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Classification of Power Quality Disturbances in Electric Power System: A Review

Devendra Mittal[1], Om Prakash Mahela[2], Rohit Jain[3]
[1](*Assistant Professor, Department of Electrical Engineering, Jagannath University Jaipur, India*)
[2](*Junior Engineer, Rajasthan Rajya Vidhyut Prasaran Nigam Ltd., Jaipur, India*)
[3](*Professor, Department of Physics, Jagannath Gupta Institute of Engineering & Technology, Jaipur, India*)

***Abstract** : The Electrical power quality issue has attained considerable attention in last decade due to large penetration of power electronics based loads and microprocessor based controlled loads. These devices introduce power quality problem on one hand and these mal-operate due to induced power quality problems on other hand. The various techniques for classification or recognition of power quality disturbances in electrical power system have been proposed so far in different papers. This paper presents a comprehensive overview of different techniques used for feature extraction and classification of power disturbance. This paper helps the researchers to know about the different methods presented so far for power quality disturbance classification or recognition, so that further work on power quality improvement can be carried out for better results.*
***Keywords**: artificial intelligence techniques, feature extraction, genetic algorithm, PQ disturbances, power system, power quality, PQ event classifier.*

I. Introduction

Electrical power system is expected to deliver undistorted sinusoidal rated voltage and current continuously at rated frequency to the consumers. In recent years, grid users have detected an increasing number of drawbacks caused by electric power quality (PQ) variations and PQ problems have sharpened because of the increased number of loads sensitive to PQ and have become more difficult to solve as the loads themselves have become important causes of degradation of quality [1].Therefore, these days, customers demand higher levels of PQ to ensure the proper and continued operation of such sensitive equipments. According to IEEE standard 1159-1995 [2], the PQ disturbances include wide range of PQ phenomena namely transient (impulsive and oscillatory), short duration variations (interruption, sag and swell), power frequency variations, long duration variations (sustained under voltages and sustained over voltages) and steady state variations (harmonics, notch, flicker etc.) with time scale ranges from tens of nanoseconds to steady sate. A number of causes of transients can be identified: lightning strokes, planned switching actions in the distribution or transmission system, self-clearing faults or faults cleared by current limiting fuses, and the switching of end-user equipment. Transient phenomena are extremely critical since they can cause over voltages leading to insulation breakdown or flashover. These failures might trip any protection device initiating a short interruption to the supplied power. Excess current produced by transients may lead to complete damage to system equipment during the transient period. Moreover, if such disturbances are not mitigated, they can lead to failures or malfunctions of various sensitive loads in power systems and may be costly. According to the survey of IEEE Transactions on Industrial Applications, power quality disturbances lead to losses of $4 billion to $10 billion in the USA alone [3].

In electricity market scenario, now electricity consumers can shift to the new service providers, if power quality is not good. Moreover, these customers can demand a higher quality of service. The utilities or other electric power providers have to ensure a high quality of their service to remain competitive and to retain/ attract the customers. Therefore the Power Quality has been a challenge for power system planners and researchers. The main task of PQ analysis involves detection, identification, recognition and classification of various types of PQ disturbances. In this work, an analysis of PQ issues, types of PQ disturbances, automatic power quality recognition system, feature extraction techniques and artificial intelligence based classification methods proposed by the researchers recently are presented.

II. Power Quality and Types of Power Quality Disturbances

The term power quality (PQ) is generally applied to a wide variety of electromagnetic phenomena occurring within a power system network. Power quality is predominantly a customer issue. Power quality can be defined as any problem manifested in voltage, current, or frequency deviation that results in failure or mal-operation of electric equipment [4]. The electric power quality is also defined as a term that refers to maintaining the near sinusoidal waveform of power system bus voltages and currents at rated magnitude and frequency. Thus electric power quality is often used to express voltage quality, current quality, reliability of service, quality of power supply etc. [5]. Power quality issue is also important for the utility companies. They are obliged to supply consumers with electrical power of acceptable quality.

