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Power Quality Disturbences Detection and Classification: A Review

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Abstract——*In recent years, power quality (PQ) has become a significant issue for both utilities and customers. Detection and classification of power quality signals is of greater importance both in case of Power quality monitoring and to mitigate the power quality events. This paper proposes a brief survey for PQ events detection and classification technique for several power quality disturbances, including voltage sags, swells, oscillatory transients, harmonics, spikes, notches etc. PQ events cover a broad frequency range with significantly different magnitude variations and can be non-stationary thus, accurate techniques are required to identify and classify these events. This paper presents a comprehensive overview of different techniques used for PQ events' classifications, Fourier transform was the core of many traditional techniques however, it is increasingly being replaced by newer approaches notably S-transformed, wavelet transformed , artificial intelligence covering fuzzy logic, neural networks and genetic algorithm in power quality is covered. The strengths, limitations, and challenges in employing the methods are discussed with consideration of the needs and expectations when analyzing power quality disturbances.*

Keywords: *Power quality(PQ); wavelets; artitifical intelligence; fuzzy logic; gentic algorithms, neural networks.*

1. INTRODUCTIONS

Power quality is the concept of powering and grounding sensitive equipment in a matter that is suitable to the operation of that equipment. In recent years, power quality (PQ) has become a significant issue for both utilities and customers. PQ issues and the resulting problems are the consequences of the increasing use of solid-state switching devices, non-linear and power electronically switched loads, unbalanced power systems, lighting controls, computer and data processing equipment, as well as industrial plant rectifiers and inverters. These electronic-type loads cause quasi-static harmonic dynamic voltage distortions, inrush, pulse-type current phenomenon with excessive harmonics, and high distortion. A PQ problem usually involves a variation in the electric service voltage or current, such as voltage dips and fluctuations, momentary interruptions, harmonics, and oscillatory transients, causing failure or inoperability of the power service equipment. Hence, to improve PQ, a fast and reliable detection of disturbances and sources and causes of such disturbances must be known before any appropriate mitigating action can be taken. Disturbances are measured by triggering on an abnormality in the voltage or the current transient voltages may be detected when the peak magnitude exceeds a specified threshold. RMS voltage variations (e.g. sags or interruptions) may be detected when it exceeds a specified level [71,136]. Steady state variation is basically a measure of the magnitude by which the voltage or current may vary from the nominal value, plus distortion and the degree of unbalance between the three phases [1,2]. These include normal rms voltage variations, and harmonic and distortion. The power quality events can further be classified according to the nature of the waveform distortion. For steady-state disturbances, the amplitude, frequency, spectrum, modulation, source impedance, notch depth and notch area attributes can be utilized. However, for non-steady state disturbances, other attributes such as rate of rise, rate of occurrence and energy potential are useful. The major cause of voltage dips on a system is local and remote faults, inductive loading, and switch on of large loads[2,3]. Voltage surges appears due to Capacitor switching, Switch off of large loads and Phase faults [95,122]. Cause of Harmonics on a system is Industrial furnaces nonlinear loads Transformers and Rectifier equipment[44]. Transients generated due to lightning, capacitive switching, Non –linear switching loads, System voltage regulation[4].

2. SIGNAL PROCESSING TECHNIQUE FOR PQ EVENTS DECTECTION

The selection of appropriate features is extremely important for classification of any problem. The features extracted by signal processing techniques are used as input to the further stages for classification [108,133]. The combination of several scalars feature forms the feature vector. For the classification of power quality events, the appropriate characteristics should be extracted. These characteristics should be chosen to have low computation time and can separate disturbances with high precision[5]. Therefore, the similarities between these characteristics should be few and the number of them must be small. Signal processing in tools, concerns the extraction of features and information from measured digital signals[45]. A wide variety of signal-processing methods have been developed through the years both from the theoretical point of view and from the application point of view for a wide range of signals including Fourier transform, Short time Fourier transform, Wavelet transform, S transform. Fourier transform (FT) has been used for extracting the frequency contents of the recorded signal[6,7]. According to the frequency contents of the signal, some of the PQ problems can be detected. But, FT is not suitable for non-stationary signals [80,113]. This is because FT provides information only about the existence of a certain frequency component, but does not give information about component appearance time[46,47]. A suitable way to obtain such information is to apply time-frequency signal decomposition where time-evolved signal components in different frequency bands can be obtained [104,128]. Although, STFT can partly alleviate this problem, but STFT still has the limitation of a fixed window width i.e. the trade-off between the frequency resolution and the time resolution[49].

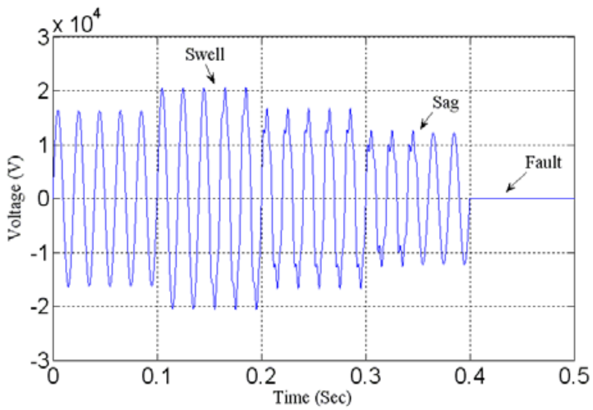

Fig. 1: Power quality disturbances Swell, Sag and Fault.

Fourier transform of signal $x(t)w(t-\tau)$ is defined Short Time Fourier Transform (STFT)[8,9].It relies on the assumption that the non-stationary signal $x(t)$ can be segmented into sections confined by a window boundary $w(t)$ within which it can be treated as the stationary one.

$$X_w(jw,\tau) = \int_{-\infty}^{+\infty} x(t)w(t-\tau)e^{-jwt} \quad (1)$$

Where $w(t) = \begin{cases} 0 & t<0, t>t_w \\ w(t) & 0<t<t_w \end{cases}$

Due to a fixed window width, STFT is inadequate for the analysis of the transient non-stationary signals. Therefore, more powerful and efficient methods and techniques are required to detect and analyze non-stationary disturbances [76,144].Wavelet analysis is a technique used for decomposing data into multiple components corresponding to different frequency bands[10,11]. This allows one to study each component separately. Wavelet analysis is a form of time-frequency technique as it evaluates signal simultaneously in the time and frequency domains. It uses wavelets, “small waves,” which are functions with limited energy and zero average.

