Automated Power Quality Assessment Using DFR Data

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Abstract - This paper describes novel techniques that can be used to assess power quality. Digital fault recorders may be used as data acquisition system for this application. A software aimed at automated assessment of power quality disturbances is located on a PC interfaced to a digital fault recorder. Examples of different software techniques for detection and classification of common power quality problems are discussed and presented.

Keywords: Power quality, digital fault recorders, signal processing, wavelet analysis, neural nets

I. Introduction

The power quality (PQ) assessment is raising strong interest in the industry as deregulation sets tighter utility competition for customers [1, 2]. Several instruments have been developed in the past to measure some properties of the power quality disturbances such as harmonics and flickers [3]. As the number of types of the power quality disturbances is increasing and their characteristics are becoming more complex, it is essential to have a universal instrument that can be used to detect and classify almost any type of the disturbance occurring at a given location. An ideal candidate for such an instrument is a digital fault recorder (DFR) due to its ability to monitor large number of analog channels at a high sampling rate. Equipped with appropriate interface for data transfer to a PC, an automated software can be developed to extract DFR data from the recorder and store it on the PC for further analysis. The software can then be enhanced to perform an automated data analysis and PQ assessment as well.

This paper provides description of the power quality assessment steps. It also explains how DFRs can be used too perform the required monitoring. Finally, a variety of different techniques for disturbance detection and classification are outlined.

II. Signal Analysis Consideration

Digital measurement of analog quantities such as currents or voltages always involves signal processing steps shown in Figure 1. It is well known in the signal processing theory that all of the processing steps indicated in Figure 1 have to be carefully designed to match given signal characteristics. This requires analysis of signals to determine their characteristics. It is important to note that false assumptions about features of a particular signal may lead to inappropriate design of the signal processing steps, which in turn, may produce measured quantities that do not reflect existing signal characteristics.

It is, therefore, extremely important to understand characteristics of the signal disturbances associated with power quality changes so that appropriate signal processing steps may be designed to allow measurements of the quantities that, indeed, characterize the disturbances. In addition, it is important to have an ability to detect and classify the disturbances so that an optimal assessment technique that fits disturbance properties can be selected.

Figure 1. Signal processing steps

Typical signal disturbances associated with power quality indicators are over-voltages, under-voltages, power outages, voltage flickers, switching transients, spikes, impulses, current harmonic distortions, etc. The following two classes of assumptions about signal characteristics have been identified and reported in [4, 5]:

Class I

A dominant signal component is a single harmonic whose frequency may slightly vary. This signal may shortly (not on a periodic basis) be corrupted by some other known signal components such as other harmonics and subharmonics, transients and noise.

Class II

The main signal is periodic and may consist of a number of harmonic components that are also periodic.

It is important to note that Class I signals such as the sinusoidal ones are straight forward to handle because measurement quantities such as amplitude, phase, frequency, active power, reactive power, apparent power, and power factor are well defined for sinusoidal signals. If the signal contains some known disturbances, digital algorithms can be defined to measure either the fundamental signal quantities or the disturbance quite accurately. In this case, the use of only several samples per cycle may be sufficient to perform the desired measurement. By monitoring the measured quantities one can perform quality assessment by determining that either the fundamental signal quantities or the disturbance levels caused by superposition of some other signals are different from the expected values.

The Class II signals are more difficult to handle since the quantities that are well defined for Class I signals are not that well defined in this case. Since the standard quantities are not directly applicable to Class II signals, there is a disagreement about their definitions for the Class II signal conditions. Typical examples are definitions of the power and the power factor for nonlinear and unbalanced situations [6]. Further characteristic of Class II signals is that measurement of these quantities requires synchronized samples taken in the entire cycle of the periodic signal. Both signals in Class I and Class II may be polluted by a noise.

Figure 2 illustrates typical signal disturbances for both of the classes.

Figure 2. Typical signal classes

III. DFR as a Data Acquisition System for PQ Assessment

Advanced DFRs can be utilized as a data acquisition system for applications in the area of power quality assessment. Digital fault recorders provide a set of programmable triggers (over-voltage, under-voltage, over-current, rate of change, etc.) that initiate capturing of data. Once triggered, DFR stores data record on a local hard drive where it can be accessed by other software (e.g., master station or automated analysis software).

