International Journal of System Signal Control and Engineering Application 1 (1): 74-88, 2008
ISSN: 1997-5422

Power Quality Monitoring and Analysis: An Overview and Key Issues

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Abstract: Power quality (PQ) issue is rising due to more penetration of power electronics derives used for improvement in the efficiency, control etc. The ongoing regulatory policy and structural changes in the electricity industry all over the world have also contributed toward major concern of PQ, making it a figure-of-merit amongst the competing distribution utilities. In this stduy, a comprehensive overview of different PQ problems, their cause, effects and suitable existing remedies has been presented. Various standards evolved to define and characterize different PQ problems as well as voltage acceptability curves proposed to quantify PQ are critically reviewed. Need objective or requirement and challenges of intelligent monitoring system using advanced signal processing and artificial intelligence tools for detection and classification of PQ disturbances have also been critically examined in this stduy. Advanced and powerful tools for the analysis, operation and control of power systems, as well as for PQ diagnosis are currently available. A comparative study has been carried out on the applicability of the state of the art techniques for assessment and analysis of PQ, which include both nonparametric decomposition based and model based techniques. Major Key issues and challenges in analyzing PQ are also outlined.

Key words: AI, adaptive filtering, denoising, model based methods orthogonal polynomial approximation, power quality, support vector machine time-frequency analysis, wavelet transform

INTRODUCTION

Both the utilities and end users of electric power are becoming increasingly concerned about the quality of power and the interest in power quality (PQ) started from incompatibility issues between equipment and power supply. Restructurings and distributed generation are 2 important reasons for the recent interest in power quality (Arrillaga *et al*., 2000; Roger *et al*., 2003; Martzloff and Gruzs, 1988). Other important reasons are the increased penetration of power electronics based equipment and the increased susceptibility of these equipments, production processes and manufacturing industry to the voltage disturbances. PQ problems encompass a wide range of different phenomenon of broad frequency range, significantly different magnitude variations and can be stationary or non-stationary (Bollen, 2000). These range from the very low magnitude low frequency (0.1% and less than 25 Hz) voltage fluctuation due to arc furnaces types of intermittent loads to a very high frequency transients (0-8.0 pu, 5 MHz) caused by lightning strikes, switching and other phenomena. Therefore, their identification is often difficult, if noise is riding on the signal (Yang and Liao, 2001; Dwivedi and Singh, 2006). The conventional methods currently used by utilities for power quality monitoring are primarily based on visual inspection of voltage and current waveforms. Highly automated monitoring software and hardware are needed in order to provide adequate coverage of the entire system, to understand the causes of these disturbances, to resolve existing problems and to predict future problems (Mark and Santoso, 2007; Bollen and Gu, 2006). Several research institutions and companies are conducting PQ research and development. Software and hardware products, such as PQSoft by Electrotek Concepts and PQNode by Dranetz-BMI have demonstrated benefits of the PQ monitoring methodology to utility companies.

Power quality analysis is based on large data gathered from the real system. The large amounts of data pose several practical problems in the storage and communication from local monitors to the central processing computers. PQ problems must be mitigated properly with help of available devices. The key steps,

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essential for assuring immunity against or reduction in the degree of severity of power quality problems in an installation, are as follows:

- Continuous and extensive monitoring of different power system quantities.
- Detection and identification of power quality related disturbances and categorizing them.
- Tracing back the identified problems to their probable causes.
- Rectification of the probable causes either automatically and/or manually.

A feasible approach to achieve this goal is to incorporate detection capabilities into monitoring equipment so that events of interest can be recognized, captured and classified automatically. Although, the fundamental signal processing techniques used in practical power quality monitoring have been based on discrete Fourier transform (DFT) and the rms, many more have been proposed in the literature. The traditional method is based on root-mean-square (rms) measurements and constrained by its accuracy (Bollen and Gu, 2006). Fourier transform (FT) has been used as an analyzing tool for extracting the frequency contents of the recorded signals. According to the frequency contents of the signals, some of the PQ problems can be detected. Approaches for automated detection and classification of PQ disturbances proposed recently are based on STFT, wavelet analysis, orthogonal polynomial approximation, artificial neural networks, hidden Markov models and bispectra (Gaouda *et al*., 1999; Huang *et al*., 2000). These techniques have been successfully employed in other pattern recognition and signal processing applications, such as speech recognition, audio processing, communications and radar and sonar applications. While, PQ waveform and speech recognition processes are very similar in nature. Recent development in the speech processing area has shown the potential of designing more accurate and more intelligent PQ monitoring algorithms, with advanced signal processing techniques (Bollen and Gu, 2006). The potential improvement on monitoring capability implies significant economic values to the utilities and PQ-sensitive energy customers.

Both the economics and the technical limitations must be considered before reaching at solutions. Also, the solutions need to be evaluated using system perspective i.e., possible solutions should be identified at all levels of system from utility supply to the end user's equipment being affected. The optimal solution is obtained from the available solutions and will depend on many factors like the type of PQ problem, the number of end users being impacted and of course the economics factor. There are discussions among utilities on offering PQ services under an insurance plane, where customers will pay premiums for defined level of services and the utility pays customer directly for events (disturbances) exceeding the terms of that service. The critical advantage of the insurance approach is that it allows customers to self-select an appropriate quality level power to match its requirements.

A brief review of signal processing techniques applicable to PQ monitoring is critically discussed in this study. The challenging issues related to these advanced techniques in automatic detection and analyses of PQ problems are highlighted. This stduy will also present the recent developments along with the conventional in more detail. Many signal processing methods can be applied for such purpose and as it is discussed later a signal processing could be very suitable for 1 application but not very suitable for another application.

