CLASSIFICATION OF POWER QUALITY DISTURBANCE WITH NEURAL PATTERN RECOGNITION TECHNIQUE

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***Abstract: The** proposed work presents a novel approach using Discrete Wavelet Transform (DWT) and Neural Pattern Recognition (NPR) technique for the detection and classification of the Power Quality (PD) disturbances. Various PQ related events were simulated including single and combined events and the generated signals were treated with DWT for feature extraction. For classification purpose the signal parameters were trained with Neural Pattern Recognition (NPR) tool. Eleven types of PQ disturbances were considered for classification. The simulation results depicted that the combined process of DWT and NPR can effectively detect and classify different PQ disturbances effectively. Compared to the conventional methods available on the literature this method needs less computations and works faster.*

***Key Words**: Power Quality, Discrete Wavelet Transforms, Neural Pattern Recognition Technique, Confusion Matrix*

1. Introduction

Continuous monitoring of PQ is a necessary service for many industries and large commercial customers. Identifying and classifying the voltage and current disturbances in a distribution system is essential in monitoring and protection. Knowledge based approaches along with signal processing techniques makes it possible to detect and classify the PQ related events which will be further helpful in choosing the appropriate mitigation method. The power supply quality and related problems are the consequences with the usage of solid state switching devices in larger scale applications like computer and data processing equipment as well as industrial plant rectifiers and inverters. A PQ problem usually associated with the variation in the quality of electric service voltage or current, such as voltage dips, fluctuations, momentary interruptions, harmonic distortion and oscillatory transients which results in malfunctioning or failure of any sensitive electrical equipment. The critical aspect of PQ studies is the data analysis and the classification of PQ events. The important and initial step in improving the power quality of a power system is to know the sources and causes of the issues from the event that caused.

Various methodologies have been discussed in the literature to detect and classify the type of PQ disturbance occurred in a power system or a distribution system. A detailed study of signal processing techniques has been discussed and analyzed [1-3]. The use of Short Time Fourier Transform (STFT) for specific PQ disturbances have been analyzed and concluded it works well [4]. And further, the shortfalls of Discrete Fourier Transform (DFT) are given elaborately in [5]. It is found that the transforms like DFT and STFT are not suitable for the non-stationary waveform, whose frequency is varying with time. For the classification of such non-stationary issues, the Wavelet Transform (WT) has been introduced [6] and found to be working well. A neural network approach for the classification of power system disturbances is introduced [7] with a time-delay neural network and feed-forward neural network. Further, the classification of PQ issues with WT [8-10] has been implemented and compared with Fourier Transform (FT) and [11] concluded that WT works well.

In recent works the signal processing techniques like the WT and S Transforms (ST) have been appended with the soft computing techniques like Neural Network (NN), Artificial Neural Network

(ANN),SupportVectorMachines(SVM) to improve the effectiveness of classification procedure[12]-[18]. And recent techniques have been presented [19].

An optimal feature selection technique with a probabilistic neural network is carried over [20]. Later the soft computing techniques were combined with the signal processing transforms for identifying and classifying the disturbances in a better way [21]-[23].

A novel dual neural-network-based methodology to detect and classify single and combined PQ disturbances has been proposed [24] which compares the previous approaches and justifies that neural network training is found to be a better choice against the conventional methods. The neural network plays a vital role in the classification procedure and there are many types of neural network tools available and the choice can be based on the application of the user. A Radial Basis Function Neural Network along with the wavelet transform has had been utilized for the detection and classification process [26].

Summarizing all the above works done, on identifying and categorizing the PQ disturbances in a power system can be effectively done with the signal processing tools and any one of the soft computing techniques. The review of various methods followed clearly reveals that performance with WT and NN gives good results so far. In the proposed work the parameters of the PQ disturbance signal are treated with DWT and further trained with NPR and it found to be effective and the results are tabulated.

The remaining section of this paper discusses about the generation of various PQD events, feature extraction from the raw signal with DWT, parameter calculations and finally classification with NPR technique and Energy Difference (ED) plots. The proposed techniques found to give effective classification accuracy.

