Detection and Classification of Power Quality Disturbances Using Wavelet Transform And Artificial Neural Network

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Abstract- A Wavelet transform and artificial neural network based method is projected in this paper for power quality disturbance detection and classification. The motivational research given by the author is to decompose a disturbed signal into another signal which represents undisturbed and a detailed variant of a real signal. And a wavelet transform classifier is adopted to extract feature of diverse distorted waveform including those also comprises harmonics. A spinster attempt is made to apply a new tool called Neuro solution for artificial neural network in the field of power quality disturbance classification.

Keywords - Power Quality Disturbances, Feature Extraction, Discrete Wavelet Transform, Back propagation algorithm, Feed forward Neural Networks.

I. INTRODUCTION

The increasing demand of electronic appliances which are introduced as nonlinear load have made the power quality problems an analytical issue more than ever. There are many types of power quality problems like voltage sag, swell, harmonics, interruptions, flicker, and transients. Expected power delivery is to be a rated sinusoidal without any distortion of voltage and current to the customer. In order to improve power quality problems an accurate measurement and effective detection in time is very necessary and challenging issues for us.

Customary power quality monitoring has been carried out through visual inspection of the utilities which is a difficult and time consuming process. The automatic classification of power quality disturbances involves three stages, namely, data generation, feature extraction, and classification. The Input stage is a preprocessing stage where power quality disturbances can be generated. This approach is primarily based on transformation and reconstruction of the original signal. In next stage one of the signal processing technique can be applied to feature extraction. In the last stage artificial neural network technique is used for decision making. Previously various techniques have been used for monitoring and recognition of power quality disturbance. According to IEEE stander-1159, the short duration voltage variation are changes of the RMS value of the voltage over short time intervals.

The most commonly used feature extraction methods are Wavelet transform, multi resolution analysis of the energy of the band, and detailed and overview coefficients, also can be used as classification Characteristics. Fourier transform, S-transform were also used as for disturbance feature extraction. The main reason for Wavelet transform success lies in the fact that the wavelet transform provides temporal information, which is not exactly available in the Fourier transform. It also handles high frequency contents in the input signal better. Apart from power quality events, it is also very useful in measurement of power flow. Fourier transform as a detection tool also presented in the literature [2], [5] - [6]. But Fourier transform technique has its limitation. Like it cannot resolve the problem associated with non-stationary signals.

Some works [7] have been introduced in an extent for the use of artificial neural network as a classification tool. Even this technique suffers from its own limited capabilities to classify large no of power quality events. It is capable only on classifying the phenomenon which varies in voltage magnitude.

In this paper, MATLAB is used to simulate six power quality disturbance signals, including voltage sag, swell, interruption, harmonics, and also flicker in order to acquire the corresponding signal.

II. WAVELET BASED CLASSIFICATION

With the help of the wavelet transform the simulation of various numbers of power quality events and corresponding waveform is obtained. The following signals with short term disturbance have been considered for analysis:

- Sinusoidal signal
- Sinusoidal signals with intermediate sag
- Sinusoidal signal with intermediate swell
- Sinusoidal signal with intermediate interruption
- Sinusoidal signal with intermediate flicker
- Sinusoidal signal with intermediate harmonics

All the signals were generated with the help of mat lab coding. Rodney says [16] that the events will follow certain characteristics and model.

Table no. I numerical model for simulation of disturbed signal

	PQD	Equations models	Parameters
1	Pure sine	$f(t) = A.Sin(\omega t)$	A=1. 0, f=50Hz
2	Sag	F (t) =A (1-α (u (t-t_1) -U (t-t_2)))Sin(ωt)	0.1< α<0.9
3	Swell	f(t)=A(1+α(u(t-t_1) -U (t-t_2)))Sin(ωt)	0.1< α<0.8
4	Harmonics	F (t) =A. Sin (ωt)+a_3Sin (3 ωt)+a_5Sin (5 ωt)	0.1<a_3<0.9 0.1<a_5<0.9
5	Interruption	F (t) =A (1-α (u (t-t_1) -U (t-t_2)))Sin(ωt)	0.9< α<0.1
6	Flicker	F(t)=A.Sin(ωt)(1+βSin(γ ωt))	0.1≤β≤0.2 0.1≤ γ≤0.2