PQ CHARACTERIZATION STANDARDS AND ACCEPTABILITY CURVES

The ultimate reason for the interest in power quality (PQ) is the economic value (Arrillaga *et al*., 2000; Keulenaer, 2003). The power quality analysis was, first, started at the end of 19th century as transformers and rotating machinery were found to be the main sources of the waveform distortion (Acha and Madrigal, 2001). The oldest mentioning of the term power quality known to the author was in a stduy published in 1968 (Kajihara, 1968). After that, many publications like (Konstantinov and Bagiev, 1990) appeared on this topic and parallel to that the term voltage quality with reference to slow variations in the voltage magnitude was used. Table 1 shows the IEC standards as well in IEEE standards that are referred for various power quality studies. PQ (M.H.J., 2003; Stones and Collinson, 2004) can be defined completely in the different ways. A utility may define it as reliability and shows that its power supply is 99.98% reliable whereas manufacturer's definition may be based on proper functioning of their equipments. But PQ is a consumer's driven issue and hence can be best defined as:

> 'Any power problem manifested in voltage, current and/or frequency deviations that result in the failure and/or mal-operation of end user's equipment'.

In others words, the best measure of power quality is the ability of electrical equipment to operate in a satisfactory manner, given proper care and maintenance and without adversely affecting the operation of other

Table 1: Power quality standards

Classification of PQ	IEC 61000-2-5: 1995; IEC 61000-2-1: 1990; IEEE 1159: 1995
Transients	IEC 61000-2-1: 1990; IEEE C62:41: 1991; IEEE 1159: 1995; IEC 816: 1984
Voltage sag/swell and interruptions	IEC 61009-2-1: 1990; IEEE 519: 1992
Harmonics	IEC 61000-2-1: 1990; IEEE 519: 1992
Voltage flicker	IEC 61000-4-15: 1997

Table 2: Classification of various power quality problems

S.No.	Categories	Duration	Voltage magnitude
I	Short duration variation		
A	Sag		
	Instantaneous	0.5-30 cycle.	0.1-0.9 pu.
	Momentary	30 cycles-3 sec.	0.1-0.9 pu.
	Temporary	3sec-1min.	0.1-0.9 pu.
B	Swell		
	Instantaneous	0.5-30 cycle.	1.1-1.8 pu.
	Momentary	30 cycles-3 sec.	1.1-1.4 pu.
	Temporary	3sec-1min.	1.1-1.2 pu.
C	Interruption		
	Momentary	0.5cycles-3sec.	<0.1 pu.
	Temporary	3sec-1min.	<0.1 pu.
II	Long Duration Variation		
A	Interruption	>1min	0.0 pu.
B	Under-voltage	>1min	0.8-0.9 pu.
C	Overvoltage	>1min	1.1-1.2 pu.
III	Transients		
A	Impulsive		
	Nanosecond	<50nsec.	0-4 pu.
	Microsecond	50-1msec.	0-8 pu.
	Millisecond	>1msec.	0-4 pu.
B	Oscillatory		
	Low frequency	0.3-50msec.	
	Medium freq.	20 µsec.	
	High freq.	5 µsec.	
IV	Voltage Imbalance	Steady state	0.5-2%
V	Waveform Distortion		
A	DC offset	Steady state	0-0.1%
B	Harmonics	Steady state	0-20%
C	Interharmonics	Steady state	0-2%
D	Notching	Steady state	
E	Noise	Steady state	0.1%

electrical equipment connected to the system. Following are some of the main reasons for the increased interest in PQ:

- Newer generation load equipment having microprocessor/microcontroller-based controls and power electronics devices. Proliferation of large computer systems into many businesses and commercial facilities.
- Increase in growth of application devices such as high-efficiency, adjustable speed motor drives and shunt capacitors.
- The complex interconnection of systems, resulting in more severe consequences if any 1 component fails.
- Equipment manufacturers striving for better performance equipments which result in increase in PQ disturbances.
- The development of much sophisticated power electronics equipment used for improving system stability, operation and efficiency.
- The complexity of industrial processes, which results in huge economic losses if equipment fails or malfunctions.
- There has been a significant increase in embedded generation and renewable sources of energy which create new power quality problems, such as voltage variations, flicker and waveform distortions.
- Deregulation of power industry, which gives customers the right to demand high quality of supply. There are some indications that information about the PQ itself will become a valuable commodity after deregulation subject to negotiations, pricing, ownership etc (Arrillaga *et al*., 2000).

The points mentioned above are the main driving factors for the increased interest in PQ and justify the increase in the volume of PQ literature. PQ problems fall into 2 basic categories:

Events or disturbances: 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.

Steady-state variations: 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 3 phases. These include normal rms voltage variations and harmonic and distortion.

These variations must be measured by sampling the voltage and/or current over time. These disturbances can further be classified according to the nature of the waveform distortion. Table 2 provides information regarding typical spectral content, duration and magnitude for each category of electromagnetic disturbances. The phenomena listed in the Table 2 can be described further by listing appropriate attributes. For steady-state disturbances, the amplitude, frequency, spectrum, modulation, source impedance, notch depth and notch area attributes can be used (Bollen and Gu, 2006). For non steady state disturbances, other some attributes such as rate of rise, rate of occurrence and energy potential are required.

QUANTIFICATION OF PQ DISTURBANCES

For quantifying the power quality distortions, power acceptability curves are used. The power acceptability curves are used to determine whether the supply voltage to a load is acceptable for the maintenance of a load process. These curves are plots of bus voltage deviation versus time duration and separate the bus voltage deviation vs. time duration plane into acceptable and unacceptable regions. Various existing power acceptability curves are listed in Table 3 and 2 most widely publicized curves have been shown and discussed in the following subsection. From economic point a view, many severe consequences of poor PQ were faced by the silicon chips and computer business equipment manufacturing industries. It is found that 1 cycle interruption makes a silicon device worthless and 5 min shut down of a chip fabrication plant causes delay from a day to a week. One second of power outage makes e-commerce sites lose millions of dollars worth of business. Therefore, the Computer Business Equipment Manufacturers Association (CBEMA) derived a curve known as CBEMA curve (Fig. 1) as a guideline for the organization's members in designing their power supplies. Essentially, the association designed the curve to point out ways in which system reliability could be provided for electronic equipment. The CBEMA curve has been in existence since 1970’s (Thallam and Heydt, 2000). Waggoner (1991) established in his publication that a detail understanding of CBEMA curve is vital in combating power quality problems, with assurance of optimum operation of sensitive electronic equipment.

