

DETECTION AND CLASSIFICATION OF POWER QUALITY DISTURBANCES USING WAVELET TRANSFORMS AND PROBABLISTIC NEURAL NETWORKS

¹ANEETA S ANTONY, ²SHILPA R, ³P S PUTTASWAMY

¹M.tech Student Signal Processing ECE dept VVCE Mysore

²Associate Professor ECE dept VVCE Mysore

³Professor EEE dept PESCE Mandya

Email: aneetaantony123@gmail.com, shilparag19@gmail.com, psputtaswamy_ee@yahoo.com

Abstract—The use of sensitive electronic equipments is on the rise lately and power quality studies have progressed a lot. Detection and classification of power quality signals is of greater importance both in case of Power quality studies and denoising. This paper proposes a detection and classification technique for several power quality disturbances, by introspecting the energy of the distorted signals at different resolutions using the Multiresolution Analysis technique (MRA) of Discrete wavelet transform (DWT) .i.e. the Energy Difference MRA (EDMRA) technique is used .This is employed on the distorted signals to extract the energy distribution features at different levels of resolution. Db4 mother wavelet is used to decompose the signal. The power quality disturbances are identified based on the energy difference of disturbance signal with pure sinusoidal signal of 50Hz at each decomposition level. This forms a feature vector that is fed to the input nodes of probabilistic neural network which classifies the power quality disturbances. To validate the efficiency and preciseness of the proposed method the simulation results are analyzed.

Keywords— Power Quality, Wavelet Energy, Probabilistic Neural Network (PNN), Multiresolution Analysis (MRA), Energy Difference Multi resolution Analysis (EDMRA).

I. INTRODUCTION

These days the power quality has become a significant issue for electrical and electronics equipments at all levels. Power quality, or more precisely, a power quality disturbance, is defined as any change in power (voltage, current, or frequency) that affects the normal operation of electrical equipments. The importance of power quality issue is primarily due to increase in use of sensitive power electronic equipments , low balanced power system, increased use of solid state devices, lighting controls, automated and data processing equipments non linear loads and loads that are power electronically switched, as well as industrial rectifiers and inverters. Power Quality (PQ) events such as sag, swell, transients, harmonics, notch, fluctuation and flicker are the most common types of disturbances that occur in a power line. High cost equipment's connected to the power line are prone to these disturbances get affected or damaged due to disturbances that randomly occur for very short durations.

Thus, it is appropriate to estimate the presence of disturbance, and classify aptly the disturbances and apply the mitigating action. In order to perform the tasks such as detection, classification and mitigation, understanding the basic properties of PQ events. In this section, PQ events (like sag, swell, transients, harmonics notch, fluctuation and flicker) and their properties are summarized. Widespread use of electronics in everything from home electronics to the control of massive and costly industrial processes has raised the awareness of power quality.

II. LITERATURE SURVEY

Disturbance like Voltage Swells was detected and classified by applying wavelet transform to the sag signal thereby extracting the features using MRA and classifying using Neural Networks. Interline Unified Power Quality Conditioner is used to compensate the Voltage Swell. Liang Wah et al. Reviews the general category of Power Quality to get accurate time information of the disturbance wavelet transform and MRA is advantageous as good time resolution at high frequencies and good frequency resolution at low frequency is obtained. The wavelet transform based MRA is a great tool to assess and analyse Power Quality Disturbance events. The time of occurrence of transients, sag, swell, can be determined using detail coefficient at level 1.

Problems in detecting voltage sag using the root mean square (rms), Fourier transform, and peak voltage detection methods is that it is slow this is overcome by using a new algorithm presented.The algorithm in the same can extract amplitude, phase and frequency information , also it can extract sinusoidal data from multicomponent signal. Wavelet transform for Denoising in real time is proposed. DWT and Inverse DWT is used in conjunction. The new approach used deals with border problems, hence data is processed continuously.

Another novel approach is the use of Modified wavelet transforms along with Neural networks is proposed for online detection and classification of signals.The different methods of classification are

reviewed and compared and inferences are drawn. Various detection methods using transforms like Hilbert transforms, Fourier transforms (FT) and S-transforms are explored. The Wavelet transform is definitely a better transform than FT and Short Time Fourier Transform (STFT). It also proposes various methods of classification which includes Neural Network, Rule-based Expert Systems Classification and Fuzzy Expert System Based Classification are also explored.

