AUTOMATED ANALYSIS OF POWER QUALITY DISTURBANCES

M Kezunovic, Y Liao *

Texas A&M University, USA

I. INTRODUCTION

With the increased use of sensitive electronic circuitry, customers become more concerned about the electric power quality (PQ). In the new open-access and competitive power market, electricity consumers are in a unique position to demand a higher quality of service. The utilities or other power providers have to ensure a high quality of their service to remain competitive and retain/attract the customers. Efficient power quality assessment tools are needed to help achieve this goal [IEEE (1), Bollen (2), Kezunovic (3)].

PQ assessment is a complex subject and may include diverse aspects such as power system and equipment modeling, PQ problem mitigation and optimization, and data analysis [3]. In most cases, automated PQ assessment is desirable because manual analysis may be difficult to carry out due to lack of time and special expertise. Specialized software tools can make use of intelligent techniques to automate the PQ assessment for improved accuracy and efficiency. Among various PQ phenomena, PQ disturbances like voltage sags, swells, and switching transients are of particular interest. This paper is focusing on automated assessment of PQ disturbances that may facilitate the overall PQ assessment. Specifically, this paper is focusing on: a.) developing better tools for automated detection, classification and characterization of PQ disturbances, b.) carrying out system and equipment modeling studies to better understand the PQ disturbances, and c.) finding the fault location if the disturbance is identified as a sag caused by a fault. Intelligent techniques like fuzzy logic, expert system and genetic algorithm, as well as signal processing techniques like Fourier transform and wavelet analysis have been utilized for developing the tools. When carrying out these studies, various assumptions made will be illustrated where appropriate.

The paper is organized as follows. First, an automated system for detecting, classifying and characterizing various types of PQ disturbances is presented. Then, study on the effects of a specific disturbance on the equipment behavior is illustrated. Next, the location of the disturbance source is pinpointed for the case where the disturbance is a sag caused by a short circuit fault. After that, the application of the developed tools is illustrated by utilizing the voltage sag disturbance as examples. Three steps of the analysis are performed. The first one is related to automated detection, classification and characterization of the disturbance. The second one explains how the developed tools can be used to perform equipment sensitivity study. The last step demonstrates the location of the fault that has led to the sag disturbance utilizing a genetic algorithm based optimization approach. Field data provided by the funding utilities are used in the study. It will be shown that using both recorded and simulated data is conducive to efficient PQ analysis.

* Y Liao is presently employed by ABB ETI, Raleigh.

II. POWER QUALITY DISTURBANCE DETECTION, CLASSIFICATION AND CHARACTERIZATION

This section presents advanced techniques for automated detection, classification and characterization of various types of power quality disturbances [1, 3]. Disturbance records in the form of sampled data are assumed to be available for this purpose.

A. Power Quality Event Detection and Classification

The flowchart of the proposed solution is shown in Fig. 1.

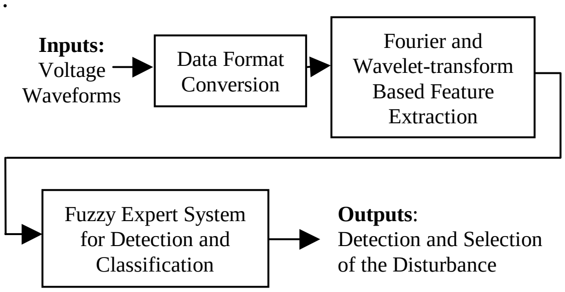

Fig. 1. Detection and classification flowchart

The sub-module "Data Format Conversion" converts the inputs from a specific recording device or simulation package format into a common data format comprehensible to other modules of the software. The "Fourier and Wavelet-transform Based Feature Extraction" module obtains unique features pertinent to specific events and "Fuzzy Expert System for Detection and Classification" module reaches a decision regarding detection and classification, as discussed next [3].

FFT and wavelet-analysis based feature extraction. A number of power quality events of various types have been simulated and corresponding waveforms obtained. The following eight distinct features inherent to different types of power quality events have been identified: the Fundamental Component (V_n), Phase Angle Shift (α_n), Total Harmonic Distortion (THD_n), Number of Peaks of the Wavelet Coefficients (N_n), Energy of the Wavelet Coefficients (EW_n), Oscillation Number of the Missing Voltage (OS_n), Lower Harmonic Distortion (TS_n), and Oscillation Number of the rms Variations (RN). The formulae for computing these features are referred to in [3].