Table 3: Power quality curves

Curve	Year	Application
ITIC curve	1996	Information technology equipment
IEEE emerald book	1992	Sensitive electronic equipment
CBEMA curve	1978	Computer business equipment
FIPS power acceptability curve	1978	Automatic data processing equipment
AC line voltage tolerances	1974	Mainframe computers
Failure rates curve for industrial loads	1972	Industrial loads

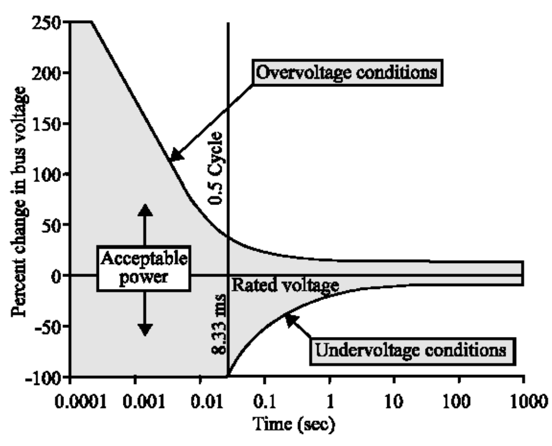

Fig. 1: The Computer business equipment manufacturers association (CBEMA) curve

Its primarily intent was to give a measure of the vulnerability of mainframe computer to the disturbance in the electric power supply. But the curve has been used as a measure of power quality indices for electric drives and solid-state loads as well. The curve is a susceptibility profile, with the vertical axis representing the percent of voltage applied to the power circuit and the horizontal axis representing the time factor involved, measured from microseconds to seconds. In the center of the plot is an acceptable area. Outside this area is a danger area on top and bottom. The danger zone at the top involves tolerance of equipment to excessive voltage levels, while the zone at the bottom sets the tolerance of equipment to a loss or reduction in applied power.

If the voltage supply stays within the acceptable area, the solid-state equipment will operate well. Computers, programmable logic controllers (PLCs), power distribution units (PDUs), instrumentation, telecom and other solid-state systems will operate reliably when applied carefully. All these units have one thing in common i.e., they are voltage and time-sensitive. In other words, voltage sags and swells, as well as outages and transients, will seriously affect their operation. Disturbances associated with powering, grounding and protecting solid-state devices can be measured, analyzed and evaluated using test equipment specifically intended for digital logic systems.

These instruments, when located near the suspected disturbance, or when measuring the unusual operation of the power distribution system, will provide data on voltage fluctuations, short-and long-term excursions and the specifics on how the disturbance places the equipment at risk. Once these measurements have been taken preferably with recording-type instruments the results can be analyzed in combination with the CBEMA curve to help understand the nature of the disturbances. The Information Technology Industry Council (ITIC) curve (Fig. 2) was derived by a working group of CBEMA, which changed its name to the Information Technology Industry Council in collaboration with EPRI's Power Electronics Application Center (PEAC). The intent was to develop a curve that more accurately reflects the performance of typical single-phase, 60-Hz computers and their peripherals and other information technology items like copiers, fax machines and point-of-sales terminals. While specifically applicable to computer-type equipment (as with the CBEMA curve), the ITIC curve is generally applicable to other equipment containing solid-state devices.

Table 4: Power quality problems and their causes, effects and solutions

Variations	Causes	Effects	Existing Solutions
Voltage variations	Load variations and switching events.	Premature ageing, pre-heating and malfunctioning of connected equipment	Line voltage regulators, UPS, motor generator sets.
Flicker	Arcing conditions, rolling mills, large industrial motors with variable loads	Disturbance in TV and other monitoring equipments, light flicker.	Filters, static VAR systems, distribution static compensators
Transients	Lightning, Capacitor Switching	Reduce life span, insulation breakdown of transformer and motor load.	Transient suppressors
Sag (Dip)	Power system faults, utility equipment malfunctions, starting large loads and ground faults	Malfunction of electronic drives, converters, motor stalling, digital clock flashing and related computer system failure.	UPS, constant voltage transformer, energy storage in electronic equipment, new energy-storage technologies.
Swell	SLG fault, upstream failure, Switching of large load, The large capacitor bank.	Insulation breakdown of equipments, Tripping out of protective circuitry in some power electronics systems.	UPS, Power conditioner
Harmonic Distortion	Nonlinear industrial loads, variable speed drives, welders, large UPS systems, Non-linear residential loads.	Overheating and fuse blowing of pf correction capacitors, overheating of neutral conductors of supply transformers, Tripping of over current protection, mal-operation of relays	Passive and active filters.
Voltage unbalance	Capacitor bank anomalies such as a blown fuse on one phase of a 3 Φ bank.	Overheating of motors, Skipping some of six half cycles that are expected in variable speed drives.	To reassess the allocation of 1 Φ phase loads from the 3Φ system.
Interruption in supply	Fault in network or by excessively large inrush currents, malfunction of customer equipment and fault at main fuse box tripping supply.	loss of computer/controller memory, equipment shutdown/failure, hardware damage and product loss	Energy storage in electronic equipment, employing UPS systems, allowing for redundancy, installing generation facilities in the customer's facility.
Under voltage	Overloaded customer wiring loose or corroded connections, unbalanced phase loading conditions, faulty connections or wiring overloaded distribution system, incorrect tap setting and reclosing activity.	Errors of sensitive equipment, low efficiency and reduced life of electrical equipment, such as some motors, heaters, lengthens process time of infrared and resistance heating processes, hardware damage and dimming of incandescent lights and problems in turning on fluorescent lights.	Regular maintenance of appliance, cable and connections, checking for proper fuse ratings, transferring loads to separate circuits, selecting a higher transformer tap setting, replacement of overloaded transformer or providing an additional feeder.
Over Voltage	Improper application of power factor correction capacitors and incorrect tap setting.	Overheating and reduced life of electrical equipment.	Ensuring that any pf correction capacitors are properly applied and changing the transformers tap setting.

