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Implementation of MODWT on Real Time Power Quality Disturbance Signal

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Abstract: ***Maximal overlap discrete wavelet transform (MODWT) is the upgradation of traditional wavelet transform (WT), has been employed for localization of different power quality disturbance signal (PQDS). Every signal has been break down up to fourth level to localize the disturbances. The co-efficient of MODWT have been again employed for classification. The selected indices have been obtained utilizing the detail coefficient of this variant of WT. These features are the inputs to the data mining classifier. Decision Tree (DT) have been implemented for discrimination of PQ disturbance signals. Various PQDS have been generated in noisy and noise free climate. Besides this, the aforementioned techniques is examined with three phase signals bring out from transmission line panels.***

Keywords: ***Artificial Neural Network (ANN), Decision Tree Classifier (DT), Maximum overlap discrete Wavelet Transform (MODWT), Power quality disturbance signals (PQDS).***

I. INTRODUCTION

Power Quality is an umbrella that covers the whole power system under which the generated disturbance are mitigated by implementing suitable devices with advanced techniques. This important aspect of power quality changes the overall beauty of the system. Various factors like the solid state devices, short circuit etc., which deviates the waveform of voltage and current from being a sinusoid [1]. These prosperity influence the quality of power, which alter the total harmony. So, a healthy system require good voltage profile in the form of enhancement power quality.

The proper localization of the various types of PQDS are needed for maintenance of voltage profile. Techniques such as the Fourier transform (FT), the short-time Fourier transform (STFT), wavelet transform (WT), Neural Network, Fuzzy logic, S-transform have been employed for study of power quality disturbance signals (PQDS) [2], [3]. The FT is a fast signal analysis method which only provides the information about the frequency component. Similarly, STFT gives the time frequency information [4]. But, it fails to analysis the transient signals perfectly [5]. Similarly, the S-transform requires large computation [6]. The beauty of wavelet transform is its Multi-Resolution Analysis called MRA. This MRA affords time-scale analysis of non-stationary signal. Similarly, This MRA property represents the signals into different time-scales. In this way, the WT gives time-frequency information.

This paper has implemented one of the brother of WT namely MODWT [7], [8], [9] to retrieve the features of the PODS. These features are employed for discriminate of the PQDS. The proper detection of the PQDS is the main gadget in PQ study. However, the commonly used methods are Artificial Neural Network (ANN) [10], fuzzy and neuro-fuzzy systems [11]. The drawback of ANN classifier is its retraining property. Moreover, the Hidden Markov Model (HMMs) are unsuitable for categorization of sluggish disturbances [12], [13]. Datamining based classifier named the decision tree (DT) is suitable to discriminate PQDS. Decision Tree (DT) [14], [15] has been here chosen to discriminate the PQDS.

Here paper is coordinated like, the Section-II illustrate about MODWT along with DWT. The extraction of feature is described in the Section-III. Section-IV gives idea regarding the classifier. Section-VI deals with PQ model development. The classification outcomes are reported in Section-VII. Section-VIII provides the final conclusion.

II. APPROACH FOR LOCALIZATION

The detection of the PQDS has been performed by implementing one of the variants of wavelet transform i.e the MODWT. The MODWT is described here. The motivation for formulation of the MODWT over the conventional DWT is the intelligence of the free election of initial point.

Maximum Overlapping Discrete Wavelet Transform (MODWT)

MODWT is an upgrade version of traditional DWT. This MODWT technique can be applied to analysis signal any length [9], [16] and [17]. The MODWT is diagrammatically represented in Fig.1. Scaling filters h_l , wavelet filters g_l of MODWT can be represented through (1) and (2)

$$\tilde{h}_l = \frac{h_l}{\sqrt{2}} \quad (1)$$

$$\tilde{g}_l = \frac{g_l}{\sqrt{2}} \quad (2)$$

The filters of MODWT are the Quadrature mirrors filters can be represented as

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$$\tilde{h}_l = (-1)^{l+1} h_{L-1-l} \quad (3)$$
$$\tilde{g}_l = (-1)^{l+1} g_{L-1-l} \quad (4)$$

where l=0,1,2,…., L-1. L is the width.