The power quality disturbances depend on amplitude or frequency or on both frequency and amplitude. Based on duration of existence of PQ disturbances, events can be divided in to short, medium or long type. The classification and identification of each disturbance are usually carried out from standards and recommendations depending on where the utilities operate (e.g. IEEE in the U.S.). Inigo Monedero *et al.* [6] defined PQ disturbances, which is given in Table I, based on the UNE standard in Spain which defines the ideal signal as a single-phase or three-phase sinusoidal voltage signal of 230 V_{RMS} and 50Hz. D. Saxena *et al.* [7] classified various PQ events in to five groups viz. short duration variation, long duration variation, transients, voltage imbalance and waveform distortion. S.Edwin Jose *et al.* [8] classified PQ disturbances on basis of values of tails of histogram obtained from simulation results.

TABLE I
TYPES OF DISTURBANCES

<table>
<tr><th rowspan="2"><u>Type of disturbance</u></th><th colspan="3" rowspan="2"><u>Disturbance subtype</u></th><th rowspan="2"><u>Time</u></th><th colspan="2"><u>Range</u></th></tr>
<tr><th><u>Min. Value</u></th><th><u>Max. Value</u></th></tr>
<tr><td rowspan="2">Frequency</td><td colspan="3">Slight deviation</td><td rowspan="2">10 s</td><td>49.5 Hz.</td><td>50.5 Hz.</td></tr>
<tr><td colspan="3">Severe deviation</td><td>47.0 Hz.</td><td>52.0 Hz.</td></tr>
<tr><td rowspan="11">Voltage</td><td colspan="3">Average voltage</td><td>10 min</td><td>0.85 Un</td><td>1.1 Un</td></tr>
<tr><td colspan="3">Flicker</td><td>-</td><td>-</td><td>7%</td></tr>
<tr><td rowspan="3">Sag</td><td colspan="2">Short</td><td>10ms-1s</td><td rowspan="3">0.1 U</td><td rowspan="3">0.9 U</td></tr>
<tr><td colspan="2">Long</td><td>1s-1min</td></tr>
<tr><td colspan="2">Long-time disturbance</td><td>>1min</td></tr>
<tr><td colspan="2" rowspan="2">Under Voltage</td><td>Short</td><td><3min</td><td colspan="2" rowspan="2">0.99 U</td></tr>
<tr><td>Long</td><td>>3min</td></tr>
<tr><td rowspan="4">Swell</td><td colspan="2">Temporary Short</td><td>10ms-1s</td><td rowspan="4">1.1 U</td><td rowspan="3">1.5 KV</td></tr>
<tr><td colspan="2">Temporary Long</td><td>1s-1min</td></tr>
<tr><td colspan="2">Temporary Long-time</td><td>>1min</td></tr>
<tr><td colspan="2">Over-voltage</td><td><10 ms</td><td>6 KV</td></tr>
<tr><td rowspan="2">Harmonics and other information signals</td><td colspan="3">Harmonics</td><td>-</td><td colspan="2">THD>8%</td></tr>
<tr><td colspan="3">Information signals</td><td>-</td><td colspan="2">Included in other disturbances</td></tr>
</table>

III. Automatic Power Quality Disturbance Recognition System

The PQ disturbance recognition scheme consists of three major parts viz. (i) feature extraction i.e. signal processing (ii) Classification of disturbance using conventional or artificial intelligence (AI) based techniques and (iii) the decision making as to what category a particular disturbance belongs. A scheme for automatic power quality disturbance recognition system is depicted in Fig. 1 [9].

