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Automatic Classification of Power Quality Disturbances: A Review

S.Khokhar, A.A.Mohd Zin, A.S.Mokhtar, N.A.Maiza Ismail, N.Zareen
Faculty of Electrical Engineering
University Technology Malaysia
Johor Baharu Malaysia

***Abstract*---The development of intelligent power quality (PQ) disturbances classification and analysis tools exploited various digital signal-processing techniques to extract important features from the PQ signals. The purpose of this paper is to present a comprehensive review and discussion of the advanced tools for the automatic classification of PQ disturbances. The digital signal-processing tools applied for feature extraction include Fourier-transform, Wavelet-transform, Stockwell-transform etc. For the classification of PQ disturbances, the artificial intelligence techniques such as artificial neural networks, fuzzy logic and support vector machine are reviewed here. A large number of features used as inputs to the classifiers may affect the accuracy rate and requires a large memory space. The optimization techniques have been used in literature for optimal feature selection, which include genetic algorithm, simulated annealing, particle swarm optimization and ant colony optimization. An extensive review provides to the researchers a clear perspective on various techniques of PQ disturbances classification.**

Index Terms*—*Power QualityD isturbances;Fe atureEx traction; Digital Signal Processing;A rtificial Intelligence;o ptimization techniques

I. INTRODUCTION

POWER QUALITY disturbances analysis becomes an exponentially increasing field of interest, particularly in the past few decades [1-5]. The PQ analysis associates power engineering and power electronics with digital signal-processing, artificial intelligence and optimization techniques [6]. The economic aspect is the ultimate reason for keen interest in PQ analysis. The PQ issues are rapidly increasing due to sources of disturbances that occur in interconnected power systems, high-voltage transmission lines, transformers, non-linear power electronic load, utilities and consumers' equipment. In order to resolve equipment disruptions, a database of equipment tolerances and sensitivity can be built from monitored data to develop equipment compatibility specifications and guidelines for future equipment enhancements. To overcome the detrimental effects of poor quality, sources and causes of disturbances should be specified before initiating any mitigation action. Therefore continuous monitoring, recognition and classification is required for these disturbances due to increasing demand of pure power as suggested in [7, 8].

Conventionally PQ monitoring has been carried out through visual inspection by the utilities, which is in fact a difficult and time-consuming process. The state-of-art techniques and methodologies of digital signal-processing and artificial intelligence (AI) techniques focused on the diagnosis of PQ have taken great interest in research owing to the sensitivity of modern equipment and made it suitable to create more intelligent automatic classification techniques [9-11]. The automatic classification of PQ disturbances involves four stages, namely, data generation, feature extraction, feature selection and classification as shown in Fig. 1. In each stage, different techniques and methodologies are used for automatic classification. The input stage is a preprocessing stage where PQ disturbances can be generated. In the next stage one of the signal processing techniques can be applied for feature extraction. The feature selection stage can be used to select best suitable features among all features by using an optimization technique. In the last stage, artificial intelligence technique is used for decision-making. In literature, various signal processing and artificial intelligent techniques have been proposed and implemented for the continuous monitoring and recognition of PQ disturbances. The Fourier transform (FT), commonly used in practice, provides information only about the existence of a certain frequency component but can not inform about the time at which this component appears [12]. To extract such information, short-time Fourier transform (STFT) and wavelet transform (WT) have been used for detection and classification. Many electrical power researchers have extensive interest in the field of AI techniques. The AI tools used for decision making in electric PQ classification include expert systems (ES), artificial neural network (ANN), support vector machine (SVM) and Fuzzy logic (FL).

In this paper, a comprehensive review on the applications of digital signal processing techniques, artificial intelligence techniques and optimization techniques used in the classification of PQ disturbances has been presented. In section II the PQ disturbances phenomena are discussed. Section III describes the most commonly used signal processing techniques for feature extraction. Artificial intelligence and optimization techniques are described in section IV and V respectively. A brief discussion about all techniques applied simultaneously is given in section VI. Finally, in section VII conclusion and future scope of work are discussed.