The n^{th} element of the 1st -stage wavelet and the scaling coefficients are

$$\widetilde{W}_{1,n} = \sum_{l=0}^{L_1-1} \tilde{h}_l X_{n-l mod N} \quad (5)$$

$$\widetilde{V}_{1,n} = \sum_{l=0}^{L_1-1} \tilde{g}_l X_{n-l mod N} \quad (6)$$

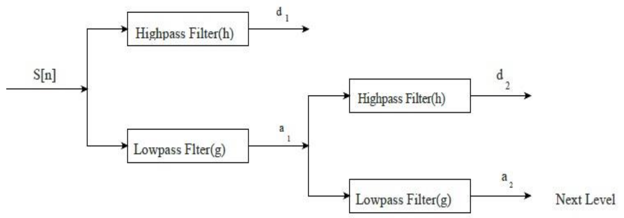

Fig. 1: Block diagram of MODWT

where n = 1,2,3,... , N and N is the length of signal (sample).

The approximations and details at stage-1 can be determined by the equations (5) and (6). The MODWT scaling coefficients V_j and W_j wavelet coefficients at j^{th} stage are represent in equations (8) and (7)

$$\tilde{A}_{1,n} = \sum_{l=0}^{L_1-1} \tilde{g}_l \tilde{X}_{1,n+l \bmod N} \quad (7)$$

$$\widetilde{D}_{1,n} = \sum_{l=0}^{L_1-1} \tilde{g}_l W_{1,n+1 \bmod N} \quad (8)$$

Likewise, the n^{th} element coefficients are represented by the equations (9) and (10).

$$\widetilde{A}_{j,n} = \sum_{l=0}^{L_j-1} \tilde{g}^0_{j,l} \widetilde{V}_{1,n+l mod N} \quad (9)$$

$$\widetilde{D}_{j,n} = \sum_{l=0}^{L_j-1} \tilde{h}^0_{j,l} \widetilde{W}_{1,n+l mod N} \quad (10)$$

The original signal can be written as follow

$$X(n) = \sum_{l=0}^{j} \widetilde{D}_j + \tilde{A}_j \quad (11)$$

III. FEATURE EXTRACTION THEORY

A. Extraction of Feature

The feature extraction has done with approximation and detail coefficients instead of direct input fed. Three selected features have been extracted as given below

$$\text{Energy } ED_i = \frac{1}{N}\sum_{j=1}^{N} \left|D_{ij}\right|^2 \quad (12)$$

$$\text{Entropy } ENT_i = -\sum_{j=1}^{N} D_{ij}^2 \log(D_{ij}^2) \quad (13)$$

$$\text{Standard Deviation } \sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(D_{ij}-\mu_i)^2\right)^{\frac{1}{2}} \quad (14)$$

where Mean $\mu_i = \frac{1}{N}\sum_{j=1}^{N} D_{ij}$ and N is the sample number. In [1], few disturbance signals like sag, sag and harmonic, swell, swell and harmonic have been discriminated by the standard deviation curve, some other signals has to classify properly. So the indices have been further given as input to classification algorithm. Moreover, features are normalized. The details of the classifier is described below.

IV. APPROACH FOR CLASSIFICATION

The indices are normalized and nourish to the DT.

Decision Tree Classifier (DT)

The DT is a Data mining based approach. DT is easy to handle, faster and simpler than the traditional techniques [18] and [19]. It requires less time and memory as compare to the traditional methods. The features from the training patterns has been implemented to construct DT [20]. The algorithm for design of DT is under given [14], [21].

1. Initiate with single node called as root node.
2. Split node with optimal criteria into two subdivision called as child node.
3. Exit node referred as the leaf node. Otherwise, repeat step−2. These leaf nodes carries the 'outcome'.

