Detection and Classification of Real-time Power Quality Event Using Discrete Wavelet Transform and Support Vector Machine

*Okelola Muniru Olajide, Oniyide Oluwaseyi John

Abstract— In this paper, detection and classification of real-time power quality events based on discrete wavelet transform and support vector machine is presented. The continuous use of non-linear loads has resulted in the deterioration of power quality. Hence there is need for effective detection and classification of these PQ problems. Real-time PQ signals such as interruption, voltage sag and voltage swell are considered. The obtained classification result shows high degree of accuracy.

Index Terms— Power Quality, Real-time Event, Discrete Wavelet Transform, Support Vector Machine.

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1 INTRODUCTION

One expects that the electrical power that is delivered to customers is of rated voltage and current and of course standard frequency. But is not the case because there is huge penetration of power electronic devices and also the restructuring of the power industry, this has put a stringent demand on the power quality supplied to consumers [1]. There are different views to power quality. Power providers view PQ from reliability aspect. Equipment manufacturer view PQ as that level of power supply that ensures efficient operation of their equipment. Consumers view PQ as that level of supply that ensures continuous operation of process and businesses. Any problem that shows in form of current, voltage or frequency distortion which gives rise to failure or inefficiency of the consumer's equipment is called Power Quality Problem. Previously, power quality problems were treated as power system transients which occur due to surges from lightening, switching operation and non-linear loads. Despite the numerous advantages that result from increase in interconnection and increased use of power electronic devices, new problems have been introduced by their use.

In new electricity market situation, now electricity users can shift to the new service providers, if quality of power is not good. Moreover, these customers can demand a higher quality of service. The utilities or other electric power providers need to make sure that they provide adequate and efficient service so as to make a breakthrough in the highly competitive market. An early study in the 19th century shows that transformers and rotating machines are the major sources of PQ problems.

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The continuoususe of non-linear loads and fault occurrence on the power system has resulted in deterioration in the power quality supplied to the customers. The commonly occurring power quality disturbances include voltage sag, voltage swell, harmonics, transients, flicker and so on. To ensure a remarkable improvement in the quality of electric power supplied to the consumers, it is pertinent to detect and identify the power quality problems [1].

In analysing PQ, DWT have been discovered to be a basic tool. It gives both frequency and time format of the PQ signal. In detection and classification of PQ, some other properties apart from stationarity which analysis of Fourier are well adapted for are required. Hence, the need for DWT [2] .only Fourier Transform FT allows the study of fixed interval of disturbance, the location cannot be detected. To conserve the revolution both in frequency and time domain, i.e. the width and location, then a non static scheme is required which is in form of DWT [3].

For PQ problems the DWT has been used as a detection technique and a great deal of achievement has been recorded [2],[4],[5],[6],[7]. In [7],[8],[9], the detection technique that was used for the PQ event is DWT. Wavelet feature extraction technique is on energy base of detail and approximation coefficient was used for automatic detection and classification of PQ problem . Milchevski et al uses two DWT, one with short filter and the other with long filter in carrying out the detection process. The influence of the choice of the wavelet was to reduce.

Vega et al in [3] describes the mathematical concept of DWT.Because of the localisation of time and frequency response properties of DWT, Daubechis 4 wavelet function was used as base function.

In present years, in patterns recognition and classification SVM have shown outstanding performance [3]. Support Vector Machines are set of related supervised learning technique which are newly introduced and are used for pattern notification and regression. SVM is a hypothetic tool which uses the theory of machine learning to improve the accuracy of prediction and it prevent automatically to the over-fit of data. SVM have rigid theoretical background which is standardize on statistical learning theory. They reduce misclassification probability of unknown patterns

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with an unknown probability data distribution. with linear discriminants most of the real world problems cannot be solved using hypothesis spaces with linear discriminants. For linearly non- separable classes, non-linear boundaries are found by SVM. SVM has better generalization performance; hence it performs better than neural networks in this regard [1].

Within power system SVM have been used for many applications as reported in [1]. In [3], to automatically classify disturbances by using their patterns 4 classification systems were implemented. The systems used are Multilayer Percetron (MLP), Kohnen ANNs, SVM and Bayes. 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 hyper plane side, whereas the distance of such groups to the hyper plane is the greatest. For simple classification of the patterns, a Radial Base Function, RBF was used as kernel. It was proved that out of the 4 classification strategies that were employed, SVM has the upmost accuracy. In [7], for every node a linear SVM model is created a binary decision tree was constructed. Seven signals were analysed. At the root node the signals were grouped into 2, first group belongs to signals without harmonics while the other group belongs to signal with harmonics. The results obtained with the use of decision tree were similar with the results using one against one or one against all technique. Approach was faster with decision tree.