It also proposes Radial Basis Function (RBF) to be a good tool for classification while Support Vector Machine (SVM) to be used for automatic classification, but comparison of SVM and RBF showed that SVM is superior, as it has satisfactorily good generalization ability and recognizes swells, sags etc correctly, for the wide range of different parameters. Classification performance depends majorly on the suitable features and not on the wavelet mother. Also, the performance for each Artificial Neural Network (ANN) depends on the pattern used and not on the mother wavelet chosen. Rodriguez et.al, proposed that a better classification can be obtained by using patterns based on energy levels of wavelet decomposition in addition to Root mean Square (RMS) values. Comparison of Back Propagation (BP) and the PNN are substantiated by suitable results. A review of Power Quality (PQ) classification approaches and in particular fuzzy logic tools is done in . Certain real time issues like PQ due to start of Motor, inrush in transformers, high impedance device faults, switching of capacitors etc need to be taken care of. Cause-based and phenomenon based classifications would be possible. Also multiple PQ events occurring together need to be mitigated. Noise tolerance of PQ signal is also of paramount importance. A power quality disturbance recognition system prototype is proposed in. The components are a simulator to generate PQ disturbances, a detector that uses the technique of DWT to extract disturbance features in the power signal and some statistical processing to improve detection accuracy. The neural network architecture used is LVQ which is Linear Vector Quantization for classification. PQ signals have some standard values of voltage and frequency according to Indian standards it is 220V and 50Hz frequency.

III. DISTURBANCES GENERATED

Any variations in voltage levels and frequencies lead to disturbances in PQ signal. For instance Harmonics are caused by, frequency variations in signals, noises like transients, flickers, fluctuations, sags and swells occur due to random change in load voltages. The Different Disturbances are generated using MATLAB 7.6 and wavelet transform is applied to the same. The Disturbances are generated for specific values of scaling and shifting, with Inline frequency of 50 Hz

and duration of 0.1 second each to visualize the noise more clearly. The Disturbances generated are as shown in the Figures below.