V. MODEL FOR POWER QUALITY DISTURBANCES

PQDS are decomposed with the MODWT up to forth finer levels. The PQD signals has been simulated with 3.2 kHz sampling frequency [22]. Allotted class labels of simulated signals is displayed in Table I.

TABLE I: Class labels

PQD events	Class
Sag	*CL*1
Swell	*CL*2
Interruption	*CL*3
Oscillatory transient	*CL*4
Flicker	*CL*5
Harmonics	*CL*6
Sag and Harmonics	*CL*7
Swell and Harmonics	*CL*8

Notch	*CL*9
Spike	*CL*10

VI. DECOMPOSITION PQ SIGNALS

A. Pure sine wave with sag

Voltage with sag is considered for study. This signal break down upto forth levels is interpreted with Fig.2. The original sine wave is presented along with the decomposed levels.

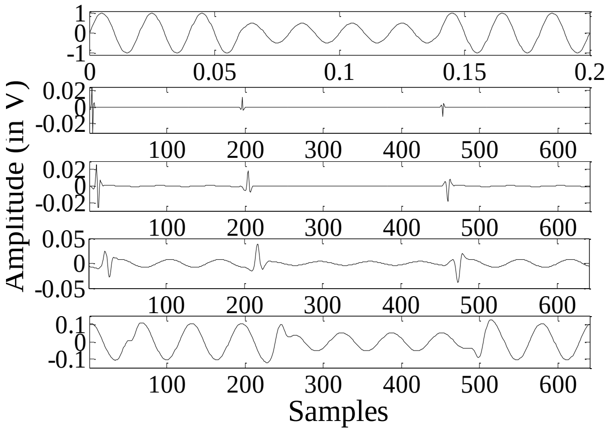

Fig. 2: Sine wave with sag

The vertical axis is taken as amplitude axis. The amplitude in volt V p.u. Horizontal axis is considered here as the time (samples) axis. In Fig.2, sag localization has been realized at all levels shown in Fig. The 1st level waveform is at the same alignment with the considered signal. All other levels are drifted towards right. This shifting helps in prediction of further occurrence of PQD.

B. Pure sine wave with swell

The above operations is also followed in this case to analyze sine wave with swell. In Fig. 3, similar results are found. Decomposition levels other than the 1st, the initial point of the signal is also sifted along with the distortions. The inception and end point of interruption is proper localized at each decomposition levels. So, MODWT can be implemented to predict the occurrence of power quality distortions.

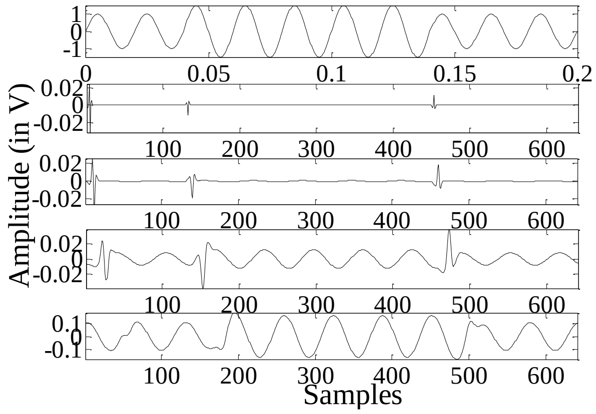

Fig. 3: Sine wave with swell

C. Pure sine wave with interruption

Voltage signal with interruption has interpreted in Fig.4. Similar to that of the previous cases, the 1st decomposition level is at same position with the considered signal. The waveform of other levels are shifted towards right due to the circular shifting property.