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \quad (2)$$

The main advantages of wavelets is that they have a varying window size, being wide for slow frequencies and narrow for the fast ones, thus leading to an optimal time–frequency resolution in all the frequency ranges[50]. The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two:

$$y[n] = (x*g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \quad (3)$$

The signal is also decomposed simultaneously using a high-pass filter h. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter[51,52]. However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist’s rule. The filter outputs are:

$$y_{low}[n] = \sum_{-\infty}^{+\infty} x[k]g[n-k] \quad (4)$$

$$y_{high}[n] = \sum_{-\infty}^{+\infty} x[k]h[2n+1-k] \quad (5)$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled. For multi level resolution the decomposition is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters[12,13]. This is represented as a binary tree with nodes representing a sub-space with different time-frequency localization.

The Slantlet Transform (SLT) primarily based on an improved model of Discrete Wavelet Transform (DWT) has evolved. The DWT utilize tree structure for implementation whereas the SLT filter-bank is implemented in type of a parallel structure with shorter support of component filters[14,15]. Data compression and reconstruction of impulse, sag, swell harmonics, interruption, oscillatory transient and voltage flicker by using two-scale SLT was implemented [73,119]. Transforming of input signal by SLT, thresholding of transformed coefficients and reconstruction by inverse SLT are three main step of proposed method.

The short term Fourier transforms (STFT) is commonly used in time-frequency signal processing. However, one of its drawbacks is the fixed width and height of the analyzing window[16,17]. This causes misinterpretation of signal components with period longer than the window width; also the finite width limits time resolution of high-frequency signal components. One solution is to scale the dimensions of the analyzing window to accommodate a similar number of cycles for each spectral component, as in wavelets. This leads to the S-transform introduced by Stockwell, Mansinha and Lowe. Like STFT, it is a time-localized Fourier spectrum which maintains the absolute phase of each localized frequency component. Unlike the STFT, though, the S-transform has a window whose height and width frequency varying [105,131]. The S-transform was originally defined with a Gaussian window whose standard deviation is scaled to be equal to one wavelength of the complex Fourier spectrum[18,19]. The original expression of S-transform is represented as:

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t) \frac{|f|}{2\pi} e^{\frac{-(\tau-t)^2 f^2}{2}} e^{-i2\pi ft} dt \tag{6}$$

ST suffers from poor energy concentration in the time-frequency domain. It gives degradation in time resolution at lower frequency and poor frequency resolution at higher frequency. In a modified Gaussian window has been proposed this scales with the frequency in an efficient manner to provide improved energy concentration of the S-transform [89,133]. In this improved ST scheme the window function has been considered as the same Gaussian window but, an additional parameter δ is introduced into the Gaussian window where its width varies with frequency [102,129]. The adjustable parameter δ represents the number of periods of Fourier sinusoid that are contained within one standard deviation of the Gaussian window[20]. If δ is too small the Gaussian window retains very few cycles of the sinusoid. Hence the frequency resolution degrades at higher frequencies. If δ is too high the window retains more sinusoids within it. As a result the time resolution degrades at lower frequencies [78,124]. It indicates that the δ value should be varied judiciously so that it would give better energy distribution in the time-frequency plane. The trade off between the time-frequency resolutions can be reduced by optimally varying the window width with the parameter δ. At lower δ value ($\delta < 1$) the window widens more with less sinusoids within it, thereby it catches the low frequency components effectively[21,22]. At higher δ value ($\delta > 1$) the window width decreases more with more sinusoids within it, thereby it resolves the high frequency components better.

Principal component analysis (PCA) technique is also used for feature extraction of PQ events[23]. PCA commonly used for data analysis using multivariate statistical technique that combines data from several variables based on each variable's variance and correlation between different variables [98,130]. By calculating eigenvectors this technique is able to obtain the main direction of data sample from 3-D space representation of voltage in sample matrix form[24,25]. The number of significant samples n corresponding to number of row of matrix S. The power system samples are column of matrix S. After generating the correlation matrix of S, denoted by E. its eigen vector (ν) and corresponding eigenvalues (λ), can be computed.

$$E = S^T . S \tag{7}$$

$$E\nu = \nu\lambda \tag{8}$$

After getting a set of eigenvectors, PCA is able to obtain the main directions of the data sample on a new space defined by those eigenvectors[64,65]. This set of eigenvectors specifies the data main directions. In this new space, it is possible to represent a new set of uncorrelated variables as a linear combination of the old correlated variables[26]. For extraction of PQ events features, establish the reference eigen value correspond to the state where there are no disturbances in the voltage signal [82,110]. Compute the error between the current eigenvalue and the correspondent reference value[55,56]. The feature vector is generated using this error and this feature vector acts as input for classification technique. It may be noted that the PCA is based on the assumption, that the dimensionality of data can be efficiently reduced by linear transformation and other assumption that most information is contained in those directions where input data variance is maximum[27,28]. As it is evident, these conditions are by no means always met, this is the serious issue with this method.

The Hilbert Transform (HT) is a signal processing method technique which is a linear operator in the mathematics [84,145]. The HT of a signal x(t) : H[x(t)] is defined as

$$H[x(t)] = x(t) * \frac{1}{\pi t} = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(t-\tau)}{\tau} d\tau \tag{9}$$

where τ is the shifting operator. The HT can be considered as the convolution of x(t) with the signal $1/\pi t$. Clearly the HT of a signal x(t) in a time domain is another time domain signal H[x(t)] [99,118]. The output of the HT is 90 degree phase shift of the original signal. The envelope of the power quality disturbances are calculated by using HT. The type of the power quality events is detected by the shape of the envelope.

Some statistical information from the coefficients of HT is used. Means, standard deviation, peak value and energy of the HT coefficients are employed as input vector of the neural network classifier[77,115]. HT poorly suited for detecting relative suppressions of power at a specific frequency.

3. CLASSIFICATION TECHNIQUES

Both conventional and artificial intelligence (AI) based classification methods are review in the literature. The limitations of conventional methods are overcome by the AI based methods. Some frequently used AI based classifiers are fuzzy classification systems, artificial neural networks and support vector machines[29,30]. Neural network is a non-linear, data driven self adaptive method and is a promising tool for classification. These can adjust themselves to the data

without any explicit specification of functional or distributional form for the underlying model. The neural network recognizes a given pattern by experience which is acquired during the learning or training phase when a set of finite examples is presented to the network. This set of finite examples is called the training set, and it consists of input patterns (i.e., input vector) along with their label of classes(i.e., output)[31,32]. In this phase, neurons in the network adjust their weight vectors according to certain learning rules.

After the training process is completed, the knowledge needed to recognize patterns is stored in the neurons' weight vectors. The network is, then, presented to another set of finite examples, i.e. the testing data set, to assess how well the network performs the recognition tasks. This process is known as testing or generalization. ANN is a universal function approximator i.e. this can approximate any function with arbitrary accuracy[53,54]. All the above mentioned attributes make ANN flexible in modeling real world complex problems[33].

