NEW AUTOMATED FAULT ANALYSIS APPROACHES USING INTELLIGENT SYSTEM TECHNOLOGIES

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U S A

Abstract - Automated fault analysis is needed for both on-line and off-line applications. Typical on-line applications are in the area of protective relaying and typical off-line applications are in the area of Digital Fault Recorder (DFR) event analysis. New intelligent system technologies using expert systems and artificial neural networks provide some unique advantages regarding fault analysis. This paper summarizes several developments related to the use of intelligent systems for automated fault analysis undertaken by Texas A&M University (TAMU) and Houston Lighting & Power (HL&P) Company.

Keywords: Automated fault analysis, Fault detection, Fault classification, Expert systems, Artificial neural networks

INTRODUCTION

The advantages of an automated system for fault analysis have been recognized in the late 60-ties [1]. However, it took considerable time before some advanced intelligent techniques were applied to develop such an automated system [2]. Over the next ten years a number of different approaches to the automated fault analysis using intelligent methods were suggested [3, 4].

Detailed analysis of the available approaches shows that the substation equipment determines the extent of the possible use of different intelligent system techniques [5]. It appears that the type of the equipment greatly affects quality of data to be used for the analysis. The data base, in turn, determines the viability of different techniques for the fault analysis [6].

This paper summarizes results of the development activity performed at Texas A&M University in the area of the use of intelligent methods for fault analysis. This development has been supported by Houston Lighting & Power Company and has resulted in a working prototype of a substation expert system for automated fault analysis [7-9]. Further enhancements of this system are under way with additional investigation of the artificial neural network (ANN) application to solving the fault detection and classification problem [10, 11]. The first section of the paper describes the expert system development, while the second part gives preliminary results from the ANN study.

FAULT ANALYSIS USING EXPERT SYSTEM

This section describes implementation of an expert system which performs automated event analysis based on the disturbance data acquired by Digital Fault Recorders (DFRs). The expert system can aid operators and protection engineers in their task of analyzing substation disturbances and fault events. The expert system has been extensively tested and evaluated using field data from the South Texas Project (STP) substation during the last year.

System Architecture

Block diagram of the expert system is given in Figure 1. The data conversion block translates the DFR data files into a format suitable for analysis performed by MATLAB, a high-performance numerical computation and visualization software. A MATLAB program analyzes raw data and calculates parameters required for the reasoning process. During the signal processing procedure, the transmission line with the most prominent disturbance is identified and the recorded data for this line are extracted from the rest of the DFR event file. Then, RMS values for currents and voltages are calculated. Those values, grouped into prefault, fault, and postfault time intervals are transferred to the CLIPS block. Also, digital contacts (breaker status, relay operation status, communication channel status) for the same line are extracted and aligned across time axis with analog waveforms. The reasoning procedure is implemented using a set of CLIPS rules in a forward chaining mechanism. The knowledge base was built by interviewing experts, using an empirical approach based on Electromagnetic Transient Program (EMTP) simulation during initial system design, and finally using actual field data from the STP substation. The output of the CLIPS block is a text report containing hypothesis on type of disturbance and protection system operation sequence. The sample text report generated by the expert system for one of the actual DFR records is given in Figure 2. In addition, graphical report containing waveforms of phase currents, voltages, as well as, digital status channels is generated using MATLAB visualization functions. Figure 3 shows one of the plots that supplements text report given in Figure 2.

