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DWT AND ARTIFICIAL NEURAL NETWORK FOR DETECTION AND CLASSIFICATION OF SHORT DURATION VOLTAGE DISTURBANCES IN DISTRIBUTION SYSTEM

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ABSTRACT*— Power Quality (PQ) has become a major problem due to increased use of sensitive electronic equipment. PQ problem mainly depends on the distribution system, because the distribution system locates the end of power system and is connected to customers directly. The short duration voltage disturbances such as voltage sag, swell, interruptions are mainly concentrated in this project, because it is mostly occur in distribution system. In the present scenario, the main issue in power quality problem is how to analyze this disturbance waveform in an efficient manner. This paper focused on detect and classify the voltage disturbances using signal processing technique and neural network in order to improve the quality of power. Wavelet transformation technique was founded to be more appropriate to analyze the voltage disturbances. This paper compares the use of various types of wavelets at different scales and levels of decomposition on analyzing voltage disturbances. The combination of features computed using Multi- Resolution Analysis (MRA) and Discrete Wavelet Transform (DWT). The classification of voltage disturbance is achieved by Neural Network is analyzed in MATLAB Simulink tool.

Key words: Power quality, Discrete Wavelet Transform (DWT), Multi- Resolution Analysis (MRA), Feature Extraction, Energy feature, Neural Network (RBNN)

I. INTRODUCTION

Poor power quality (PQ) may cause many problems for affected loads, such as malfunctions, instabilities, short lifetime, and so on. Short duration voltage disturbances are mainly occuring in distribution system. These disturbances include voltage sag, voltage swell, interruptions. In order to improve power quality, the sources and causes of such disturbances must be known before appropriate mitigating actions can be taken.

A feasible approach to achieve this goal is to incorporate detection capabilities into monitoring equipment so that events of interest will be recognized, captured, and classified automatically. Hence, good performance monitoring equipment must have functions which involve the detection, localization, and classification of power quality events. In particular, when the disturbance type has been classified accurately, the power-quality engineers can define the major effects of the disturbance at the load and analyze the source of the disturbances so that an appropriate solution can be formulated. Amongst the different signal processing techniques used in the extracting of features of disturbances from a large number of power signals, the most widely used techniques are Fast Fourier transform (FFT) and the windowed Fourier transform (WFT) which comprises of the short time Fourier transform (STFT) and the wavelet transform (WT).Wavelet analysis is becoming a common tool for analyzing localized variations of power within a time series [1]. By decomposing a time series into time-frequency space, one is able to determine both the dominant modes of variability and how those modes vary in time. In power system analysis, wavelet transform have received attention because its efficiency for the analysis of transients compared to other types transforms. The wavelet transform has been used for numerous studies in power system protection, power quality, power system transients, load forecast and power system measurement. In [12], MRA techniques of WT and DWT is used to extract features in power signal .Most of them use sampled voltage and current waveforms, based-on the Parseval's theorem. The proposed work is Feature extraction and Energy features of distorted signals takes place for easier classification and classification is based on Radial Basis Neural Network.

II. WAVELET TRANSFORM

Wavelet Transform provides the timescale analysis of the non-stationary signal. It decomposes the signal to time scale representation rather than time- frequency representation. Wavelet transform (WT) expands a signal into several scales belonging to different frequency regions by using translation and dilation of a fixed wavelet function known as Mother Wavelet. Wavelet based signal processing technique is one of the new tools for power system transient analysis and power quality disturbance classification. The Discrete Wavelet Transform and Multi Resolution Analysis (MRA) provides a short window for high frequency

WT are most important one to extract information and as a basis for signal representation to achieve both good time and frequency position. The process representation using wavelets is provided by a series expansion of dilated and translated versions of the basis function, also called the mother wavelet, multiplied by appropriate coefficients. So, the first step of the wavelet transform is to determine the mother wavelet. For a wavelet of order N, the basis function can be represented as

$$\boldsymbol{\psi(n) = \sum(-1)^{j} c_j (2N + J - N + 1)} \quad \textbf{(2.1)}$$

where Cj is coefficient. The basis function should satisfy some conditions The basic function integrates to zero.

