Use of Intelligent Techniques in the Power Quality Assessment Applications

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Abstract: This paper presents two new intelligent systems for power quality assessment applications. One is for automated power quality disturbance detection and classification, and the other is for power system model validation. Seeking improved performance over existing approaches for power quality disturbance detection and classification, a novel fuzzy-expert system utilizing fuzzy logic and expert system techniques has been proposed. The common types of power quality disturbances such as the voltage sags, swells, interruptions, flickers, impulses, etc. are considered. Membership selection and rule sets building of the fuzzy-expert system are illustrated in detail. A genetic algorithm based system for validating the power system model in capacitor switching studies has also been developed. The problem formulation and the proposed new solution are illustrated. The implementation of the two new systems is stressed. The feasibility of the developed systems for practical applications is demonstrated by evaluation studies.

Keywords: Fuzzy-Expert System, Genetic Algorithms, Artificial Intelligence, Power Quality Assessment, Modeling and Simulation, Signal Processing.

I. INTRODUCTION

In a power system, faults, dynamic operations, or non-linear loads often cause various types of power quality (PQ) disturbances such as voltage sags, swells, interruptions, switching transients, impulses, notches, flickers, harmonics, etc. [1-4]. On the other hand, the increased use of sensitive electronic circuitry by industrial, commercial and residential customer, as well as the progress of utility deregulation and competition have imposed greater demand on the quality of power. Consequently, PQ assessment aimed at analyzing PQ disturbances and designing a better system has assumed greater importance [3]. Existing tools for carrying out PQ assessment may not be completely satisfactory. More efficient solutions for performing PQ assessment are needed [3].

PQ assessment is a complex subject and may contain diverse aspects such as power system and equipment modeling, PQ monitoring, PQ problem mitigation and optimization, and data analysis [1, 3]. This paper is not intended to consider all of these topics, but to concentrate on specific aspects related to automating the PQ assessment. This may facilitate the overall PQ assessment.

The paper is focusing on developing better tools for: a) automating the detection and classification of PQ disturbances, and b) validating the power system model in capacitor switching studies. Specifically, we are investigating applications of intelligent techniques such as fuzzy-expert system and genetic algorithms for achieving more efficient solutions for these aspects of PQ assessment.

Generally speaking, the PQ disturbance detection and classification problem may consist of two steps [3-4]. The first step includes 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: the extracted features are further processed by an inference engine to determine the types of the events. This paper will be focusing on only the decision making step, while the first step is referred to [3-5]. For decision making, neural network based approaches have been developed. However, the correct identification rates resulting from the existing approaches are still low and not quite satisfactory [4]. This paper proposes a novel fuzzy expert system for decision making [6].

Another intelligent system presented in the paper deals with power system model validation. PQ event modeling and simulation may be useful for understanding the power quality phenomena and solving various types of power quality problems [1, 3]. The accuracy of the system model used in the simulation studies needs to be verified before the model may be used for performing PQ studies. No systematic solutions for model validation have been proposed. Motivated by its global optimization capability, the genetic algorithm is attempted.

In the rest of the paper, the fuzzy-expert system for automated detection and classification of PQ disturbances is presented first. Then the application of genetic algorithms for validating the power system model in capacitor switching studies is illustrated. Finally, conclusions, acknowledgements and references are given.

II. AUTOMATED POWER QUALITY DISTURBANCE DETECTION AND CLASSIFICATION

Fuzzy logic refers to a logic system that generalizes the classical two-valued logic for reasoning under uncertainty. It is good at reasoning by utilizing concepts and knowledge that do not have well-defined or sharp boundaries (i.e., vague concepts). A fuzzy expert system is an expert system that uses a collection of fuzzy sets and rules, known as the rule base or knowledge base, instead of Boolean sets for reasoning about data [6]. Power quality disturbance detection and classification deals with real-world data that may be very likely inaccurate. In a normal expert system consisting of a set of crisp rules for determining the type of the disturbances, it may be difficult to draw a conclusion if the actual situation does not exactly match the assumptions of certain rules. This situation can be easily handled by a fuzzy-expert system because a partial membership is allowed in fuzzy logic. Fuzzy logic essentially realizes the needed non-linear functional mapping by tuning the parameters contained in the rule sets. The computation of the output variable usually takes the steps such as fuzzification, inference, composition and defuzzification.

Motivated by the capability of fuzzy logic to deal with ambiguity contained in the input data, we have developed a fuzzy expert system based decision making system for PQ disturbance detection and classification. The flowchart of the proposed solution is shown in Fig. 1.