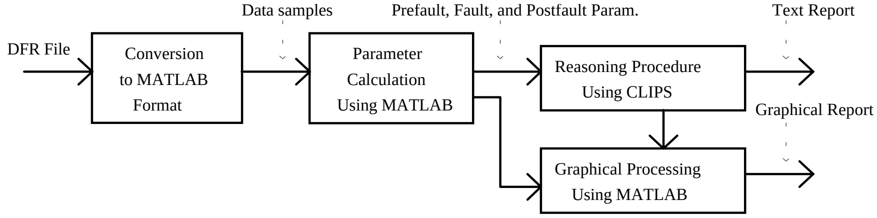

Figure 1. Expert System Block Diagram

Date\Time Stamp of Event: 06/28/93, 00:02:18.760
Event number: 002
Sample rate: 5.99 [kHz]
Number of pretrigger samples: 1198 (12.0 cycles)
Total number of samples: 2926 (29.3 cycles)
Size of the event in tracks: 10 (320Kb)
Machine name: S.T.P.
Serial number: 20299
Converted 1755 samples starting from sample 898.

******* EVENT DESCRIPTION USING ANALOG DATA*******
Holman44 is the circuit with largest current disturbance.
The disturbance is a phase A to ground fault.
The fault is cleared by the protection system at this substation.

Prefault Values: ; Fault Values: ; Postfault Values:
I0pf = 0.0178 [kA] ; I0f = 3.7900 [kA] ; I0f = 0.0029 [kA]
Iapf = 0.3911 [kA] ; Iaf = 3.7450 [kA] ; Iaf = 0.0010 [kA]
Ibpf = 0.3757 [kA] ; Ibf = 0.2886 [kA] ; Ibf = 0.0030 [kA]
Icpf = 0.3968 [kA] ; Icf = 0.4417 [kA] ; Icf = 0.0023 [kA]
Prefault Values: ; Fault Values: ; Postfault Values:
V0pf = 0.0006 [kV] ; V0f = 0.0112 [kV] ; V0f = 0.0005 [kV]
Vapf = 294.90 [kV] ; Vaf = 255.60 [kV] ; Vaf = 294.60 [kV]
Vbpf = 295.60 [kV] ; Vbf = 290.80 [kV] ; Vbf = 294.70 [kV]
Vcpf = 294.90 [kV] ; Vcf = 288.70 [kV] ; Vcf = 294.80 [kV]

Vabpf = 511.20 [kV] ; Vabf = 472.90 [kV] ; Vabf = 510.00 [kV]
Vbcpf = 512.00 [kV] ; Vbcf = 510.60 [kV] ; Vbcf = 511.00 [kV]
Vcapf = 510.30 [kV] ; Vcaf = 463.90 [kV] ; Vcaf = 510.30 [kV]
All above values are peak values.

******* PROTECTION SYSTEM OPERATION ANALYSIS *******
Primary relay operation starts at 0.0878 sec [5.2698 cycles]
and ends at 0.1045 sec [6.2700 cycles].
The middle 52B contacts operates at 0.1142 sec. [6.8520 cycles].
The bus 52B contacts operates at 0.1162 sec. [6.9720 cycles].
The bus breaker status change
after trip is applied is 0.0284 sec [1.7022 cycles].
The middle breaker status change
after trip is applied is 0.0264 sec [1.5822 cycles].