$$\int_{-\infty}^{\infty} \boldsymbol{\psi(t)dt = 0} \quad \textbf{(2.2)}$$

The basis function must be oscillators or have a wave shape. For processes with finite energy the wavelet continuous wavelet transform and wavelet series. Discrete wavelet transform (DWT) is sufficient to decompose and reconstruct most power quality problems. It provides enough information, and offers high reduction in the computational time . Discrete wavelet transforms are suitable for processing real data in which the signal is known only at sampling points with spacing dependent on the sampling rate. The WT in this case has discretised scale and location parameters. Using a logarithmic uniform spacing in the discretization of the scale and location domains provides an orthonormal wavelet basis which characterizes completely N signal observations with N wavelet coefficients The WT assumes that the full period of the signal is being analyzed. Discontinuity of high frequency components are occurring when the analyzed section is different value at the beginning and at the end of two consecutive windows, so the high frequency effects can be recognized .

III.MULTI-RESOLUTION ANALYSIS

The MRA technique is used to decompose the distorted signal into different resolution levels. It has the ability to detect and identify different voltage disturbances by localization property in time and partitioning of the signal energy at different frequency

series expansion gives an optimal approximation to the original series. Many different wavelet bases can be used for the transformation attaining the properties above. The selection of a basic function is motivated by the data features to be extracted. Alternative functions move different characteristics of the raw data set between scales. In this paper, we adopt Daub4 mother wavelet, which is the most compact wavelet and it has a much simple implementation The multi resolution decomposition separates the signal in to details at different scales, the remaining part, being a coarser representation of the signal, is called ‘‘approximation”. Each detail (Dj) and approximation signal (Aj) can be obtained from the previous approximation Aj-1 via a convolution with high-pass and low pass filters, in the fig.(1) The wavelet transform can be done in three different ways, which are, discrete wavelet transform,

levels. The wavelet function will generate the detail version of the decomposed signal and the scaling function will generate the approximated version of the decomposed signal. The mathematical expression of MRA is as follows,

$$V_j = W_{j+1} \oplus V_{j+1} = W_{j+1} \oplus W_{j+2} \oplus \cdots \oplus W_{j+n} \oplus V_n \quad \textbf{(3.1)}$$

Where V_{j+1} approximated version of the given signal at scale j+1.

W_{j+1} detailed version that displays all transient phenomena of the given signal at scale j+1.

$\oplus$ denotes a summation of two decomposed signals.

n is the decomposition level.

IV. PARSEVAL’S THEOREM IN DWT

The used scaling function and the wavelets form an orthonomal basis, and then Parseval’s theorem relates the energy of the distorted signal to the energy in each of the expansion components and their wavelet coefficients. This means that the norm or the energy of

the signal can be partitioned in terms of the expansion coefficients. According to the Parseval's theorem, the energy of the signal is calculated with the following formula:

$$\frac{1}{N}\sum_t |x(t)|^2 = \frac{1}{N_j}\sum_k |w_{j,k}|^2 + \sum_{j=1}^{J}\left(\frac{1}{N_j}\sum_k |w_{j,k}|^2\right) \quad (4.1)$$

V. FEATURE EXTRACTION, RECOGNITION, AND CLASSIFICATION

In general, when a disturbance occurs, the stable signal will generate a discontinuous state at the start and end points of the disturbance duration. To analyze the distorted signal, DWT technique is used through one-level decomposition of the MRA will cause the wavelet coefficients at the start and end points of the disturbance to generate severe variation. Therefore, we can easily obtain the start time and end time of the disturbance duration from the variations in absolute wavelet coefficients and calculate the disturbance duration.

As seen in (3.2), the energy of the distorted signal can be partitioned at different resolution levels in different ways depending on the power-quality problem. Therefore, we will examine the coefficient w of the detailed version at each resolution level to extract the features of the

$$P_j = \frac{1}{N_j}\sum_k |w_{j,k}|^2 = \frac{||wj||2}{Nj} \quad (5.1)$$

Where ||wj|| is the norm of the expansion coefficient w_j.

In DWT, the wavelet function Daubanchie "db4"w as performed, thus resulting in the larger energy distributions of the decomposition levels

.