These data records contain snapshot of recorded quantities (usually voltages, currents and relaying contacts) during disturbance. In addition, several cycles of prefault data are available by default.

DFR triggers, as presently implemented, may not necessarily operate for every case of disturbance that is of interest for power quality assessment. One such a case may be triggering on a slow variation of load characteristics.

This shortcoming may be avoided by using the analysis system illustrated in Figure 3. The system consists of a digital fault recorder and external PC. Two units are connected via high-speed parallel communication link. A digital fault recorder serves as a data acquisition front-end, providing continuous data flow toward the monitoring system PC. At the same time, DFR maintains its basic function of recording the events according to the internal triggers and storing those events on the local hard drive inside the recorder. These stored events are available remotely per request over a dial-up line, using master station software provided by the DFR manufacturer.

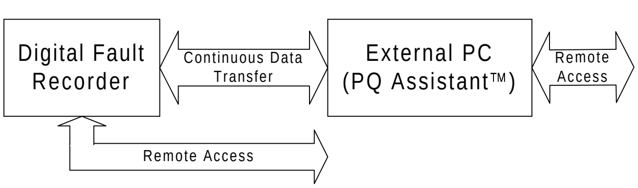

Figure 3. Block diagram of power quality analysis system

Continuous data stream from the DFR is divided into blocks of fixed size. These data blocks are time tagged and queued at a prespecified memory location on a PC side. Signal processing algorithms that are part of the PQ Assistant™ software access and process these incoming data blocks in real-time. These algorithms are similar to DFR internal triggers, but involve more extensive and complex computation. The PQ Assistant™ software is currently being developed by Test Laboratories International, Inc. The proposed system is modular and additional functionality can be easily added.

Texas A&M University developed similar data acquisition system for Houston Lighting & Power Company that is being evaluated for real-time monitoring of a generator unit [7, 8]. Also, a software package that uses the similar concept of automated fault disturbance analysis has been developed by Texas A&M University and licensed to Test Laboratories International, Inc. [9].

IV. PQ Assistant™ Application

This section describes steps and technologies to be used for implementation of the proposed power quality assessment system.

A. Disturbance Detection and Classification Using Neural Nets

The first step of the analysis involves disturbance detection and classification. The authors work in the related field of transmission line fault detection and classification using neural nets suggests that similar approach could be utilized for PQ assessment application as well [10-12].

The application, as defined in the context of this paper, requires that disturbance detection and classification are determined in the following manner:

- The processing has to be performed in time to allow real-time assessment of the incoming DFR data.
- The outcome of the processing has to be presented in a symbolic form (class names) since the detection and classification results of the neural net computation may be further utilized for disturbance characterization using signal processing algorithms.
- The neural net training has to be quite efficient and straightforward since the application requires a fast and simple procedure for adapting to different PQ disturbances.

Disturbance detection and classification is defined as a multi-class problem. Figure 2 shows selected disturbance types that are relevant to the power quality assessment application.

In this case the application is considered to be a mapping problem. Supervised learning can be used where sets of associated input/output pairs are presented to a net that then "learns" a model of that process. However, the training process of multilayer networks is computationally demanding and in some instances tens of thousands of iterations are needed to achieve convergence. Such performance may not be suitable for real-time detection and classification. Since our problem is a classification problem, where only discrete labeling of classes is needed, the use of feedforward networks may not be fully justified under stringent processing time requirements.

Another possible approach for the neural net application to our problem is to exploit data self-organization obtained through the use of unsupervised learning. After the learning (cognition phase), the user defines or labels clusters according to some criterion. The net is then ready for the classification task (recognition phase). Therefore, the concept of data self-organization through the use of unsupervised learning is valuable for discovering how an ensemble of patterns is distributed in the pattern space.

To overcome the mentioned limitations of the multilayer feed-forward networks, and to take advantage of the suitability of self-organizing networks to perform a classification through the clustering process, a new neural net approach has been developed and applied in our study. It incorporates advantages of both supervised and unsupervised training procedures and yet meets the requirements presented earlier. The proposed method utilizes the concept of supervised clustering which demonstrates following important properties:

- The number of iterations in the learning process is greatly reduced using unsupervised learning with supervised class membership inheritance process.
- The training is far less complex than in standard supervised learning.
- Combining symbolic and numeric data is readily available.