II. POWER QUALITY DISTURBANCES

A PQ disturbance is any problem manifested in voltage, current, and/or frequency deviations that results in failure or

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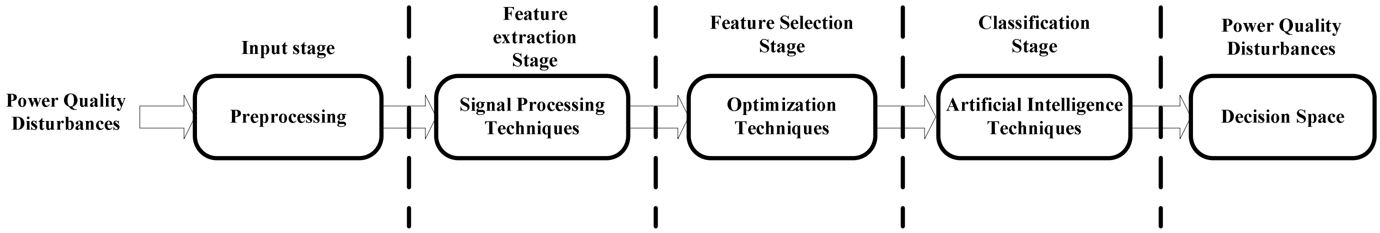

Fig. 1. Various stages of power quality disturbances classification

misoperation of customer equipment"[13]. In literature, PQ studies are carried out into two different aspects. First aspect deals with the classification of PQ disturbances using automatic recognition techniques and the second aspect is the classification of PQ events, which cause these disturbances [14]. The PQ events can be divided into two main categories: fault events and switching events. The fault events in a three-phase system create PQ disturbances like sag or interruption in a faulty phase and swell in non-fault phase. The switching events cause transients and harmonics types of PQ disturbances. Fig. 2 shows a tree diagram for various types of PQ disturbances. The variations in voltage magnitude cause sag, swell and interruption types of PQ disturbances. The transient disturbances are sudden and non-stationary short duration events such as impulsive and oscillatory transients. The periodic waveform distortion can be categorized as harmonics.

III. SIGNAL PROCESSING TECHNIQUES

Feature extraction in automatic classification has a major role because each disturbance has unique features than the others. The proper feature extraction technique from a given disturbance is therefore the basic task to classify the PQ disturbances accordingly. In literature, various digital signal processing techniques are presented for feature extraction such as discrete Fourier transform (DFT) [15], the short-time Fourier transform [16, 17], the wavelet transform [18-36], the Stockwell transform (ST) [37-49], the Gabor transform (GT) [50], the Winger distribution function (WDF) [51] and hybrid of these techniques.