2. Wavelet Transform

Wavelet Transform and multi-resolution analysis provides a short window for high-frequency components and a long window for low-frequency components and hence, provides an excellent time-frequency resolution. This allows WT for signal analysis with localized disturbances components and also for classifying low and high-frequency power

a detailed comparative study of the merits and demerits of many of the
All these techniques involve a training process with the database of the known disturbances and utilized for further testing and classifying. A new approach with the fuzzy expert system with Kalman filter [21], WT with SVM [22] have been considered and found to be fruitful.
quality problems. Using the properties of WT and the feature of the decomposed waveforms along with the neural pattern recognition technique, it is possible to extract important information from a disturbance signal and determine the type of disturbance. The energy of the distorted signal is partitioned at different resolution levels and in different ways depending on the event available.

Wavelet Transform analysis is an effective signal-processing technique that can give better results on the analysis of no stationary signals. Waves are oscillating functions of time or space or both. Wavelets are small waves with oscillating wave-like characteristics whose energy is concentrated in time over relatively small intervals. These wavelets possess zero mean and fast decaying characteristics at both sides of the peak value. Each wavelet is associated with a scaling function. The scaling function provides the scaling characteristic to the wavelet and the choice of the scaling function depends on the wavelet chosen.

The DWT can be implemented using a multistage filter bank with the wavelet function as the low-pass (LP) filter and its duals the high-pass (HP) filter, as shown in Fig.1 which represents a three level decomposition tree. Down sampling by two at the output of the LP and HP filters scales the wavelet by two for the next stage. g(n) and h(n) are the outputs of the HP filters, respectively, and represent the detailed version of the high-frequency components of the signal and the approximation version of the low-frequency components. Most of the analysis purpose we make use of the detailed coefficients because, with the approximate coefficients it is found to be too difficult to estimate advanced features, other than the basic feature like mean, max etc. And, a number of orientations are needed for a single event with the approximate coefficients, which will be a time-consuming task. Whereas with the detailed coefficient we can group or classify the events at the initial stage itself.

The DWT is the discrete form of the WT and it does the one-dimensional decomposition of the given signal with respect to the specifications provided by the user. The specifications include the type of mother wavelet and a number of level of decomposition to be done for the input signal. After the decomposition, the DWT will result in approximate and detailed coefficients of the signal to be analyzed, as in fig.2. The decomposition was performed for various scales and translations which will be based on the choice of the mother wavelets.

There are many types of families of mother wavelets available in the wavelet toolset namely, Daubechies, Coiflets, Symlets, Discrete Meyer, Biorthogonal wavelets etc. In this work, the familiar Daubechies (Db) was used for decomposition. The wavelets should have the annotation with the number of coefficients like Db4, Db6, Sym2, Coif5 etc. wavelets.