The Probabilistic neural network (PNN) was first proposed by Spetch in 1990[66]. The development of PNN relies on the Parzen window concept of multivariate probability estimates. The PNN combines the Baye's strategy for decision-making with a non-parametric estimator for obtaining the Probability Density Function (PDF). The PNN architecture includes four layers; input, pattern, summation, and output layers. The input nodes are the set of measurements[67,68]. The second layer consists of the Gaussian functions formed using the given set of data points as centers. The third layer performs an average operation of the outputs from the second layer for each class. The fourth layer performs a vote, selecting the largest value. The associated class label is then determined. The input layer unit does not perform any computation and simply distributes the input to the neurons. PNN technique has some drawbacks like large memory requirements and slow execution networks[34].

The RBFN (Radial basis function network) model consists of three layers: the inputs and hidden and output layers. The input space can either be normalized or an actual representation can be used [83,123]. This is then fed to the associative cells of the hidden layer, which acts as a transfer function. The hidden layer consists of radial basis function like a sigmoidal function used in MLP network. The output layer is a linear layer. The RBF is similar to Gaussian density function, which is designed by the "center" position and "width" parameter [107,132]. The RBF gives the maximum output when the input to the neuron is at the center and the output decreases away from the center [146]. The width parameter determines the rate of decrease of the function as the input pattern distance increases from the center position. Each hidden neuron receives as net input the distance between its weight vector and the input vector [88,148]. The output of the RBF layer is given as

$$O_k = \exp(-[X - C_k]^T [X - C_k] / 2\sigma_k{}^2) \quad (10)$$

K=1,2…..N, where N is the number of hidden nodes. O_k is the output of kth node of hidden layer .X is the input pattern. C_k is the center of RBF of kth mode of the hidden layer. σ_k spread of the kth RBF. Each neuron in the hidden layer outputs a value depending on its weight from the center of the RBF. The RBFN uses a Gaussian transfer function in the hidden layer and linear function in the output layer [81,120]. The output of the jth node of the linear layer is given by

$$Y_j = W_j{}^T O_j \quad (11)$$

Where j = 1,2,...,M , where M is the number of output nodes. Yj is the output of the jth node. Wj is the weight vector for node j. Oj represents output vector from the jth hidden layer. Choosing the spread of the RBF depends on the pattern to be classified [74,126]. The learning process undertaken by a RBF network may be visualized as follows. The linear weights associated with the output units of the network tend to evolve on a different "time scale" compared to the nonlinear activation functions of the hidden units [75,134]. Thus, as the hidden layer's activation functions evolve slowly in accordance with some nonlinear optimization strategy, the output layer's weights adjust themselves rapidly through a linear optimization strategy [96,139]. The important point to note is that the different layers of an RBF network perform different tasks, and so it is reasonable to separate the optimization of the hidden and output layers of the network by using different techniques, and perhaps operating on different time scales [72,116].

Logistic Model Tree (LMT) is a machine for supervised learning issues [79,85]. The LMT combines linear logistic regression and tree induction. The LogitBoost algorithm for building the structure of logistic regression functions at the nodes of a tree is used. Also, the renowned Classification and Regression Tree (ACRT) algorithm for pruning are employed. The LogitBoost is employed to pick the foremost relevant attributes in the data when performing logistic regression by performing a simple regression in each iteration and stopping before convergence to the maximum likelihood solution [90,100]. The LMT does not require any tuning of parameters by the user. A LMT includes standard Decision Tree (DT) structure with logistic regression functions at the leaves. Compared to ordinary DTs, a test on one of the attributes is related to every inner node. LMT based classifier used for identification of nine power quality disturbances. Sag, swell, interruption, harmonics, transient, and flicker, was studied [114,127]. Simultaneously disturbances consisting of sag and harmonics, as well as swell and harmonics, are also considered. The sampling frequency is 3.2 kHz. The feature vector composed of four features extracted by ST method [97,141]. The features are based on the Standard Deviation (SD) and energy of the transformed signal and are extracted as follows: Feature 1: SD of the dataset comprising the elements corresponding to the maximum magnitude of each column of the S-matrix. Feature 2: Energy of the dataset comprising of the elements corresponding to the maximum magnitude of each column of the S-matrix [86,103].Feature 3: SD of the dataset values corresponding to the maximum value of each row of the S-matrix. Feature 4: Energy of the dataset values corresponding to the maximum value of each row of the S-matrix. RBF networks have the disadvantage of requiring good coverage of the input space by radial basis functions [143]. RBF centers are determined with reference to the distribution of the input data, but without reference to the prediction task. As a result, representational resources may be wasted on areas of the input space that are irrelevant to the learning task [101,135]. A common solution is to associate each data point with its own centre, although this can make the linear system to be solved in the final layer rather large, and requires shrinkage techniques to avoid over fitting [91,109].

Support vector machine (SVM) is one more technique for power quality events classification [57]. The main purpose of the SVM algorithm is to construct an optimal decision function, f(x), that accurately predicts unseen data into two classes and minimization of classification error[35,36].

$$\mathrm{f(x)} = \mathrm{sign(g(x))} \quad (12)$$

The function g(x) in above equation is the decision boundary and is derived from set of training samples. Where each training sample x_i has M features describing a particular signature and belongs to one of two classes

$$Y = \{y_1, y_2, \dots y_n\}, y\epsilon\{-1,1\} \quad (13)$$

The decision boundary is called hyperplane[37]. The SVM calculates an optimal separating hyperplane by maximizing the margin between the separating hyperplane and the data. If two classes are linearly separable, the hyperplane f(x) = 0 can be determined such that separates the given feature vectors[69,70].

$$\mathrm{f(x)} = \mathrm{w.x} + \mathrm{b} = \sum_{\mathrm{k}=1}^{\mathrm{m}} \mathrm{w_k}\,.\mathrm{x_k} + \mathrm{b} = 0 \quad (14)$$

Where w and b denote the weight vector and the bias term, respectively. The position of the separating hyperplane is defined by setting these parameters. Thus the separating hyperplane satisfy the following constraints:

$$y_i f(x_i) = y_i(w.x_i + b) \geq 1 \quad (15)$$

ξ_i are positive slack variables that measure the distance between the margin and the vectors x_i that lie on the incorrect side of the margin[58,59]. Then, in order to obtain the optimal hyperplane, the following optimization problem must be solved[38,39]:

$$\text{Minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m} \xi_i \quad i \dots m \quad (16)$$

$$\text{Subject to } \begin{cases} y_i(w.x_i + b) \geq 1 - \xi_i \\ \xi_i \geq \end{cases}$$