Next, the statistical properties of the parameters for various power quality events can be obtained. Extensive studies have evinced that the extracted parameters display distinctive patterns under different types of events. Based on these distinctive patterns, appropriate fuzzy rules can be established for distinguishing between different types of events as shown below.

A Fuzzy expert system for detection and classification. The core of the rule set of the implemented fuzzy expert system is illustrated as follows [Yen and Langari (4)].

a) Detection: For detection, one rule is used as follows
Rule 1: if THD_n is A_2 or PS_n is B_2 or V_n is C_3 or V_n is C_1 then DETECT=1

b) Classification: fifteen rules are used as follows
Rule 1: V_{n+1} is A_4 and N_n is F_1 and OS_n is G_1 then IMPULSE=1
Rule 2: V_n is A_1 or V_{n+1} is A_1 then INTERRUPTION =1
Rule 3: V_n is A_6 or V_{n+1} is A_6 then SWELL=1
Rule 4: V_n is A_5 and PS_n is C_1 and PS_{n+1} is C_1 and EW_{n+1} is D_1 and $\{TS_{n+1}$ is H_2 or $[TS_{n+1}$ is H_4 & TS_{n+2} is $H_1]\}$ then SWELL=1
Rule 5: V_{n+1} is A_5 and $\{PS_n$ is C_2 or PS_{n+1} is $C_2\}$ then SWELL=1
Rule 6: V_{n+1} is A_2 then SAG=1
Rule 7: V_{n+1} is A_3 and $\{PS_n$ is C_2 or PS_{n+1} is $C_2\}$ then SAG=1
Rule 8: V_{n+1} is A_3 and $\{PS_n$ is C_1 and PS_{n+1} is $C_1\}$ and $\{THD_{n+1}$ is B_1 or $[THD_{n+1}$ is B_2 and OS_{n+1} is $G_4]\}$ then SAG=1
Rule 9: V_{n+1} is A_3 and PS_n is C_1 and PS_{n+1} is C_1 and OS_n is G_2 and THD_{n+1} is B_2 and THD_{n+2} is B_2 and THD_{n+3} is B_2 then NOTCH=1
Rule 10: V_{n+1} is A_3 and N_n is F_2 and OS_n is G_2 then NOTCH=1
Rule 11: V_{n+1} is A_4 and PS_n is C_1 and PS_{n+1} is C_1 and THD_n is B_3 and THD_{n+3} is B_1 and $\{OS_n$ is G_4 or OS_{n+1} is $G_4\}$ then TRANSIENT=1
Rule 12: V_{n+1} is A_4 and TS_{n+1} is H_3 and TS_{n+2} is H_3 and TS_{n+3} is H_3 and OS_{n+1} is G_4 then HARMONIC=1
Rule 13: THD_{n+1} is B_4 and THD_{n+2} is B_4 and THD_{n+3} is B_4 and OS_{n+2} is G_4 then HARMONIC=1
Rule 14: TS_{n+1} is H_4 and TS_{n+2} is H_4 and TS_{n+3} is H_4 and OS_{n+2} is G_4 then HARMONIC=1
Rule 15: If RN is K_1 then FLICKER=1

In the above rules, $A_i, B_i, C_i, D_i, F_i, G_i, H_i,$ and K_i are the membership functions for the input patterns, where the common trapezoidal and triangular functions are used.

The fuzzy partitions and the corresponding membership functions can be obtained based on both the statistical studies and the expert's knowledge. Opinions from operators can be conveniently incorporated into the system in practical applications.

The output for the detection part is the variable "Detect" whose value reflects the credibility that certain disturbance exists. The outputs for the classification parts are fuzzy variables "Flicker", "Impulse", "Interruption", "Swell", "Sag", "Notch", "Transient", and "Harmonic" whose values represent the degree to which the event belongs to each of these categories. The type of the event selected will be the one with the largest membership. In cases where two or more types of disturbances have the same largest membership value, all of them will be selected for further analysis.

Extensive evaluation studies have demonstrated that the fuzzy DMS results in a correct identification rate of 99%, and that the proposed methods for feature extraction and decision making are efficient and feasible.

The next step for automated power quality monitoring is the event characterization.

B. Power Quality Event Characterization

The characterization of power quality events is aimed at extracting distinctive and pertinent parameters for describing specific event waveforms [1-3]. These parameters may be useful for system planning, troubleshooting and system control. Particularly, these parameters play an essential role in the equipment sensitivity study that aims at improving the immunity or ride-through ability of the loads sensitive to specific types of power quality events, as will be illustrated in the next section. Hence event characterization is an important step for making a successful power quality contract.

