A Novel Software Implementation Concept for Power Quality Study

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***Abstract*—A novel concept for power quality study is proposed. The concept integrates the power system modeling, classifying and characterizing of power quality events, studying equipment sensitivity to the event disturbance, and locating point of event occurrence into one unified frame. Both Fourier and wavelet analyzes are applied for extracting distinct features of various types of events as well as for characterizing the events. A new fuzzy expert system for classifying power quality events based on such features is presented with improved performance over previous neural network based methods. A novel simulation method is outlined for evaluating the operating characteristics of the equipment during specific events. A software prototype implementing the concept has been developed in MATLAB. The voltage sag event is taken as an example for illustrating the analysis methods and software implementation issues. It is concluded that the proposed approach is feasible and promising for real world applications.**

***Index Terms*—Pattern classification, power quality, signal processing, wavelet transforms.**

I. Introduction

In a power system, faults, dynamic operations, or nonlinear loads often cause various types of power quality disturbances such as voltage sags, voltage swells, switching transients, impulses, notches, flickers, harmonics, etc. [1], [2]. On the other hand, the increased use of sensitive electronic circuitry by industrial and residential customer, as well as the progress of utility deregulation and competition have imposed greater demand on the quality of power. Consequently, the studies aimed at detecting and analyzing as well as eliminating or minimizing the effects of power quality disturbances on industrial and customer loads have assumed greater importance.

One critical aspect of power quality studies is the ability to perform automatic power quality monitoring and data analysis. Usually, utilities install power quality meters or digital fault recorders at certain locations so that various power quality events can be recorded and stored in the form of sampled data for further analysis.

Efficient and prompt detection, classification, and characterization of the events as well as further identification of the location of these events facilitate maintenance and control of the system, and improve system stability and reliability. Another principal aspect of a power quality study is coordination between the power system behavior and equipment performance. It is desired that the response of the sensitive equipment during the event be explained and correlated to specific features of the event, so that either the system behavior or the equipment operating characteristics can be tuned for improved ride-through ability or immunity of the equipment to specific events [3].

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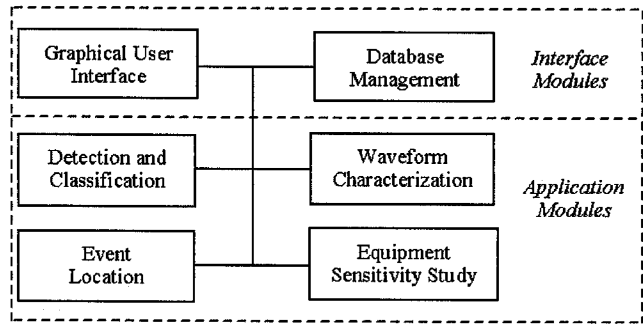

Fig. 1. Overall software structure.

It has been noted that the activities of detecting and classifying of power quality events, characterizing and locating events, studying equipment sensitivity, and modeling of the system and equipment are closely related and interdependent. Hence, it is natural and desirable that the data processing and analysis as well as modeling and simulation of the system and equipment be studied in one unified framework. This paper provides a new software implementation concept for such an integration.

The developed software mainly consists of four application modules and two interface modules. In the rest of the paper, the overall software structure is described first. The functionality of each module is illustrated. Then, a new fuzzy expert system for detection and classification of various types of events is described [4], [5]. Presented next is a novel simulation approach for testing the operating characteristics of the equipment during specific power quality events [6], [7]. Finally, an example is given to illustrate the approach and advantages if these different application modules as well as the system and equipment models are interconnected.

II. Overall Software Structure

The proposed concept has been implemented in MATLAB. The structure of the software is depicted in Fig. 1.