Where C is the error penalty. By introducing the Lagrangian multipliers α_i, the above-mentioned optimization problem is transformed into the dual quadratic optimization problem, as follows:

$$\text{Maximize } L(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{m} \alpha_i \alpha_j y_i\, y_j\, (x_i x_j) \quad (17)$$

$$\text{Subject to } \sum_{i=1}^{m} \alpha_i y_i = 0, \alpha_i \geq 0, i = 1,2 \dots m \quad (18)$$

Thus, the linear decision function is created by solving the dual optimization problem, which is defined as:

$$f(x) = sign(\sum_{i,j=1}^{m} \alpha_i y_i \left(x_{i,} x_j\right) + b) \quad (19)$$

If the linear classification is not possible, the nonlinear mapping function φ can be used to map the original data x into a high dimensional feature space that the linear classification is possible[60,61]. Then, the nonlinear decision function is:

$$f(x) = sign(\sum_{i,j=1}^{m} \alpha_i y_i K(\,x_i, x_j) + b) \quad (20)$$

Where $K(x_i, x_j)$ is called the kernel function, $K(x_i, x_j) = \varphi(x_i)\varphi(x_j)$. Linear, polynomial, Gaussian radial basis function and sigmoid are the most commonly used kernel functions [62,63]. However, from a practical point of view perhaps the most serious problem with SVMs is the high algorithmic complexity and extensive memory requirements of the required quadratic programming in large-scale tasks [41,42].

The functionality of an automated pattern recognition system can be divided into two basic tasks, the description task generates attributes of PQ disturbances using feature extraction techniques, and the classification task assigns a group label to the PQ disturbance based on those attributes with a classifier [93,149]. The description and classification tasks work together to determine the most accurate label for each unlabeled object analyzed by the pattern recognition system. Feature extraction is a critical stage because it reduces the dimension of input data to be handled by the classifier

[106,125]. The features which truly discriminate among groups will assist in identification, while the lack of such features can prevent the classification task from arriving at an accurate identification. The final result of the description task is a set of features, commonly called a feature vector, which constitutes a representation of the data. The classification task uses a classifier to map a feature vector to a group [121,150]. Such a mapping can be specified by hand or, more commonly, a training phase is used to induce the mapping from a collection of feature vectors known to be the representative of the various groups among which discrimination is being performed [111,140]. Once formulated, the mapping can be used to assign identification to each unlabeled feature vector subsequently presented to the classifier[147]. So, it is obvious that a good feature extraction technique should be able to derive significant feature vectors in an automated way along with determining less number of relevant features to characterize the complete systems [112,142].

4. ANALYSIS

In literature, large number of reported articles has been used various feature sets. Feature set plays key role in any classification system. This leaves a question that how these features will perform when applied to events therefore, it is important to investigate the discriminative power of each PQ identification feature proposed in the literature before one may use it for the purpose. In view of this, a comprehensive analysis is desirable. However, results reported were quite encouraging on most occasions, which were obtained using only a selected number of events in experimental study. Table 1 summarizes some of the benchmark work in PQ analysis where RR shows the recognition rate.

Table 1: Detailed analysis.

Ref.	FE	Classifier/Optimization	Data used	Noisy data considered or not	RR
Uyar et al.[72]	WT	NN	Synthetic	Yes	97.81
Reaz et al. [70]	WT	NN, fuzzy system	Practical	No	98.91
Behera et al. [69]	ST	Fuzzy expert/PSO	Synthetic	Yes	99.00
Biswal et al. [84]	ST	Fuzzy C-means/PSO	Synthetic	No	95.41
Samantaray [104]	ST	DT-F	Practical	Yes	97.56
Eristri and Demir [105]	WT	SVM	Synthetic	Yes	9543
He and Starzyk [53]	WT	SOLAR	Synthetic	No	94.70
Giang [106]	WT	NN	Synthetic	No	90.43
Liao [107]	WT	RBF	Synthetic	Yes	96.60
Biswal et al. [108]	TTT	FCM-HACO	Synthetic	No	94.80
He et al. [109]	WT	NN	Synthetic	No	95.50
Hu et al. [110]	WT	SVM	Synthetic	No	98.50
Hooshmand and Enshaee [111]	FT,WT	Fuzzy system/PSO	Synthetic	Yes	98.00
Meher and Pradhan [63]	WT	Fuzzy system	Synthetic	Yes	96.87
Abdel-Galil et al. [52]	FT,WT	HMM	Synthetic	No	95.71
Ferreira et al. [49]	HOS	NN	Synthetic	No	100
Kaewarsa et al. [33]	MWT	MWBNC	Synthetic	No	98.03
Uyar et al. [112]	ST	NN	Synthetic	Yes	99.56
Gargoom et al. [44]	HT, CT	k-NN	Synthetic	No	80.60
Zhu et al. [66]	WT	Fuzzy system	Practical	Yes	95.31
Lee and Dash [113]	ST	NN	Synthetic	Yes	94.70
Mishra et al. [114]	ST	PNN	Synthetic	No	97.60
Eristri and Demir [115]	WT	SVM	Practical	Yes	95.81
Xiao et al. [41]	ST	SVM	Synthetic	No	92.30
Masoum et al. [116]	WT	NN	Practical	Yes	98.81
Shukla et al. [47]	HT	PNN	Synthetic	No	97.50

The papers by Eristi [115], Hooshmand [111] and Meher [63] used Wavelet transform to extract features. WT is an efficient tool for Detection & classification of disturbances in power quality. The paper by Uyar et al. [72] and Behera et al. [67] implemented S-transform because ST has an advantage in that it provides multiresolution analysis while retaining the absolute phase of each frequency. However most of identification performed based on synthetic data vey less based on real time events. In Table 1 most of researchers calculated the results based on synthetic data. Therefore, real time power signal analysis having lots of scope for researchers.

5. CONCLUSION AND FUTURE SCOPE

This paper presents a detailed survey in the field of power quality events analysis technology which is now become main area of research in the field of power system. Researchers have attempted to characterize the different PQ events using different feature set. Artificial intelligence and advanced mathematical techniques have become essential to the analysis of power quality. The paper presents a survey of literature for application of intelligent technique like fuzzy logic, expert system and neural networks in power quality. Advanced mathematical tool like wavelet theory is also reviewed. However, it is concluded that power quality analysis technology still need more research especially in the field of real time analysis this area is not much explored by the researcher still has a way to grow.

REFERENCES

[1] Bollen MHJ. What is power quality? Electric Power Systems Research 2003;66(1):5–14.