Figure 2. Expert System Text Report

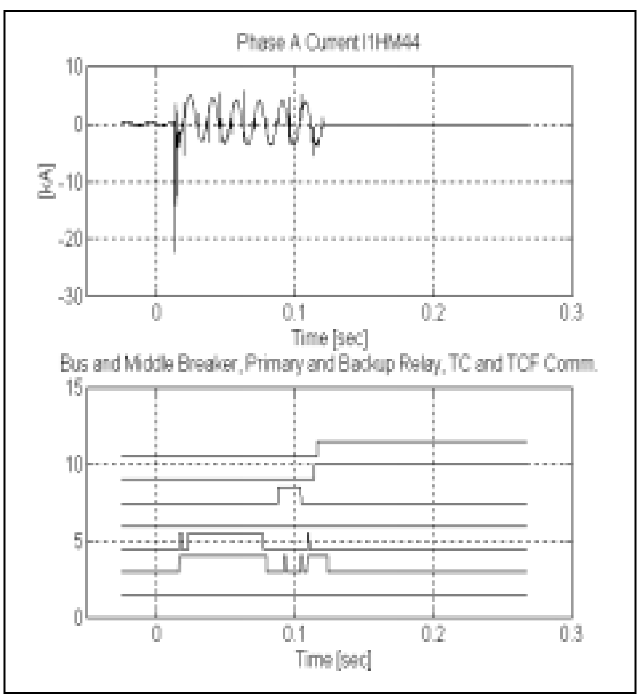

Figure 3. Part of the Expert System Graphical Report

Test Results

Presently, the expert system is located at Texas A&M University (TAMU) and connected with the DFR at the STP substation via dial-up modem link. This configuration is shown in Figure 4. Communication between the expert system computer and the STP substation DFR is facilitated using Rochester TR1625 master station software. Every recorded event at the STP substation is retrieved and archived at the expert system computer. Upon completed retrieval of an event, classification and analysis are executed, and the report is generated and stored. The textual part of the report is then faxed to the HL&P Engineering Design office in Houston for their evaluation. The graphical files are stored in the PC Paintbrush (PCX) format. These files are then sent to the HL&P Engineering Design office using PC Anywhere communication software. In this way, protection engineers in Houston are able to evaluate performance of the expert system.

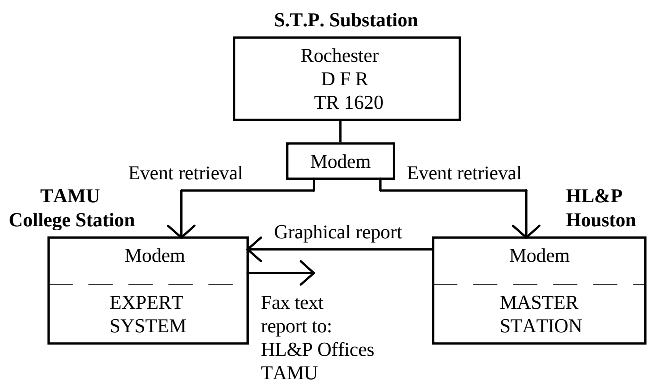

Figure 4. Initial Testing Configuration

The operating experience is gained based on 61 actual disturbances recorded at the STP substation. Table I gives the summary of the processed events for the STP substation in the period from June 1993 - May 1994. For the events that were covered by the knowledge base, the expert system did the analysis correctly. Only small threshold changes were made in the existing rules to fine tune the expert system performance.

Table I. Summary of the Events Processed by the Expert System for the STP Substation

Event Type	Number of Events
Phase A to Ground	6
Phase B to Ground	8
Phase C to Ground	10
Phase A to Phase B	1
Bus Switching	2
Faults Beyond STP	29
Local DFR Initialization	5

However, during field testing, several new types of events (which have not been covered by the initial knowledge base) have been identified and additional rules have been added. An example is bus switching at the STP substation. Also, in the case of remote line faults (beyond the next substation) expert system is not always able to give a detailed textual report. To overcome this problem, additional fault location software will be added. The fault location algorithm will use data from a local end of the line with the largest disturbance. With that additional information about fault location, expert system will be able to more accurately deal with remote faults. As a result of the overall performance assessment, both the designers and the protection engineers feel very confident that the performance of the expert system is outstanding and that it is ready to be installed at the STP substation.

Future Activities

Eventually, the expert system computer will be located at the STP substation. This configuration is shown in Figure 5. In this case, expert system computer will poll DFR in regular time intervals (e.g., every 10 min.) and every new event will be downloaded to local hard drive. Classification and analysis procedure are automatically invoked, and report is generated. Then, textual part of the report will be faxed to the Dispatcher, HL&P Engineering Design office, local operator, and Texas A&M University. Depending on the length of the DFR record, the expert system will need between 1.5 and 3 minutes to complete the analysis locally at the substation and start faxing the condensed report (see Figure 2). The size of the report is not greater than 2 Kbytes, which is negligible compared to the size of the original DFR record (ranging from 256 to 800 Kbytes). This will replace the existing practice in which a stream of recorded data is sent from the STP substation to HL&P once a dial-up call from HL&P offices is placed. Potential savings obtained by the local automated analysis and the condensed report communication, when compared with the communication time and the manpower required for the manual analysis, are substantial.