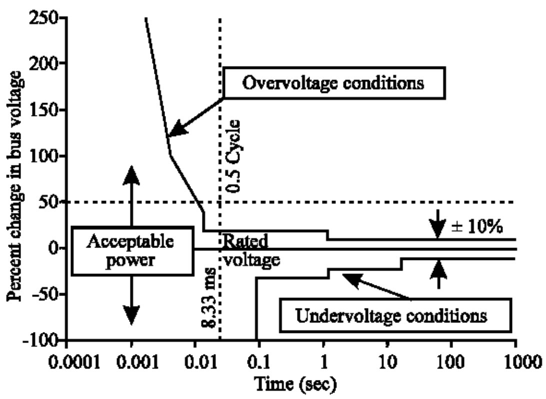

Fig. 2: Information Technology Industry Council (ITIC) power acceptability curve

It is necessary to point out here that the ITIC curve is not intended to reflect the performance of all electronic-based equipment. There are too many variables, such as power loading, nominal operating voltage level and process complexity, in applying an ITIC curve. Table 4 shows the causes, effects and solution for various power quality problems. Both the economics and the technical limitations must be considered before reaching at solutions. Also, the solutions need to be evaluated using system perspective i.e., possible solutions should be identified at all levels of system from utility supply to the end user's equipment being affected.

The optimal solution is obtained from the available solutions (Singh *et al*., 1999) and will depend on many factors like the type of PQ problem, the number of end users being impacted and, of course, the economics factor (Munoz, 2007).

POWER QUALITY MONITORING

PQ monitoring is an integral part of overall system performance assessment procedures. Instrumentation for the measurement of conducted disturbances in power systems has undergone tremendous development during the last decade. In McEachern (2001) the author has presented a brief history of the subject from the 1920s' development of a lightning strike recorder through to the 1960s' power quality monitors, the mid-1980s' graphic power quality monitors. From a pure measurement view

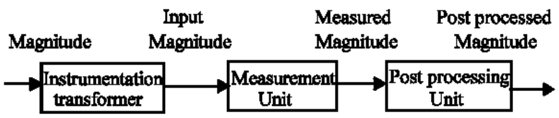

Fig. 3: PQ measurement process

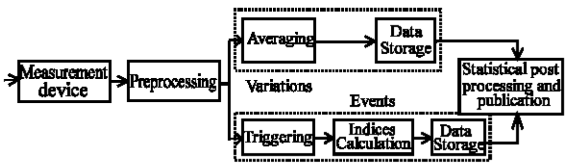

Fig. 4: General scheme of power quality measurements

point (Mark and Santoso, 2007) there is no difference between PQ measurement and the measurement of voltages and currents, for protection and control purposes. The difference is in the further processing and application of the measured signals. Figure 3 shows main elements of PQ instrumentation system.

PQ measurements are performed for the number of reasons and monitoring of high reliability systems has a number of important objectives such as:

- Continuous evaluation of the electric supply system for disturbances and power quality variations.
- Performance of power conditioning equipment, such as static switches, UPS systems, other ride through technologies and backup generators.
- Evaluation of power quality characteristics of the equipment within the facility like harmonic interaction between loads and power conditioning equipment and inrush characteristics for loads.
- Complete documentation of disturbances and power system conditions for any event that actually disrupts facility operation.
- Document actual energy use for the different parts of the facility. This will help allocate costs and will provide improved information for facility designs in the future.

A simple classification of power quality monitoring could be:

Local monitoring: Its objective consists of determining the quality of power that is delivered to a single customer.

System monitoring: Its objective consists of determining the quality of power and the behavior of the electrical system globally.

The substation is an important location because it is the point of common coupling for many voltage variations. Customer service locations are monitored to understand the disturbances entering from the power system into the customer facility and the impacts of the equipment operation on the power system are assessed. Conventionally, utility engineers conduct PQ monitoring through visual inspections. This process is, of course, laborious and time consuming. Due to increased awareness of power quality, the need of PQ monitoring system is important. Reference (Bollen and Gu, 2006; McEachern, 2001) shows the monitoring requirements for different types of power quality issues. The existing instruments that can be utilized for power quality evaluation could be classified into 2 sets according to their degree of specialization: general-purpose instrumentation and specific-purpose instrumentation. General purpose instrumentation includes oscilloscopes and spectrum analyzers. The input data for any PQ monitoring device is obtained through transducers like CT, PT and Hall Effect transducers etc. Figure 4 shows the scheme of power quality measurements. Signal processing forms an important part in power quality monitoring and analysis of voltage and current measurements from sampled waveforms. Signal processing techniques are needed for the characterization (feature extraction) of variations and events, for the triggering mechanism needed to detect events and to extract additional information from the measurements (Bollen and Gu, 2006).

MONITORING USING ADVANCED DIGITAL SIGNAL PROCESSING (DSP) TECHNIQUES

Built-in event diagnosis and assessment units are the key to these monitoring systems. One way to improve the performance of a monitoring system is to incorporate a more reliable and accurate waveform recognition algorithm, which recognizes a broader range of PQ events. Therefore, an intelligent monitoring system should incorporate detection capabilities into monitoring equipment so that events of interest can be recognized and captured automatically. Moreover, a good performance monitoring equipment must have capability to detect, localize and classify transient events as well. Signal processing techniques play an important role in these regards. Time-frequency representations of the signal, like short time Fourier transform (STFT) and wavelet transform (WT) have emerged as effective tools for more efficient characterization of the PQ waveforms for detection, automated disturbance classification (Gaouda *et al*., 1999; Zhu *et al*., 2004) and for power system protection (Huang *et al*., 2000). The other possible power system applications of WT analysis are detection of high-impedance faults and PQ data compression (Santano *et al*., 1997). Model based methods like Kalman filtering, AR (autoregressive) model and RLS or LMS based adaptive filtering can provide accurate information regarding harmonics and changes at fundamental frequency (Bollen and Gu, 2006; Dwivedi and Singh, 2004).

Advanced parametric or model based methods for processing of PQ data: Some high resolution line spectral analysis based models viz. harmonic or sinusoidal models, multiple signal classification (MUSIC) model, estimation of signal parameters via rotational invariance techniques (ESPRIT) method and Kalman filters (KF) based methods are critically reviewed in this section for estimation of harmonics and inter-harmonics. To characterize harmonics and inter-harmonic disturbances, sinusoidal models (Bollen and Gu, 2006) are the most suitable choice where waveform distortion is related to disturbances in a narrow band or disturbances in discrete frequencies (harmonics and inter-harmonic frequencies). Mathematically, a discrete-time signal v(k) of finite length L can be represented by a sinusoidal model with N sinusoidal component as:

$$v(k) = \sum_{n=1}^{N} a_n \cos(k\omega_n + \phi_n) + \varepsilon(k)$$

where, a_n is the magnitude ϕ_n is the initial phase angle, $\omega_n = 2\pi f_n$ is the harmonic (or inter-harmonic) frequency and ε is the noise. As the frequency resolution in the model based method is high (provided that the model is correct), the estimation of interharmonics become a realistic issue. It has limitation that the model order N is usually not true for practical applications.