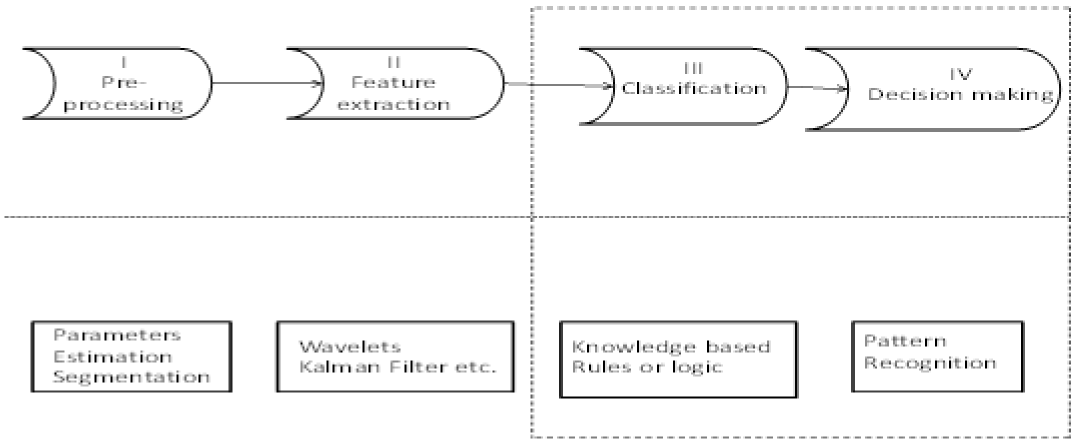

Fig. 1 block diagram of automatic disturbance recognition system

In the figure, Block-I represents a pre-processing stage. In this block estimation of signal components is performed. Then, an algorithm for signal segmentation in different stages is applied, e.g. pre-event, during-event and post-event stages. Block-II represents a feature extraction stage. Feature extraction can be done through any of the techniques such as Fourier transforms, S-transform, wavelet transform, Hilbert Huang transform etc. Block-III represents the classification stage based on defined rules, e.g. knowledge based expert systems, pattern recognition or any logic to discriminate different types of events. The artificial neural network, support vector machine based system, rule-based expert system, fuzzy expert system, genetic algorithm, adaptive neuro-fuzzy system etc. are commonly used for classification of PQ events. Finally, Block-IV represents the decision making stage. In this stage the type of event is assigned to an actual type event. In most of the classifiers, the decision making stage is merged with the classification stage. Normally, expert system and fuzzy logic are used as decision making tools.

IV. Feature Extraction Techniques

In order to improve the quality of electric power supplied, it is essential to detect and identify the power quality problem distinctive features of the disturbance waveforms. Feature may directly be extracted from the original measurement (e.g. RMS values), or from some transformed domain (e.g. Fourier, wavelet, STFT, HHT, and S-transform), or from the parameters of signal models (e.g. sinusoid KF and AR models). The RMS magnitude of voltage supply is used in the power quality standards for detection and characterization of voltage events [10]. The method is simple and easy to implement but it does not give information about the phase angle or the point on wave where the event begins [5]. RMS method has important limitations in the detection and estimation of magnitude and duration of voltage events. Commonly used feature extraction techniques are mentioned below:

IV.1 Fourier Transform

The most used classical signal processing is the Fourier transform (FT). This transform represents a signal as a sum of sinusoidal terms of different frequencies, named frequency spectrum [11]. This technique is suitable for stationary signals and extracting spectrum components of the signals at specific frequencies, but it is not efficient when the signal contains short-term transient disturbances [12]. P. Kailasapathi *et al.* [13] described that FT can be applied to both continuous signal and discrete signal. It can be either periodic or aperiodic. Anton *et al.* [14] presented that the FT based signal processing techniques are Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT).

The DFT is the widely used discrete signal processing algorithm. An approach to compute the DFT is to use a recursive computation scheme. The most popular approach is the Goertzel's Algorithm. Goertzel algorithm is used to implement the non-uniform discrete fourier transform [15]. Rosendo *et al.* [16] described that in the windowed discrete Fourier transform (WDFT), the amplitude for any given spectral component of the DFT gives the average of windowed tie series. The choice of window size is, however, completely arbitrary.