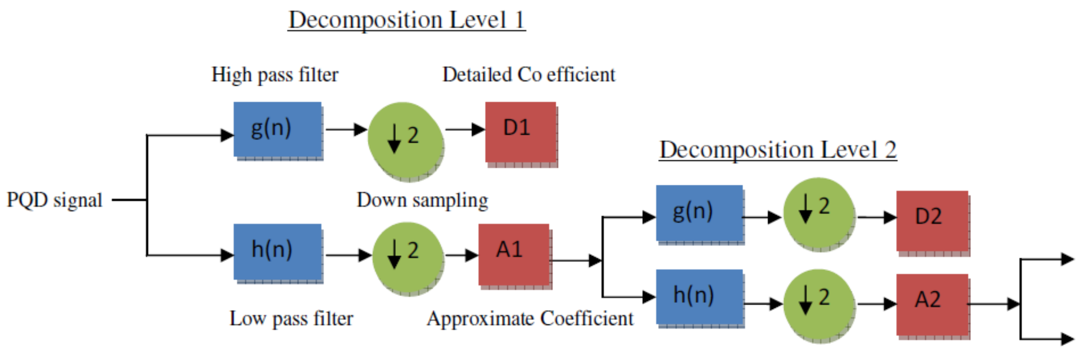


Fig.1 The wavelet decomposition tree

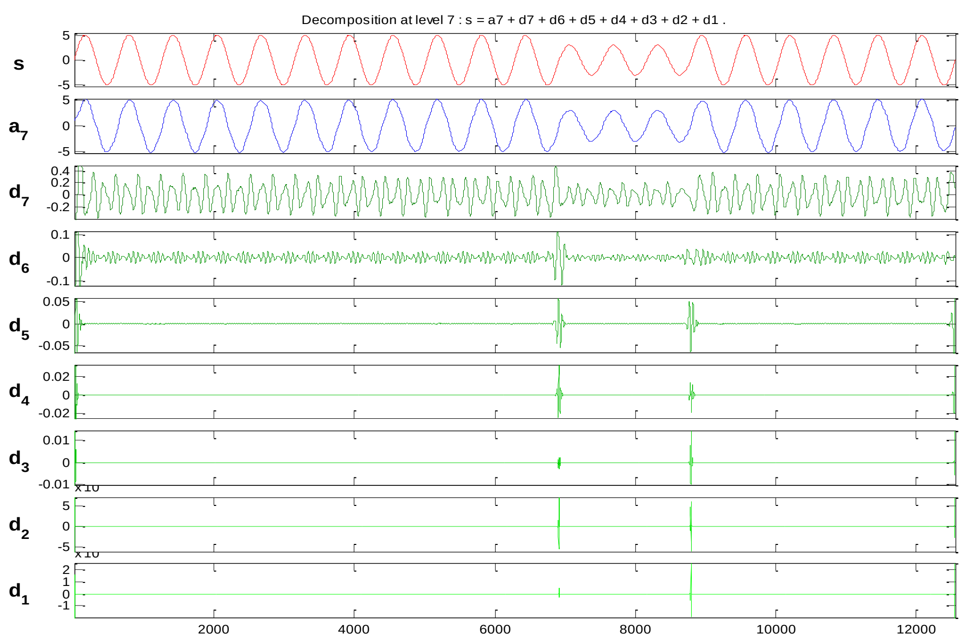
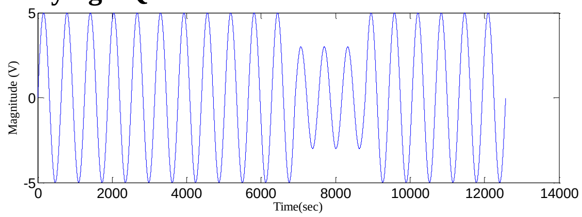


Fig.2 Wavelet decomposition for sag up to level 7

3. Classifying PQ events with NPR



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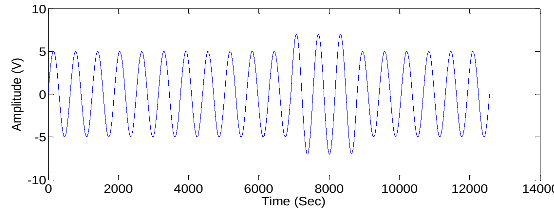

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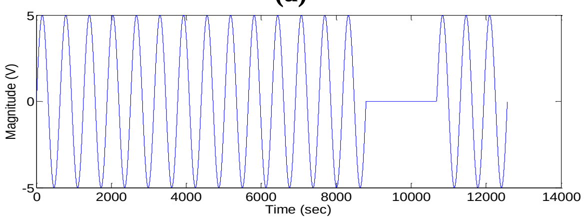

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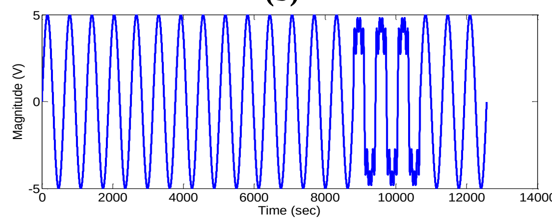

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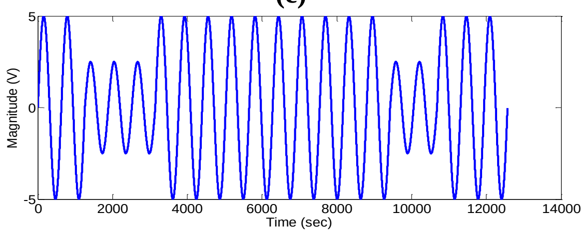

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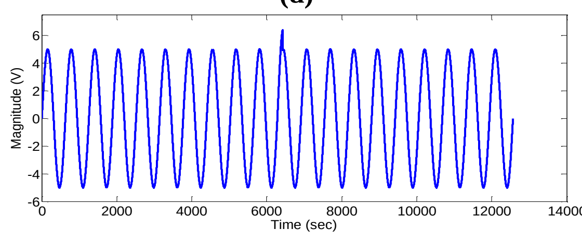