2. Methodology

This research work is mainly to classify electrical signals consisting of voltage sag, voltage swell and interruption. Before classification, 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 real-time signals.

Real-time power quality signals are obtained from the reading on FLUKE 435, a power quality analyser.

Discrete Wavelet Transform technique (DWT) was used for the feature extraction. Discrete wavelet transform is used instead of Discrete Fourier Transform (DFT) because it gives information on both frequency and location of the components.

The discrete wavelet transform is given by;

$$\text{DWT}\,[m,n]=\frac{1}{\sqrt{a_0^m}}\sum_{k=-\infty}^{\infty} f[k]\psi\left[\frac{k-nb_0a_0^m}{a_0^m}\right] \qquad 1$$

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 is calculated with the equations below;

$$ED_i=\sum_{k=1}^{N} c^2{}_{ik}, \quad j=1\ldots,5 \qquad 2$$

$$EA_m=\sum_{k=1}^{N} b^2{}_{ik}, \qquad 3$$

where $d_{jk} j= 1 \ldots, 5$ is the detail coefficient of 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, $ED_j$is the detail coefficients energy at the decomposition level $j$and $EA_m$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 shows the flow chart of the adopted methodology.

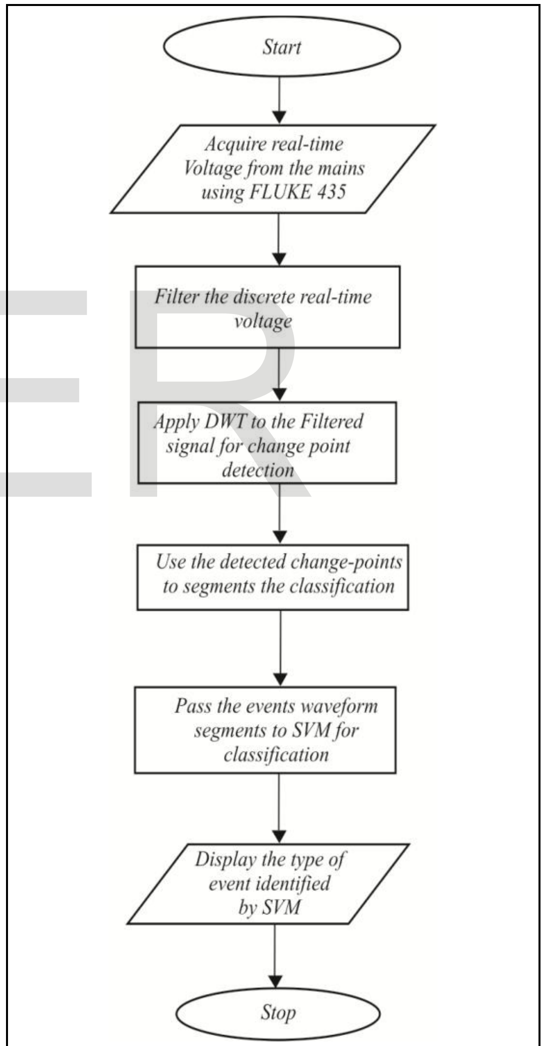

Fig. 1. Flow chart for the methodology

From Fig. 1, the real-time power quality voltage signals are obtained from the mains using Fluke 435. The signals are obtained from household and office appliances such as fans, laptop, television, blender, washing machine and so on. These obtained signals contain various PQ problems such as voltage swell, voltage dip and interruption. The discrete real-time signals obtained are then

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filtered to remove noise. The filtered signals are then passed to DWT for change point detection. The detected change points are then used as feature vectors, passed to the SVM for the classification of various power Quality events. 1000 samples of the signal are used in the testing phase.
Table one shows the data used for the research work

3 Results and Discussion

Below are the results of the real time signals taken using Fluke 435 and showing its DWT decomposition.
Fig. 2 shows the real time signal for TV set with voltage dip. DWT was applied to the signal and was able to detect the change points for voltage dip at 600s, 800s, 1750s, 2600s, 2800s, and 3750s.
Fig. 3 shows the real time signal for laptop with voltage dip. The applied DWT was able to detect the change points for dip at points 220s and 230s.
Fig. 4 shows the real-time signal for blender. Change points are detected at 550s, 1600s and 2600s