Because different types of event waveforms require different parameters for description, the waveforms need to be classified before characterization. The detection and classification system presented above can be used for accomplishing this task. After the type of the event is identified, the corresponding characterization algorithms can be selected for extracting more accurate and pertinent parameters.

The overall structure of the proposed approach for event characterization is depicted in Fig. 2. The inputs are the voltage waveforms that have already been identified as certain types by the detection and classification system described above. The outputs are the waveform parameters pertinent to the input waveforms. The "Fourier and Wavelet Analysis Based Characterization" module is used to process the voltage waveforms utilizing signal processing techniques to obtain the waveform parameters of interest. The wavelet analysis is used for better localizing the time related parameters, while the Fourier transform is utilized for obtaining the magnitude related parameters.

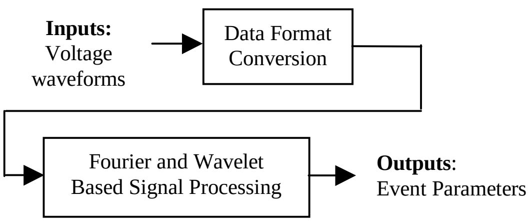

Fig. 2. Event characterization flowchart

III. EQUIPMENT SENSITIVITY STUDY

After a disturbance is detected and characterized, quite often it may be needed to study how the disturbance affects the behavior of the sensitive equipment of interest [3]. This section presents an approach for equipment sensitivity study. Examination of how sag parameters affect the equipment behavior is emphasized next. As well known, some customer loads may trip or mis-operate due to the voltage sags. With the advent of electronic devices, the trip or mis-operation may no longer be just attributed to the sag magnitude and duration. Instead, other factors like points-on-wave, unbalance ratio, and phase angle shift may also play an essential role in the behavior of the modern loads during voltage sag events. Through equipment sensitivity study, the software can explain why a specific load failed during a sag event, or predict how well a load will perform during an actual sag event.

The overall structure for evaluating the equipment behavior under voltage sag events is depicted in Fig. 3. The inputs are the voltage sag waveforms that can either be recorded in the field or generated by specific simulation packages. The outputs are the operating characteristics of the equipment during the specified sag events. The block “Voltage Sag Characterization” computes various sag parameters. The block “Sag Parameter Tuning” allows the user to tune or edit the sag parameters, obtained from the block “Voltage Sag Characterization”, to certain values. The “Recorded Voltage Sag Waveforms” provide us with a set of initial sag parameters based on which further tuning can be made. The recorded waveforms are optional and if they are unavailable, the user can input any desired initial sag parameter and then tune them for testing. In either case, by tuning the sag parameters such as the sag magnitude, sag duration, phase angle shift, etc., the software allows the user to observe and study how specific sag parameters affect the operating characteristics of the equipment under test. This is what we call the equipment sensitivity study. The block “Voltage Sag Generator” reconstructs the voltage sag waveforms based on the selected sag parameters. The constructed voltage waveforms serve as the voltage source for testing the equipment. The voltage sources can either be one phase or three phase depending on the equipment being evaluated. The “Equipment Model” allows development of mathematical models for the equipment. Equipment sensitivity study during other types of disturbances can be performed similarly.

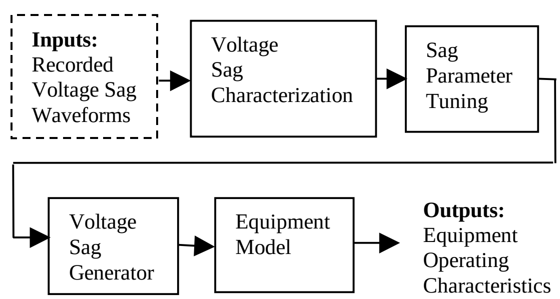

Fig. 3. The overall structure for equipment behavior evaluation

IV. LOCATION OF THE DISTURBANCE SOURCE

Prompt and accurate location of the disturbance source is often an important step in solving the related problems. This work focuses on locating the fault that caused the sag disturbance. It is assumed that recorded data coming from sparsely located recording devices are available. To improve the accuracy for fault location, the “waveform matching" based approach may be used. In this approach, simulation studies are carried out to obtain simulated waveforms under specified fault conditions [Kezunovic and Liao (5)]. The simulated waveforms are then compared with the recorded ones. By iteratively posing faults in the system, running simulations, and comparing the simulated waveforms with the recorded ones, an optimal estimate of the fault location may be obtained. It may be determined as the one specified in the simulation studies that allows simulating the waveforms that best match the recorded ones. The matching is made at the phasor level presently. PSS/E software is utilized to carry out the short circuit studies [PTI (6)].