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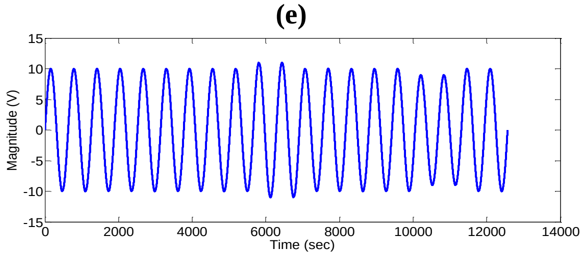

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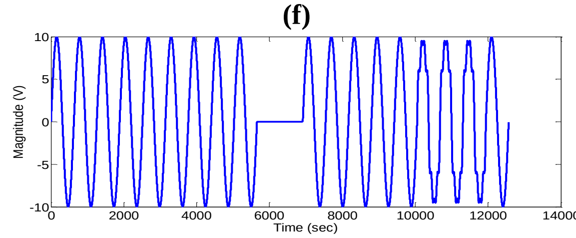

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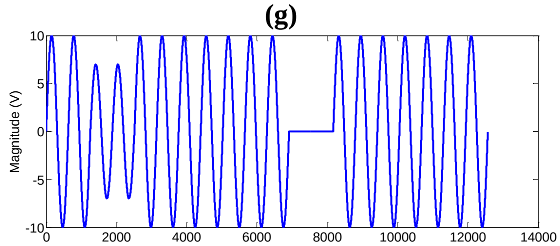
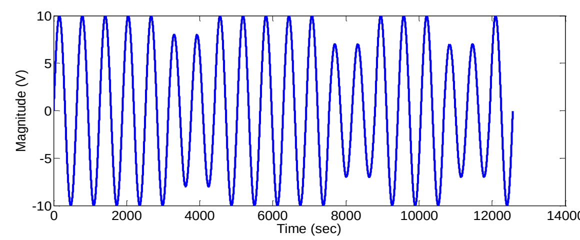


(i)



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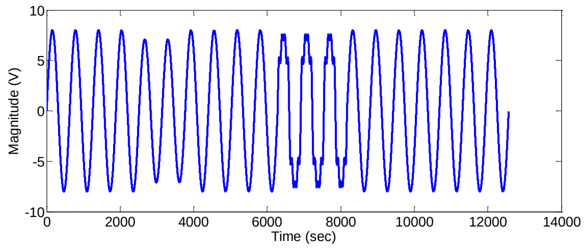


(k)

Fig.3(a)Sag(b)Swell(c) Momentary Interruption(d) Harmonics (e) Voltage fluctuation(f)Transients(g) Sag and swell(h)Momentary Interruption and harmonics (i)Sag and Momentary Interruption (j)Sag and Voltage fluctuation(k)Sag and harmonics