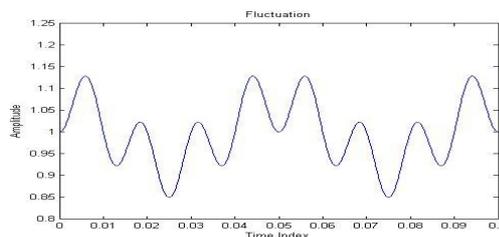


Fig.1 Fluctuation

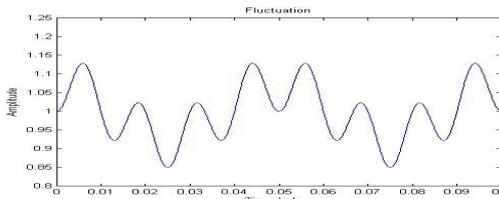


Fig.2 Flicker

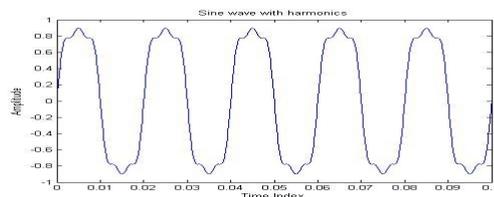


Fig.3 Harmonics

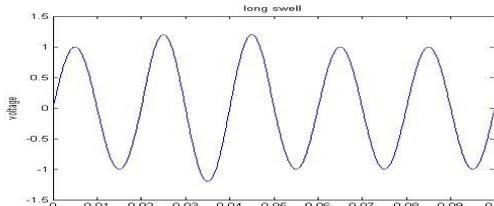


Fig.4 Swell

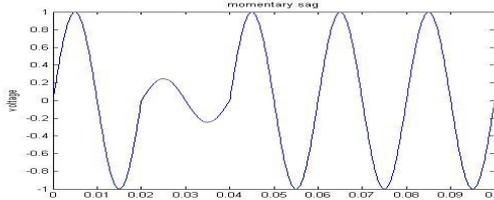


Fig.5 Sag

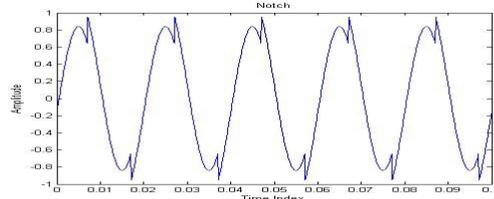


Fig.6 Notch

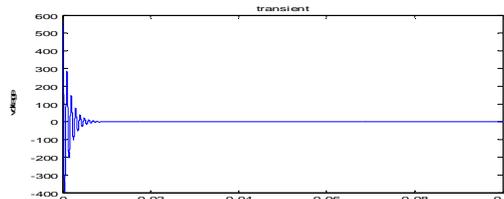


Fig.7 Transient

The equations used for generation of the disturbances are tabulated in Table I

TABLE I DISTURBANCES GENERATED

Disturbance	Equation
Fluctuation	$c=1+0.15*(\sin(0.6*(2*\pi*f*t)))*(\sin(2*\pi*f*t))$
Flicker	$y1=0.2*\sin(0.2*(2*\pi*f*t));$ $c=(1+y1)*\sin(2*\pi*f*t)$
Harmonic	$y1=\sin(2*\pi*f*t);$ $y2=0.19*\sin(3*(2*\pi*f*t))$ $y3=0.09*\sin(5*(2*\pi*f*t))$ $c=y1+y2+y3;$
Swell	$y=u(t-0.02)-u(t-0.05); z=1+(0.2*y);$ $x=1.*z; t1=\sin(2*\pi*f*t);$ $c=x.*t1;$
Sag	$y=u(t-0.02)-u(t-0.04); z=1-(0.754*y);$ $x=1.*z; t1=\sin(2*\pi*f*t);$ $c=x.*t1;$
Notch	$p=\text{sign}(\sin((2*\pi*f*t)+180))$ $n=0.4, v=0.4, c=\sin(2*\pi*f*t)+(n*p*v);$
Transient	$w=2*\pi*f; x1=\cos(w*t);$ $a=(-0.1-t)/.0015; x2=.7*\exp(a);$ $wn=2*\pi*1000; x3=\cos(wn*(t-0.01));$ $c=(x2.*x3);$

IV. WAVELET TRANSFORMS

Wavelets are functions that satisfy certain requirements. Wavelets must integrate to zero and the very name suggests that, it waves above and below the horizontal axis. The diminutive connotation of wavelet suggests the function has to be well localized. There are few more requirements for successful application of wavelet which depends on each of the specific applications.

The vector returned by discrete wavelet transform and that of the input is same. To our advantage generally, even in this vector many data are almost zero. This aids to the decomposition into a set of wavelets which are orthogonal to shifting and scaling values. By using the shifting and scaling functions we decompose the signal at different scales. A wavelet can be defined within a certain time span, starting at $f(t_0) = 0$ and ending at $f(t_{end})$ at 0. This then gives us time localization. On the other hand, a Fourier transform is an integral so there is no time localization. Even if we transform a wavelet to its frequency domain, still the position in time of the transformed wavelet is got by the relative phase relation of different contributing frequencies. A Fourier transform (FT) will show what frequencies are present in the signal. A wavelet transform (WT) will give what frequencies are present and where (or at what scale level). If signals are changing in time, the FT wouldn't tell when (time) this has occurred.

A. DB4 wavelet

The Daubechies wavelets are chosen as they have the highest number of vanishing moments, for given support width $N=2A$. Where A is the number of vanishing moments. The two naming schemes in use,

DN using the length or number of taps, i.e. D8 or rather db4 refers to the number of vanishing moments which is 4. So D8 and dB4 are the same wavelet transforms, but dB4 representation is widely used form. Db4 gives a detailed discussion about the characteristics of the filters and how to construct them. The decomposition procedure starts with passing a signal through these filters. In the time series the low frequency components are the approximations and details form the high frequency components. Thus Multi resolution analysis leads to a fast and hierarchical scheme.