The MUSIC method employs a harmonic model and estimates the frequencies and power of the harmonics in the signal. It is a noise-subspace based method (Bollen and Gu, 2006). But MUSIC method is less accurate due to the large difference between the fundamental frequency power and the harmonic or inter-harmonic frequency power. Therefore, some preprocessing such as applying DFT, notch filtering or a high pass filter with stop-band to remove fundamental component is needed before applying the music algorithms. ESPRIT method also employs harmonic model and estimates the frequencies and power of the harmonics. But the ESPRIT is a signal-subspace-based method rather than a noise-subspace based method. Both methods can estimate the parameters in the sinusoidal models, however, methods based on the signal subspace are often more reliable. Therefore, ESPRIT is more preferable for line spectrum estimation.

KFs are special types of filters and their solutions are based on a set of state-space equation. KF are useful tools for many power system applications, such as real time tracking of harmonics (Saiz and Guadalupe, 1997), estimating voltage and current parameters in power system protection (Girgis and Qui, 1989) and estimating the power system transients. Contrary to MUSIC and ESPRIT methods which are used for high-resolution spectral line estimations and are based on batch processing methods (like DFT), KF offers recursive estimation for each new incoming signal samples. KF when used for PQ analysis uses a sinusoidal model and state variables are set to be the parameters of power system harmonics and inter-harmonics. Under such a condition the frequencies have to be specified which is a major problem. The application of Kalman filter is also limited when there is a relatively large variation in the power system frequency. But KFs are advantageous because of their applicability for non-stationary signals. There are several versions of KFs but extended Kalman filters (EKFs) (Haykin, 2001; Moon and Stirling, 2000) can take care of nonlinear system model where KF is extended through a linearization procedure. KF provides rather a good estimation for the magnitudes of fundamental and the harmonics, even though the fundamental-signal component is 25-100 times stronger than the harmonics. This is very encouraging and a clear advantage of the KF as compare with the MUSIC or ESPRIT method, which usually requires a pre-processing of signal to reduce the strong influence of the fundamental component.

In the literature, there exist a lot of references on the theories and application of signal processing techniques which are beyond the scope of this stduy. Readers can refer to Haykin (2001) and Mitra (2001) for more details on the basic signal theories and (Bollen, 2000; Gu and Styvaktakis, 2006) for application to power system. Some PQ signals can better be described by broadband spectra such as current taken by arc furnaces and the high frequency part of active rectifiers (e.g., used in drives, in interface for distributed generation and in most of the energy saving lamps). Under such conditions, methods like AR (autoregressive) and ARIMA (autoregressive moving-average) models (Gu *et al*., 2000; Grenier, 1983) are the most suitable. Further, these methods are not suitable especially when the signals contain both narrow-band and broadband components. The nonparametric methods like WT and wavelet packet (Barros and Diego, 2008) transform are more suitable for such signals.

Non-parametric or transformation based processing of PQ waveform data: This class of methods primarily transforms or decomposes the signal into time-dependent frequency (or frequency related) component using some basis functions. Mathematical transformations are applied to the signals to obtain further information those are not readily available in the raw signal. The PQ signals in practice are time-domain signals in their raw format. When we plot time-domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency spectrum is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal. The transform of a function/sequence may require less storage; hence provide data compression/reduction. Another important aspect of transformation is that an operation may be easier to apply on the transformed function, rather than the original signal.

The Fourier transform (FT) has been used as an analyzing tool for extracting the frequency contents of the recorded signal. According to the frequency contents of the signal, some of the PQ problems can be detected (Allen and Rabiner, 1977; Altes, 1980). The time-evolving effects of the frequency in non-stationary signals are not considered in the FT techniques. Although, the short-time Fourier transform (STFT) can partly alleviate this problem, The STFT still has the limitation of a fixed window width, which means the trade-off between the frequency resolution and the time resolution should be determined a priori to observe a particular characteristic of the signals (Gu and Bollen, 2000). The limitation of a fixed window width in fact is inadequate for the analysis of the transient non-stationary signals.

To improve the effectiveness of the FT, many researchers have proposed the use of the wavelet transform (WT) approach to analyzing the power system disturbances (Perunicic *et al*., 1998; Zhu *et al*., 2004). The WT approach prepares a window that automatically adjusts to give proper resolutions of both the time and the frequency. In this approach, a larger resolution of time is provided to high-frequency components of a signal and a larger resolution of frequency to low-frequency components. These features make the WT well suited for the analysis of the power system transients caused by various disturbances. The other possible power system applications for WT analysis are detection of high-impedance faults and PQ data compression (Santano *et al*., 1997). Thus, wavelet analysis provides immediate information that can be obscured by Fourier analysis. It is able to perform local analysis (analyze a localized area of a larger signal) and also capable of revealing aspects of data that other signal analysis techniques misses the aspects like trends, breakdown points, discontinuities in higher derivatives and self-similarity.

SIGNAL PROCESSING APPLICATIONS

Most of the real world PQ waveform data are non-stationary i.e., they are statistically time variant and their characteristics change with time. Quantifying such PQ disturbances, therefore, requires time dependent or dynamic attributes of the measurement. It is a well known fact that early detection can often lead to a cure. Digital signal processing (DSP) or signal processing, in short, concerns the extraction of important features and information from measured signals. DSP can play an important role in detection of PQ disturbances and in finding the triggering point of a digital fault recorder. PQ data is available in the form of sampled voltage and/or current waveforms. From this, waveform information is extracted such as magnitude and frequency. This section describes various possible applications of DSP in PQ monitoring such as detection, time localization and feature extraction, de-noising and data compression (Gaouda *et al*., 1999; Perunicic *et al*., 1998; Hua and Bollen, 2000; Santoso, 1996; Abdel-Galil *et al*., 2004; Huang *et al*., 2000; Santano *et al*., 1997; Gu and Styvaktakis, 2006).