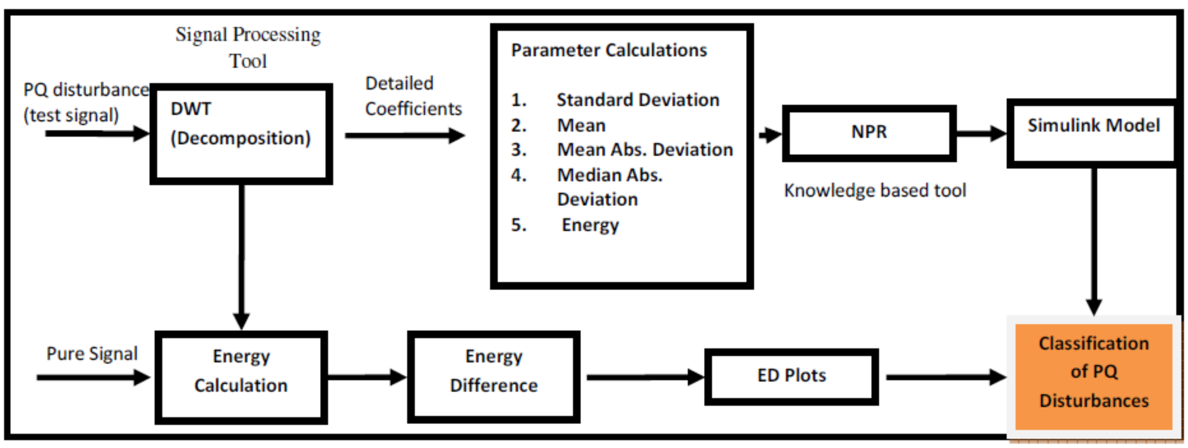


Fig 4. Block Diagram

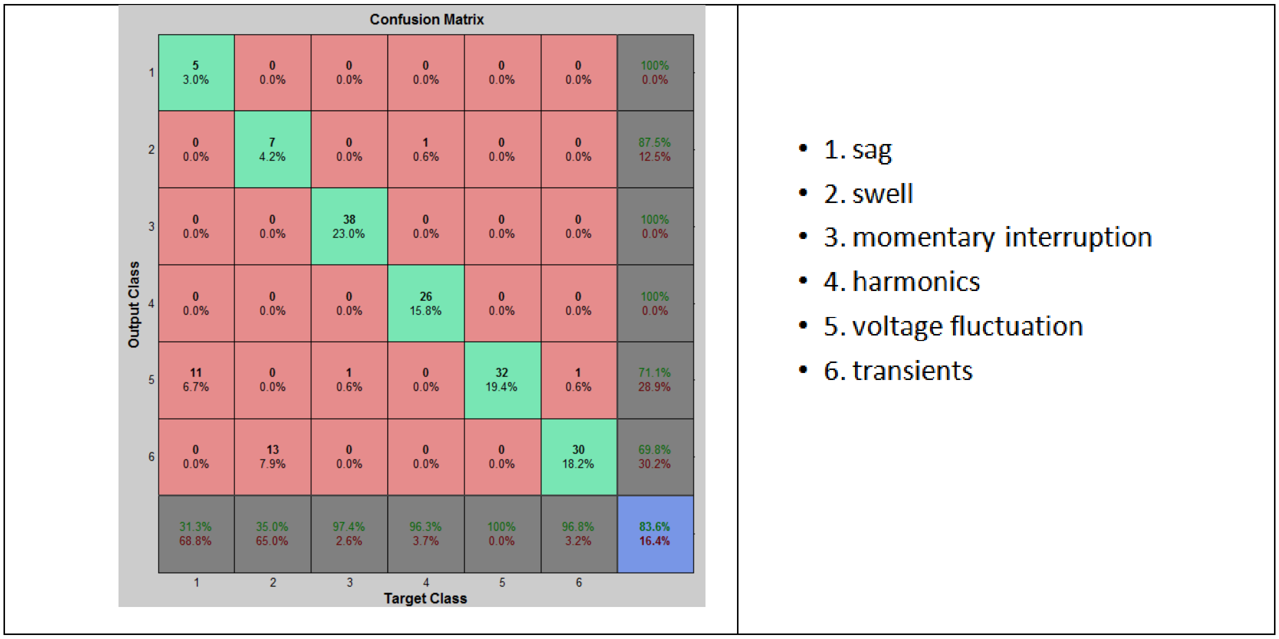


Fig.5 Confuion matrix for individual disturbance signals

Fig.6 Confusion matrix for 5 mixed disturbance cases

Each of these disturbances was generated at various levels and at various time instants. Every signal is passed through DWT filters.Db4 mother wavelet was used and decomposition consists of 7 levels. After the decomposition, the detailed coefficient is considered for further processing. For each of the disturbance case, parameters like standard deviation, mean, mean absolute deviation, median absolute deviation, and energy are calculated. These calculated parameters values are used as input data for training the neural network. The neural network is trained with the NPR toolset. The NPR trained data is used to frame a simulation model. This model will be used to test any kind of unknown disturbance and it classifies the power quality disturbance based on the training process. The training process gives us two outputs, the percentage values on a confusion matrix and ROC plots for validating the process of training.

4. NPR technique

The NPR technique results in a confusion matrix after it trains the set of input data. The confusion matrix is a matrix plot, between the target and output data. On the confusion matrix plot, the rows correspond to the predicted class (Output Class), and the columns show the true class (Target Class). The diagonal cells showing, how many (and what percentage) of the samples are trained by the network correctly and estimates the classes of observations. That is, it shows what percentage of the true and predicted classes match. The off-diagonal cells show where the classifier has made mistakes. The column on the far right of the plot shows the accuracy for each predicted class, while the row at the bottom of the plot shows the accuracy for each true class. The cell in the bottom right of the plot shows the overall accuracy.