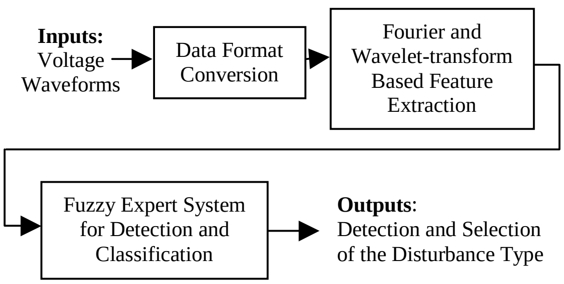

Fig. 1 Detection and classification flowchart

The sub-module "Data Format Conversion" converts the inputs from a specific recording device or simulation package 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.

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). A more detailed description on these features is referred to [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 [6].

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, and the following trapezoidal and triangular functions are used [6, 7]:

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

$$\mu(x) = \mathrm{trimf}(a,b,c) = \begin{cases} (x-a)/(b-a) & a \le x \le b \\ (x-c)/(b-c) & b \le x \le c \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

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", etc. 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. This proposed system has been implemented in MATLAB [7].

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

III. POWER SYSTEM MODEL VALIDATION UTILIZING GA

A. Genetic Algorithms

Generally speaking, the GA is a simple yet powerful tool for finding the global solution to an optimization problem. It is suitable for large-scale optimization problems, has tendency to find the global optimal solution and shows little effects of the discontinuities in the objective function on the overall optimization performance [8-9]. The GA solution to the problem: Maximize $y = f(x_1, x_2, ..., x_n)$, where y is a real valued function and $x_i \in [a_i, b_i]$, takes the following main steps [8].

1) Encoding and Decoding: The most commonly used binary encoding approach is described here. Suppose the variable x_i ($a_i \le x_i \le b_i$) is to be represented by a binary string (also called chromosome) of length L_{bi}. Then the encoded value x_{bi} for the variable will be

$$x_{bi} = \mathrm{round}((x_i - a_i)(2^{L_{bi}} - 1)/(b_i - a_i)) \tag{3}$$

and the decoding process is given by

$$x_i = (b_i - a_i)x_{bi}/(2^{L_{bi}} - 1) + a_i \tag{4}$$

2) Fitness Evaluation: This stage evaluates the performance of a solution according to the following fitness function

$$y = f(x_1, x_2, ..., x_n) \tag{5}$$

The larger the value obtained by this equation, the better the solution is.

3) Selection of Parents: A parent is defined as a vector of binary strings of all the variables obtained through the encoding process that will be used to produce the offspring. The standard Roulette wheel approach is adopted here.

4) Crossover and Mutation: Crossover and mutation are the two processes through which the parents produce the offspring. In the crossover, the two parents exchange some bits of their binary strings. In the mutation, the offspring obtained through the crossover process complement some bits of their binary strings. Appropriate values for the crossover probability P_c and mutation probability P_m need to be selected. Normally we take $P_c = 0.6 \sim 0.9$ and $P_m = 0.01 \sim 0.1$. Elitism principle is adopted during which the best chromosome (or a few chromosomes) is (are) first copied to the new population, and the rest is done in the classical way. Elitism can greatly increase the performance of GA because it prevents losing the best found solution.

In practical applications, an initial value for the solution is given. Then the above procedure is iterated until the convergence criterion is met. The criterion is normally defined as when the offspring strings are dominated by an individual string or the total iteration times exceed a specified value or the fitness value reaches a specified value. The general flowchart of the genetic algorithm is shown in Fig. 2. In the figure, the ranges of the variables can be estimated according to their typical values.