[2] Khan AK. Monitoring power for the future. Power Engineering Journal 2001;15(2):81–5.

[3] Gaouda AM, Salama MMA, Sultan MR, Chikhani AY. Application of multiresolution signal decomposition for monitoring short-duration variations in distribution systems. IEEE Transactions on Power Delivery 2000;15(2):478–85.

[4] IEEE, Recommended practice for monitoring electric power quality, 2009.

[5] Kandil MS, Farghal SA, Elmitwally A. Refined power quality indices. IEE Proceedings on Generation of Transmission & Distribution2001;148(6):590–6.

[6] Lin T, Domijan A. Real time measurement of power disturbances: part 1.

[7] Survey and a novel complex filter approach. Electric Power Systems Research 2006;76(12):1027–32.

[8] Kezunovic M, Lia A new method for classification and characterization of voltage sags. Electric Power Systems Research 2001;58(1):27–35.

[9] Ignatova V, Granjon P, Bacha S. Space vector method for voltage dips and swells analysis. IEEE Transactions on Power Delivery 2009;24(4):2054–61.

[10] Kucuk D, Salor O, Inan T, Cadirci I, Ermis M. Pqont: a domain ontology for electrical power quality. Advanced Engineering Informatics 2010;24(1):84–95.

[11] Jaramillo SH, Heydt GT, O’Neill-Carrillo E. Power quality indices for aperiodic voltages and currents. IEEE Transactions on Power Delivery2000;15(2):784–90.

[12] Gu IYH, Bollen MHJ. Time-frequency and time-scale domain analysis of voltage disturbances. IEEE Transactions on Power Delivery2000;15(4):1279–84.

[13] Gaouda AM, Salama MMA. Monitoring nonstationary signals. IEEE Transactions on Power Delivery 2009;24(3):1367–76.

[14] Biswal B, Dash PK, Panigrahi BK. Non-stationary power signal processing for pattern recognition using hs-transform. Applied Soft Computing 2009;9(1):107–17.
[15] Biswal B, Dash PK, Panigrahi BK, Reddy JBV. Power signal classification using dynamic wavelet network. Applied Soft Computing 2009;9(1):118–25.
[16] Morsi WG, El-Hawary ME. Novel power quality indices based on wavelet packet transform for non-stationary sinusoidal ans non-sinusoidal disturbances. Electric Power Systems Research 2010;80(7):753–9.
[17] classification of transients using dominant frequency signature. Electric Power Systems Research 2008;78:21–9.
[18] Chen Z, Spooner E. Grid power quality with variable speed wind turbines IEEE Transactions on Energy Conversion 2001;16(2):148–54.
[19] Tande JOQ. Applying power quality characteristics of wind turbine for assessing impact on voltage quality. Wind Energy 2002;52.
[20] Moslehi K, Kumar R. A reliability perspective of the smart grid. IEEE Transactions on Smart Grid 2010;1(1):57–64.
[21] Addison PS. The Illustrated Wavelet Transform Handbook. Institute of Physics; 2002.
[22] Jurado F, Acero N, Ogayar B. Application of signal processing tools for power quality analysis. IEEE Canadian Conference on Electrical & Computer Engineering 2002;1:82–7.
[23] Azam MS, Fang T, Pattipati KR, Karanam R. A dependency model-based approach for identyfying and evaluating power quality problems. IEEE Transactions on Power Delivery 2004;19(3):1154–66.
[24] Santoso S, Grady WM, Powers EJ, Lamoree J, Bhatt SC.Characterization of distribution power quality events with fourier and wavelet transforms. IEEE Transactions on Power Delivery 2000;15(1):247–54.
[25] Tarasiuk T. Hybrid wavelet-fourier spectrum analysis. IEEE Transactions on Power Delivery 2004;19(3):957–64.
[26] Ramos PM, Serra AC. Comparison of frequency estimation algorithms for power quality assessment. Measurement 2009;42(9):1312–7.
[27] Gu IYH, Bollen MHJ. Estimating interharmonics by using sliding-window esprit. IEEE Transactions on Power Delivery 2008;23(1):13–23.
[28] Gaouda AM, Kanoun SH, Salama MMA, Chikhani AY. Wavelet-based signal processing for disturbance classification and measurement. IEE Proceedings Generation, Transmission & Disribution 2002;149(3):310–8.
[29] Poisson O, Rioual P, Meunier M. Detection and measurement of power quality disturbances using wavelet transform. IEEE Transactions on Power Delivery2000;15(3):1039–44.
[30] Gencer O, Ozturk S, Erfidan T. A new approach to voltage sag detection based on wavelet transform. International Journal of Electrical Power and Energy Systems 2010;32(2):133–40.
[31] Ribeiro MV, Romano JMT, Duque CA. An improved method for signal processing and compression in power quality evaluation. IEEE Transactions on Power Delivery 2004;19(2):464–71.
[32] Keinert Fritz. Wavelets and Multiwavelets. Chapman & Hall, CRC Press; 2008.
[33] Kaewarsa S, Attakitmongcol K, Kulworwanichpong T. Recognition of power quality events by using multiwavelet based neural networks. International Journal of Electrical Power and Energy Systems 2008;30(4):254–60.
[34] P.F. Ribeiro, Wavelet transform: an advanced tool for analyzing nonstationary distortions in power systems, in: Proceedings of IEEE ICHPS IV,Bologan, 1994.
[35] Gerek ON, Ece DG. Power-quality event analysis using higher order cumulants and quadratic classifiers. IEEE Transactions on Power Delivery 2006;21(2):883–9.
[36] Zhao F, Yang R. Power quality disturbance recognition using s-transform. IEEE Transactions on Power Delivery 2007;22(2):944–50.
[37] Gerek ON, Ece DG, Barkana A. Covariance analysis of voltage waveform signature for power-quality event classification. IEEE Transactions on PowerDelivery 2006;21(4):2022–31.
[38] Dash PK, Chilukuri MV. Hybrid s-transform and kalman filtering approach for detection and measurement of short duration disturbances in power networks. IEEE Transactions on Instrumentation & Measurement 2004;53(2):588–96.
[39] Nguyen T, Liao Y. Power quality disturbance classification utilizing stransform and binary feature matrix method. Electric Power Systems Research 2009;79(4):569–75.
[40] Salem ME, Mohamed A, Samad SA. Rule-based system for power quality disturbance classification incorporating s-transform features. Expert System with Application 2010;37(4):3229–35.
[41] Xiao X, Xu F, Yang H. Short duration disturbance classifying based on stransform maximum similarity. International Journal of Electrical Power and Energy Systems 2009;31(7-8):374–8.
[42] Dash PK, Panigrahi BK, Sahoo DK, Panda G. Power quality disturbance data, compression, detection and classification using spline wavelet and stransform. IEEE Transactions on Power Delivery 2003;18(2):595–600.
[43] Dash PK, Panigrahi BK, Panda G. Power quality analysis using s-transform. IEEE Transactions on Power Delivery 2003;18(2):406–11.
[44] Gargoom AM, Ertugrul N, Soong WL. Automatic classification and characterization of power quality events. IEEE Transactions on Power Delivery 2008;23(4):2417–25.
[45] Gargoom AM, Ertugrul N, Soong WL. A comparative study on effective signal processing tools for optimum feature selection in automatic power quality events clustering. 40th IAS Annual Industrial Applied Conference 2005;1:52–8.
[46] Gargoom AM, Ertugrul N, Soong WL. Investigation of effective automatic recognition systems of power quality events. IEEE Transactions on Power Delivery 2007;22(4):2319–26.
[47] Shukla S, Mishra S, Singh B. Empirical-mode decomposition with hilbert transform for power-quality assessment. IEEE Transactions on Power Delivery 2009;24(4):2159–65.
[48] Suja S, Jerome J. Pattern recognition of power signal disturbances using stransform and tt-transform. International Journal of Electrical Power and Energy Systems 2010;32(1):37–53.
[49] Ferreira DD, Cerqueira AS, Duque CA, Ribeiro MV. Hos-based method for classification of power quality disturbances. IET Electronics Letters 2009;45(3):183–5.
[50] M.V. Ribeiro, C.A. Marques, C.A. Duque, A.S. Cerqueira, J.L.R. Pereira, Power quality disturbance detection using hos, IEEE Power Engineering Society General Meeting, 2006.
[51] Macias JAR, Exposito AG. Self-tunning of kalman filters for harmonic computation. IEEE Transactions on Power Delivery 2006;21(1):501–3.
[52] Abdel-Galil TK, El-Saadany EF, Salama MMA. Power quality event detection using adaline. Electric Power Systems Research 2003;64(2):137–44.