Subsection C contains example of how to use the neural net for classification of common disturbances needed for PQ analysis application. Summary of the classification results is provided as well. It should be noted that the use of neural nets requires convenient tool for performing neural net training. A digital simulator can be utilized to automate the training procedure [13].

B. Disturbance Characterization Using Signal Processing

This section summarizes various signal processing algorithms used for measuring different power quality indicators.

Table I gives some basic algorithms for calculation of phasor quantities for Class I type signals.

TABLE I.

The Basic Algorithms for Class I

Direct Measurements	• Active power	$P = \frac{VI}{2}\cos\phi$
	• Reactive power	$Q = \frac{VI}{2}\sin\phi$
	• Voltage RMS^2	$V_{RMS}^2 = \frac{V^2}{2}$
	• Current RMS^2	$I_{RMS}^2 = \frac{I^2}{2}$
Derived Measurements	• Apparent power	$S = \sqrt{V_{RMS}^2 - I_{RMS}^2}$
	• Power factor	$PF = \frac{P}{\sqrt{V_{RMS}^2 - I_{RMS}^2}}$
	• Frequency deviation	$\delta - \delta_0 = \Delta t(\omega - \omega_0)$

Some of the algorithms for calculation of phasor quantities for Class II type signals are given in Table II [6].

TABLE II.

The Algorithms for Class II

Direct Measurements	• Active harmonic power	$P_k = \frac{V_k I_k}{2}\cos(\phi_k - \psi_k)$, $(k \neq 0)$
	• Reactive harmonic power	$Q_k = \frac{V_k I_k}{2}\sin(\phi_k - \psi_k)$, $(k \neq 0)$
	• Total active power	$\sum_{k=0}^{M} P_k = P_T$
	• Boudenau reactive power	$Q_B = \sum_{k=1}^{M} Q_k$
	• RMS^2 for voltage harmonics	$\frac{V_k^2}{2} = V_{kRMS}^2$
	• Total RMS^2 for all voltage harmonics	$V_T^2 = \sum_{k=0}^{M} V_{kRMS}^2$
	• Losses	$L = \sum_{k=2}^{M} c_k V_{km}^2$
Derived Measurements	• RMS for harmonics	$\sqrt{V_{kRMS}^2}$
	• Apparent harmonic power	$S_k = \sqrt{V_{kRMS}^2 I_{kRMS}^2}$
	• Harmonic power factor	$PF_k = \frac{P_k}{S_k}$
	• Total apparent power	$S_T = \sqrt{V_T^2 I_T^2}$
	• Total power factor	$PF_T = \frac{P_T}{S_T}$
	• Fryze reactive power	$Q_F = \sqrt{S_T^2 - P_T^2}$
	• Boudenau distortion power	$D = \sqrt{S_T^2 - P_T^2 - Q_B^2}$
	• Total harmonic distortion (THD)	$\frac{\sum_{k=2}^{M} V_{kRMS}^2}{V_{1RMS}^2}$
	• Kusters reactive power	$\frac{\sum_{k=1}^{M} kQ_k}{\sum_{k=1}^{M} k^2 V_{kRMS}^2} \cdot V_T$
	• Reactive current	$i_q = i(t) - \frac{P_T}{V_{TRMS}^2} n(t)$

C. Combination of Different Techniques

This example demonstrates the use of signal processing, wavelets, and artificial neural networks in a system to detect and classify some power quality problems which commonly occur on transmission systems. Sampled voltage signals used as inputs to the system are subjected to signal processing techniques and wavelet analysis, then resulting sets of coefficients are introduced to a trained neural network, which classifies them as power disturbance event types.

To initially train the neural networks and set up the classification system, simulated data are used. This is done by creating 10 cycles of an undisturbed sinusoid then applying the modification window to the sinusoid, using mathematical formulas, so that the resulting waveforms resembles recognized classes of power disturbance events. An example of this is illustrated in Figure 4, which shows a sinusoid (top) which is multiplied by a modification window (center) to produce a simulated sudden sag disturbance (bottom).