The application module "Detection and Classification" automatically detects and classifies the type of the disturbance captured in the recorded or simulated waveforms. The types of disturbances include the voltage sag, swell, outage, harmonic, notch, flicker, impulse, and switching transient. After the disturbance is detected and classified, the waveform is further

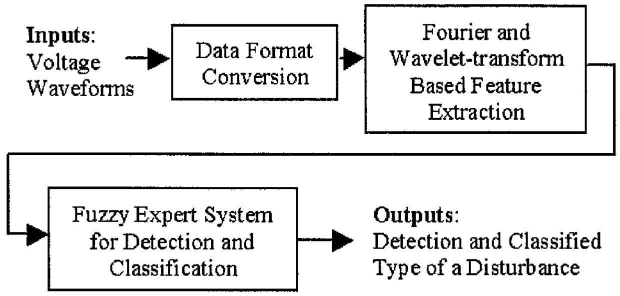

Fig. 2. Detection and classification flow chart.

processed by the module "Waveform Characterization." Eight different submodules corresponding to the eight types of events have been designed. The software automatically selects the appropriate submodule for computing parameters pertinent to the event. Then, one may proceed to the module "Equipment Sensitivity Study" for evaluating how various waveform features affect the behavior of the equipment during the event. Finally, the module "Event Location" aims at accurately pinpointing the location of the event occurrence. Presently, we are focusing on locating faults that caused the sag event using the waveforms recorded by a limited number of DFRs and related power system data. Short-circuit studies are employed to obtain an optimal fault location estimate subject to a defined performance criterion by iteratively posing faults in the system, running simulations, and comparing the simulated waveforms with the recorded waveforms. The criterion for the optimal estimate is stated as the one where the simulated waveforms match best the recorded waveforms. The "Graphical User Interface" provides a friendly environment for using the software. The "Database Management" facilitates data saving, retrieving as well as exchanging the internal or external data.

Due to the space limitation, the two interface modules are not elaborated here. The detailed analysis of the module "Waveform Characterization" is referred to an earlier paper [8]. The module "Event Location" is still under development and detailed results will be presented in future papers. Section III and Section IV will give more details on the application modules "Detection and Classification," and "Equipment Sensitivity Study."

III. Detection and Classification of Power Quality Events

At present, this module automatically detects and classifies the types of the voltage disturbances. The functional diagram is shown in Fig. 2. The submodule "Data Format Conversion" converts the inputs from a specific recording device or simulation package format into a common format comprehensible to other modules of the software.

Largely speaking, the detection and classification problem consists of two steps. The first step is feature extraction, during which the distinct and dominant features (or patterns) of various events are selected and obtained using appropriate techniques. The second step is called decision making, during which the extracted features are further processed by an inference engine to determine the types of the events. Appropriately chosen features are essential for both simplifying the decision making system (DMS) and improving the correct identification rate of the system.

Various approaches for both feature extraction and DMS have been proposed for classifying the power quality events. Both Fourier transform and wavelet transform techniques have been suggested for feature extraction earlier [4], [9], [10]. Our work has shown that a combination of these two techniques works better for feature extraction than either of these two alone.

For decision-making, a neural network based system was presented in [4]. The author suggests using the time-delay network to capture the temporal features of the input signals. One drawback of using neural network is the difficulty of the training process. Some authors have proposed using the fuzzy logic to model the uncertainties of the training error so that the learning rate can be finely tuned to improve the convergence of the system [5]. However, this method still belongs to the category of neural network and does not utilize fuzzy logic to model the uncertainties of the input patterns.

Fuzzy logic based DMS is well suited to solve the real-world problems. It bridges the quantitative and qualitative considerations. It has found wide applications in the areas of load forecasting, harmonic tracking, power metering, etc. [11], [12]. In this work, application of fuzzy logic techniques to the detection and classification of power quality events is explored.