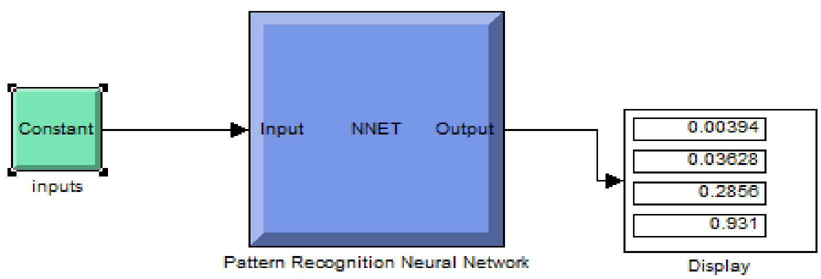


Fig.7 Simulation model of the pattern recognition network

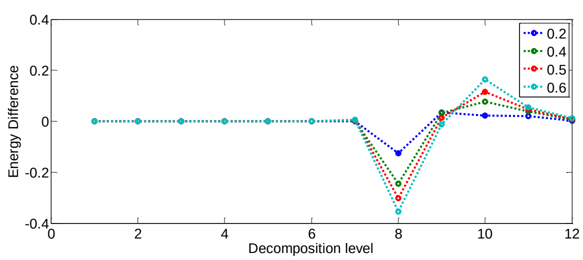
Table1 Classification of disturbed signal with the NPR trained network

S.no.	sag	swell	momentary interruption	harmonics	voltage fluctuation	transient	sag & swell	harmonics & interruption	Sagand interruption	sag& fluctuation	sag& harmonics
s1	**0.87**	0.02	0.02	0.00	0.03	0.07	0.00	0.00	0.00	0.00	0.00
s2	**0.87**	0.01	0.07	0.00	0.07	0.04	0.00	0.00	0.00	0.00	0.00
s3	0.00	**0.95**	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
s4	0.01	**0.64**	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00
s5	0.63	0.00	**0.90**	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00
s6	0.01	0.00	**0.99**	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
s7	0.00	0.00	0.01	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00
s8	0.00	0.00	0.00	**0.97**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
s9	0.00	0.00	0.01	**0.99**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
s10	0.00	0.05	0.00	0.00	**0.71**	0.00	0.00	0.00	0.00	0.00	0.00
s11	0.09	0.01	0.24	0.00	**0.74**	**0.00**	0.00	0.00	0.00	0.00	0.00
s12	0.34	0.32	0.11	0.00	0.00	**0.70**	0.00	0.00	0.00	0.00	0.00
s13	0.00	0.43	0.31	0.00	0.00	**0.82**	0.00	0.00	0.00	0.00	0.00

s14	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.01	0.00	0.01	0.00
s15	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.01	0.00	0.05	0.00
s16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00
s17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00
s18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.93**	0.06	0.00
s19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.78**	0.00	0.40
s20	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.03	**0.92**	0.00
s21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	**0.93**	0.00
s22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	**0.97**
s23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	**0.97**

The disturbances were trained in two sets like 6 cases of individual disturbances and 5 cases of mixed disturbances as shown in fig5 and fig.6. In this fig.5, the first six diagonal cells show the number and percentage of correct classifications by the trained network. For example, 5 inputs were correctly classified as sag. This corresponds to 3% of all 138 inputs. Similarly, 7 cases were correctly classified as well. This corresponds to 4.2% of all inputs. One of the swell inputs was incorrectly classified as harmonics and this corresponds to 0.6% of all 138 inputs in the data. Similarly, 11 of the voltage fluctuation input samples were incorrectly classified as sag and this corresponds to 6.7% of all data. Out of 43 transients' predictions, 69.8% were correct and 30.2 % were wrong. Overall, 83.6% of the predictions were correct and 16.4% were wrong classifications.