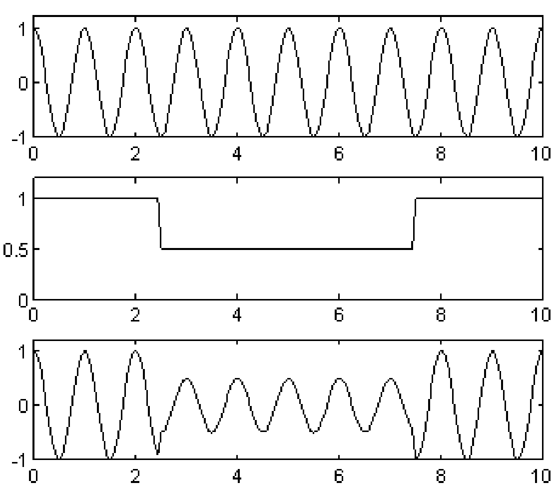

Figure 4. Creation of sudden sag disturbance

Several disturbance classes are simulated to include many events, such as sags and transients, which may be encountered in a transmission system. To create variety within disturbance classes, parameters such as height, width, and damping are varied in the mathematical formulas. This way, many different examples of each class of events are used to train the neural networks so that the training will be well generalized.

The next step is to enhance the disturbance. Input signals may be filtered to remove the fundamental sinusoidal component so that the waveform is more susceptible to classification. A wavelet transform further enhances the disturbance, while reducing the filtered signal samples to a smaller number of coefficients.

The Continuous Wavelet Transform (CWT) applied to a signal produces a surface of wavelet coefficients for continuously varying scale and translation variables. Each disturbance type produces a characteristic plot, an example of which is shown in Figure 5. By studying the CWT of some disturbance signals, one can determine which scale and translation variables will be most productive in the classification task.

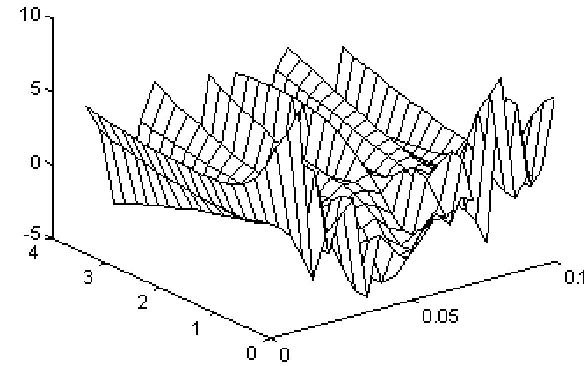

Figure 5. CWT surface plot of power system voltage

A group of discrete scale and translation variables for the wavelet is chosen, guided by information in the CWT plots. These wavelet variables are used to compute the Discrete Wavelet Transform (DWT). The DWT similarly produces a surface of wavelet coefficients, but using integer scales and translations, so DWT methods are well suited for computer implementation. Comparison of DWT surface plots also reveals a characteristic pattern for each disturbance type. A typical DWT surface plot is shown in Figure 6. The resulting set of wavelet coefficients, representing some power system voltage waveform with or without a disturbance, constitutes an input vector ready for introduction to the neural network.

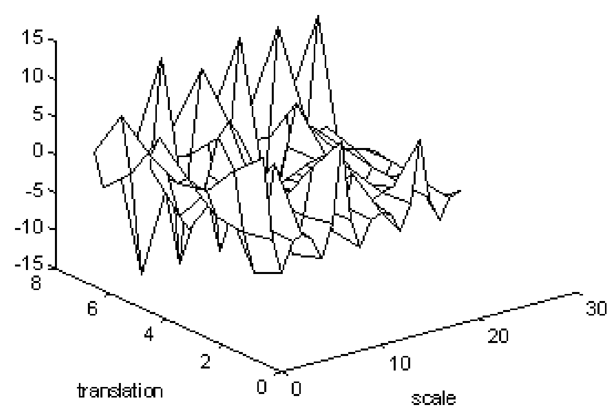

Figure 6. DWT plot of power system voltage

The artificial neural network used in this example is a self-organizing map implemented with 48 neurons. The neural network was trained by generating input vectors for about 200 examples of each of eight disturbance types. The network was subjected to 10,000 presentations, selected at random from the training set. The trained network was then operated in recall mode with the input of all training set vectors. The initial result was that the network did not distinguish certain disturbance classes well; cases with similar frequency components tended to be grouped together. To resolve these “mixed group” classifications, additional self-organizing maps were created to address specific types of class confusion. Any case which is assigned to a "mixed group" by an ANN is introduced to another ANN for further classification.