The Pure sine wave is with magnitude 'A' and time Period't' in millisecond, and '**ω**' represents the phase angle shift. Voltage sag is a temporarily voltage drop in magnitude ranging from 0.9pu to 0.1pu. It has a typical duration from half a cycle to 1min. On the contrary, voltage swell has been a momentary voltage rise frequently caused by unbalance faults from the neighboring phase. The swell magnitude is positive ranges from 1.1pu to 1.8pu. Flicker is also a power quality disturbance in whichthe voltage magnitude swings over time. It is consistently caused by electric arc furnace and wind farm. Theflicker magnitude and flicker frequency are modulated with the power system sinusoidal waveform. A harmonic is a periodic power quality disturbance that is caused by nonlinear loads on the distribution system. Harmonic limits are defined in IEEE standard 519-1992 and it is measured as total harmonic distortion.

III. APPROACHES TO THE PROBLEM

A. The Wavelet Transformation Method

Wavelet transform can be executed in two different ways in signal processing as discrete wavelet transform and continuous wavelet transform. DWT is enough to decompose and reconstruct most power quality problems. It offers the high reduction in computation time.

Discrete wavelet transform is one of the form of the wavelet transform. It provides time domain signal into its identical wavelet domain. The given signal is decomposed through WT and any change in the precision of the signal is detected at wavelet resolution levels. After that the energy of the given signal is calculated and the relationship between this signal and one of the corresponding fundamental component is established. Effectively analyzing the distorted signals in time-frequency domain as it is defined in [11]. It can be describers mathematically as in [10] as follows:

$$f(x) = \sum_{i,j} a_{i,j}\ \Psi_{i,j}(x) \qquad (1)$$

Where i and j represent the integer values and stands for wavelet expansion functions $\Psi_{i,j}(x)$stands for the two coefficients of discrete wavelet transform (DWT) of$f(x)$.

Basically, the DWT evaluation has two stages. The first consists of the wavelet coefficients $h_d(n)$and $g_d(n)$ determination. These coefficients represent the given signal f (n)in the wavelet domain. From these coefficients, the second stage is achieved with the calculation of both the approximated and the detailed version of the original signal, these wavelet coefficients are called cA1 (n)and cD1 (n)as stated below.

$$cA_1(n) = \sum_k S(n).h_d(-k+2n) \qquad (2)$$

$$cD_1(n) = \sum_k S(n).g_d(-k+2n) \qquad (3)$$

Next, in the same way, the calculation of the approximated (cA_2 (n)) and the detailed (c$D_2(n)$)version associated with the level 2 is based on the level 1 wavelet coefficient of approximation (cA_1(n)).The process is continued, always adopting the "n-1" wavelet coefficient of approximation to evaluate the "n" approximated and detailed wavelet coefficients. If all the wavelet coefficients are noted, the discrete wavelet transform in the time domain can be determined. This is achieved by "building" the corresponding wavelet coefficients along the different resolution levels. By using the DWT and monitoring the particular features of the several decomposition levels of a signal, and some conclusions can be drawn. This information can be used to detect, to locate and to classify the disturbance. A Matlab program was developed and implemented in the wavelet toolbox.

1. Choice Of Mother Wavelet

Daubechies' wavelets with 4, 6, 8, and 10 filter coefficients work well in most disturbance detection cases. In power quality disturbance detection, usually, we can classify disturbances into two classes, fast and slow transients. In case ofthe fast transient, the waveforms are shown with sharp edges, abrupt and rapid changes, and a fairly short duration in time. In this case, Daub4 and Daub6, due to their concentration, are specifically good at detecting and restraining such disturbances. On the other hand, the slow transient case, the waveforms are marked with a slow change or smooth amplitude change. Daub4 and Daub6 may not be able to detect such disturbances, since the time-interval in integral evaluated at the pointand is very short. However, if Daub8 and Daub10 are used, the time interval integral is long enough and, thus, the slow changes can be sensed by these such wavelets.

B. Features Of The Signals

Total Harmonic Distortion (THD)

In terms of approximate and detail coefficients the Total Harmonic Distortion (THD) is given by (4)

$$\boldsymbol{THD} = \frac{\sqrt{\frac{1}{N_j}\sum_n [cD_j(n)]^2}}{\sqrt{\frac{1}{N_6}\sum_n [cA_6(n)]^2}} \quad (4)$$

Where $N_j$is the number of detail coefficients at scale j [10].