The trained network for various kinds of power quality issues has been framed into a Simulink model using MATLAB. This model can be used to test any kind of disturbance now. For the signal to be tested the parameters were calculated and these values were fed as input to the network model and one particular column of the output set becomes high and hence indicating the classification of the



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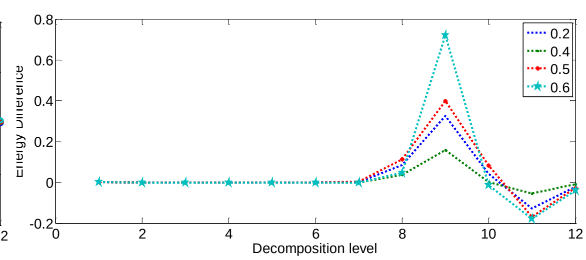

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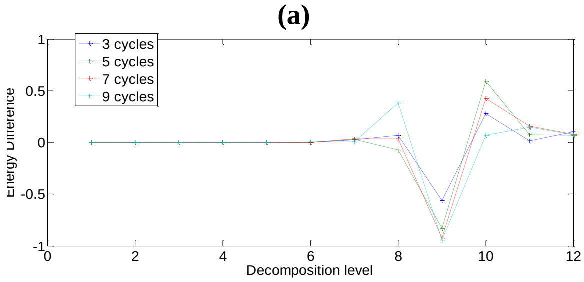

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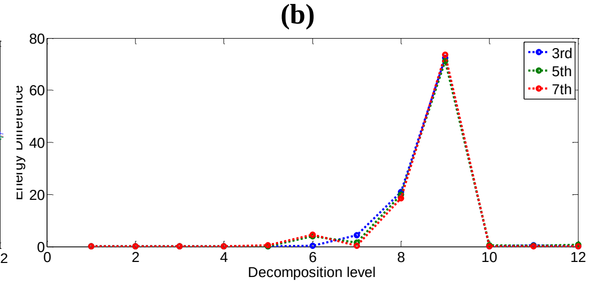

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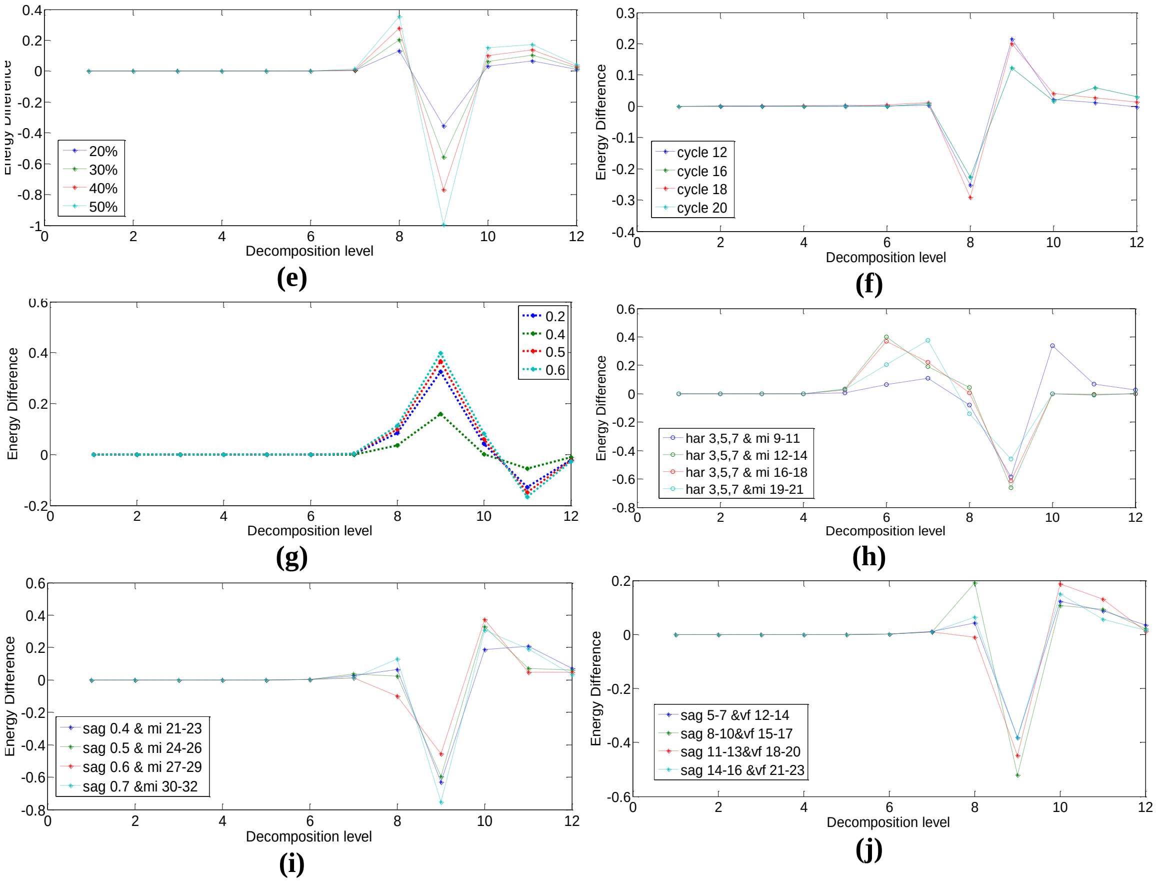