- The energy distribution remains unaffected by the time of disturbance occurrence.
- The outline of energy distribution remains the same despite variations in the vibration amplitude of the same disturbance type.
- The low-level energy distribution will show apparent variations when the distorted signal contains high-frequency elements. On the contrary, the high-level energy distribution will show apparent variations when the distorted signal contains low-frequency elements.

By normalise the equations

$$P_j^D = P_j^{1/2} \quad (5.2)$$

One pure sine-wave signal (frequency = 50 Hz, amplitude 1p.u) and three short duration voltage disturbance signals are generated. The disturbance signal includes voltage sag, voltage swell, interruptions. Because these disturbances are mostly occuring in distribution system. A four-level decomposition of the distorted signal is carried out using Daubechies(db4) family.The detailed energy distribution up to 13-level decomposition (P_1^D~P_{13}^D) of each signal is also obtained. These experimental results describe clearly the properties of energy distribution of Parseval's theorem in DWT applications.

VI.RADIAL BASIS NEURAL NETWORK

The Radial Basis Neural Network (RBNN) model is one of the supervised learning networks. An RBFN is a three layer feed-forward network that consists of one input layer, one middle layer and one output layer as shown in Fig.1. Each input neuron corresponds to a component of an input vector **x**. The middle layer consists of *n* neurons and one bias neuron. Each input neuron is fully connected to the middle layer neurons except the bias one. Each middle layer neuron computes a kernel function (activation function) which is usually the following Gaussian function:

$$y_i = \begin{cases} \left(-\frac{||x-c_i||}{2\sigma_i^2}\right) & i=1.2.....,n \\ 1 & i=0 \quad \text{(biasneuron)} \end{cases} \quad (6.1)$$

where we call $\mathbf{c}_i$ and s_i the center and the width of the *i*-th neuron in the middle layer, respectively. ||.|| k:denotes the Euclidean distance. The weight vector between the input layer and the *i*-th middle layer neuron corresponds to the center $\mathbf{c}_i$. And in an RBFN the net input to the *i*-th middle layer neuron is j$\mathbf{x}$-$\mathbf{c}_i$ rather than $\mathbf{x}$-$\mathbf{c}_i$. The kernel function decreases rapidly if the width s*i* is small, and slowly if it is large. The output layer consists of *m* neurons which correspond to the possible classes of the problem and it is fully connected to the middle layer.

Each output layer neuron computes a linear weighted sum of the outputs of the middle layer as

$$Z_j = \sum_{i=0}^{n} y_i\, w_{ij} \quad (6.2)$$

where *wi j* is the weight between the *i*-th middle layer neuron and the *j*-th output layer neuron.

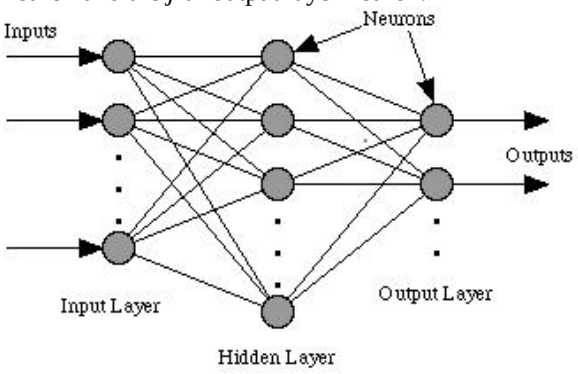


Fig.1 Architecture of Radial Basis Neural Network

The training of RBF is done in three sequential stages. The first stage of the learning consists of determining the unit centers w_{ij}. Next, the unit widths σ is determined using a heuristic approach that ensures the smoothness and the continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least squares objective function.RBF Neural Networks (RBFNN) can be viewed as alternative tool for learning in neural networks. While, RBFNN exhibit the same properties as back propagation networks such as generalization ability and robustness, they also have the additional advantage of fast learning and ability to detect outliers during estimation.

The probabilistic Neural Network (PNN) is a feed forward network. The multilayer feed forward network can be used to approximate non-linear functions where the network structure is sufficiently large. For the determination of those highly non-linear parameters learning should be based on non-traditional optimization techniques. A viable alternative is the Radial Basis Function neural network (RBF).In this study, we will perform a 13-level decomposition of each discrete distorted signal to obtain the detailed version coefficients wavelet coefficients of one-level decomposition. These features would be applied to the PNN for recognizing and classifying the distorted signals. The calculation procedures of the proposed classifier is shown in Fig.2.