The method was tested for 50 "unseen" cases of each disturbance type. A classification error is said to have occurred when a case is classified in an incorrect group or an undefined group (consisting of an untrained or "dead" neuron). Assignment to an undefined group is a case in need of further analysis by a human expert. Most types of disturbances in the training set are distinguished well. Overall results from the test cases, expanded in Table III, are 95% correct, 4% undefined, and 1% incorrect.

This method of analyzing power system signals appears quite promising for power quality monitoring applications where an assessment of disturbance types is needed. It may be incorporated into an automated classification system, to reduce the amount of data that must be seen by human experts.

TABLE III.

Results of Testing Classification Method

Class Tested	Correctly Identified	Undefined	Incorrect
Undisturbed sinusoid	100%		
Sudden sag	84%	16%	
Gradual sag	100%		
DC offset	100%		
Subharmonic	100%		
Oscillating transient	94%	2%	4% DC offset
Flicker	82%	14%	4% oscillating transient
Noise	100%		

V. Conclusions

Discussion given in this paper leads to the following conclusions:

- Power quality assessment is a complex problem since there is a variety of power quality disturbances that need to be detected and classified.
- A specialized hardware aimed at transferring data from DFR to PC may be the most efficient way to capture and process power quality data.
- An automated software for PQ disturbance detection and classification can be developed using signal processing, neural nets and wavelets.

REFERENCES

[1] R. C. Dugan, *Electrical Power Systems Quality*, New York: McGraw-Hill, 1996.

[2] S. S. Venkata, G. T. Heydt, "Proceedings of the NSF Workshop on Electric Power Quality," Grand Canyon, Arizona, January 1991.

[3] Basic Measuring Instruments, *Handbook of Power Signatures*, Santa Clara, CA: Basic Measuring Instruments

[4] M. Kezunovic and B. Perunicic, "Digital Signal Processing Algorithms for Power Quality Assessment", *IECON '92*, San Diego, CA, November 1992.

[5] M. Kezunovic, P. Spasojevic and B. Perunicic, "New Detection Techniques for Power System Disturbance Monitoring and Analysis", *ISCA International Conference on Computer Applications in Industry and Engineering*, Honolulu, Hawaii, December 1993.

[6] M. Kezunovic, E. Soljanin and B. Perunicic, "New Approach to the Design of Digital Algorithms for Electric Power Measurements", *IEEE Trans. On Power Delivery*, Vol. 6, No. 2, April 1991.

[7] M. Kezunovic, I. Rikalo, C. W. Fromen, D. R. Sevcik, and K. W. Tielke, "Real Time Generator Monitoring System," *AVO International Technical Conference*, Dallas, Texas, July, 1996.

[8] M. Kezunovic, I. Rikalo, J. Sun, X. Wu, C. W. Fromen, D. R. Sevcik, and K. W. Tielke, "Implementation Framework for an Expert System for Generator Monitoring," *International Conference on Intelligent System Applications to Power Systems*, Orlando, Florida, February, 1996.

[9] DFR Assistant™ Product Description, *Test Laboratories International Inc*., 1996.

[10] M. Kezunovic, I. Rikalo, "Detect and Classify Faults Using Neural Nets," *IEEE Computer Applications in Power*, Vol. 9, No. 4, pp. 42-47, October 1996.

[11] M. Kezunovic, I. Rikalo, D. J. Sobajic, "Real Time and Off Line Transmission Line Fault Classification Using Neural Networks," *International Journal of Engineering Intelligent Systems*, Vol. 4, No. 1, pp. 57-63, March 1996.

[12] M. Kezunovic, I. Rikalo, and D. J. Sobajic, "High Speed Fault Detection and Classification with Neural Nets," *Electric Power Systems Research Journal*, Vol. 34, No. 1, pp. 109-116, 1995.

[13] Relay Test Assistant™ Product Description, *Test Laboratories International Inc*., 1996.