A. FFT and Wavelet-Analysis Based Feature Extraction

A number of power quality events of various types have been simulated and corresponding waveforms are obtained. The following eight distinct features inherent to different types of power quality events have been extracted: 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 given as follows:

$$V_n = \sqrt{2}abs(V^n[1])/N \tag{1}$$

$$\alpha_n = \mathrm{angle}(V^n[1]) - \mathrm{angle}(V^1[1]) \tag{2}$$

$$THD_n = \sqrt{\sum_{k=2}^{int(N/2)} \{abs(V^n[k])\}^2 \Big/ V^1[1]} \tag{3}$$

$$N_n = \mathrm{peak}(abs(WC^s)) \tag{4}$$

$$EW_n = \sum_{k=1}^{le} abs(WC^n[k]) \tag{5}$$

$$OS_n = \mathrm{root}(v^s_{\mathrm{miss}}) \tag{6}$$

$$TS_n = \sqrt{\sum_{k=2}^{10} \{abs(V^n[k])\}^2 \Big/ V^1[1]} \tag{7}$$

$$RN = \mathrm{root}(V^s_{rms} - \mathrm{mean}(V^s_{rms})). \tag{8}$$

In (1)–(8)

$V^n[k]$ is the Discrete Fourier Transform (DFT) for the samples contained in the nth data window defined as

$$V^n[k] = \sum_{i=0}^{N-1} v[i+(n-1)*N]e^{-j(2\pi ki/N)} \tag{9}$$

$v[i]$ represents the sampled input signal, $i = 0, 1, \ldots, L-1$ with L the length of the signal, N is the number of samples in one data window (one cycle), j is the imaginary unit, and $n = 1, 2, \ldots 10$, WC^n is the wavelet coefficients for the samples contained in the nth data window [9], and WC^s is defined as an array composed of $WC^n[k]$ for $k = 1, 2, \ldots, le$, with le the length of WC^n.

$$v_{\text{miss}}[i] = v[i] - 2/N^* abs(V^1[1])^* \cos\{\text{angle}(V^1[1]) + 2\pi(i-1)/N\} \tag{10}$$

v_{miss}^s is defined as an array composed of $v_{\text{miss}}[i]$, $i = 0, 1, \ldots, L-1$

$$V_{\text{rms}}^n = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} v^2[i+(n-1)N]} \tag{11}$$

where

- V_{rms}^s an array composed of V_{rms}^n, $n = 1, 2, \ldots, 10$;
- $abs(.)$ gives the absolute value of the argument;
- $int(N/2)$ equals $N/2$ if N is even, and $(N-1)/2$ if N odd;
- $\text{angle}(.)$ returns the phase angle of the input argument;
- $\text{root}(.)$ returns the number of roots (or zero-crossings) of the argument;
- $\text{peak}(.)$ returns the number of peaks of the argument;
- $\text{mean}(.)$ gives the mean of the argument.

In our work, ten cycles of samples of the three-phase voltage signals (in per unit) are used. The Daubechies-4 wavelet family and the second scale wavelet detail coefficients are utilized. Detailed analysis on the wavelet transform and multiresolution decomposition techniques is referred to [9], [10].

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 to distinguish between different types of events as shown below.

B. Fuzzy Expert System for Detection and Classification

The core of the rule set of the implemented fuzzy expert system is illustrated as follows [13].

1) Detection: For detection, one rule 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.

2) Classification: Fifteen rules follow.

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 OUTAGE=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 and 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 these 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, and the following trapezoidal and triangular functions are used:

$$\mu(x) = \text{trapmf}(a, b, c, d) = \begin{cases} (x-a)/(b-a), & a \le x \le b \\ 1, & b \le x \le c \\ (x-d)/(c-d), & c \le x \le d \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

$$\mu(x) = \text{trimf}(a, b, c) = \begin{cases} (x-a)/(b-a), & a \le x \le b \\ (x-c)/(b-c), & b \le x \le c \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

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. For example, the membership functions for Total Harmonic Distortion are shown as follows:

B1: trapmf(-0.2 -0.1 0.048 0.05)

B2: trapmf(0.048 0.05 1.1 1.2)

B3: trapmf(0.075 0.08 1.1 1.2)

B4: trapmf(0.26 0.3 1.1 1.2).