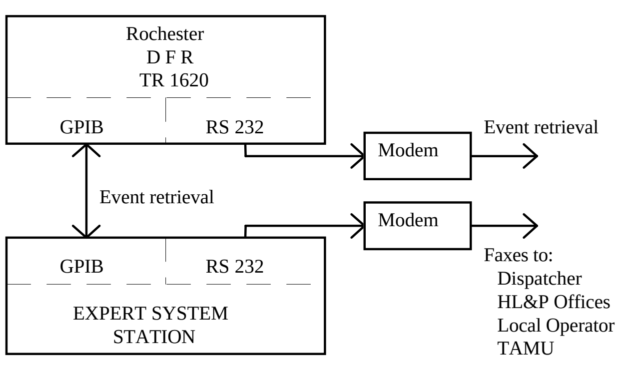

Figure 5. Final Expert System Configuration

FAULT ANALYSIS USING ARTIFICIAL NEURAL NETWORK

This section is concerned with the application of an Artificial Neural Network (ANN) to fault analysis for both the real-time applications such as protective relaying of transmission lines and the off-line applications such as post-mortem study of fault events recorded with Digital Fault Recorders (DFRs). A supervised learning ANN of the same type is utilized for both applications. It has been demonstrated that the ANN approach reaches performance of the existing techniques in both application areas and yet shows some additional benefits [10, 11].

Outline of the ANN Algorithm

The ANN algorithm used in both applications implements a supervised "follow the leader" approach [11]. Figure 6 shows the block diagram of the learning process for the algorithm used in this study, that contains both unsupervised (USL) and supervised (SL) part. Unsupervised learning self-organizes presented data and discovers its collective properties. Initially, the whole data set, containing all patterns, is processed using unsupervised clustering algorithm similar to ISODATA self-organizing procedure. Figure 7 shows the configuration of the unsupervised clustering part. The output is stable family of clusters, defined as a hyperspheres in N dimensional space, where N denotes number of features in each pattern. In the supervised part, non-homogeneous clusters are separated from homogeneous (clusters containing only label uniform patterns). Class membership is assigned to homogeneous clusters. Training data set is, then, reduced to contain only patterns from non-homogeneous clusters. Vigilance parameter ρ is decreased, and the whole procedure is reiterated.