Hence the mother wavelet chosen is dB4 wavelet. The dB4 Scaling function and wavelet obtained in Matlab are shown in Fig. 8. An important property of dB4 is that, if a signal is linear over the support of a dB4 wavelet, then the corresponding fluctuation value is zero. Higher energy compaction is another advantage

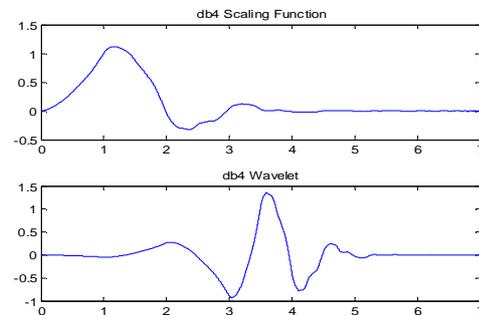


Fig.8 dB4 wavelet

B. Multi Resolution Analysis (MRA)

A multiresolution analysis (MRA) also called as multiscale approximation (MSA) is the design method used for Discrete Wavelet Transforms (DWT).The Multi Rresolution Analysis was introduced by Mallat.

Considering $V_i; i \geq 2$ a sequence of linear subspaces. The MRA can be described through a nested set of subspaces which are spanned by a single scaling function ϕ .The translations and dilations are given by $\phi(2^{me} - k)$.

The Nested set of subspaces are shown

$$V_1 \subseteq V_2 \subseteq V_3 \dots \dots \dots \text{ i.e. } V_i \subseteq V_{j+1} \quad (1)$$

From above Equation we can see that, as i go to infinity, V_i enlarges to become all energy signals (L_2), as i goes to negative infinity V_i shrinks down to only zero.

Also $i \in \mathbb{Z}$, define W_i to be the orthogonal complement of V_j in V_{j+1} , then

$$V_{j+1} = V_j \oplus W_j \text{ and } W_j \perp W_j' \quad (2)$$

From the above Equations we can infer that V_i represents the larger scale or rather the approximations and W_i represents the smaller scale. In MRA, any signal $s(t)$ is completely decomposed

into the approximation coefficients, given by scaling functions ϕ and the detail coefficients, given by the wavelets ψ where

$$\psi_{mn} = 2^{-\frac{m}{2}} \psi(2^m t - n) \tag{3}$$

$$\phi_{mn} = 2^{-\frac{m}{2}} \phi(2^m t - n) \tag{4}$$

A hierarchical fast scheme is given by the Fig 9. The approximations are the low-frequency components of the time series and the details are the high-frequency components i.e. V and W respectively in Vector Space.

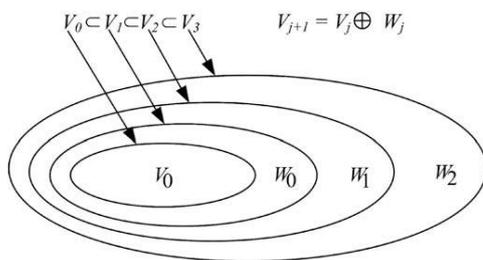


Fig.9 Nested Subspace of MRA

To map a time domain signal $s(t)$ into the wavelet domain and to represent at various scales or resolution levels, the tool used is MRA which makes use of the DWT. The representation can be expressed in terms of the following expansion coefficients:

$$S_{\text{signal}} = [S_0 | d_0 | d_1 | \dots | d_{f-n}]$$

Where, S_{signal} is the input signal, S_0 presents the last **approximate coefficients** and d_i give the detail coefficients at different resolution levels, The detail coefficients d_j , and the approximated coefficients c_j can be used to reconstruct a detailed version **D1** and an approximated version **A1**, of signal $f(t)$ at that scale. Splitting of the signal into low pass and high pass filter components is the first step followed by decimation (or down sampling) which is an efficient multi-rate digital processing technique for changing the sampling frequency of a signal in the digital domain and efficiently compressing the data. Every second sample is dropped resulting due to convolution process. Since half of the data is decimated there is a chance of losing information but the wavelet and the scaling function coefficients will act as digital filters that limit the band of the input s_{j+1} and prevent aliasing.

The wavelet transform is used for feature extraction of different power quality disturbances. The signals are decomposed in 12 levels by DWT.