Detection and triggering of pq monitoring system using KF and WT: A triggering point is a time instant at which a PQ event starts or ends. The triggering method detects the presence of an event with starting and ending instants (Bollen and Gu, 2006). The current methods for detecting power quality disturbance is based on a point-to-point comparison of adjacent cycle or a point-to-point comparison of the rms values of the distorted signal with its corresponding pure signal and/or transformation of the data into the frequency domain via FT (Santoso *et al*., 1996). But its drawback is that it fails to detect disturbances that appear periodically, such as flat-top and phase controlled load wave-shape disturbances and also these are not suitable for non-stationary signals. Therefore, existing automatic recognition methods need much improvement in terms of their versatility, reliability and accuracy. For this, more powerful and sophisticated methods or techniques are required to detect and analyze non-stationary distortions. In this study methods is discussed: one of which exploit the prominent residuals from KF and other is based on finding singular points from multi-scale wavelet decomposition of PQ signal.

Residual signal from a model can be used for detecting transition points and for analyzing and characterizing the disturbances. The basic idea in KF residuals based detection and triggering method is to fit the PQ data into a chosen KF model. The residual obtained is constantly observed for the changes to detect the disturbances as the large residuals from a KF model usually appears around the transition points of the data (Bollen and Gu, 2006). This is because at the transition points, a much higher order model is required to model the disturbance. Therefore, while using a fixed model throughout the whole data sequence, large residuals will appear around the transition points as a result of model mismatch. Largest residual error is also caused by the discontinuity of model between adjacent blocks. Consequently, transition points are detected by allocating the time where the model residuals are prominent.

The key idea in orthogonal polynomial approximation (OPA) residuals based detection and triggering approach is to approximate a given disturbance signal in the least square sense, such that the uncorrelated part (disturbance) of the signal is not present in the approximated version of the signal. It is, therefore, possible to detect and localize power quality (PQ) disturbances by analyzing the difference of the original and approximated signals. This is achieved by choosing the degree of the polynomial using the criterion of minimum error-variance. The orthogonal polynomial approximation (Ralston, 1965) has certain advantages over the wavelet representation as, in the case of wavelet decomposition, the step size is fixed whereas with the polynomial approximation one can choose much smaller step size for more detailed information. With polynomial approximation, the decomposition and reconstruction of a signal are the one-step process with direct implementation. Since the orthogonal polynomials are generated with arbitrarily spaced points, the approximation can be used for non-uniformly sampled data. The study (Dwivedi and Singh, 2004) has proposed a new and simple approach for the detection and localization of the power quality disturbances. Theoretical analysis and the results presented in the stduy clearly reveal the potential capability of the proposed technique in power quality assessment. Comparative study of the proposed technique with discrete wavelet transform (DWT) offers encouraging results because of its simplicity and other advantages over DWT (Dwivedi and Singh, 2004).

The wavelet transform is a mapping of a 1-D time domain signal into a 2-D time-scale joint representation, where scale has an inverse relation with frequency (Daubechies, 1990). Wavelets are functions, used to efficiently describe a signal by decomposing it into its constituents at different frequency bands (or scales). These functions are generated by mean of dilation (stretching) and translation (shifting) operations of a basis function (called mother wavelet) and capture features that are local both in time and frequency. This property is not shared by other family of functions, such as the Fourier basis. When representing a signal in a wavelet basis, narrow wavelets will detect sharp features of the signal and broader ones more global features, making wavelet useful for noise removal, feature extraction and compression of PQ waveform data. The discontinuities in the PQ waveform data due to disturbances in the form of sharp edges, transitions and jumps are reflected in the wavelet transform coefficients (WTCs). Therefore, a DWT-based PQ monitor can capture non-periodic and high-frequency transient disturbance waveform. Signal reconstruction may be effected through the application of the inverse DWT (Mallat, 1989).

DE-NOISING OF PQ WAVEFORM DATA

Few studies (Mallat, 1989; Ribeiro *et al*., 2007) which uses WT denoising for compression of PQ waveform are available in literature but these do not discuss the impact of these techniques on detection and feature extraction. Though, both residual based methods and WT exhibit notable capabilities for detection and localization of the disturbances, especially for the use of PQ monitoring instrument, however, its capabilities are often significantly degraded due to the presence of noise riding on the signal (Yang and Liao, 2001; Dwivedi and Singh, 2006). In particular, when the spectrum of the noise coincides with that of the transient signals, the effects of the noise cannot be excluded by filters without affecting the performance of the DSP based methods. The disturbance component of the waveform carries the most important information for detection and classification of the disturbances. Therefore, even if the magnitude of noise level present is not very high compared to fundamental component, for many PQ disturbances especially transients, it is comparable to disturbance energy. Hence, the presence of noise not only degrade the detection capability of wavelet based PQ monitoring system but it also affects the energy distribution patterns of disturbances in wavelet domain and thus will increase the miss classification rates of many DWT-based classification schemes (Yang and Liao, 2001; Dwivedi and

Singh, 2006; Bollen and Gu, 2006; Gaouda *et al*., 1999; Perunicic *et al*., 1998; Santoso *et al*., 2000; Ibrahim and Morcos, 2002; Zhu *et al*., 2004). Many researchers felt the adverse effect of noise on wavelet based PQ monitoring and demonstrated that the performance of the WT in detecting the disturbance would be greatly degraded, due to the difficulty of distinguishing the noise and the disturbances (Yang and Liao, 2001; Dwivedi and Singh, 2006; Bollen and Gu, 2006; Ashton and Swift, 1990; Gouda *et al*., 2002).