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster. The radix is the size of FFT decomposition. Radix-2, radix-4, radix-8, spilit radix are the types of radix. The FFT algorithms are found to be more accurate than evaluating the DFT definition direct computation when round-off error is present [17].

The STFT is the classical method of time frequency analysis. It is a Fourier related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. In essence, STFT extracts several frames of the signal to be analyzed with a window that moves with time. If the time window is sufficiently narrow, each frame extracted can be viewed as stationary so that Fourier transform can be used. With the window moving along the time axis, the relation between the variance of frequency and time can be identified [18]-[20]. Non-stationary signals characterized by wide range of frequency spectrum with transient and sub-harmonic components are difficult to analyze with STFT [21]. For non-stationary signals, the STFT does not track the signal dynamics properly due to the limitations of a fixed window width chosen a priority [19].

IV.2 S-Transform

Stockwell *et al.* [22] introduced the S-Transform (ST) to track the dynamics properly. The S-transform is a time-frequency spectral localization method, similar to the STFT and continuous wavelets. The S-transform is conceptually a hybrid of STFT and wavelet analysis, bridges the gap between them, containing elements of both but having its own characteristic properties. Just like the STFT, the S-transform uses a window to localize the complex Fourier sinusoid, but unlike the STFT, the width and height of the window scale with frequency in analogy with wavelets. S-transform employs a moving and scalable localizing Gaussian window. It combines a frequency dependent resolution with simultaneous localizing the real and imaginary spectra [23]-[24]. Leonowicz *et al.* [25] stated that the basic functions for the S-transform are Gaussian modulated cosinusoids whose width varies inversely with the frequency. Ming He Zhang *et al.* [26] employed S-Transform for the analysis and detection of power quality disturbances. Ameen M. Gargoom *et al.* [27] proposed the analysis of power quality events using amplitude and phase spectrum derived from the S-Transform of signal. Nguyen e*t al.* [28] presented Discrete S-Transform (DST) for feature extraction. Yokeeswaran *et al.* [29] presented Discrete Orthogonal S-Transform (DOST) using time series for representation. The transformation matrix is orthogonal, meaning that the inverse matrix is equal to the complex conjugate transpose. An orthogonal transform is referred to as an energy preserving transform.

IV.3 Wavelet Transform

Wavelet Transform (WT) is used as a feature extraction tool to identify power quality disturbances [30]. The wavelet transform traces the signal changes in time domain and simultaneously decomposes the signal in frequency domain. In the wavelet transform based approach, a mother wavelet is employed for finding the wavelet coefficients of the signal which affects the effectiveness in identifying the disturbance present in the signal [31]. The mathematics of wavelet transform was extensively studied and can be referred in papers [32] and [33]. Wavelet transforms are classified into discrete wavelet transform (DWT) and continuous wavelet transforms (CWT). Lalit Behera *et al.* [34] presented the theory of CWT and DWT and used DWT for time series data mining of power quality events occurring due to power signal disturbances. The wavelet transform has been introduced as powerful tool for voltage flicker signal extraction and harmonic detection [35].The main disadvantage of WT is its batch processing, which in turn, results in some delay. Feature extraction technique using the standard deviation of the wavelet coefficients is discussed in [36]. Perumal *et al.* [37] employed multi-resolution analysis (MRA) based modified wavelet transforms for detection and classification of power quality disturbance waveform. The use of continuous wavelet transform (CWT) to analyze non-stationary harmonic distortion has been proposed in [38].