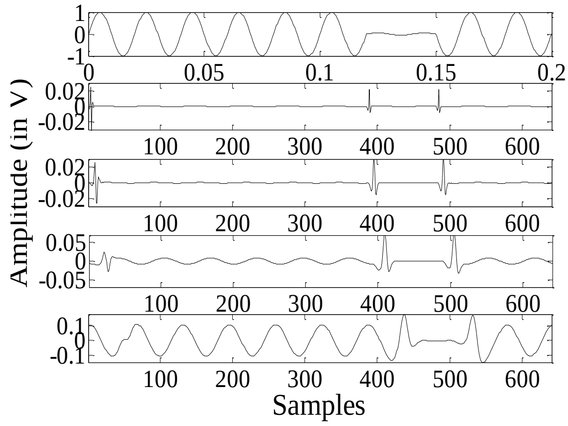

Fig. 4: Sine wave with interruption

The inception and end point of interruption is proper localized at each decomposition levels. Finer levels are more shifted which is the main beauty of this MODWT.

D. Sag and harmonics

Considering voltage signal with the sag and harmonic interpreted in Fig.5. From the inspection of 1st two levels of Fig. 2 and Fig. 5, it is observed that the magnitude of these levels of pure sinusoidal voltage are almost zero except inception and end point of sag. Whereas for harmonic signal, there are some magnitude for 1st two levels. Similar to that of other cases, the origin point of signals are shifted along with the distortion in MODWT operations.

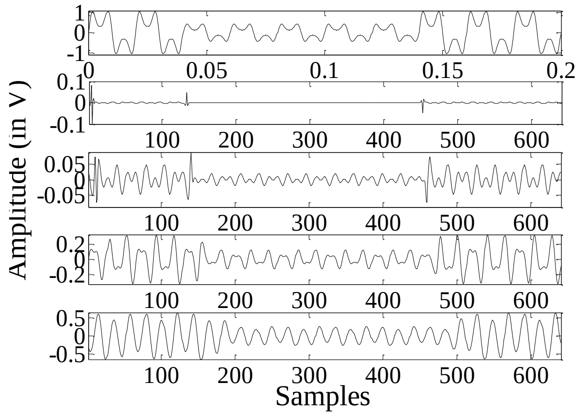

Fig. 5: Sag and harmonic

E. Swell and harmonics

Considering voltage signal with the swell and harmonic. From the inspection of 1st two levels of Fig. 2 and Fig.6, like the previous case it is observed that for pure sinusoidal voltage signal, the magnitude of these levels are almost zero except inception and end point of swell. Whereas for harmonic signal, there are some magnitude for 1st two levels.

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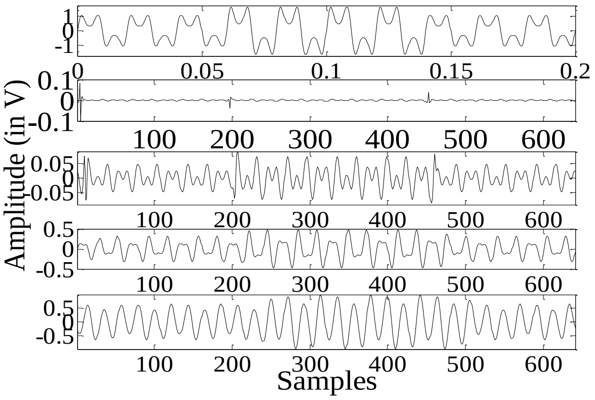


Fig. 6: Swell and harmonic

Similar to that of other cases, the origin point of signals are shifted along with the distortions. Other PQDS are processed similarly.

VII. RESULT S AND DISCUSSIONS

The PQDS are discriminated in terms of classification accuracy. %CA is determined with employment of classifier named as DT. Total 32000 signals has been simulated. For construction of classification data set, signals have been resolved up to seventh levels. For each dataset classification, 30% of input are reserve as the testing sets. With 70% of data, training model is built.White Gaussian noise is incorporated with pure PQDS. The considered signal set is doped with 20 dB noise. The Table II provides %CA of all considered classes in the noise free environment using MODWT and DT. The end row of the Table II carries the average %CA. Similar procedure has been realized for noisy data set.