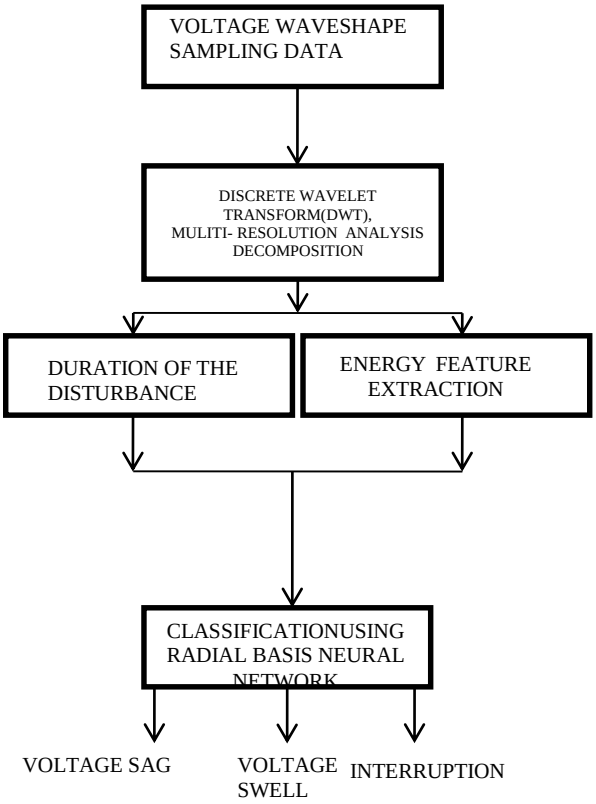


Fig.2 Flowchart for classifier

VII. SIMULATION RESULTS

1. CREATION OF VOLTAGE DISTURBANCES

To verify the feasibility of the proposed method, we used the Power System Block set Toolbox in Mat lab to generate one pure sine-wave signal (frequency = 50 Hz, amplitude = 1 p. u.) and distorted signals. These distorted signals included are voltage sag/swell, and Interruptions. The sampling rate of the system is 256 points/per cycle. The Daubanchie "db4"with level 13 wavelet was adopted to perform the DWT.

The different events are created using the MATLAB Simulink tool by creating the event generation model.The Voltage disturbances such as voltage sag, swell and interruptions are generated by changing the load conditions and/or adding the high frequency sine wave to the original wave.

2.DETECTION OF VOLTAGE DISTURBANCES

The voltage disturbances are created with the help of MATLAB. Wavelet Transform is used for

detection and identification of PQ events at its instants of occurrence. The disturbances are imported from the mat lab simulink to wavelet tool box. To extract the feature from the original PQ signals and the comparison based on the calculation of the energy of the reconstructed signals from the wavelet coefficients.For the detection of voltage disturbances, the discrete wavelet transform with MRA technique is used to decompose the signals with different levels (scales) of resolutions is shown in Fig.3.,Fig.4.and Fig.5. From the decomposed signals the original time-domain signal can be recovered without loss of any information.

With the help of appropriate resolution level, we can .able to detect and localize the voltage disturbance present in the signal. To detect and analyze Daubechies (Db) family is used here. The use of detail coefficient of the level of the wavelet decomposition, using Daubechies (Db) as the mother wavelet to detect the beginning and the end of voltage disturbances is shown in Table.1. Feature extraction of energy distribution pattern is used in order to select the most suitable WT and most significant coefficient in each decomposition level of MRA is shown in Fig.6.and Energy features of distrorted signal is shown in Table.2.