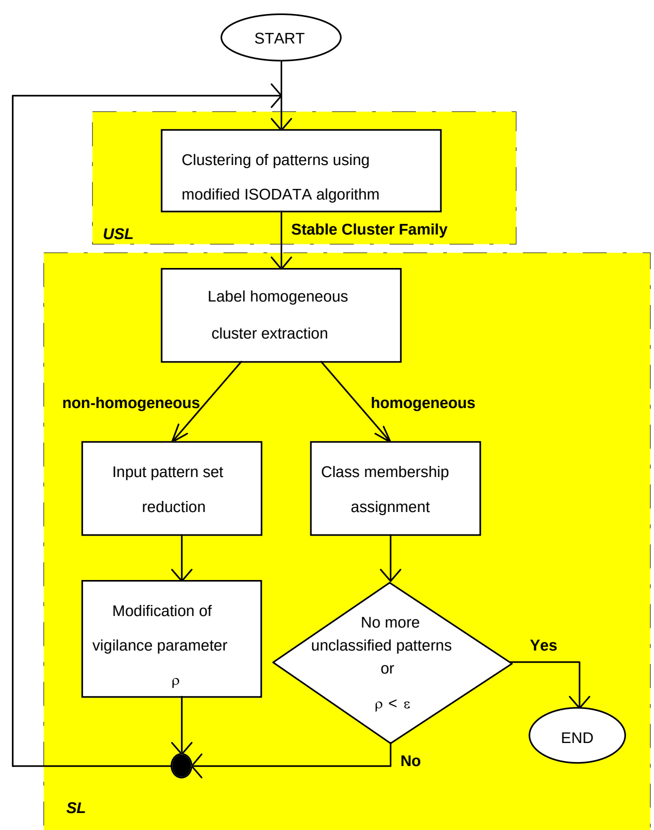

Figure 6. Artificial Neural Network Learning Process

After completion of the training procedure, all generated clusters contain uniform data patterns, and are characterized by their centroids, corresponding radii (i.e., vigilance parameter ρ), and inherited class membership. Figure 8. shows schematic illustration of the outcome of the training process in the feature space. It can be observed that cluster topology is not uniform, and that two or more clusters may have the same class membership.

A detailed algorithm description with all equations and implementation issues is reported in [10, 11].

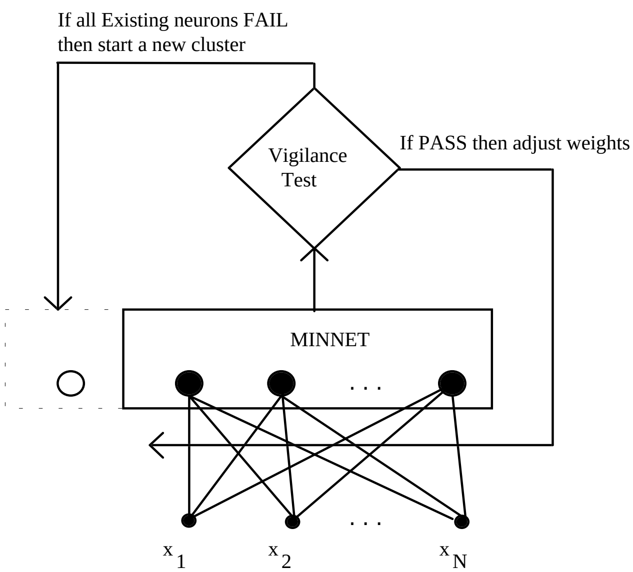

Figure 7. The ANN Implementation of ISODATA Clustering Procedure

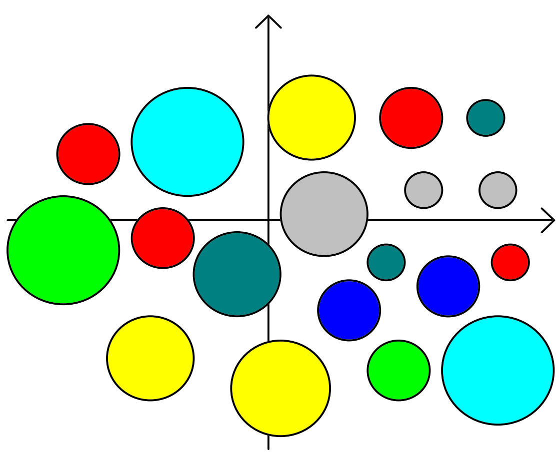

Figure 8. Schematic Illustration of the Outcome of the Training Process

EMTP Simulation Models

Two different EMTP models were used for training and then testing of the artificial neural network. One model represents part of an actual 161 kV power system with 3 buses and 3 sources. All lines are short and mutually coupled. The transmission line of interest was one between buses 2 and 3. It is fully transposed and 21.5 km long. One line diagram of this system is shown in Figure 9.

The other system represents part of an actual 345 kV power system. This system has long compensated lines. Faults were simulated on lines #1 and #2. The one line diagram of this system is given in Figure 10.