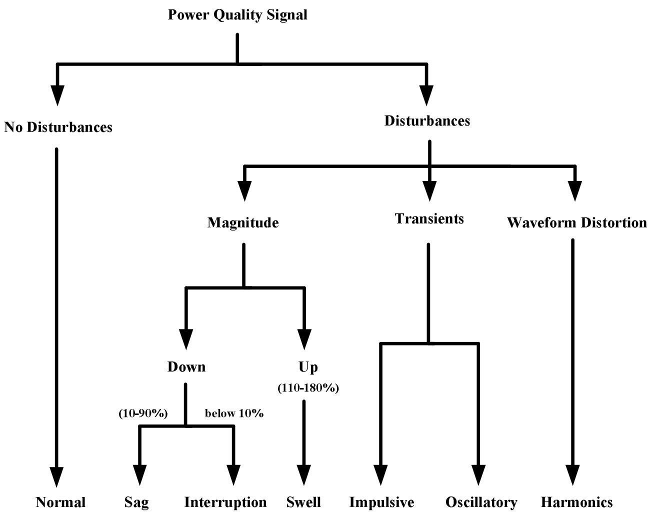

Fig. 2. Tree diagram of PQ disturbances showing various types of PQ disturbances

The Fourier transform is most commonly used signal processing techniques in practice to analyze the recorded stationary periodic signals. It decomposes a PQ signal into a sum of sinusoidal terms with different magnitude, phase shift and frequency, and then identifies their spectral contents present in the signal. However, most of the PQ disturbances are non-stationary and transient in nature. Their frequency components change with time such as voltage sags, voltage swells and harmonics have varying time and frequency characteristics. The classical FT usually used for PQ analysis is not suitable for non-stationary or transient PQ signals because it provides information only about the frequency component but does not provide any information regarding the temporal or time localization behavior of these components.

The STFT has overcome the drawback of time-frequency resolution and can be implemented to non-stationary PQ signals. The STFT operates in a fixed window size and focuses on a certain period of time, which can locate the magnitude variations to some extent. In [16] a comparison was made between STFT and WT for harmonics related voltage disturbances. The STFT found more suitable than WT because the band-pass filter outputs from STFT are well associated with harmonics. The extraction of a fundamental or any single harmonic component is very difficult by using WT [17]. Even the STFT has a fixed frequency resolution for all frequencies, once the size of the window is selected, it provides easier interpretation in terms of harmonics [17]. The fixed width of the window function does not provide a good time-frequency resolution. The information of the non-stationary signal is usually lost. Thus, the STFT is not suitable for the transients PQ signals with rapid changes.

The WT overcomes the problem of time-frequency resolution to some extent by using an alternative time-frequency analysis approach known as multiresolution analysis (MRA). In MRA, the PQ signal can be analyzed at different resolutions of certain frequencies. The signal is decomposed into various frequency components where each component is analyzed with a resolution matched to its scale. The disturbed signal is detected and decomposed across the time-plane and frequency-plane simultaneously. The decomposition is made across the multiple frequency bands rather than a discrete number of frequency components as in FT [23].

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The researchers in the field of PQ analysis are extensively interested in the WT for characterization and classification of PQ disturbances. The detection of the PQ shortfalls and the classification of different kinds of disturbances prove the feasibility of the WT in the area of PQ studies [24]. The authors in [25, 26], proposed the applications of WT for the analysis of electromagnetic power system transients associated with faults and switching. The multiresolution property of wavelets in time and frequency domains facilitates the detection of physically relevant features in transient signals to recognize the source of the transient [25]. The WT [11, 27] has been applied for the compression of PQ data where corresponding WT coefficients (WTC) were kept for classification while others were discarded. In [28] the spline WT (SWT) was proposed for PQ data compression. The only SWT may not provide a satisfactory result for high compression of signals [29]. Therefore, in [29] authors proposed a hybrid compression technique using the spline WT (SWT) and radial basis function neural network for PQ data compression. The WT is usually degraded due to unsatisfactory performance of PQ transient signals under noisy environment. A de-noising approach [30] has been proposed to detect PQ transient disturbances in the presence of noise. In [31], authors proposed DWT for the analysis of harmonics in power systems. In [32, 33], authors suggested a combined classifier consisting of a rule-based and wavelet-packet based hidden Markov model (WP-HMM) methods for the automatic classification of PQ disturbances. The rule-based method was used for the classification of time-characterized feature disturbances and the WP-HMM for the frequency characterized feature disturbances. In [34, 35] authors proposed WT based neural classifier; which was carried out in the wavelet domain with a set of multiple neural networks. In [36], authors proposed WT for feature extraction and k-means based a priori algorithm for feature selection as input to the SVM for the recognition of three phase event type PQ disturbances.

A recent digital signal-processing method known as wavelet neural network (WNN), which combines the properties of the WT with the advantages of ANN, has been proposed for approximating arbitrary nonlinear functions [52-56]. In [56] authors proposed WNN for the recognition of PQ disturbances. The WNNs have better performances for classification of combined PQ disturbances than the traditional neural networks because of proper selection of feature vectors [56]. In [54], researchers suggested an adaptive wavelet networks (AWNs) model of synthetic PQ disturbance detection and classification.