The fault location estimation has been mathematically formulated as an optimization problem of which the fault location and fault resistances are unknown variables. An efficient GA based searching scheme is developed for obtaining the globally optimal solution [Goldberg (7)]. The detailed method is referred to in our earlier paper [5].

V. APPLICATION EXAMPLES

This section presents examples illustrating the applications of the developed methodology and tool for automated analysis.

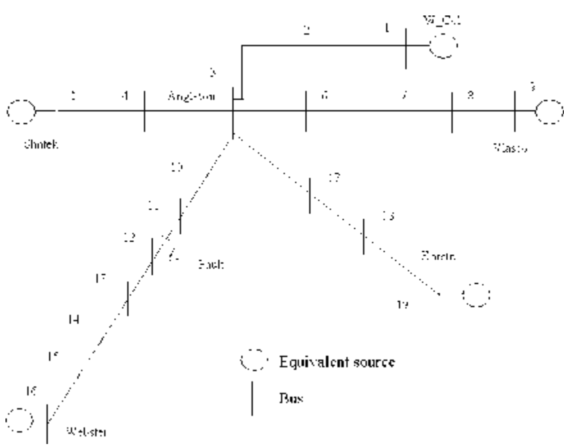

Fig. 4. A sample power system

Fig. 4 depicts a portion of the 138 kV Reliant Energy HL&P transmission system that is used here for illustration purposes.

A short circuit fault has caused the voltage waveforms as shown in Fig. 5. The waveforms were recorded at Angleton substation. First, the sag disturbance captured in the waveforms is identified using the fuzzy expert system. Then the waveform parameters are extracted using the proposed characterization approaches as listed in Table 1.

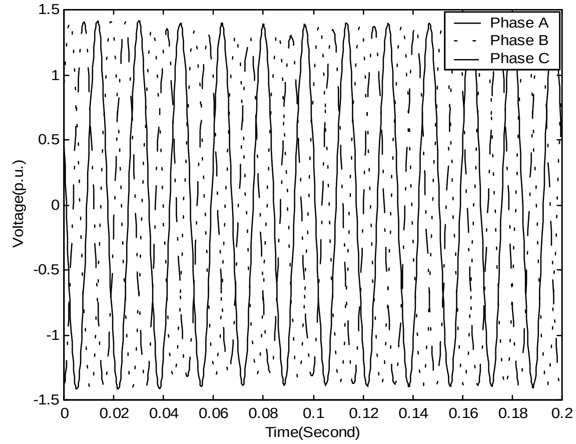

Fig. 5. A recorded sag waveform

Table 1. Characterization results of the sag waveforms

Sag Parameters	Phase A	Phase B	Phase C
Minimum rms value (p.u.)	0.981	0.929	0.932
Maximum rms value (p.u.)	1.0	1.001	1.0
Average rms value (p.u.)	0.991	0.972	0.973
Final rms magnitude (p.u.)	0.993	0.994	0.994
Peak value (p.u.)	1.418	1.411	1.430
Sag starting time (ms)	0	47.0	51.2
Sag end time (ms)	0	100.1	100.1
Sag duration (ms)	0	53.1	48.9
Sag initial angle(degrees)	0	335.1	303.7
Sag initial phase angle shift (degrees)	0	-1.67	2.21
Sag initial phase angle shift rate (degrees/sec.)	0	-87.51	127.51
Sag end angle(degrees)	0	28.13	270.0
Sag end phase angle shift (degrees)	0	2.91	-2.23
Sag end phase angle shift rate (degrees/sec.)	0	74.2	-87.5
Total harmonic distortion	0.015	0.027	0.044
Rms magnitude unbalance ratio	0.064		
Three-phase phase angle difference deviation (degrees)	3.92		

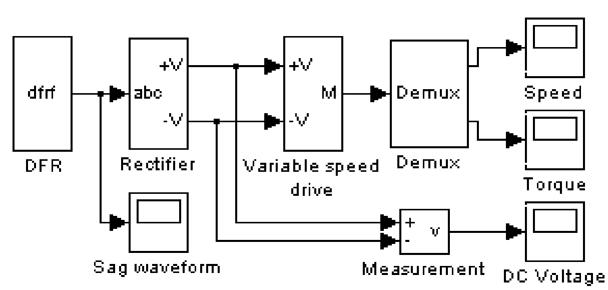

Fig. 6. The testing diagram for the VSD

Then a variable speed drive modeled in MATLAB as shown in Fig. 6 is subjected to the recorded waveforms and its operating characteristics can be obtained as listed in Table 2 [MathWorks (8)]. In Fig. 6, the block "DFR" imports the voltage waveforms from the recorded data file. The block titled "Rectifier" provides the DC voltage for the block titled "Variable Speed Drive". The scopes are used for examining quantities of interest.