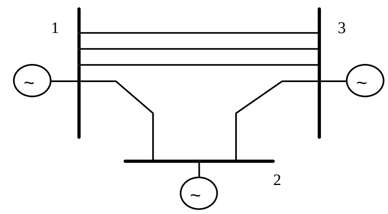

Figure 9. One line diagram of the 161 kV power system used for EMTP modeling

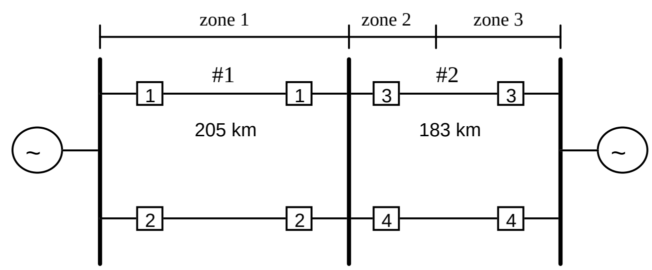

Figure 10. One line diagram of the 345 kV power system used for EMTP modeling

ANN Performance Evaluation

In this section, the summary of ANN performance for both real-time and off-line applications is given. Due to the limited space, only condensed results are shown. For more elaborate and detailed results and discussion readers are referred to papers [10, 11].

For the real-time application, the ANN classificator has to perform fault detection and fault type classification. Both of these tasks are time restricted (for transmission systems this time is usually 1 cycle). ANN classifier was trained using 200 fault patterns. For this application fault cases were generated using the 161 kV model. Input feature vector to the ANN contained samples of phase currents (all three phases). It was organized in the form of the sliding data window with fixed window length of 1 cycle (33 samples at 2 kHz). The ANN was implemented and tested on IBM PC compatible computer with Intel 486 DX-2 microprocessor. Computational time for fault detection logic was 0.2 ms, and for fault classification logic was 15 ms. Taking into consideration that data sampling frequency was 2 kHZ, it can be concluded that fault detection was operating in real-time, while fault classification required more time. Further work is being done to evaluate possible enhancement of the ANN computational performance by using special digital signal processors (DSPs) for real-time embedded applications.

After training, the ANN was tested using 80 "never seen" fault cases, that were generated using 161 kV EMTP model. Those test fault patterns included all types of transmission line faults (phase to ground, phase to phase, two phase to ground, three phase, and three phase to ground). Also different fault resistances as well as fault incidence angle were used. It has been observed that fault incidence angle was parameter that had the most important influence on the overall ANN performance. Classification rate that ANN reached for this application ranged from 52% for faults that had the incidence angles different from the ones used for initial training of the ANN, to 92% for "never seen" faults that had incidence angles similar to the ones used for the ANN training.

The off-line application is a typical pattern recognition problem, where ANN first reorganizes and classifies training patterns according to their collective properties. After completing of the training procedure, ANN is capable to make a *generalization* (i.e., to classify new "unseen" cases).

More than 2000 different fault cases were generated using the 345 kV EMTP model. Training of the ANN was conducted using 397 fault patterns. These fault patterns included all types of line faults, different fault resistances, different fault incidence angles, covering only boundaries of zone1, zone2, and zone3. The lines #1 and #2 (see Figure 10) were segmented and faults were simulated on every 10% of the length of both lines. Faults generated on line #2 were regarded as remote faults with respect to line #1. Training procedure for this particular ANN is very fast. Not more than 10 minutes of the IBM RISC 6000/340 computer time was needed to finish the training.

The testing of the ANN is then performed using 1980 "never seen" fault cases at every 10% of the lines, covering all three zones. The ANN classification rate is given in Table II. Rows in the table show classification results for different types of inputs in ANN.

Table II. Classification Results of the ANN

ANN Inputs	**Classification Rate [%]**
all currents and voltages	86.82
only 3- phase currents	87.68
only 3- phase voltages	72.68

CONCLUSIONS

The results presented in this paper indicate that:

- Application of intelligent systems to automated fault analysis enabled development of some practical solutions.
- Implementation of a substation expert system prototype demonstrates benefits of the automated fault analysis.
- Future developments using the ANN processing seem to be quite promising when a fast, system wide, fault analysis is to be considered.

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