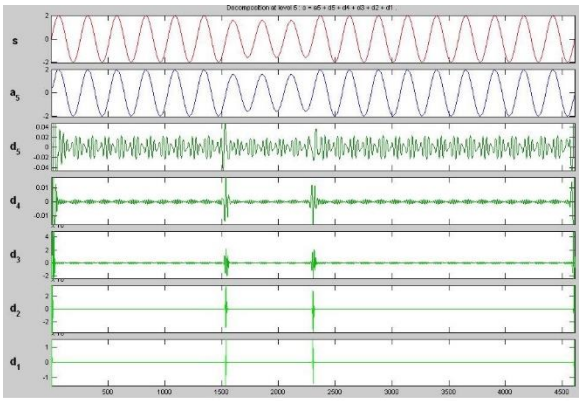


Fig.3 Multi resolution voltage sag decomposition

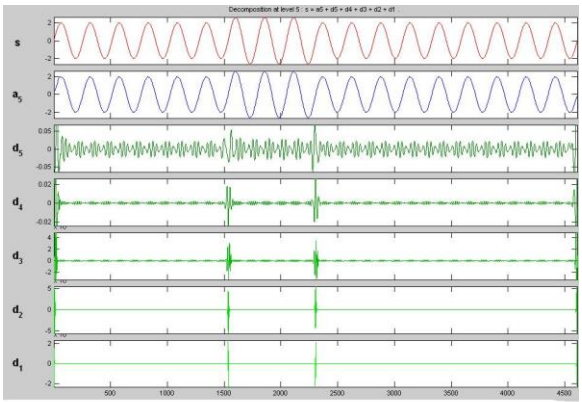


Fig.4 Multi resolution voltage swell decomposition

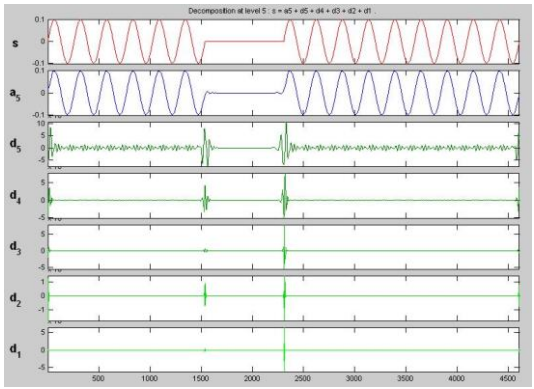
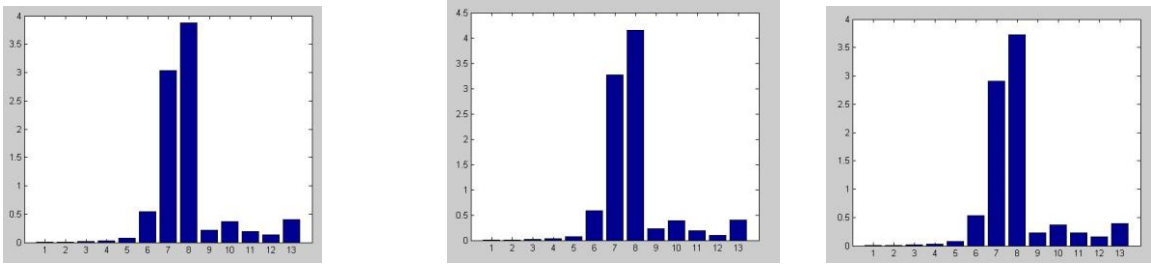


Fig.5. Multi resolution Interruption decomposition

The classifier is modeled to classify the PQ events in the original signal, which is extracted from the power systems. In order to train the classifier model, it requires the different power quality events with the particular sampling rate.The experimental results are able to recognize and classify the voltage sag, swell and interruption. RBNN is a most powerful tool for the classification of voltage disturbances in all condition. In this model, training and learning function and default neuron value are directly considered. But the direct MATLAB coding is used for the proposed work for simplification and fine tuning. Classification for swell 2, pure sine wave, sag 0.1, interruption 0.25 using Neural Network tool.