S-transform [37], an effective signal processing technique, is defined as the "phase correction" of the continuous WT (CWT) with a particular mother wavelet multiplied by the phase factor. In [39, 40], authors proposed a multiresolution S-transform to produce optimal feature vectors for a Fuzzy classifier system in the classification of PQ disturbances. The multiresolution property of S-transform can be considered either as a phase-corrected version of the CWT or a variable window STFT that localizes both real and imaginary spectra of the signal at the same time. In [41], authors presented a hybrid approach of S-transform and extended Kalman filter (EKF) for short duration PQ disturbances in electrical power networks. In [42] authors suggested the S-transform with SVM multi-class classifier for PQ disturbances recognition. In [43] authors proposed S-transform based fuzzy expert system for the identification and classification of PQ disturbances. The proposed method found suitable for recognition and classification of PQ disturbances due to high identification rate and strong noise rejection. The authors in [44, 45], suggested S-transform based probabilistic neural network (PNN) for the classification of PQ disturbances. The methodology requires less number of features of the signals largely without losing its original property, low memory space and less learning time for the classification. In [46], authors proposed S-transform based artificial neural network with multilayer perceptron for the classification of PQ disturbances. For feature extraction, the standard statistical techniques were applied to the plots of the S-transform amplitude (STA) matrix as well as directly on the STA matrix contours. In [47] authors proposed S-transform and logistic model tree for the identification of PQ events. The proposed algorithm requires fewer features, reduced memory space and less learning time. In [48] authors proposed S-transform based HMM for PQ disturbances classification. The HMM is an efficient and powerful signal processing method which computes the maximum possible probability between training and testing data signals for identification and classification. Recently in [49] authors proposed a new approach for PQ disturbances analysis using an orthogonal time-frequency representation of S-transform known as discrete orthogonal S-transform (DOST) which shows the superiority over other signal processing transforms in a more efficient way to analyse PQ disturbances. The S-transform has good time resolution for PQ disturbances localization but is not suitable for higher order harmonic signals analysis.

IV. Artificial Intelligence techniques

The artificial intelligence techniques employed in automatic classification of PQ disturbances use the extracted features as inputs. The most commonly used AI techniques such as ANN, FL and SVM in combination with signal processing techniques have been used for decision-making and classification of PQ disturbances.

The artificial neural network consists of very simple elements, inspired by biological nervous systems, operating in parallel. Authors in [34] presented a theoretical basis of wavelet-based neural classifier for the PQ disturbances classification which consists of WT for detection and feature extraction, learning vector quantization (LVQ) to learn and generalize the features and decision making scheme and in [35] presented its practical implementation. In [57], researchers introduced Adaline technique, a smallest and linear building block of the ANN, for the PQ events detection. Its simplicity due to easier calculations enables suitable for

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practical implementation. In [58] authors proposed multi-wavelet based neural classifier for the automatic classification of transient PQ disturbances. In [59], authors proposed independent component analysis (ICA) method to decouple the multiple PQ disturbances and applied to ANN for the classification of the individual PQ disturbances. In [44], authors presented S-transform based PNN classifier for the PQ disturbances analysis. The classification performance of PNN is much better than feedforward and learning vector quantization neural networks. In [20] authors proposed WT based MRA applied to an actual power system with ANN classifier through graphical user interface (GUI). In [60] authors proposed the backpropagation ANN based on the combination of wavelet energy entropy (WEE) and wavelet energy weight (WEW) features for the classification of power system transient disturbances.