Fig.7(a)Sag (b) Swell (c) Momentary Interruption (d) Harmonics (e) Voltage Fluctuation (f) Transients (g) Sag and swell (h) Harmonics and Interruption (i) Sag and Interuption (j) Sag and voltage fluctuation

disturbance. This fig.7 shows the network model which has been trained for identifying the pattern of the given disturbance signal and classify it based on the trained data. For instance, the given disturbance was a sag and it has been classified correctly as [0.003 0.03 0.2 0.93] instead of [0 0 0 1] which is almost closer to the correct classification.

Using the above network model a set of 23 signals has been tested and classified as in table1. The network model is trained to classify any of the 11 power quality disturbances as listed the table below. The output set will display 11 values out of which only one will be highest comparatively. For example, if the outputs with the test signal s1 the first output value is 0.87 while the remaining values are nearly zero and that shows the presence of sag.

5. Classifying PQ events with Energy Difference Pattern

The plot drawn for energy difference between a pure sine wave and a disturbed signal was also used to classify the type of disturbance. In this work different kinds of disturbances like sag, swell momentary interruption, voltage fluctuation etc were generated. The disturbance signal is passed through db4 wavelet and after decomposition, the energy of the coefficients is calculated, which was compared with the energy of the pure sinusoidal waveform. The energy difference (ED) was plotted against the level of decomposition for every disturbance fig.8. The magnitude of energy difference is the measure to classify the type of disturbance.

Table 2. Classification of power quality issues with Energy Difference

SIGNAL/ DECOMPOSITION LEVEL	D1	D2	D3	D4	D5	D6	D 7	D8	D9	D10	D1 1	D1 2	Type of disturbance
T1	0	0	0	0	0	0	0	-0.3		0.18	0	0	Sag
T2	0	0	0	0	0	0	0		0.4	-0.15	0	0	Swell
T3	0	0	0	0	0	0	0	0.4	-0.9	0.6	0	0	Momentary Interruption
T4	0	0	0	0	0	0	0	20	70		0	0	Harmonics
T5	0	0	0	0	0	0	0	0.4	-1	0.1	0	0	Voltage Fluctuation
T6	0	0	0	0	0	0	0	-0.3	0.2	0	0	0	Transient
T7	0	0	0	0	0	0	0	0.3	-0.3	0	0	0	sag & swell
T8	0	0	0	0	0	0.4	0	-0.6	0	0.4	0	0	Harmonics & Interruption
T9	0	0	0	0	0	0	0	0.2	-0.8	0.4	0	0	sag& Interruption
T10	0	0	0	0	0	0	0	0.2	-0.55	0.2	0	0	Sag & voltage fluctuation

The classification of power quality disturbance with the ED plot has been tabulated in table2. From the energy difference pattern of sag negative deviation at the 8th level of decomposition and positive deviation at 10th level and 8th level shows the maximum deviation. Similarly, the deviation is maximum at 9th level for harmonics and so on. From the above patterns, we can conclude the nature of power quality issue and the classification can be done with greater accuracy with a simple procedure.

6. Conclusion

This paper has presented a new approach for the PQ disturbance classification. The approach uses the NPR toolset of the neural network. The data were decomposed with DWT, and the details of the disturbed signal are confined and narrowed down to the point of disturbance. Because of this, the training process is becoming sharper. Eleven types of PQD issues were considered and it can be further extended for any number of signals. And the classification is also done based on the ED possessed by the respective disturbance signal when compared with a undisturbed signal The procedure can be considered for real-time disturbances identification and classification too. Results obtained conclude that the classification using NPR technique is found to be more accurate when compared to that with the ED plots.

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