Energy of the Signal

The energy of the signal has been calculated using approximate and detail coefficient where j represents the level of decomposition as given by eq. (5) [12].

$$\int |f(t)| = \sum_k |Ci(k)|^2 + \sum_{j=1}^{I} \sum_k |Dj(k)|^2 \quad (5)$$

Where C_j(k)is the approximate coefficient at j^{th} level and D_j(k)is the detail coefficient at j^{th} level.

Entropy

In information theory, entropy is used to quantify the amount of information. The entropy reflects the information content of symbols independent of any particular probability model. Image analysis takes the concept of entropy in the sense of information theory (Shannon entropy), where entropy is used to quantify the minimum descriptive complexity of a random variable. Because the entropy can provide a good level of information to describe a given image, we can compute the entropy of the distribution level.

Functions verifying an additive-type property are well suited for efficient searching of binary-tree structures and the fundamental splitting property of the wavelet packet decomposition. Classical entropy-based criteria match these conditions and describe information-related properties for an accurate representation of a given signal. Entropy is a common concept in many fields, mainly in signal processing. The following example, lists different entropy criteria. Many others are available and can be easily integrated. In the following expressions, s is the signal and (si)i the coefficients of s with an orthonormal basis.

The entropy E must be an additive cost function such that E (0) = 0 and E(s) $=\sum_i ((s_{\,i})$

The (normalized) Shannon entropy

$$E_1(s_i) = s_i^2 \log(s_i^2) \text{ so}$$

$$E_1\,(s) = -\sum_i s_{\,i}^2 \log(s_i^2)$$

With the convention 0log (0) =0.

The “log energy” entropy

$$E1, 3\,(psi) = \log(s_i^2) \quad \text{so}$$

$$E3\,(s) = \sum_i lo\,((s_{\,i}^2)$$

With the convention log (0) =0.

Standard Deviation

There are two common textbook definition for standard deviations of data vector X.

1. $S = (\frac{1}{n-1}\sum_{i=1}^{n}(x_{\,i} - \bar{x})^2\,)^{1/2}$
2. $S = (\frac{1}{n}\sum_{i=1}^{n}(x_{\,i} - \bar{x})^2)^{1/2}$

Where

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_{\,i}$$

And n is the number of elements in a sample. The two forms of equation differ only in (n-1) versus n in the divisor. The result s of standard deviation is the square root of an unbiased estimator of the variance of the population from which X is drawn, as long as X consists of independent, identically distributed samples.

Extensive studies have evinced that the extracted Parameters display distinctive patterns under different types of events.

D. Artificial Neural Network

At present, artificial neural networks are emerging as the technology of choice for many applications, such as pattern recognition, prediction, system identification, and control. In

This paper the ANN is used for classification of the power quality disturbance.

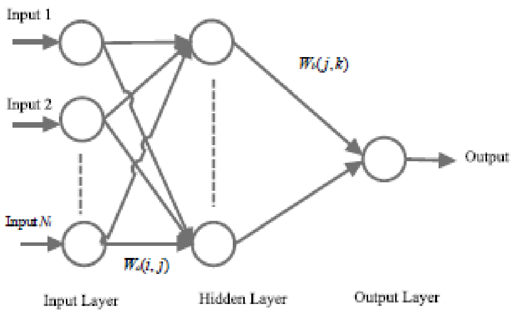

Figure 1 Multilayer Feed forward Neural

ANNs are characterized by their topology, of processing element (PEs) called neurons. In Multilayer Feedforward Neural Network (MFNN) the PEs is arranged in layers and only PEs are connected in adjacent layers. The MFNN structure used in this paper consists of three layers, namely input layer, a hidden layer, the output layer as shown in Figure1.