In [61] authors proposed a Fourier linear combiner and a fuzzy expert system for the classification of PQ disturbances signals. The approach is computationally simple and fairly accurate. In [39] authors proposed S transform based fuzzy logic approach for the classification of PQ disturbances in the presence of various noise levels. The classifier used 14 rules based on trapezoidal membership function for most of the signals. In [62] authors proposed WT and FT based fuzzy expert and ANN for detection and classification of PQ disturbances. The proposed technique showed that the fuzzy expert system is most suitable for the PQ disturbances analysis. In [63], authors proposed a WT and linguistic rule approach based on extended fuzzy reasoning for the classification of PQ signals. In [64] authors proposed S-transform and rule-based decision tree for the classification of PQ disturbances. In [65] authors proposed the concept of linear Kalman filter together with DWT to extract the features for the inputs to the fuzzy expert systems. The captured signal was passed through DWT to recognize its noise; the covariance of the noise with captured signal was fed to the Kalman filter to increase its rate of convergence. The outputs of the Kalman filter were passed through a fuzzy expert system.

The SVM is recently applied powerful tool for the data classification and regression problems. The combination of two SVM classes produces a multiclass SVM classifier. Thus, for the classification of test data, pair wise competition is performed among all the machines. In [66] authors proposed DWT based SVM for the classification of power system disturbances. In [14] authors proposed application of DWT based SVM on actual PQ disturbances in a three phase system.

V. Optimization Techniques

Most of the classifiers have a problem of selection of the parameters for the classification of PQ disturbances. The selection of the parameters is usually done empirically, which results poor classification accuracies. The optimization techniques such as genetic algorithm (GA) [67, 68], particle swarm optimization (PSO) [69], ant colony optimization (ACO) [70] have been used to select appropriate features for improving classification efficiency.

Table 1. Comprehensive analysis of all techniques used simultaneously

reference	features extractor	classifier	optimizer	accuracy
[72]	FT, WT	Fuzzy logic	PSO	98%
[67]	WPT	FkNN	GA	96.33%
[68]	WPT	SVM	GA,SA	98.33%
[69]	ST	ANN	FIPS	98.1%
[70]	TTT	FCA	HACO	95.86%

The GA is one of the search techniques that is based on the natural selection and used for nonlinear optimization problems. In PQ studies, the GA [67] is used to improve the classification accuracy and find the best feature set for the inputs to the classifiers. In [68] authors proposed GA for the selection of the best features from WPT. A PNN-based feature selection [69, 71] was proposed by adding fully informed particle swarm (FIPS) with an adaptive probabilistic neural network (APNN). The proposed technique was applied to optimize the smoothing parameters of APNN by gradually discarding less effective features to enhance the accuracy of the predictions derived from the classification model. A fuzzy C-means clustering algorithm (FCA) with hybrid ant colony optimization (HACO) and variant of S-transform known as time-time transform (TTT) [70] proposed for PQ disturbances classification. In [72], PSO is used with fuzzy logic to accurately determine the membership function parameters for the fuzzy system. In [73] authors proposed S-transform based fuzzy expert system using a data mining principle. The parameters of Gaussian and trapezoidal member functions of the concerned fuzzy sets were optimized using a fuzzy PSO technique.

VI. Discussion

The feature extraction has a great importance in automatic classification of PQ disturbances. It is important to know that, what types of feature extraction techniques are useful for the classification. This requires a comprehensive review of the techniques and methodologies used for the automatic classification of PQ disturbances. Hooshmand et al. [72] proposed PSO to accurately determine the membership function for the Fuzzy systems. Panigrahi and Pandi [67] proposed wavelet packet transform (WPT) and Fuzzy k-nearest neighbor (FkNN). The genetic algorithm (GA) used to select 16 best features form all 96 features of WPT coefficients.

VII. Conclusion

The paper presents a detailed survey on the techniques used for automatic classification of PQ disturbances. The methods used by various researchers for distinctive feature extraction for the PQ signals are FT, WT, ST, GT and rarely combination of two of them. The various optimization techniques like GA, PSO and ACO used for proper feature selection to reduce the size of features. The AI techniques used for the PQ disturbances classification include ANN, FL

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and SVM. The survey shows that a lot of work has been done on synthetic data of PQ signals, only few researchers focused on real-time PQ analysis. Therefore, there is a need of future work in PQ analysis by considering real-time disturbances signals.

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