IV.4 Hilbert Huang Transform

The development of the Hilbert Huang Transform (HHT) was motivated by the need to describe nonlinear distorted waves in detail, along with the variations of these signals that naturally occur in non-stationary processes [39].The Hilbert Huang Transform is an adaptive data analysis method designed for analyzing non-stationary signals. In HHT, the signal is decomposed into a finite small number of components, called Intrinsic Mode Functions (IMF). This process of decomposition is called Empirical Mode decomposition (EMD). The EMD decomposes the signal in terms of IMFs each of which is a mono-component function. A signal can be analyzed in details for its frequency, amplitude and phase contents by using EMD followed by HT [40]. The method has been applied to many important problems in various fields including medical [41], geophysics [42] and power engineering [43]. Jayasree *et al.* [44] employed automated classification of power quality disturbances using HHT and RBF neural networks. Nilanjan Senroy *et al.* [45] presented an innovative algorithm of improved Hilbert Huang method based on masking signals for power quality applications. The rationale for the improvements is that the original EMD method is unable to separate frequency modes lying within one octave. The proposed method is shown to efficiently separate modes existing in distorted signals typically encountered in power quality applications. Elango *et al.* [46] presented performance comparisons of Back Propagation Algorithm (BPA) network and Radial Basis Function (RBF) network for power quality disturbance classification. Features are extracted from the electrical signals by using Hilbert Huang Transform.

V. Artificial Intelligence Based Classification Methods

Both conventional and artificial intelligence (AI) based classification methods are reported in literature. Artificial intelligence (AI) may be broadly defined as the automation of activities that are associated with human thinking, such as decision-making, problem-solving, learning, perception, and reasoning [47] for the resolution of complex problems. In the classification of electrical disturbances, all of the factors that make AI a powerful tool are present. We get information which is massive electrical signals are constantly being received and distorted; there is an important noise component so that a classification of the disturbances must be carried out [48]. The main intelligent tools for PQ classification include expert systems, fuzzy logic, and artificial neural networks.

V.1 Neural Network Based Classification

Neural network is a nonlinear, data driven self adaptive method and is a promising tool for classification, and have been successfully applied to a variety of real world classification tasks in industry, business and science [49]. Applications include classification of power quality disturbances [50]. 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). 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. Artificial Neural Network (ANN) is a universal function approximator i.e. this can approximate any function with arbitrary accuracy. All the above mentioned attributes make ANN flexible in modeling real world complex problems [51]

The probabilistic Neural Network (PNN) is a supervised neural network that is widely used in the area of pattern recognition. The fact that PPNs offer a way to interpret the network's structure in terms of probability density functions (PDF) is an important merit of this type of networks in the learning processes [52]. The standard training procedure for PNNs requires a single pass over all to the patterns of the training set. This characteristic renders PNNs faster to train suitable for classification of power system faults. The architecture of PNN is composed radial basis layer and competitive layer. The PNN is a supervised neural network that is used for classification [53].

Santoso *et al.* [54] have classified six types of PQ events using wavelets and multiple neural networks. The classifier uses wavelet transform coefficient at five-scale signal decomposition level as input to multiple neural. The squared wavelet transform coefficients (SWTC) at each scale are used as inputs to the multiple neural networks for classifying the disturbances type. The architecture of the network is learning vector quantization (LVQ). The final decision for the disturbances type is made by combining the outcomes of multiple neural networks by using two decision making schemes. One is simple voting scheme and the other is Dempster-Shafer theory of evidence. Murat Uyar *et al.* [55] proposed an ST-based neural network classification process for the automatic classification of PQ disturbances. It performs a feature extraction and a classification algorithm composed of feature extractor based on time-frequency statistical features of the ST and a NN classifier based on multilayer perceptron (MLP) with RPROP learning algorithm. The algorithm is capable in classifying the distorted PQ signals accurately even under different noise conditions. Mishra *et al.* [53] proposed an S-transform based probabilistic neural network (PNN) classifier for classification of 11 types PQ disturbances with only four extracted features. Integrating S-transform with PNN can effectively detect and classify PQ disturbances even under noisy condition. Comparison of PNN with other two well known neural networks i.e., feed forward multilayer back propagation (FFML-BP) and learning vector quantization (LVQ) shows that PNN classifies events more effectively than FFML and LVQ.