[53] He H, Shen X, Starzyk JA. Power quality disturbances analysis based on edmra method. International Journal of Electrical Power and Energy Systems 2009;31(6):258–68.
[54] Styvaktakis E, Bollen MHJ, Gu IYH. Expert system for classification and analysis of power system events. IEEE Transactions on Power Delivery 2002;17(2):423–8.
[55] Styvaktakis E, Gu IYH, Bollen MHJ. Voltage dip detection and power systems transients. IEEE Power Engineering Society Summer Meeting 2001;1:683–8.
[56] Abdel-Galil TK, EI-Saadany EF, Youssef AM, A Salama MM. Disturbance classification using hidden markov models and vector quantization. IEEE Transactions on Power Delivery 2005;20(3):2129–35.
[57] Huang S-J, Hsieh C-T. Feasibility of fractal-based methods for visualization of power system disturbances. International Journal of Electrical Power and Energy Systems 2001;23(1):31–6.
[58] Nguyen HT, Walker EA. A First Course in Fuzzy Logic. third ed. Chapman and Hall/ CRC; 2006.
[59] Bizjak B, Planinsic P. Classification of power disturbances using fuzzy logic. International Conference on Power Electronics Motion Control 2006:1356–60.
[60] [60] Andami H, Jalilian A. Voltage notch detection using fuzzy expert system. IEEE Canadian Conference on Electrical and Computer Engineering 2003;1:479–82.
[61] Al-Hasawi WM, El-Naggar KM. A genetic based algorithm for voltage flicker measurement. International Journal of Electrical Power and Energy Systems 2004;26(8):593–6.
[62] Samantaray SR. Decision tree-initialised fuzzy rule-based approach for power quality events classification. IET Generation Transmission & Distribution 2010;4(4):538–51.
[63] Meher SK, Pradhan AK. Fuzzy classifiers for power quality events analysis. Electric Power Systems Research 2010;80(1):71–6.
[64] Al-Kandari AM, Soliman SA, Alammari RA. Power quality analysis based on fuzzy estimation algorithm: voltage flicker measurements. International Journal of Electrical Power and Energy Systems 2006;28(10):723–8.
[65] Chilukuri MV, Dash PK. Multiresolution s-transform-based fuzzy recognition system for power quality events. IEEE Transactions on Power Delivery 2004;19(1):323–30.
[66] Zhu TX, Tso SK, Lo KL. Wavelet-based fuzzy reasoning approach to power quality disturbance recognition. IEEE Transactions on Power Delivery 2004;19(4):1928–35.
[67] Liao Y, Lee J-B. A fuzzy expert system for classifying power quality disturbances. International Journal of Electrical Power and Energy Systems 2004;26(3):199–205.
[68] Kezunovic M, Liao Y. A novel software implementation concept for power quality study. IEEE Transactions on Power Delivery 2002;17(2):544–9.
[69] Behera HS, Dash PK, Biswal B. Power quality time series data mining using stransform and fuzzy expert system. Applied Soft Computing 2010;10(3):945–55.
[70] Reaz MBI, Choong F, Sulaiman MS, Mohd-Yasin F, Kamada M. Expert system for power quality disturbance classifier. IEEE Transactions on Power Delivery 2007;22(3):1979–88.
[71] Mohamed E. Salem Abozaed Detection and Classification of Power Quality Disturbances Using S-Transform and Wavelet Algorithm World Academy of Science, Engineering and Technology Vol:7 2013-06-28.
[72] Uyar M, Yildirim S, Gencoglu MT. An effective wavelet-based feature extraction method for classification of power quality disturbances signals. Electric Power Systems Research 2008;78(10):1747–55.
[73] H. Amarís, C. Alvarez, M. Alonso, D. Florez, T. Lobos, P. Janik, J. Rezmer, Z. Waclawek, Application of advanced signal processing methods for accurate detection of voltage dips, in: 13th IEEE ICHQP, 2008.
[74] E. Pérez, J. Barros, Application of advanced digital signal processing tools for analysis of voltage events in power systems, IEEE J. 46 (2009) 211–224.
[75] G.W. Chang, C.-I. Chen, Performance evaluation of voltage sag detection methods, IEEE PES Gen. Meet. (2010).
[76] P.F. Ribeiro, Wavelet transform: an advanced new tool for analyzing nonstationary harmonic distortion in power systems, IEEE Int. Conf. Harmonics Power Syst. (1994) 365–369.
[77] S. Santoso, E.J. Powers, W.M. Grady, Electric power quality disturbance detection using wavelet transform analysis, in: IEEE – SP Int. Symposium on Time–Frequency and Time Scale Analysis, 1994, pp. 166–169.
[78] S. Santoso, E.J. Powers, W.M. Grady, P. Hofmann, Power quality assessment via wavelet transform analysis, IEEE Trans. Power Deliv. 11 (1996) 924–930.
[79] D.C. Robertson, O.I. Camps, J.S. Mayer, W.B. Gish, Wavelets and electromagnetic power system transients, IEEE Trans. Power Deliv. 11 (1996) 1050–1058.
[80] P. Pillay, A. Bhattacharjee, Application of wavelets to model short-term power system disturbances, IEEE Trans. Power Syst. 11 (1996) 2031–2037.
[81] W.A. Wilkinson, M.D. Cox, Discrete wavelet analysis of power system transients, IEEE Trans. Power Syst. 11 (1996) 2038–2044.
[82] G.T. Heydt, A.W. Galli, Transient power quality problems analyzed using wavelets, IEEE Trans. Power Deliv. 12 (1997) 908–915.
[83] C.H. Lee, Y.J. Wang, W.L. Huang, A literature survey of wavelets in power engineering applications, Proc. Natl. Sci. Counc. ROC(A) 24 (2000) 249–258.
[84] Biswal B, Dash PK, Panigrahi BK. Power quality disturbance classificationusing fuzzy c-means algorithm and adaptive particle swarm optimization. IEEE Transactions on Industrial Electronics 2009;56(1):212–20.
[85] Lai MJ. On the digital filter associated with Daubechie's wavelets. IEEE Trans Signal Process 1995;43(9):2203–5.
[86] Huang SJ, Yang TM, Huang JT. FPGA realization of wavelet transform for detection of electric power system disturbances. IEEE Trans Power Deliver 2002;17(2):388–94.
[87] Panda G, Dash PK, Pradhan AK, Meher SK. Data compression of power quality events using the slantlet transform. IEEE Trans Power Deliver 2002;17(2):662–7.
[88] Chilukuri MV, Dash PK. Multiresolution S-transform-based fuzzy recognition system for power quality events. IEEE Trans Power Deliver 2004;19(1): 323–30.
[89] Gaing ZL. Implementation of power disturbance classifier using wavelet-based neural networks. In: IEEE Bologna Power Tech Conference; 2003.
[90] Gaing ZL. Wavelet-based neural network for power disturbance recognition and classification. IEEE Transact Power Deliver 2004;19(4):1560–8.
[91] Daubechies I. Ten lectures on wavelet. Philadelphia, USA: Society for Industrial and Applied Mathematics; 1992.
[92] IEEE Std 1364-2005: IEEE standard for Verilog hardware description language; 2006.