IV. RESULT AND ANALYSIS

The aim of extraction for each of power quality disturbances is to reconstruct the original distorted signal from its time domain in its energy form. The energy of any type of these events is the key factor for classification. Each one PQDs generated are decomposed into 6 levels and the results for selected

PQDs as shown in Figures

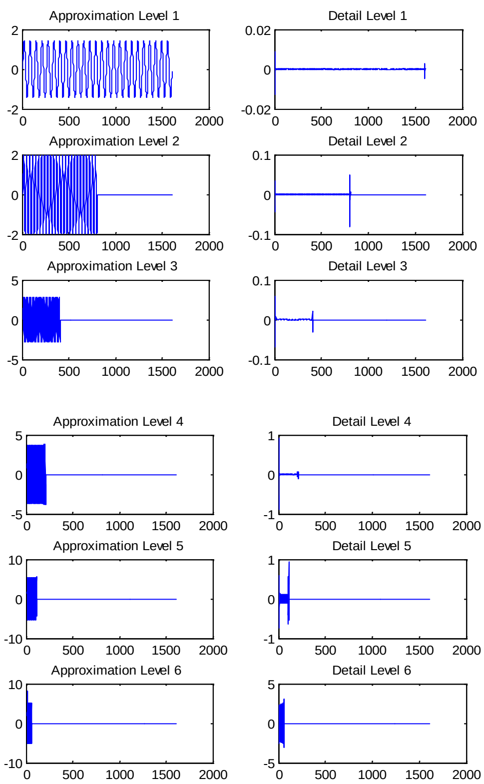

Fig:1 pure sine wave of voltage signal and feature extraction based on DWT.