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," "Outage," "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 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 outputted for further analysis.

C. Evaluation Studies and Implementation Approaches

Three hundred fifty events of various types have been generated using both algebraic equations and Electromagnetic Transients Program (EMTP). The advantage of using algebraic equations over using EMTP for evaluation is the flexibility of adjusting signal noise contents as well as various waveform parameters such as the event occurrence time, harmonic contents, sag depth, etc. The fuzzy DMS results in a correct identification rate of 99%. For comparison purposes, a feed-forward one-hidden layer neural network with 17 input neurons, ten hidden neurons, and eight output neurons is implemented using the same features as inputs. The correct identification rate is 97%. The correct identification rate reported in [4] is 93%. These studies show that the proposed methods for feature extraction and decision making are efficient for the detection and classification. The feasibility of the proposed feature extraction approach is further justified as follows.

Fourier transform is suitable for analyzing stationary signals and extracting spectrum components at specific frequency, while wavelet transform more adapts to dynamic signals and is appropriate for capturing time-localized short period phenomena. Our considered disturbances range from very slow changing signal like flicker to very fast changing signal such as transient. Therefore, in order to deal with all these phenomena, it is appropriate and efficient to apply both the wavelet and Fourier transform to extracting the distinctive features.

IV. Equipment Sensitivity Study

This module aims at providing a tool for equipment sensitivity study, i.e., how various event parameters affect the equipment operating characteristics. Examination of how sag parameters affect the equipment behavior is emphasized next. As well known, some customer loads may trip or misoperate due to the voltage sags. With the advent of electronic devices, the trip or misoperation 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 [6]–[8], [14]. 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 a particular 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 be 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 the various sag parameters as described in [8] and discussed in Section II of the paper. The block "Sag Parameter Tuning" allows the user to tune or edit the sag parameters,

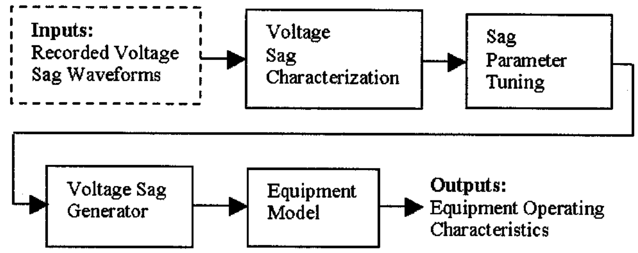

Fig. 3. Overall structure for equipment behavior evaluation.

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. However, the recorded waveforms are optional and if they are unavailable, the user can input any desired initial sag parameters 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 tuned 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.

Through the sensitivity studies, the operating characteristics of the equipment during various sag events can be evaluated and responses tabulated. For example, by changing only the phase angle shift while fixing all the other sag parameters at specified values, we can obtain one table describing the equipment operating characteristics versus the phase angle shift. In the same way, the operating characteristics of the equipment versus other parameters can be obtained and archived. By comparing the parameters of a specific sag event with the saved equipment operating characteristics, automatic equipment behavior diagnosis can be realized.

Note that the above procedure also applies to the equipment sensitivity study under other types of events except that the waveforms of the concerned types are used instead of the sag events.

V. Example of the Software Use

A typical distribution system shown in Fig. 4 is taken as an example to illustrate the proposed concepts. In the figure, DFR1 and DFR2 represent the digital fault recorders.

Now suppose that a shunt fault occurs on feeder3 and is cleared after a period of time. The fault recorders will be triggered and the voltage and current waveforms at buses 3 and 5 during the fault will be recorded. Meanwhile, it is known that the sensitive load "load1" was tripped. The purpose of our software is to analyze the two recordings to extract as much useful information as possible and explain why "load1" was tripped. Specifically, the following functions are facilitated by our software.