The energy of detail coefficients at each level of the decomposed signals is calculated. Those energy values are used to calculate the energy difference values. The energy distribution of a distorted signal can be used as a discriminatory feature for classification. Energy at each decomposition level as a new input variable PNN. The energy at each

decomposition level is calculated using the following equations:

$$ED_i = \sum_{j=1}^n |D_{ij}|^2 \quad i=1 \tag{8}$$

$$EAL = \sum_{j=1}^n |A_{ij}|^2 \tag{9}$$

Where $i=1, 2 \dots l$ is the wavelet

Decomposition level from level 1 to level l . N is

The number of the coefficients of detail or approximate at each decomposition level. ED_i is the energy value of the detail coefficient at decomposition level i and EAL is the energy of the approximate at decomposition level l . Then, for an l level wavelet decomposition, we construct a $(l+1)$ dimensional feature vector for future analysis. For each of the disturbance, the DWT coefficients generated have variations which are used to recognize the various power signal disturbance and thereby classifying the different power quality problems. By applying DWT, the distorted signal can be mapped into the wavelet domain and represented by a set of wavelet coefficients. There are different wavelets that can be used to decompose the distorted signal and extract the feature vector.

As per paper, In order to calculate the minimum decomposition level, the level where the maximum energy deviation can be achieved with respect to the reference signal is required. On the basis of that number of decomposition level is required to specify. If f_s is sampling frequency and f_{ref} is the frequency of the reference signal then

$$\log_2 \left(\frac{f_s}{f_{ref}} \right) - 1 \leq N \leq \log_2 \left(\frac{f_s}{f_{ref}} \right) \tag{5}$$

Where $f_s = 5 \text{ KHz}$ and $f_{ref} = 50 \text{ Hz}$

From Eq.8 we get

$$5.64 < N < 6.64$$

Hence N can be considered as 6. Now $N_{\text{min}} = 2 * N$
 (7) Therefore we get $N_{\text{min}} = 2 * 6 = 12$. Hence we have chosen 12 levels of decomposition and the maximum deviation is at 6th level.

V. PROBABILISTIC NEURAL NETWORK

Rather than the conventional programming techniques with nesting, looping, etc. the Neural network can perform certain special tasks. Even if an element of the neural network fails, due to its parallel nature it can proceed without any problems. Due to instantaneous learning it does not require reprogramming. It is well suited for various kinds of classification. The probabilistic Neural Network (PNN) in particular is a supervised neural network that is widely used in the area of pattern recognition. The fact that PNNs offer a way to interpret the network's structure in terms of Probability Density Functions (PDF) is an important merit of this type of networks in the learning processes. The standard training procedure for PNNs requires a single pass over all to the patterns of the training set. This

characteristic renders PNNs faster to train suitable for classification of power system faults. The architecture of PNN is composed radial basis layer and competitive layer. The Probabilistic Neural Network is a supervised neural network that is used for classification. The advantages of neural networks is quite obvious. The Feed forward neural networks in particular have a fixed computation time, computation Speed is very high, as a result of the parallel structure, it learns general solutions of presented training data, and neural networks eliminate the need to develop an explicit model of a process. Neural networks can model parts of a process that cannot be modeled or are unidentified. PNN is a Feed Forward network got from Bayesian Network. If an explicit mathematical model is not required, then the network can be 'programmed' in a fraction of the time required for traditional development. Ability to generalize to situations not taught to network previously. PNN can be taught to compensate for system changes from initial training model (on-line). Changes can be made more easily just by adding or removing nodes in PNN.

VI. METHODOLOGY

Thus the steps to extract feature vector are as follows

- The sampled waveform is decomposed into different resolution levels (i) according to MRA.
- Then the energy of the detail information at each decomposition level i is calculated according to equation 10
- In order to identify different kinds of PQ disturbances, the energy difference (ED) at each decomposition level is calculated, which is the difference of the energy at each level E_i with the corresponding energy of the reference (normal) waveform at this level E_{ref}

The energy difference value of each level of each noise is used for classification using PNN. The inputs to the neural network are the pre processed distorted signal. The biggest advantage is the fact that the probabilistic approach works with a one-step-only learning. Practically one of, the most important advantages of the probabilistic neural network is the easy training and quick results, which simplifies its use in real-time because as soon as one pattern representing each category has been observed, the network can begin to generalize to new patterns.

VII. RESULTS

The Wavelet transform dB4 at level 4 is applied to the disturbances using the MATLAB code and also compared with the wavelet tool box which is successively shown for two of the disturbances namely Fluctuation and Flicker.

This is shown in Figure 10 and 11.

The outcome is detection of the faults in power quality which is required for distribution, transmission and renewable energy systems. Results would substantially contribute to the faster development of modern energy efficient power electronics and reliable and sustainable power engineering.

This would help us to accurately find the time of occurrence of disturbances. The difference of Energy values which form the feature vector to PNN is obtained and classification is done.