Wavelet threshold de-noising technique can be used to alleviate the effect of noise on PQ recognition. Yang and Liao (2000) proposed a correlation based noise-suppression algorithm but this algorithm is not suitable for disturbances which do not travel across the scale and has computational complexity and problem of increased falls alarm rate with low SNR. Gaouda *et al*. (2002), used the reconstructed version of the original signal by discarding all the coefficients of few higher level details, in the presence of noise to detect and localize the disturbances. But, discarding all the coefficients of higher resolution levels has the risk of loosing high frequency transient features, completely. Elmitwally *et al*. (2001), used Stein's Unbiased Risk Estimate (SURE) for denoising PQ waveforms but SURE performs well, when the wavelet representation at any given scale is not very sparse, which is certainly not true for most of the PQ disturbances. Yang *et al*. (2001) proposed another de-noising scheme based on Kolmogorov-Smirnov (KS) goodness-of-fit test to determine the threshold for noise-shrinkage. But there are some fundamental problems in the formulation of the method and the procedure described by them cannot yields the claimed results, because the Brownian bridge process formed using DWT coefficients has been compared with uniform distribution function, which is not correct. The test statistics formulated and used neither resemble the standard KS-test nor any other known test statistics, though the critical point obtained are used from KS-test for distributions. The correct formulation of a KS-test statistics using Brownian-bridge stochastic process is described in (Shorack and Wellner, 1986) and proof is provided for how the supremum functional of a sample Brownian bridge process corresponds to the KS goodness of fit test statistic (Ogden, 1997). After rectifying these problems, denoising of the PQ waveforms data can be performed by correct implementation of data analytic wavelet thresholding using Brownian bridge stochastic process corresponding to KS goodness-of-fit test (Ogden, 1997). The technique used in Dwivedi and Singh (2006), exploits the local structure of wavelet coefficients, namely the intrascale dependencies of WT coefficients representing PQ disturbances, in an adaptive manner. Despite the simplicity of this method, both in its concept and implementation, the results obtained after denoising of the PQ signals are among the best reported in the literature.

Adaptive filtering based technique for online monitoring of pq disturbances: A PQ monitor captures actual voltage and current waveforms, when certain threshold levels are exceeded such as magnitude of DWT coefficients threshold. The main problem with DWT based event detection method is that, in most cases, the pre-disturbance waveforms are assumed to be sinusoidal, which may not always be possible. Practically, a large number of equipment operates on the power system, which draws or injects different nature of current and also electromagnetic interactions takes place throughout the system. Therefore, under the normal operation, the waveforms may have harmonics, noise and notches, which degrade the detection capability of a DWT, based monitoring system. To minimize the miss-alarm rate for DWT based denoising methods can be used. However, there may be dynamic changes in the systems load configurations that will change the systems steady state condition. As the filter coefficients of wavelet filter are fixed at each decomposition stage, DWT based detectors cannot adapt itself to the dynamic changes in the load configuration and may generate repeated detection and processing of the same steady disturbance. Hence, the analysis tool, capable of adapting itself to the dynamic changes in systems' load configuration, is needed to detect new events and to avoid detection of the same steady state variation repeatedly.

To overcome the problem associated with DWT based PQ detector, least mean squares (LMS) type adaptive filter based predictor has been proposed in (Dwivedi *et al*., 2007) to accommodate changes in systems steady state condition. But, as an adaptive filter constantly changes the filter coefficients and, hence, the frequencies which are allowed to pass, it is not a good idea to use adaptive filter for feature extraction, although one can extract some information by analyzing adaptation error. Despite the inability to adapt to the dynamic load changes, the DWT has been found to be a very effective means to extract frequency information of the disturbance for its classification. An adaptive filter on the other hand adapts its filter coefficients continuously with changing monitored signal. Therefore, an adaptive filtering and DWT based hybrid system has been proposed in Ribeiro *et al*. (2007) for the detection and analysis of transient disturbances. Adaptive filter based monitoring avoids the detection of the same steady state variation repeatedly. Extensive tests conducted on the data obtained from a practical distribution system confirm the effectiveness of the proposed approach (Dwivedi *et al.*, 2007) in automatic detection and diagnosis of transient PQ violations.

ARTIFICIAL INTELLIGENCE (AI) APPLICATIONS TO CLASSIFY OF PQ DISTURBANCES

The features extracted using signal processing techniques are then used as the input to the classification system. These obtained features reduce the burden over the classifiers. For classification AI techniques are used. Some frequently used classifiers are rule-based expert systems, fuzzy classification systems, artificial neural networks, kernel machines and support vector machines. Rule based expert systems and Fuzzy expert systems are known as deterministic approach whereas statistical-based methods use advanced signal-processing techniques. Artificial neural network (ANN) and support vector machine (SVM) are the statistical based classifiers. The artificial neural network is the most popular method in literature often combined with a set of wavelet filters for feature extraction and fuzzy logic for the decision making

Bollen *et al.* (2007) shows the advantage of statistical classifiers over the expert system based approach. In, Styvaktakis *et al.* (2001), expert systems are used for the classification of voltage dip. Beside few, more study (Kazibwe and Sendaula, 1992; Kezunovic and Rikalo, 1999) used the expert system as the classifier. The rules are based on if then condition so as the number of events or features increases, the complexity of the expert system also increases. However, its poor learning ability and adaptability limits its application in the real practice. Fuzzy logic (FL) possesses the strong inference capabilities of expert systems as well as the power of natural knowledge representation. The rules of this AI technique are subjectively based on modeling human experience and expertise. The designed system is then tested for proper output. Main disadvantage with this is that if the system does not perform satisfactorily then the rules are reset again to obtain the efficient results i.e., it is not adaptable according to the variation in the data. References (Dash *et al.*, 2000; Ibrahim and Morcos, 2001) present the application of this technique in classification.

Neural network is a non-linear, data driven self-adaptive method and is a promising tool of classification. They can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model (Santoso *et al.*, 2000). They are universal functional approximators i.e., they can approximate any function with arbitrary accuracy. All the above mentioned attributes make ANN flexible in modeling real world complex relationships. Finally, neural networks are able to estimate the posterior probabilities, which provide the basis for establishing classification rule and performing statistical analysis. But the drawback associated with this technique is that it offers us a way for signal classification under black box models without guaranteeing the performance. The generalization performance of NN is not guaranteed and could be poor depending on the selection of the training data. The performance is heavily dependent on the training data set and the structure (or topologies) of the neural networks (e.g., the number of hidden layers and neurons and the interconnection of sub-neural networks if employed).