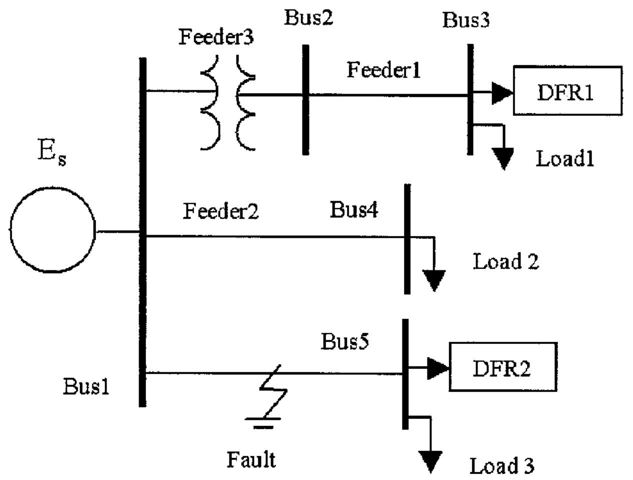

Fig. 4. Sample power system.

TABLE I
SAG PARAMETERS FOR THE VOLTAGE WAVEFORMS AT BUS 3

Parameters \ Phases	A	B	C
Sag Initial Time (ms)	301.6	0	301.8
Sag Initial Angle (degree)	1.6	0	121.4
Sag End Time (ms)	384.4	0	384.9
Sag Recovery Angle (degree)	337.5	0	56.25
Initial Phase Shift (degree)	20.34	0	-23.88
End Phase Shift (degree)	-20.30	0	23.76
Minimum rms Magnitude (p.u.)	0.61	1.0	0.59
Maximum rms Magnitude (p.u.)	1.0	1.0	1.0
Sag Duration (ms)	82.8	0	83.1
Maximum THD	0.05	0	0.04
Maximum PADD (degrees)	51.60		
Maximum rms Unbalance Ratio	0.56		

A. Detection and Classification

In this stage, the software automatically detects the occurrence of the event and classifies it as the voltage sag event.

B. Characterization

After the disturbance is identified as a sag event, various sag parameters will be computed. Table I shows the characterization results for the voltage waveforms at bus 3.

C. Equipment Sensitivity Study

This stage evaluates the operating characteristics of the equipment of interest ("load1" here) during the sag event. By replaying the sag waveforms and tuning various sag parameters, the effects of specific parameters on the equipment behavior can be obtained. A comparison of the results of equipment sensitivity study with the sag parameters of the actual waveforms, the specific sag parameter that is responsible for the trip of the equipment can be pinpointed. Table II shows results of such an analysis. It can be seen that the phase angle shift is the main factor that caused the trip of "load1." Definitions of the sag type and critical values are referred to [8] and [14].

TABLE II
EQUIPMENT BEHAVIOR ANALYSIS RESULTS

Parameters	Critical Values	Actual sag parameters	Difference	Affect
Sag Type	C	C	\	\
Phase Angle Shift (Degree)	10	23.88	13.88	Yes
Sag Magnitude (p.u.)	0.59	0.59	0	No
Sag Duration (ms.)	83.1	83.1	0	No

D. Event Location

This stage aims at pinpointing the location of the fault that has caused the recorded waveforms. A possible result is shown as "The fault is located on feeder3 and is 1.2 km from bus1."

To improve the ride-through ability or immunity of "load1" to the sag events, the system parameters or structures may be changed and the same or similar faults can be posed and simulated. Then, steps A–C are iterated until satisfactory coordination between the system and the equipment is achieved. In the proposed software environment, any modification of the system model is clearly evinced in the data analysis results, so that the correlation between the system model, event parameters and the equipment behavior can be better understood.

VI. CONCLUSION

A new practical approach is presented and implemented for integrating power quality data processing and analysis as well as modeling and simulation of the system and equipment into one unified frame. New techniques for detection, classification, and characterization of power quality events as well as equipment sensitivity study have been proposed. It is shown that the proposed methods are efficient in facilitating power quality studies. Our experience during developments of the software prototype provides some implementation guidance for practical applications.

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