[93] Blair GM. Verilog: accelerating digital design. IEE Electron Commun Eng J 1997;4(9):68–72.
[94] [46] A.M. Gaouda, S.H. Kanoun, M.M.A. Salama, A.Y. Chikhani, Wavelet based signal processing for disturbance classification and measurement, IEE Gener. Transm. Distrib. 149 (2002) 310–318.
[95] A.M. Gaouda, S.H. Kanoun, M.M.A. Salama, A.Y. Chikhani, Pattern recognition applications for power system disturbance classification, IEEE Trans. Power Deliv. 17 (2002) 677–683.
[96] Z.L. Gaing, Wavelet-based neural network for power disturbance recognition and classification, IEEE Trans. Power Deliv. 19 (2004) 1560–1568.
[97] T.K. Abdel-Galil, M. Kamel, A.M. Youssef, E.F. El-Saadany, M.M.A. Salama, Power quality disturbance classification using the inductive inference approach, IEEE Trans. Power Deliv. 19 (2004) 1812–1818.
[98] T.X. Zhu, S.K. Tso, K.L. Lo, Wavelet-based fuzzy reasoning approach to power-quality disturbance recognition, IEEE Trans. Power Deliv. 19 (2004) 1928–1935.
[99] H. He, J.A. Staryk, A self-organizing learning array system for power quality classification based on wavelet transform, IEEE Trans. Power Deliv. 21 (2006) 286–295.
[100] P. Gao, W. Wu, Power quality disturbances classification using wavelet and support vector machines, in: 6th IEEE Int. Conf. on Intelligent Systems Design and Applications, 2006, pp. 1–6.
[101] V. Vega, C.A. Duarte, G. Ordó˜nez, Obtaining patterns for classification of power quality disturbances using biorthogonal wavelets, rms value and support vector machines, in: 9th Int. Conf. EPQU, 2007, pp. 1–6.
[102] F.B. Costa, K.M. Silva, K.M.C. Dantas, N.S.D. Brito, A wavelet-based algorithm for disturbances detection using oscillographic data, Int. Conf. Power Systems Transients (2007) 1–6.
[103] F.B. Costa, B.A. Souza, N.S.D. Brito, A wavelet-based algorithm to analyze oscillographic data with single and multiple disturbances, IEEE PES Gen. Meet 2008.
[104] Samantaray SR. Decision tree-initialised fuzzy rule-based approach for power quality events classification. IET Generation Transmission & Distribution 2010;4(4):538–51.
[105] Eristi H, Demir Y. A new algorithm for automatic classification of power quality events based on wavelet transform and svm. Expert Systems With Applications 2010;37(6):4094–102.
[106] Gaing Z-L. Wavelet-based neural network for power disturbance recognition and classification. IEEE Transactions on Power Delivery 2004;19(4):1560–8.
[107] Liao C-C. Enhanced rbf network for recognizing noise-riding power quality events. IEEE Transactions on Instrumentation & Measurement 2010;59(6):1550–61.
[108] Biswal B, Dash PK, Mishra S. A hybrid ant colony optimization technique for power signal pattern classification. Expert Systems With Applications 2011;38(5):6368–75.
[109] He Z, Gao S, Chen X, Zhang J, Bo Z, Qian Q. Study of a new method for power system transients classification based on wavelet entropy and neural network. International Journal of Electrical Power and Energy Systems 2011;33(3):402–10.
[110] Hu G-S, Zhu F-F, Ren Z. Power quality disturbance identification using wavelet packet energy entropy and weighted support vector machines. Expert Systems With Applications 2008;35(1-2):143–9.
[111] Hooshmand R, Enshaee A. Detection and classification of single and combined power quality disturbances using fuzzy systems oriented by particle swarm optimization algorithm. Electric Power Systems Research 2010;80(12):1552–61.
[112] Uyar M, Yildirim S, Gencoglu MT. An expert system based on s-transform and neural network for automatic classification of power quality disturbances. Expert System With Application 2009;36(3):5962–75.
[113] Lee IWC, Dash PK. S-transform-based intelligent system for classification of power quality disturbance signals. IEEE Transactions on Industrial Electronics 2003;50(4):800–5.
[114] Mishra S, Bhende CN, Panigrahi BK. Detection and classification of power quality disturbances using s-transform and probabilistic neural network. IEEE Transactions on Power Delivery 2008;23(1):280–7.
[115] Eristi H, Demir Y. A new algorithm for automatic classification of power quality events based on wavelet transform and svm. Expert Systems With Applications 2010;37(6):4094–102.
[116] Masoum MAS, Jamali S, Ghaffarzadeh N. Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks. IET Science Measurement & Technology 2010;4(4):193–205.
[117] Sullivan MJ, Vardell T, Johnson M. Power interruption costs to industrial and commercial consumers of electricity. IEEE Trans Ind Appl 1997;33(6):1448–58.
[118] Consortium for electrical infrastructure to support a digital society, the cost of power disturbance to Industrial and Digital Economy Companies. An initiative by EPRI and the Electrical Innovation Institute; June 2001.
[119] US–Canada power system outage task force. Final report on the August, 14, 2003 blackout in the United States and Canada: causes and recommendations; April 2004. p. 1–4.
[120] Hamid EY, Kawasaki ZI. Wavelet-based data compression of power system disturbances using the minimum description length criterion. IEEE Trans Power Deliv 2002;17(2):460–6.
[121] Dash PK, Panigrahi BK, Sahoo DK, Panda G. Power quality disturbance data compression, detection, and classification using integrated spline wavelet and S-transform. IEEE Trans Power Deliv 2003;18(2):595–600.
[122] Panda G, Dash PK, Pradhan AK, Meher SK. Data compression of power quality events using the Slantlet transform. IEEE Trans Power Deliv 2002;17(2):662–7.
[123] Poisson O, Rioual P, Meunier M. New signal processing tools applied to power quality analysis. IEEE Trans Power Deliv 1999;14(2):561–6.
[124] Poisson O, Rioual P, Meunier M. Detection and measurement of power quality disturbance using wavelet transform. IEEE Trans Power Deliv 2000;15(3).
[125] Santoso S, Grady WM, Powers EJ, Lamoree J, Bhatt SC. Characterization of distribution power quality events with Fourier and wavelet transform. IEEE Trans Power Deliv 2000;15(1):247–54.
[126] Dash PK, Panigrahi BK, Panda G. Power quality analysis using S-transform. IEEE Trans Power Deliv 2003;18(2):406–11.
[127] Karimi M, Mokhtari H, Iravani MR. Wavelet based on-line disturbance detection for power quality application. IEEE Trans Power Deliv 2000;15(4): 1212–20.
[128] Mokhtari H, Ghartemani MK, Iravani MR . Experimental performance evaluation of a wavelet-based on-line voltage detection method for power quality application. IEEE Trans Power Deliv 2002;17(1):161–72.