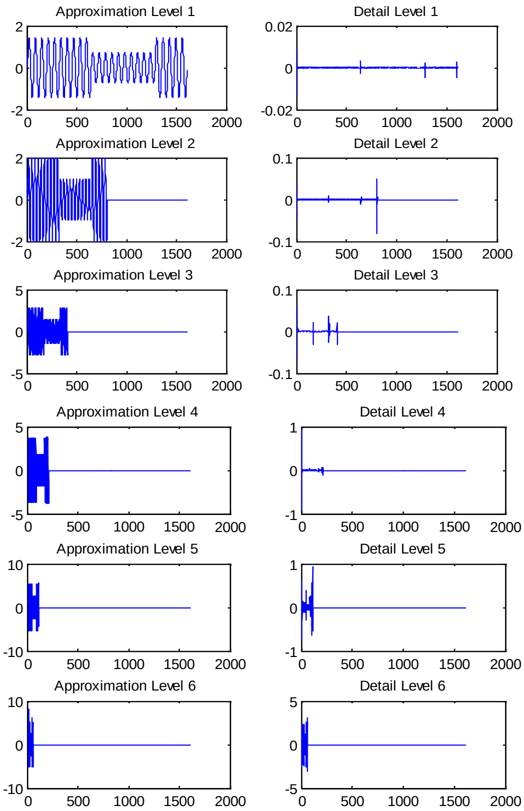

Fig: 2 Voltage sag signal and feature extraction based on DWT

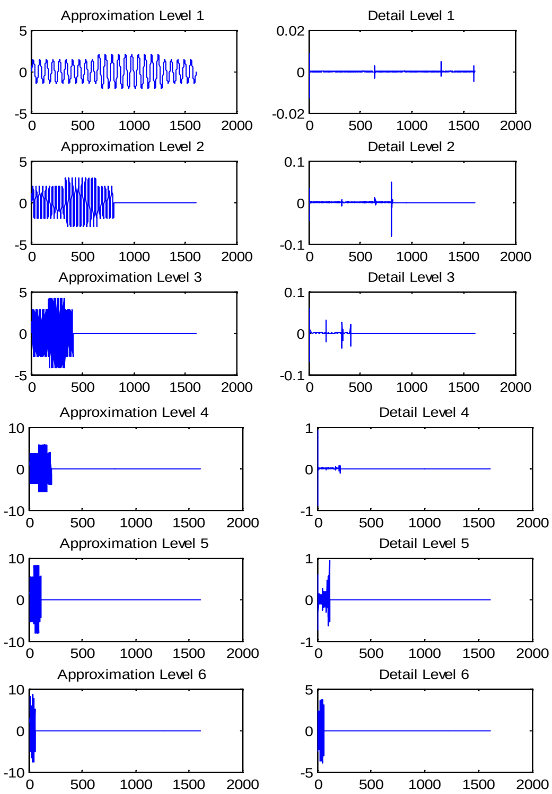

Fig: 3 Voltage swell signal and feature extraction based on DWT

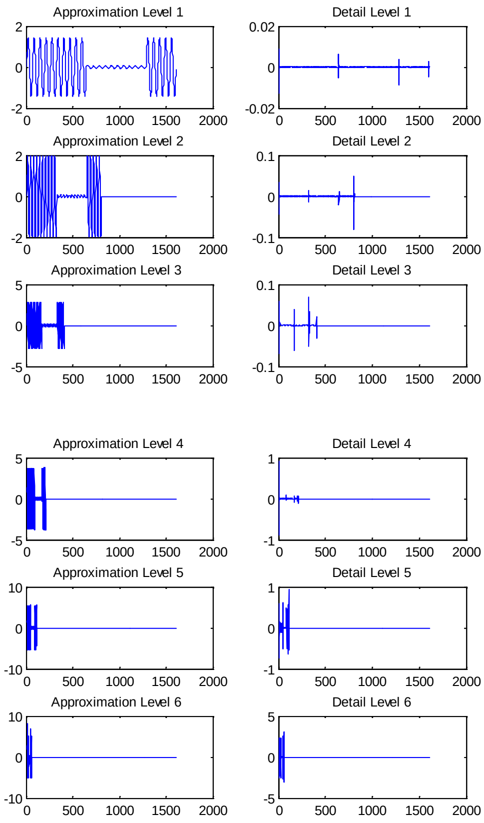

Fig: 4 interruption signal and feature extraction based on DWT

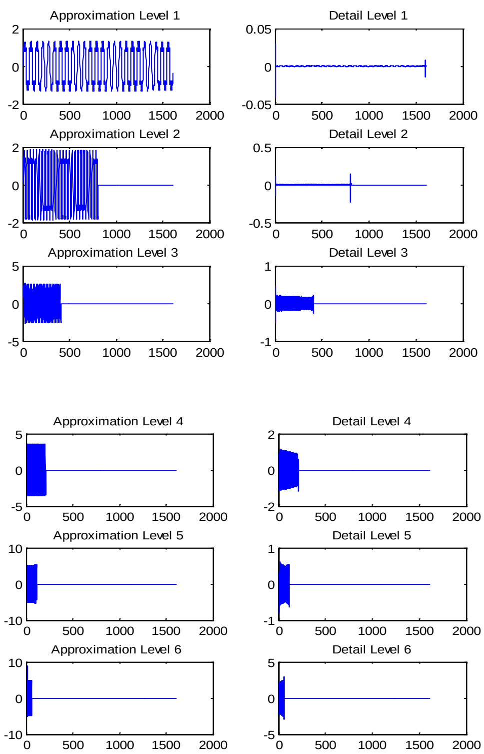

Fig: 5harmonic distortion in signal and feature extraction based on DWT

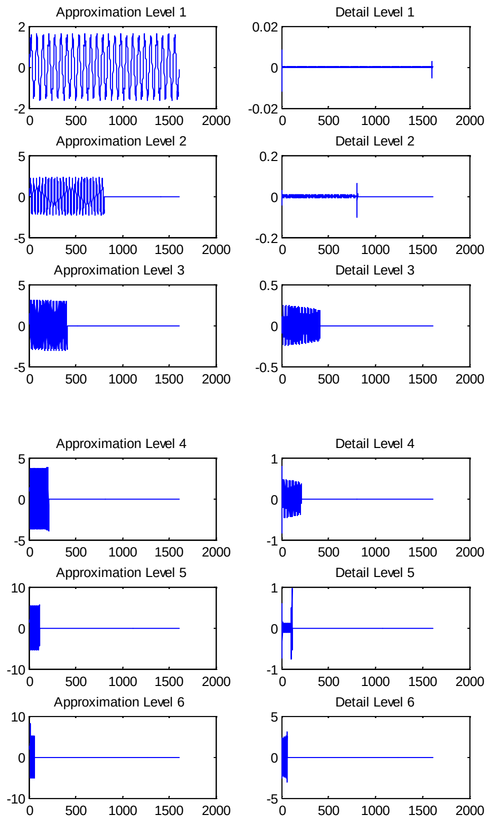

Fig: 6 flicker signal and feature extraction based on DWT

In order to prove the accuracy and the efficiency of the classifier, various power quality disturbance signals were generated by their modeled equations. Feature extractions have been done using discrete wavelet transform DWT as discussed in III Approaches to the problem. Thereafter, each of these disturbances has been checked by 6 multi-level of DWT decompensation. 6 types of power quality disturbances were studied by taking into account their characteristics: magnitude and frequency according to IEEE standard requirements [18]. The signals are then used for training and classification by ANN.One hidden layer from 20 neurons were used to examine the best performance training. Table II shows the accuracy of one hidden layer with the success percentage of each disturbance.