TABLE II: Pure Signals

Class	%CA
CL1	99.52
CL2	100
CL3	99.34
CL4	100
CL5	100
CL6	99.23
CL7	100
CL8	100
CL9	100
CL10	100
Total % CA	99.14

TABLE III: 20 dB noise signal

Class	%CA
CL1	98.13
CL2	98.11
CL3	99.01
CL4	100
CL5	99.96
CL6	100
CL7	100
CL8	99.96
CL9	100
CL10	100
Total % CA	98.41

Table II and Table III, have interpreted with the %CA of the PQDS. From Tables, it is interpreted that classification accuracy of DT slightly decreased with presence of noise.

Real PQDS classification

Eight different class of three phase PQDS have been captured from 380 kV transmission line panel. The length of line is 360 km. Fig 7 is the representation of experimental set up. The natural load of this demo panel is 600 MW. The applied voltage is 380 V. With variation of load and creating faults, the various distortions have been inserted in to pure sine wave signal. These three phase real signal data set have been fed to DT. The %CA of three phase PQD have been shown in Table IV.

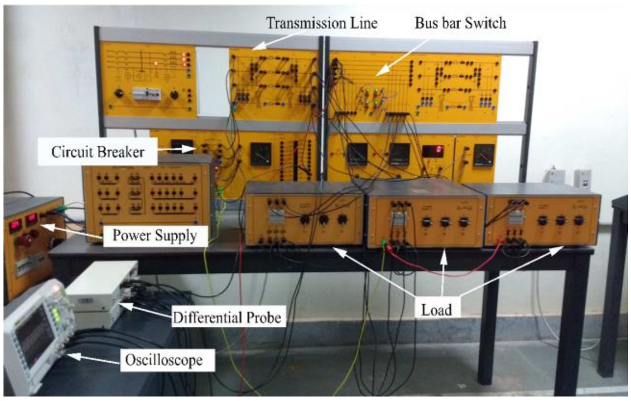
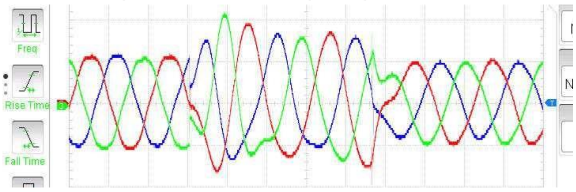
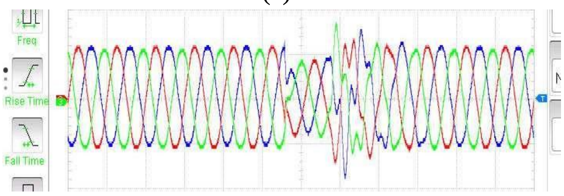


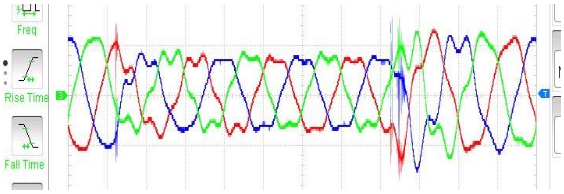
Fig. 7: Setup for signal generation



(a)



(b)



(c)

Fig. 9: PQDS (a) Swell (b) Sag (c) Sag with harmonics

TABLE IV: CA % of three phase real time signal

Class	%CA
CL1	97.82
CL2	98.90
CL3	100
CL4	97.02
CL1+CL2	99.79
CL6	99.32
CL7	97.36
CL8	97.28
Total % CA	98.97

From Table IV, it is analyzed that the aforementioned techniques are performed satisfactorily for the classification of real data. The DT classifier has provided good results. *%CA* of MODWT based data set is identical to synthesized signal.

VIII. CONCLUSION

The distortions have been properly localized with proper shifting in finer levels of MODWT. The %CA of simulated and the real signals have been obtained by MODWT with the combination of DT. The unresponsive to commencement of time series enhances suitability of MODWT. So MODWT is a good candidate for real time environment application. The decision has better classification rate. DT also perform satisfactorily on real time signal.

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