Table.1 Time duration results for voltage disturbances

Voltage disturbances	Time duration		Time difference
	Start (sec)	End (sec)	
Sag, Swell, Interruption	0.00015	0.6151	0.61495



a)Detailed energy distribution of Sag **b)Detailed energy distribution of swell** **c) Detailed energy distribution of Interruption**

Fig.6 Detailed energy distribution

Table.2: Energy features of distorted signals

Voltage disturbances	P_1^D	P_2^D	P_3^D	P_4^D	P_5^D	P_6^D	P_7^D	P_8^D	P_9^D	P_{10}^D	P_{11}^D	P_{12}^D	P_{13}^D
Sine	**0.0163**	**0.0677**	**0.227688**	**0.3624**	**1.0503**	**8.0663**	**44.55**	**57.341**	**3.0538**	**5.2010**	**2.8413**	**1.9304**	**5.7285**
Voltage Sag	**0.0215**	**0.0679**	**0.2289**	**0.3649**	**1.0505**	**7.9637**	**43.843**	**56.518**	**3.076**	**5.1921**	**2.9604**	**2.0638**	**5.7133**
Volatge Swell	**0.0215**	**0.0679**	**0.2289**	**0.365**	**1.0598**	**8.189**	**45.327**	**58.237**	**3.078**	**5.2313**	**2.7586**	**1.8040**	**5.7439**
Interruption	**0.4464**	**0.434**	**0.493**	**1.1725**	**1.2731**	**8.7109**	**43.761**	**56.021**	**6.4076**	**6.69747**	**5.9493**	**2.5125**	**5.2932**

VIII.CONCLUSION

To analyze Daubechies (Db) family is the detail coefficient of the level of the wavelet decomposition, to detect the beginning and the end of voltage disturbances. The proposed work for Feature extraction of energy distribution pattern is effective and used in order to select the most suitable WT and most significant coefficient in each decomposition level of MRA and RBNN is a most powerful tool for the classification of voltage disturbances in all condition, simplification and fine tuning and Classification for swell 2, pure sine wave, sag 0.1, interruption 0.25 using Neural Network tool.

VIII.REFERENCES

[1]Zwe-Lee Gaing, "Wavelet-Based Neural Network for Power Disturbance Recognition and Classification" IEEE Transactions on Power Delivery, Vol. 19, No. 4, October 2004.

[2] A.M. Gaouda et al, "Power Quality Detection and Classification Using Wavelet-Multiresolution Signal Decomposition" IEEE Transactions on Power Delivery, Vol. 14, No. 4, October 1999.

[3] G. T. Heydt, P. *S.* Fjeld, C. C. Liu, D. Pierce, L. Tu and *G.* Hensley, "Applications of the Windowed PFT to Electric Power Quality Assessment" IEEE Transactions on Power Delivery, Vol. 14, No. 4, Octobcr 1999.

[4] M. sushma, G. Tulasi Ram Das,"Detection and classification of voltage sells using adaptive decompsition an d avelet transforms", Journal of theoretical and applied information technology in 2005-2008.

[5] T.Lachman, A.P.Memon, T.R. Mohamad and Z.A.Memon ," Detection of power quality disturbances using wavelet transform technique", International Journal for the advancement of science and arts, VOL.1, NO.1,2010.

[6] Inigo Monedero et al, "Classification of Electrical Disturbances in Real Time Using Neural Networks" IEEE Transactions on Power Delivery, Vol. 22, No. 3, July 2007.

[7] Manish Kumar Saini, "Classification of power quality events – A review"Electrical Power and Energy Systems vol. 43, pp. 11–19, 2012.

[8] K. M. Silva, "Fault Detection and Classification in Transmission Lines Based on Wavelet Transform and ANN" IEEE Transactions On Power Delivery, Vol. 21, No. 4, October 2006.

[9] D. Saxena, S.N. Singh and K.S.Verma, " Wavelet based denoising of power qulity events for characterization", International Journal of Engineering, science and Technology, Vol. 3, No. 3, 2011, pp 119-132.

[10] S.K. Meher , A.K. Pradhan and G. Panda, "An integrated data compression scheme for power quality events using spline wavelet and neural network" Electric Power Systems Research, vol. 69, pp. 213–220, 2004.

[11] Saurabh Kamble,Department of electrical engineering S.V. National institute of technology Surat, India "Detection of power quality disturbances using wavelet transform and artificial neural network",IEEE Xplore: 25 September 2014.

[12] Kuldeep Singh, Anand Tewari "Classification of Power Quality Disturbances using Wavelet Transform and Neural Network" International Journal of Engineering Research & TechnologyVolume. 4 - Issue. 05 , May – 2015.