Adaptive neuro-fuzzy systems (ANFS) are fuzzy logic systems that have the ability to self-modify their membership functions (MF), progressing towards achieving a predetermined desired performance. ANFS are derived from a general category of intelligent networks known as adaptive networks. Adaptive networks subsume almost all kinds of neural network paradigms. An adaptive network is a network structure consisting of a number of nodes connected through directional links. Each node represents a process unit and the links between nodes specify the causal relationship between the connected nodes. All or parts of the nodes are adaptive, which means that the output of these nodes depends on modifiable parameters pertaining to these nodes. The learning rule specifies how these parameters should be updated to minimize a prescribed error measure. In the most general case each node in an adaptive network may have a node function different from the others. Links in an adaptive network have no weights or parameters associated with them. Adaptive fuzzy logic (AFL) is a fuzzy-logic-based paradigm that grasps the learning abilities of ANN or the optimization capabilities of genetic algorithm to enhance the intelligent system's performance using a priori knowledge (Huang *et al.*, 2002).

Support vector machine (SVM) armed with the statistical learning (VC) theory (Cristianini and Taylor, 2000) may provide a good solution and compromise. SVMs are designed to minimize the classification error on the test rather than on the training set. The classification error on the test set is guaranteed by the upper bound that is dependent on the choice of mapping function. Meanwhile, the SVM takes the complexity of the learning machines, which is associated with a VC dimension. Choosing appropriate kernels in a SVM that are suitable to each particular application problem is essential. Different kernels in a SVM are a superior choice for designing a classification system. References (Janik and Lobos, 2006; Gu *et al.*, 2004) demonstrate the application of SVM as the classifier for the disturbances.

Using applications of SVMs to classify power system disturbances is clearly a good direction for future research and development in power system applications.

KEY ISSUES AND CHALLENGES IN MONITORING AND ANALYSIS OF PQ

The following are the some of the major issues in DSP based automatic monitoring and analysis of PQ disturbances:

- The measurement locations have significant influence on the resulting values of the characteristics. For example, the harmonic distortion at the terminal of a piece of equipment may be different from the distortion at the service entrance which may in tern be different from the distortion in the substation. The impact of measurement location may be much bigger than the impact of any of the details for obtaining the characteristics. The optimal location of measurement location must be ascertained.
- In practice, signals captured by the monitoring devices are often corrupted by noise and this has the impact on the recovery of important features from the signal for automatic recognition of PQ disturbances. Many signal processing fields including communications, bioinstrumentation, seismology and radar, suffer from this problem. Virtually, every electrical device that generates, consumes or transmits power is a potential source of electromagnetic noise. The common sources of noise are transformers, power electronic devices, control circuits, arcing equipment, Earth's magnetic field, electrical storms and improper grounding of the equipments. In addition, noise also gets added with signal during measurements and data transfer over communication channels if used. An effective de-noising technique is still a challenge for proper detection and analysis of PQ events.
- An adaptive filter constantly changes the filter coefficients and, hence, the frequencies which are allowed to pass, it is not a good idea to use adaptive filter for feature extraction. Integrating adaptive filter with DWT can result in an intelligent monitor capable of adapting to the dynamic changes in the system. DWT alone, in such conditions would result in repeated alarm and processing of the data or in some cases may fails to detect the disturbance. It can be used as a feature extractor, because of its excellent signal representation property in time-frequency plane.
- Selections of model order is the other challenging issue need to be resolved. The model order should be set sufficiently high to accommodate the principal line spectral components contained in the possible types of events (e.g., transformer saturation, arcing, capacitor switching and other events). Selection of threshold in residual based method to detect an events start and end points is also an important and challenging issue as a low threshold makes the detection scheme more sensitive to changes and can lead to false alarming while too high a setting can result in increased missed alarm rate.
- PQ disturbances cover a wide frequency range; therefore an important issue to be resolved with WT is the selection of number of level of DWT decomposition to avoid the possible loss of some important information for classification. Though Daubechies db4 wavelet has been used most frequently because of its compactness and localization properties in time-frequency plane, in most of the wavelet based monitoring and analysis methods proposed. Finding a suitable single mother wavelet for all application is difficult.
- It has not been proved that FT or WT or model based methods is the optimal starting point for generating classification features. The wavelet transform has limited utility in detecting and extracting sag disturbance features because the gradient of the disturbance events are comparable to that of the background signal. This problem has to be resolved.
- Development of an efficient tool using advanced artificial intelligence (AI) and/or DSP techniques to achieve general event classification rather than individual fault detection is essential.
- Integration and comparisons of developed algorithms and tools and to test these using actual/practical PQ data are another area of concern.
- Most of the signal processing techniques developed and demonstrated used their own way of generating PQ events making the comparison of these methods very difficult. Therefore, accumulation of a comprehensive standard PQ database similar to that of many other signal processing fields, for testing and comparisons of the state of the art techniques is also needed.
- PQ issue is one of the criteria for customers in the competitive power market. Assessing the cost of PQ problem is another key issue.

CONCLUSION

Power quality monitoring has advanced from conventional discrete time monitoring to ongoing continuous monitoring of a system's performance. In the present article, different PQ problems, their cause, impact, suitable remedies and various standards and voltage acceptability curves have been presented and explained in general and applications of some important advanced DSP and AI tools are reviewed in particular. Major Key issues and challenges related to these advanced techniques in automatic detection and analyses of PQ problems are highlighted. New intelligent system technologies using DSP, expert systems, AI and machine learning provide some unique advantages in intelligent monitoring of PQ distortions. And many existing signal processing methods can be applied for intelligent monitoring as discussed in this article, but it is found that a signal processing method could be very suitable for one application but not very suitable for another application. For example for steady state variations conventional FT and model based techniques are found to be more suitable but for PQ event detection wavelet transform based techniques are the best. Therefore, possible integration of these existing techniques may serve the purpose and one of them can be integration of adaptive filtering for detection of new event and WT for feature extraction. More research work is needed to rectify problems associated with these techniques before they could be applied to real systems monitoring and analyses. Accumulation of a comprehensive standard PQ database for testing and comparisons of the state of the art techniques is urgently needed.

ACKNOWLEDGEMENT

Financial support obtained by the Department of Science and Technology, India vide project no. DST/EE/20040252 is gratefully acknowledged.

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