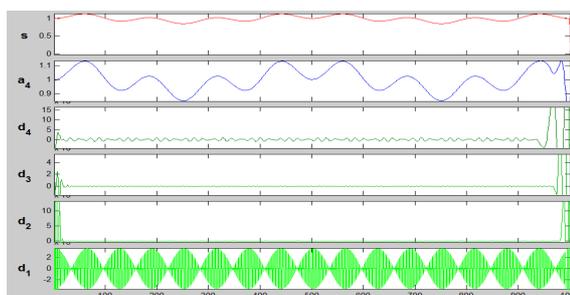
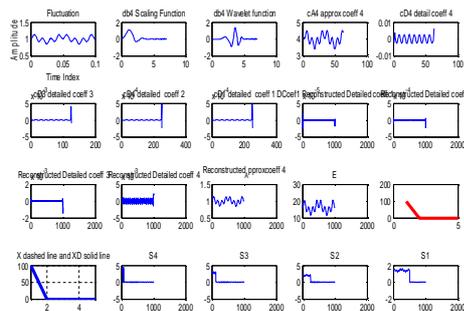


Fig.10 Fluctuation analysis using Matlab and Wavelet tool box

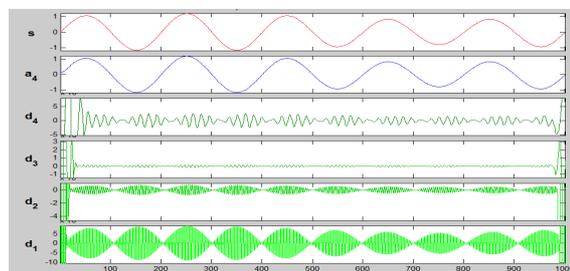
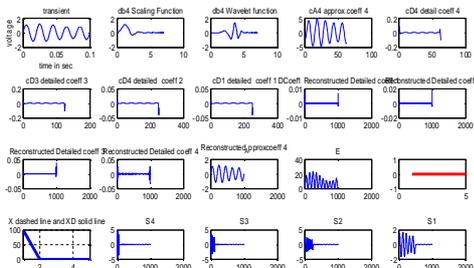


Fig.11 Flicker analysis using Matlab and Wavelet tool box

The energy difference values computed for pattern recognition are used to construct the training and testing data to model the PNN program with the help of Matlab R2008a. Here the size of the input vector is $12 * 7 * 24$ which comes to 2016, where the number of coefficients for each 7 types of distortions is 12. 24

sets of data are given for training in each class. The targets of this expert system are given as 1 2 3 4 5 6 7 which represents sag, swell, flicker, fluctuation, harmonics, notch and transients respectively. The Classification using PNN is done for the seven signals mentioned above the results of two of them namely Fluctuation and Flicker disturbances are shown.

```

Command Window
File Edit Debug Desktop Window Help
New to MATLAB? Watch this Video, see Demos, or read Getting Started.
testing network
1 2 3 4 5 6 7
1 for group or 2 for individual signal
individual signal or group of signals2
WHICH NOISE DO YOU WANT AS INPUT
1-Sag
2-Swell
3-flicker
4-fluctuation
5-harmonic
6-notch
7-Transient
Enter input noise to load demo data3
(3,1) 1
0
0
-0.0005
-0.0105
-1.2376
-15.7074
-1.9382
-0.0914
-0.0182
-0.0327
0.1703
-0.0113
Noise is identified to be of class
3
Hence Noise Input is flicker

```

Fig.12 Classification of Noise as Flicker using PNN

```

Command Window
File Edit Debug Desktop Window Help
New to MATLAB? Watch this Video, see Demos, or read Getting Started.
testing network
1 2 3 4 5 6 7
1 for group or 2 for individual signal
individual signal or group of signals2
WHICH NOISE DO YOU WANT AS INPUT
1-Sag
2-Swell
3-flicker
4-fluctuation
5-harmonic
6-notch
7-Transient
Enter input noise to load demo data4
(4,1) 1
0
0
0.0094
1.1507
18.6541
2.3763
0.0404
0.0211
0.0194
0.2014
0.0067
Noise is identified to be of class
4
Hence Noise Input is fluctuation

```

Fig.13 Classification of Noise as Fluctuation using PNN

CONCLUSION

The detection and classification of power quality is of utmost importance these days. Wavelet transforms are used for disturbance detection and for classification purpose PNN is used. Since energy difference of the coefficients pattern remain same in noisy environment, it is used as feature vector for the PNN network, this is done by computing energy values of different power quality disturbances and comparing with that of the pure signal. This PNN model used identifies the 7 different types of disturbances present in signals including transient disturbance, harmonic distortion and fluctuation with high accuracy. Consequently the proposed approach has the potential for diagnosis of power quality disturbances in the area of power quality monitoring.