V.2 Support Vector Machine Based Classification

Support Vector Machine (SVM) can be treated as a special neural network. In fact, a SVM model is equivalent to a two-layer, perceptron neural network. With using a kernel function, SVM is an alternative training method for multi-layer perceptron classifiers in which the weights of the network are identified by solving a quadratic programming problem under linear constraints, rather than by solving a non-convex unconstrained minimization as in standard neural network training [56]. SVMs are based on minimization of the misclassification probability of unseen patterns with an unknown probability distribution of data and have solid theoretical foundation rooted in statistical learning theory. Real world problems often require hypothesis spaces that are more complex than those using linear discriminants. SVMs are able to find non-linear boundaries if classes are linearly non-separable. The main issue of interest in using SVM for classification is its generalization performance. SVM performs better than neural networks in terms of generalization [57].

Axelberg *et al.* [58] proposed SVM based algorithm for classification of common types of voltage sag disturbances. The results have shown high classification accuracy which implies that, the SVM classification technique is an attractive choice for classification of voltage sag and other PQ disturbances. It has also been found that the accuracy of the proposed method is also dependent on the features given to the classifier. Whei-Min Lin *et al.* [59] presented an integrated model for recognizing power quality disturbances using a novel wavelet multiclass support vector machine (WMSVM). Disturbance Events Detection System (DEDS) with WMSVMs was developed. WMSVMs were designed with simple network architecture to shorten the processing time. The proposed architecture could effectively detect information from distorted waves using WT and MSVM techniques. Valdomiro *et al.* [60] proposed a PQ disturbance detection and identification technique which combines advantages of disturbances identification strategy based on DWT, with the advantages of the ANNs and SVM to classify information automatically was implemented. Once the disturbance is detected, it is possible to locate it from the detail sequence at first decomposition level. Karthikeyan *et al.* [61] presented a wavelet transform and support vector machine based algorithm for classification of power quality disturbances. The features extracted through the wavelet transform are trained by a SVM for classification of power quality disturbances. Five types of disturbances are considered for the classification problem. The proposed approach using wavelet transform and support vector machine produces over all classification rate of 98.8%.

V.3 Rule-based Expert Systems Classification

Expert systems were proposed to identify, classify and diagnose power-system events successfully for a limited number of events [54]. An expert system for classification and analysis of voltage dips using Kalman filter for estimation of the amplitude has been shown in [62]. Rule-based expert systems are highly dependent on "if…then" clauses. To formulate a rule-based system for PQ disturbance classification, a knowledge base is composed using a set of rules in the form of expertise knowledge from a detailed analysis of the extracted features [63].

Chung *et al.* [64] presented a rule –based method used to classify time-characterized disturbances, and then, a wavelet method has been utilized to obtain a more flexible time frequency information. A hidden Markov model has also been adopted to determine the disturbance existence. Alex Wenda *et al.* [63] proposed a new approach for the automatic detection and classification of power quality disturbances through the Internet by combining the S-transform, a rule based expert system and a MATLAB web server. The S-transform is used to obtain the time frequency characteristics of power quality events under noisy conditions, and a set of features is extracted for pattern classification of power quality disturbances. A rule-based expert system is also developed in which the system classifies various power quality disturbances. Finally, a MATLAB web server is used to integrate the graphical and computational process with remote access through the internet.

V.4 Fuzzy Expert System Based Classification

It is usually appropriate to use fuzzy logic when a mathematical model of a process doesn't exist or does exist but is too difficult to encode and too complex to be evaluated fast enough for real time operation. The accuracy of the fuzzy logic systems is based on the knowledge of human experts; hence, it is only as good as the validity of the rules. As the power system data is highly uncertain and the power disturbance monitoring is a pattern classification problem [65].