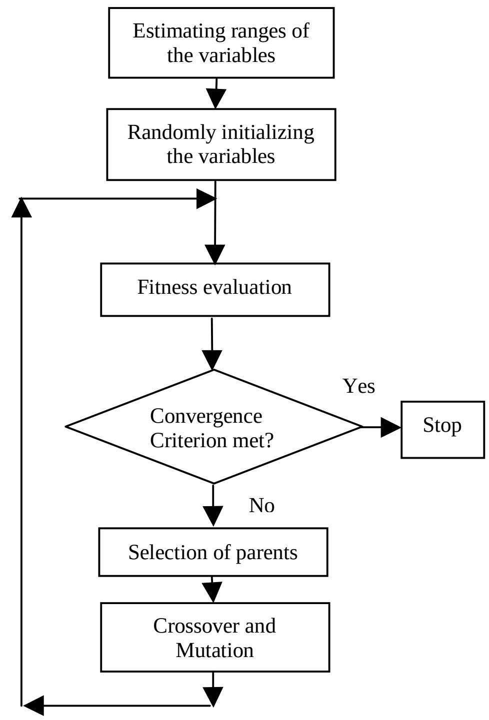

Fig. 2 The general flowchart for the genetic algorithm

B. Model Validation Using GA

(1) Problem Formulation: The system model validation is to verify the accuracy of the system model and evaluate certain parameters used for the simulation studies. The validation is done by comparing the simulated waveforms and data recorded during specific events. The data usually include the voltage or/and current waveforms that may be collected by diverse types of digital recorders. Without losing generality, all the data here are supposed to be recorded by the DFRs. By replaying the event using simulation packages like Electromagnetic Transients Program (EMTP) and comparing the simulated and recorded waveforms, the degree of accuracy of the system model can be evaluated [10]. If the matching does not satisfy pre-defined criteria, certain model parameters or configurations may be modified. The event is replayed and then the simulated and recorded waveforms are compared again. This process is iterated until certain pre-defined criteria are met. The number of unknown or uncertain parameters of a system may be several depending on the size of the system. The most credible values for these parameters are those values that will generate the waveforms that best match the recorded waveforms. In the work presented here, we are trying to match the frequency spectra of the voltages and currents obtained from the EMTP simulations and those obtained from the DFRs using Fourier transform. The mathematical formulation of the problem is illustrated next using a capacitor switching example.

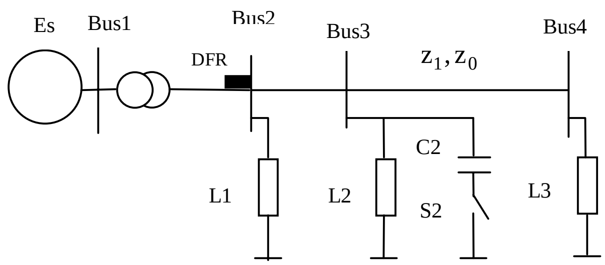

Fig. 3 A sample distribution system

The one-line diagram of a sample distribution system is shown in Fig. 3. L_1, L_2, and L_3 represent the loads. C_2 is the capacitor bank installed at bus3 for improving the power factor of load L_2. S_2 is the switch used for controlling the open or close status of C_2. z_1 (= $r_1 + jx_1$) and z_0 (= $r_0 + jx_0$) are the positive sequence and zero sequence impedance of the feeder between bus3 and bus4. For simplicity, suppose that for the system, only z_1 and z_0 are the parameters that have uncertain values and need to be evaluated. Suppose that a switching event occurred when the switch S_2 closes the capacitor bank C_2. The voltage and current waveforms during the switching event were recorded by the DFR installed at bus2.

Suppose that the switch S_2 is a normal switch without any supplementary synchronizing control circuits, and the closing times for the three phases are designated as T_a, T_b and T_c respectively. Due to mechanical limitations of the physical switch, these closing times are rarely the same and normally satisfy the following equations [9].

$$|T_a - T_b| < \delta \tag{6}$$

$$|T_a - T_c| < \delta \tag{7}$$

$$|T_b - T_c| < \delta \tag{8}$$

δ denotes the maximum difference between the closing times for different phases and is chosen as 3 ms here.

Then the problem of evaluating r_1, x_1, r_0 and x_0 can be formulated as finding the values for r_1, x_1, r_0, x_0, T_a, T_b and T_c that minimize

$$f_c(r_1, x_1, r_0, x_0, T_a, T_b, T_c) = \sum_{k=1}^{N_v} \{r_{kv} \sum_{n=1}^{H_v} | V_{ks}^n - V_{kr}^n |\} + \sum_{k=1}^{N_i} \{r_{ki} \sum_{n=1}^{H_i} | I_{ks}^n - I_{kr}^n |\} \tag{9}$$

or maximize

$$f_f(r_1, x_1, r_0, x_0, T_a, T_b, T_c) = -f_c(r_1, x_1, r_0, x_0, T_a, T_b, T_c) \tag{10}$$

where

$f_c(r_1, x_1, r_0, x_0, T_a, T_b, T_c)$: the defined cost function.

$f_f(r_1, x_1, r_0, x_0, T_a, T_b, T_c)$: the defined fitness function. The larger the value of the fitness function, the better the solution is.

k : the index of the voltage or current quantities

n : the harmonic order for voltages or currents.

r_{kv} and r_{ki} : the weights for the errors of the voltages and currents respectively.

V_{ks}^n and V_{kr}^n : the voltage magnitude of the n-th harmonic occurring during the event obtained from EMTP simulation and from DFRs respectively.