REFERENCES

[1] Dr. M.sushama, Dr G.tulasi ram das, Dr. A. Jaya laxmi"Detection, Classification Localization, And Controlling of Voltage Swells Using Iupqc through Wavelet

Based Neural Networks" Journal of Theoretical and Applied Information Technology 2005 - 2009 JATIT.

- [2] Liang Wah Cheok Tapan Kumar Saha Zhao Yang Dong. "Power quality investigation with wavelet techniques." School of Information Technology and Electrical Engineering ,The University of Queensland, St Lucia, QLD 4072, Australia
- A. Saxena*1, S.N. Singh and K.S. Verma "Wavelet based denoising of power quality events for characterization" International Journal of Engineering, Science and Technology Vol. 3, No. 3, 2011, pp. 119-132
- [3] Raj Naidoo, Member, IEEE, and Pragasen Pillay, Fellow, IEEE "A New Method of Voltage Sag and Swell Detection" 1056 IEEE TRANSACTIONS on Power Delivery, Vol. 22, No. 2, April 2007
- [4] Hilton de O. Mota1 and Flávio H. Vasconcelos "Data processing system for denoising of signals in real-time using the wavelet transform" Electrical Engineering Post-graduate Program – PPGEE – UFMG,
- [5] Perumal Chandrasekhar and Vijayarajan Kamaraj "Detection and Classification of Power Quality Disturbance waveform Using MRA Based Modified Wavelet Transform And Neural Networks" Journal of ELECTRICAL ENGINEERING, VOL. 61, NO. 4, 2010, 235–240
- [6] Devendra Mittal1, Om Prakash Mahela2, Rohit Jain "Classification of Power Quality Disturbances in Electric Power System." IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE) ISSN: 2278-1676 Volume 3, Issue 5 (Nov. - Dec. 2012),
- [7] P. Janik and T. Lobos "Automated Classification of Power Quality Disturbances using SVM and RBF Networks"Rodriguez, J. Aguado, J.J. Lopez, F. Martin, F. Munoz, E. Ruiz, J. Munoz and M. Medina "Wavelet and Artificial Neural Network Comparison Results in Classification of Power Quality Disturbances" Department de Ingeniería Electrical Universidad de Málaga
- [8] N.Karthik, Dr.Shaik Abdul Gafoor, Dr.M.Surya Kalavathi "Classification of Power quality problems by wavelet Fuzzy expert system." International Journal of Advances in Engineering Sciences Vol.1, Issue 3, July, 2011
- [9] S. Sujal, Jovitha Jerome "Power Signal Disturbance Classification Using Wavelet Based Neural Network" Serbian Journal Of Electrical Engineering Vol. 4, No. 1, June 2007, 71-83
- [10] Subhamita Roy and Sudipta Nath "Classification of Power Quality Disturbances using Features of Signals." International Journal of Scientific and Research Publications, Volume 2, Issue 11, November 2012 ISSN 2250-3153
- [11] Votive, a, 2Jovitha Jerome and N. Malmurugan "A Novel Method of Voltage Sag and Swell Estimation for Power System Applications Signal and Harmonic Detection", American Journal of Engineering and Applied Sciences 6 (2): 233-240, 2013 ISSN: 1941-7020
- [12] Lütfü SARIBULUT1, Ahmet TEKE, Mohammad BARGHI LATRAN and Mehmet TÜMAY "Fundamentals and literature review of wavelet transform in power quality issues."Journal of Electrical and Electronics Engineering Research Vol. 5(1), pp. 1-8 May, 2013 DOI 10.5897/JEEER2013.0435 ISSN 2141 – 2367 ©2013 Academic Journals
- [13] Robi Polikar "The Wavelet Tutorial" -Part 1 "Fundamental Concepts and an Overview of Wavelet Theory".