Table 2. Changes of VSD parameters due to the sag disturbance

Parameters	Normal Value	During Sag Value	Change	Percent Change
Stator current in rms (A)	12.8	12.3	-0.5	-3.9
Rotor current in rms (A)	18.2	18.0	-0.2	-1.1
DC voltage (V)	352.0	311.4	-40.6	-11.5
Rotor speed (rpm)	1785.5	1673.6	-111.9	-6.3
Electromagnetic torque (N. m.)	23.2	19.8	-3.4	-14.7

It is seen from Table 2 that the largest drop of the rotor speed is 6.3% of the normal speed. This is due to the DC voltage drop caused by the sag. This study tells us that the variable speed drive would have had a 6.3% speed drop if it had been powered through bus 3. If the maximum allowable speed drop is 5% for example, then pre-cautions are needed for this drive.

The next step is to locate the short circuit fault using the genetic algorithm based approach. The GA uses the following parameters: population size: 30, crossover probability: 0.85, mutation probability: 0.05, coding binary string length for fault location: 9, and coding binary string length for fault resistance: 8. Fault location ranges from 0 to the sum of the length of all the lines, as shown in Fig. 4. Fault resistance ranges from 0 to 0.4 p.u. The fault is found to be between bus 11 and bus 12 with error within 1 mile.

After the fault is located, additional short circuit studies can be performed along the line between Angleton and Webster with changing fault location, fault resistance, fault type and fault clearing time, then the voltage waveforms under these fault conditions can be generated. The variable speed drive tested above can be subjected to these simulated waveforms for testing. Statistical testing results on the operating characteristics can be obtained, and a general picture of how the drive behaves under different fault conditions are thus acquired. Better pre-caution measures can be taken to prevent the mis-operation or trip of the drive during various types of faults.

It is noted that all the results obtained such as those shown in Table 1 and Table 2, and the fault location result are saved in a database, and can be conveniently retrieved and presented to the operator when needed.

VI. CONCLUSIONS

This paper presents recent developments related to automated analysis of PQ disturbance. The proposed approaches consist of several steps that may be closely related to each other. The PQ disturbance is first detected and classified by an automated system. After the type of the disturbance is identified, the distinctive features of the waveform are extracted using appropriate modules. Then, the behavior of the equipment of interest can be studied under this specific disturbance. If this disturbance is identified as a sag caused by a fault, the genetic algorithm based search approach is utilized to locate the fault. Examples are presented to illustrate the applications of the developed methodology and tools. It is found that appropriate interaction between data analysis and system modeling is an efficient way for carrying out PQ studies. Both recorded and simulated data have been evinced to be useful for PQ analysis.

VII. ACKNOWLEDGEMENTS

The work presented in this paper was funded by the Texas Higher Education Coordinating Board Advanced Technology Program. The co-funding is provided by TXU Electric and Reliant Energy HL&P. The funding utilities also provided field data used for testing and illustrating the applications of the developed tools.

VIII. REFERENCES

1. IEEE Std 1159, 1995, "IEEE Recommended Practice for Monitoring Electric Power Quality", IEEE Inc., New York, pp. 1-59.
2. M. H. J. Bollen, 2000, "Understanding Power Quality Problems: Voltage Sags and Interruptions", IEEE, Inc., New York, pp. 139-253.
3. Kezunovic M, 2000, "Advanced assessment of power quality events", 9th International Conference on Harmonics and Quality of Power, Florida.
4. John Yen and Reza Langari, 1999, "Fuzzy Logic: Intelligence, Control, and Information", Prentice Hall, pp. 109-137.
5. M. Kezunovic and Y. Liao, 2001, "Fault location estimation based on matching the simulated and recorded waveforms using genetic algorithms", to be presented at the 7th International Conference on Developments in Power Systems Protection, Netherlands.
6. Power Technologies, Inc., 1997, "PSS/E 25 Program Operation and Application Manuals".
7. Goldberg D E, 1989, "Genetic Algorithms in Search, Optimization and Machine Learning", Addison Wesley, Reading, MA.
8. MathWorks, Inc., 1997, "MATLAB Manuals".