I_{ks}^n and I_{kr}^n : the current magnitude of the n-th harmonic during the event obtained from EMTP simulation and from DFRs respectively.

H_v and H_i : the total number of harmonics calculated for the voltage and current waveforms respectively.

N_v and N_i : the total number of the voltage and current quantities respectively.

The term harmonic here is used to represent the spectra of the signal, and does not mean the steady state harmonics. All the spectra components are calculated using one cycle Fourier transform on the sampled voltage data in the cycle immediately following the occurrence of the switching event.

It is noted that the largest fitness value defined by (8) is equal to zero and can be reached if the spectra of the simulated waveforms exactly match those of the DFR waveforms. Therefore, the best estimate for the unknown parameters would be the one that maximizes (8).

For this multi-variable optimization problem, it is difficult to use the gradient-based method to find the global optimal solution because of the multi-modality nature of the problem. An exhaustive search through every possible solution may be too time-consuming and hence impractical. Applications of GA for solving this problem are illustrated as follows.

When applying the GA to the system model verification and parameter evaluation, (8) will be the actual form for the fitness function. r_1, x_1, r_0, x_0, T_a, T_b and T_c are the seven changing variables. In the flowchart as shown in Fig. 2, the ranges during which the variables vary can be decided as follows. r_1, x_1, r_0, and x_0 can be selected as typical values according to the type of the feeder used. T_a, T_b and T_c can be selected from 0 to 16.67 ms subject to (6-8).

(2) An Example: This section presents an example for illustrating the concept described above. Part of a distribution system provided by the TXU Electric and Gas is depicted in

Fig. 3. A switching event is created by switching in the capacitor C_2. The transient overvoltage waveforms at bus2 caused by the switching event are recorded using Dranetz 4300 recorder with a sampling frequency of 7680 Hz and shown in Fig. 4.

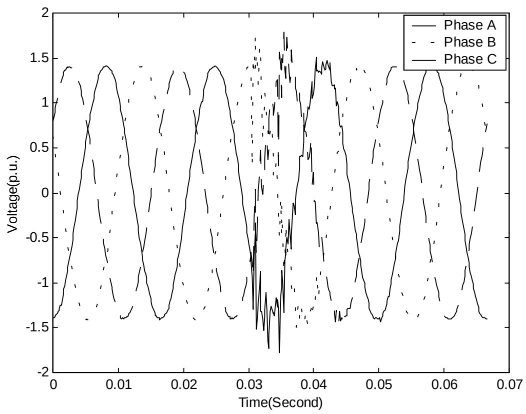

Fig. 4 The recorded voltage waveforms at bus2

In the GA based approach, the length of the strings for the each of the three variables is chosen as 10 bits. The number of population in each generation is selected as 10. The crossover probability is chosen as 0.8 and mutation probability chosen as 0.01. After 66 iterations, the GA obtains the following results: $T_a = 0.0306$, $T_b = 0.03137$, $T_c = 0.03138$, $r_1 = 0.38$, $x_1 = 0.88$, $r_0 = 1.24$, and $x_0 = 3.10$ with time in second and impedance in p.u.. The simulated voltage waveforms with these parameters are plotted in Fig. 5 that shows a quite close matching between the simulated and the recorded waveforms. This verifies that the model of the system as well as the estimated parameters are reasonably accurate.

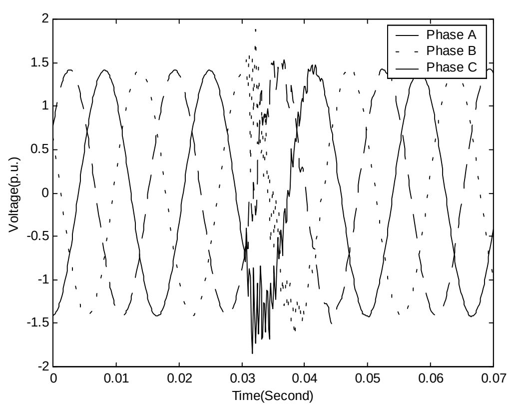

Fig. 5 The simulated voltage waveforms at bus2

IV. CONCLUSIONS

This paper presents new software developments on the applications of intelligent techniques for automated power quality assessment. A fuzzy-expert system for automated power quality disturbance detection and classification has been proposed and implemented. A genetic algorithm based solution for validating the system model in capacitor switching simulation studies has been developed. The implementation of the proposed intelligent systems is addressed. Feasibility of the proposed approaches for practical applications has been demonstrated by case studies utilizing both the simulated and field data.

V. ACKNOWLEDGEMENTS

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VII. BIOGRAPHIES

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