Table II : Classification accuracy of ANN with one hidden layer

Neural	PQDs	Accuracy Rate (%)
C1	Voltage sag	99
C2	Voltage swell	100
C3	Interruption	83
C4	Harmonics	100
C5	Flicker	100
C6	Normal	100

V. CONCLUSION

Detection and identification of power quality disturbances methods were generated successfully. Based on discrete wavelet transform DWT it has been ensured that wavelet transform can overcome Fourier transform limits with non-stationary disturbances which are mentioned in this paper. Thereafter, Features of these disturbances were extracted to 6 levels and energy of each level was calculated and used for building the data needed for the classifier. Training of the ANN was implemented and database of 152 signals was randomly generated with different varying. The results were investigated, trained and tested to evaluate the classification system technique. As a result, the accuracy of the power quality disturbance classification was more than 99% of all the cases which indicate the performance efficiency of an ANN classifier for power quality disturbances.

REFRENCES

[1]. Thapar A, Saha TK, Dong ZY. Investigation of power quality categorization and simulating its impact on sensitive electronic equipment. IEEE Power Energy Soc GenMeet2004;1:528–33.

[2]. Surya Santoso, Edward J. Powers, and W. Mack Grady, “Electric Power Quality Disturbance Detection Using Wavelet Transform Analysis”.

[3]. Flore RA. State of the art in the classification of power quality events, an overview. In: 10th international conference on harmonics and quality of power, vol. 1; 2002.p.17–20.

[4]. J. S. Huang, M. Negnevitsky and D. T. Nguyen, “Wavelet Transform Based Harmonic Analysis”.

[5]. Resende, J.W., Chaves, M.L.R. And Penna, C., “Identification of power quality disturbances using the MATLAB wavelet transforms toolbox”.

[6]. Ricardo A. Lima, Claudio A. Reineri and Fernando H. Magnago “Hybrid Power Quality Harmonic Analysis”.

[7]. Atish K. Ghosh and David L. Lubkeman, “The classification of power system disturbance waveforms using a neural network approach”, in IEEE Transactions on Power Delivery, Vol. 10, No. 1, January 1995.

[8]. Biswal B, Dash PK, Mishra S. A hybrid ant colony optimization technique for power, signal pattern classification. Expert Syst Appl 2011;38:6368–75.

[9]. Kwan Kian Hoong, So Ping Lam, Chu Yun Chung. An output regulation based unified power quality conditioner with Kalman filters. IEEE Trans IND Electron 2012;59 (November(11)):4248–62.

[10]. M. Uyar, S. Yildirim and M. T. Gencoglu, "An effective wavelet based feature extraction method for classification of power quality disturbance signals," Electr. Power Syst. Res., vol. 78, pp. 1747-1755,2008.

[11]. I. Daubechies, Ten Lectures on Wavelets. SIAM, 1992..

[12]. Darrow K, Hedman B, Bourgeois T, Rosenblum D. The role of distributed generation in power quality and reliability. Final Report, Prepared for: New York State Energy Research and Development Authority; 2005.

[13]. Kezunovic Mladen, Liao Yuan. A novel software implementation concept for power quality study. IEEE Trans Power Deliv 2002;17 (April (2)): 544–9.

[14]. IEEE recommended practice for monitoring electric power quality. IEEE Standards Board, IEEE Std. 1159-1995, New York: IEEE, Inc.; June 1995.

[15]. IEEE Standards Association, "1159-2009. IEEE Recommended Practice for Monitoring Electric Power Quality Industrial and Commercial Applications," 2009.

[16]. Rodney H G. Tan, Ramachandaramurthy V K, “Numerical model framework of power quality events”, European journal of scientific research, ISSN 1450-216, 43 (2010), no. 1, 30-47Proceedings of 2011 International Conference on Signal Processing, Communication, Computing and Networking Technologies (ICSCCN 2011)978-1-.

[17]. Bollen MHJ, Gu IYH. Signal processing of power quality disturbances. New York, USA: IEEE Press; 2006.

[18]. Saxena D, Verma KS, Singh SN. Power quality event classification: an overview and key issues. Int J Eng Sci Technol 2010;2(3):186–99.