[129] Elmitwally A, Abdelkader S, Elkateb M. Universal power quality manager with a new control scheme. IEE Proc – Gen Transm Distrib 2000;147(3): 183–9.
[130] Gaouda AM, Salam MMA, Sultan MR, Chikhani AY. Power quality detection and classification using wavelet-multiresolution signal decomposition. IEEE Trans Power Deliv 1999;14(4):1469–76.
[131] Gaouda AM, Kanoun SH, Salama MMA, Chikhani AY. Wavelet-based signal processing for disturbance classification and measurement. IEE Proc – Gen Transm Distrib 2002;149(3):310–8.
[132] Santoso S, Powers EJ, Grady WM, Hofmann P. Power quality assessment via wavelet transform analysis. IEEE Trans Power Deliv 1996;11(2):924–30.
[133] Liao Y, Lee JB. A fuzzy-expert system for classifying power quality disturbances. Int J Electr Power Energy Syst 2004;26:199–205.
[134] Yang HT, Liao C-C. A de-noising scheme for enhancing wavelet-based power quality monitoring system. IEEE Trans Power Deliv 2001;16(3):353–60.
[135] He H, Starzyk JA. A self organizing learning array system for power quality classification based on wavelet transform. IEEE Trans Power Deliv 2006;21:286–95.
[136] Daubechies I. Ten lectures on wavelets. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics; 1992.
[137] Burrus CS, Gopinath RA, Guo H. Introduction to wavelets and wavelet transforms: a primer. Prentice Hall; 1998.
[138] Mallat S. A theory for multiresolution signal decomposition: the wavelet representation. IEEE Trans PAM 1989;11:674–93.
[139] Zhang H, Liu P, Malik OP. Detection and classification of power quality disturbances in noisy conditions. IEE Proc – Gen Transm Distrib 2003;150(5):567–72.
[140] O'shea P. A high-resolution spectral analysis algorithm for power-system disturbance monitoring. IEEE Trans Power Syst 2002;17(3):676–80.
[141] Dugan RC, Mcgranaghan MF, Santoso S, Beaty HW. Electrical power systems quality. McGraw-Hill; 2002. p. 28–9.
[142] IEEE standards coordinating committee 22 on power quality, IEEE recommended practice for monitoring electric power quality. IEEE Std 1159- 1995. The Institute of Electrical and Electronics Engineers Inc.; 1995. ISBN: 1-55937-549-3.
[143] Walker JS. A primer on wavelets and their scientific applications. New York: Chapman and Hall/CRC; 1999.
[144] Santoso S. Power quality disturbance waveform recognition using waveletbased neural classifier – Part 1: theoretical foundation. IEEE Trans Power Delivery 2000;15(1):222–8.
[145] Santoso S. Power quality disturbance waveform recognition using waveletbased neural classifier – Part 2: application. IEEE Trans Power Delivery 2000;15(1):229–35.
[146] Borrás D, Castilla M, Moreno N, Montano JC. Wavelet and neural structure: a new tool for diagnostic of power system disturbances. IEEE Trans Industry Appl 2001;37(1):184–90.
[147] Kaewarsa S, Attakitmongcol K, Kulworawanichpong T. Recognition of power quality events by using multiwavelet-based neural networks. Electric Power Energy Sys 2008;30:254–60.
[148] Huang J, Negnevitsky M, Nguyen DT. A neural-fuzzy classifier for recognition of power quality disturbances. IEEE Trans Power Delivery 2002;17(2):609–16.
[149] Al-Kandari AM, Soliman SA, Alammari RA. Power quality analysis based on fuzzy estimation algorithm: Voltage flicker measurements. Electric Power Energy Sys 2006;28:723–8.
[150] Al-Hasawi WM, El-Naggar KM. A genetic based algorithm for voltage flicker measurement. Electric Power Energy Sys 2004;26:593–6.