Ortiz *et al.* [66] have proposed a fuzzy expert system for detection and classification of voltage sags. Abdelsalam *et al.* [67] proposed a new algorithm for power system disturbance classification. It is a two stage system that employs the great potentials of the discrete wavelet transform, Kalman filter and a fuzzy-expert system. For the first stage, the captured voltage waveform is passed through the DWT to determine the noise inside it. The covariance of this noise is then calculated and fed together with the captured voltage waveform to the Kalman filter to provide the amplitude and the slope of this waveform. These are considered as an input to the fuzzy-expert system in the second stage to determine the class to which the waveform belongs. Dash *et al.* [68] proposed a hybrid scheme using Fourier linear combiner and fuzzy expert system. The captured waveforms have been passed through a Fourier linear combiner block to extract amplitude and phase of the fundamental signal. The proposed method was found to be accurate and robust in presence of noise. It is computationally simple and gives classification result in less than a cycle.

V.5 Genetic Algorithm Based Classification

Genetic Algorithm (GA) is a probabilistic search method inspired by the biological evolution process [69]. The principle of GA is the survival of the fittest solutions among a population of potential solutions for a given problem. Thus, new generations produced by the surviving solutions are expected to provide better approximations to the optimum solution. The solutions correspond to chromosomes that are encoded with an appropriate alphabet. The fitness value of each chromosome is determined by a fitness function. New generations are obtained using genetic operators, crossover and mutation, with certain probabilities on the fittest members of the population. Initial population can be randomly or manually defined. Population size, number of generations, probability of crossover and mutation are defined empirically. The fitness value corresponding to a chromosome is usually defined as the classification accuracy obtained with the selected features [70].

Upender *et al.* [71] proposed a technique consisting of a preprocessing unit based on discrete wavelet transform in combination with genetic algorithm for classifying the power system fault disturbances. The DWT acts as extractor of distinctive features in the input current signals, which are collected at source end. The information is then fed into GA for classifying the faults. Brahmadesam *et al.* [72] proposed an efficient Genetic-Wrapper Algorithm based data mining for feature subset selection in a power quality pattern recognition application. The wrapper based approach integrates multi-objective genetic algorithms and the target learning algorithm in order to evolve optimal subsets of discriminatory features for pattern classification. The wavelet transform and the S-transform are utilized to produce representative feature vectors that can accurately capture the unique and salient characteristics of each disturbance.

V.6 Adaptive Neuro-Fuzzy System Based Classification

Adaptive Neuro-fuzzy system (ANFS) is a hybrid system incorporating the learning abilities of ANN and excellent knowledge representation and inference capabilities of fuzzy logic that have the ability to self modify their membership function to achieve a desired performance. An adaptive network, which subsumes almost all kinds of neural network paradigms, can be adopted to interpret the fuzzy inference system. ANFS utilizes the hybrid-learning rule and manage complex decision making or diagnosis systems. ANFS has proven to be an effective tool for tuning the membership functions of fuzzy inference systems [73].

An adaptive neuro fuzzy system to learn power quality signature waveform is proposed in [74]. The adaptive fuzzy systems are very successful in learning power quality waveform. The new adaptive neuro-fuzzy tool will enhance the performance of the existing power quality service. Chandra Sekhar *et al.* [75] proposed a hybrid approach of neuro-fuzzy based learning and classification approach based on the online learning systems. The effect of fault diagnosis for the suggested fault location tool is evaluated over the conventional fault diagnosis based approaches.

VI. Conclusion

The problem of power quality has been discussed in this paper. This paper is a survey of work published on power quality disturbances and techniques for detection and classification of electrical power disturbance. The transformed feature extraction techniques and artificial intelligence techniques of PQ events classification are highlighted in particular. These methods are suitable for large and complex networks. This paper provides a general literature survey useful for the research on power quality disturbances in electrical power system.

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