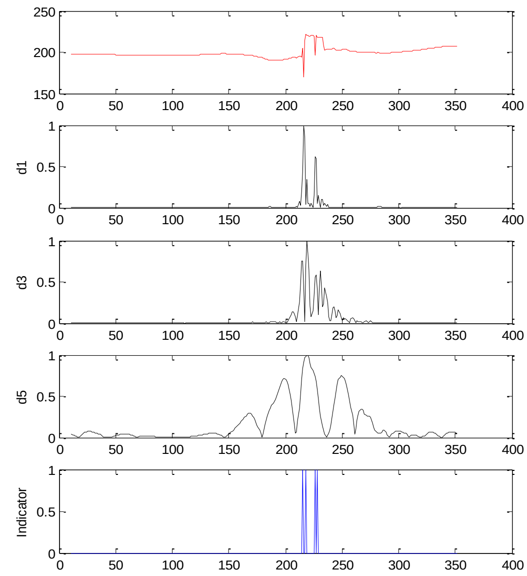

Fig. 3. DWT decomposition of voltage swell for laptop.

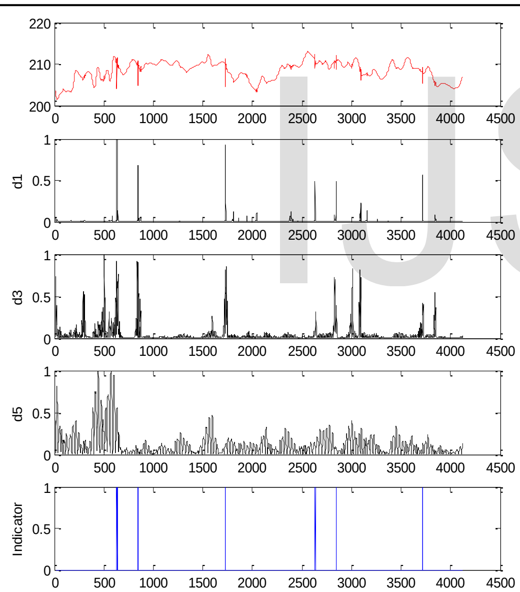

Fig. 2. DWT decomposition of voltage dip for Tv signal

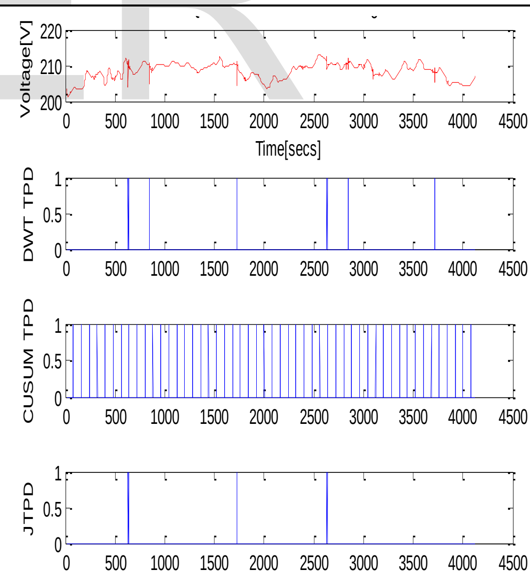

Fig. 4. DWT decomposition of blender signal

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TABLE 1
SVM PERFORMANCE ON TESTED SIGNALS

PQ Event	*CorrectlyClassified*	*Mis-classified*	*Classification Rate (%)*	*Training Time (sec)*	*Testing Time(sec)*
Dip	*990*	*10*	*99*	*4.97643*	*0.182615*
Swell	*743*	*258*	*74.3*	*3.44762*	*0.137733*
Interruption	*998*	*2*	*99.8*	*3.40082*	*0.046269*

Table 1 shows the performance of the SVM when tested with signals containing dip, swell and interruption.It is shown that out of 1000 tested voltage dip signals, 990are correctly classified while 10 are misclassified, for swell classification, out of 1000 tested signals, 743 are correctly classified while 258 are misclassified, for interruption classification, 998are correctly classified while 2 is misclassified. Hence, the developed SVM have the accuracy of 99%, 74.3% and 99.8% for voltage dip, voltage swell and interruption respectively

4 CONCLUSION

In this paper a unique method for classification of power quality disturbances based on discrete wavelet transform and support vector machine was developed for real time PQ signal. High classification 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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