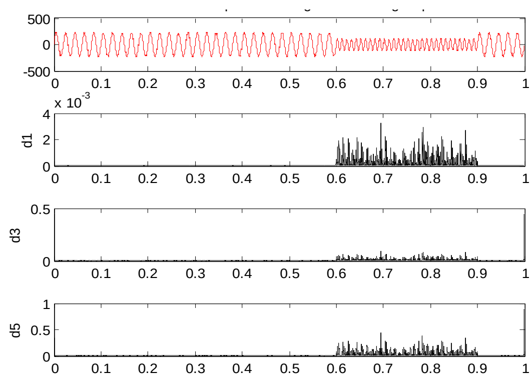

Fig. 4.Signal for voltage dip event with DWTdecomposition

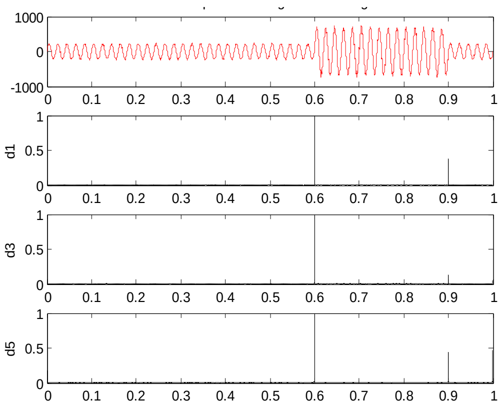

Fig. 5.Synthetic signal for voltage swell with DWT decomposition

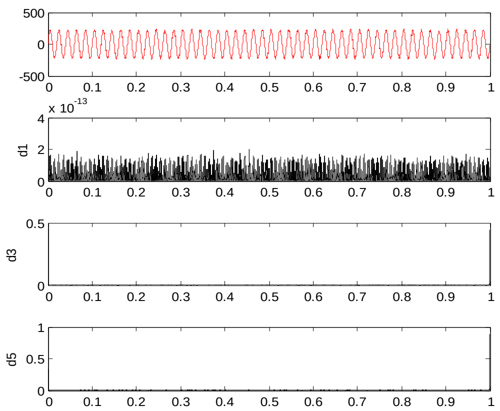

Fig. 6.DWT decomposition for normal voltage signal

In Figure 3, voltage interruption was introduced between 0.6s and 0.9s. DWT was able to detect the change points at 0.6 and 0.9, that is, there exist normal waveform between 0s and 0.6s, at 0.6s, there was interruption up to 0.9s. From 0.9s to 1s, we have normal voltage waveform

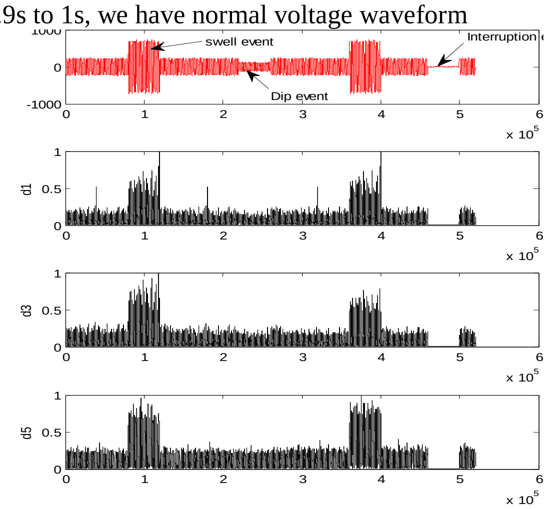

Fig. 7.DWT decomposition for normal, swell, dip and interruption events.

. In figure 4, voltage dip was impressed on the original waveform from point 0.6s to 0.9s. DWT detected the change point at 0.6s and 0.9s. Normal voltage signal exists between point 0s and point 0.6s, and there was occurrence of voltage dip between point 0.6s and point 0.9s, and remaining part of the waveform contains normal voltage waveform. In figure 5, there was an introduction of voltage swell at point 0.6s to 0.9s. DWT detected the change points at 0.6s and 0.9s. Normal sinusoidal voltage waveform occurred between point 0 and point 0.6s. Voltage swell occurred between 0.6s and 0.9s and the remaining part of the waveform is normal sinusoidal voltage waveform. Figure 7 shows the combination of all the possible waveforms under consideration; and that is normal voltage waveform, voltage dip, interruption and voltage swell. DWT was able to detect the different change points between the various events as clearly shown in the various decomposition level of the waveforms.

Table II. SVM performance on tested signals

PQ Event	Correctly Classified	Mis-classified	Classification Rate (%)	Training Time (sec)	Testing Time(sec)
Dip	94	6	94	9.68766	0.608872
Swell	75	26	75	8.14325	0.491091
Interruption	99	1	99	6.34924	0.143053

Table II shows the performance of the SVM when tested with signals containing dip, swell and interruption.It is shown that out of 100 tested voltage dip signals, 94 are correctly classified while 6 are misclassified, for swell classification, out of 100 tested signals, 75 are correctly classified while 26 are misclassified, for interruption classification, 99 are correctly classified while 1 is misclassified. Hence, the developed SVM have the accuracy of 94%, 75% and 99% for voltage dip, voltage swell and interruption respectively.

IV. CONCLUSION

In this paper, a unique method for classification of power quality disturbances based on discrete wavelet transform and support vector machine was presented. High classification accuracy rate of this method is as a result of the use of discrete wavelet transform. Analysing the properties of the power disturbances signals, SVM that uses one against one classification was developed. This reduced the number of operations made in the testing phase.

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