Design and Evaluation of Context-Dependent Protective Relaying Approach

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***Abstract*--This paper introduces a new concept of robust protective relays based on unique type of self-organized neural network. An advanced approach for protective relay testing and evaluation is presented as well. Proposed relaying solution detects and subsequently classifies the faults. A new interactive simulation environment based on MATLAB is selected as the main software environment for synthesis and evaluating of complex protection algorithms. Other application programs may be connected with MATLAB and used for simulation of specific power system faults and events.**

***Keywords*--power system modeling, protective relaying, neural networks, clustering methods, electromagnetic transients, simulation environment.**

I. Introduction

THE protective relaying of power systems is a well-known problem. It was solved a long time ago by introducing the traditional relaying principles such as overcurrent, distance, under/over voltage, differential, etc. All of these principles are based on the notion that the relay settings are computed ahead of time based on some well-known and easily anticipated fault conditions. In addition, the settings are determined in such a way that the relay does not operate under the normal conditions.

The idea of using neural networks in protective relaying is not new. In the past neural networks were used to improve the recognition of the standard impedance computations used in distance relaying of transmission lines [1].

The approach taken in this paper was to develop a context dependent protective relaying scheme. The approach was to use neural networks to implement a pattern recognition algorithm where the prevailing system conditions (context) are taken into account through the learning mechanism. The approach is to apply the neural network directly to the samples of voltages and currents, and produce the fault detection, as well as fault type and zone classification in real time. A special type of neural network had to be used [2-5]. In this way, any prevailing conditions at the location of the relay are taken into account by having the self-tuning of the pattern recognition algorithm each time the change occurs. To make sure that the tuning takes place in a timely manner, an on-line learning may be implemented. In this way the new relay does not have traditional settings, and hence it is not prone to the wrong settings being present in the relay because the prevailing conditions have deviated from the ones used to calculate the settings.

Evaluation of any protective relaying solution require modeling of the power network and protective relays, and simulating the interactions for a variety of the events in power system. These events encompass many scenarios, including various faults and normal operating states corresponding to specific time scales.

The use of electromagnetic transient programs EMTP [6] and ATP [7] for power system simulation has been known for a long time. Existing modeling approaches in EMTP/ATP do not facilitate interfacing complex relay models to the power network models, and automatic simulation of a large number of scenarios is practically impossible. The relays can be modeled more accurately and efficiently by using either C language or a commercial software package such as MATLAB [8]. In recent years, few new approaches have been proposed to connect the electromagnetic transient programs with MATLAB [9-11].

The software environment presented in this paper uses MATLAB as the main engineering tool for performing modeling and simulation of power systems and relays as well as for interfacing the user and simulation programs. Through one interface the operator is able to design the relays, set models of the appropriate power systems, interface the relay models to models of the power system, define power system disturbance scenarios and to initiate various simulations corresponding to specific time intervals of the disturbance.

The paper is organized as follows. Section II gives a short background comparing the traditional vs. advanced protection design and evaluation. A new context-dependent protective relaying approach, based on specific type of neural network is introduced in section III. Section IV defines a new simulation environment for protective relaying algorithm design and evaluation. Selected model of an actual power network as well as an overview of power system faults and normal operating states are given in section V. Section VI provides simulation results obtained by training and testing the neural network based protection algorithm. The conclusion is given at the end.

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II. Background

In the traditional protective relaying approach, selected prevailing power system conditions are mapped into a range of short circuit studies using the power system model and simulations of the worst-case fault conditions. Based on those studies, the relay settings are determined and subsequently entered into the relays. With such settings, the relays should be able to detect and classify the faults under the selected prevailing conditions in the network. If the prevailing conditions change so that the power system operates in the mode that has not been anticipated during the short circuit studies, the traditional relaying approach may not be reliable any more due to potentially "wrong" settings.

The problem of selecting the right settings is the problem of making sure that both dependability and security of the relay operation are maintained [12]. The dependability in this application means that the relay will always operate correctly when there is a fault. The security in this application means that the relay will not operate when there is no fault. It is well known from the protective relaying practice that the settings are determined in a conservative way by performing the worst-case simulation studies. As a consequence, the final solutions are biased towards either dependability or security to make sure that the one or the other can be guaranteed. In an ideal case, the trade off is to be avoided and the scheme should be both dependable and secure. Any new relaying approach that aims at the simultaneous dependability/security improvement would need to be based on a principle that is quite different from the traditional principles mentioned above.

The new context-dependent relaying strategy proposed in this study is based on eliminating the traditional relay setting concept. The controller (relay) is designed to have a more complex decision making approach where the patterns of input signals constitute the decision-making criterion. The pattern space is formed based on the training procedure where the history of patterns is used to tune the pattern recognition capability of the controller (relay).

Introducing any new relaying principles places a special burden on the process of demonstrating that the performance of the new solution is better than the performance of the existing one. In the relaying application this translates into selecting an evaluation environment that is very realistic and allows an elaborate comparison of the performance. A software environment that has the required user interfaces to allow different simulations to be setup and controlled using a powerful set of application programs is not readily available and needs to be developed.

III. Identifying Context Using Neural Networks

Neural networks can be employed to solve complex power system protection problems, particularly those where traditional approaches have difficulty in achieving the desired speed, accuracy and selectivity [1]. They are adaptive, learn from environment and improve their performance, and have generalization ability, i.e. to successfully classify patterns that have not been presented in the training process. Also they allow for nonlinear mappings capturing complex relationships among the data. Neural networks try to identify natural groupings of data from a large data set through clustering. They divide a set of objects into subgroups or clusters, each having members that are as much alike as possible. Each cluster belongs to one of possible classes, and number of classes corresponds to desired number of neural network outputs, determined by the given classification task.

This paper introduces a new protective relaying principle for transmission lines that is based on the neural network utilization instead of using traditional setting. The approach employs a pattern recognition algorithm where the prevailing system conditions are taken into account through the learning mechanism [4,5].

A. Neural Network for Fault Detection and Classification

The problems which impose special requirements on this task are the large number and dimensionality of training patterns, and large number of classes. This depends on whether selected classification includes fault type, fault zone, fault impedance, or any combination between them. Consequently, a very large number of clusters may be expected due to the specific nature of the process.

The classification problem is very complex and traditional clustering techniques may be useless. To be able to produce the fault detection and classification in real time, a special type of neural network is used. The neural network belongs to the group of Self-Organizing Maps which learn to classify input vectors according to their grouping in the input space. This is a unique neural network with flat structure and no feature extraction, and its main properties are well described with Adaptive Resonance Theory [13]. The proposed neural network does not contain hidden layers and the network structure depends only on the type of the input data set. The input vector comprises samples associated with the three phase current and/or voltage signals in the transmission line. The length of the input vector determines the number of neurons in the input layer. This is convenient for protection purpose because we have a great amount of input data (current and voltage samples in a given time window). The protection algorithm is based on directly using local waveform samples without computing impedance or phasor. Neural network algorithm makes a final decision based only on the samples presented. Outputs of this neural network are naturally in the discrete form. There is no need for dubious transformation from continuous to discrete output as is the case in some other neural networks.

A new neural network context identification method incorporates the advantages of both supervised and unsupervised learning procedures (Fig. 1). Both learning techniques are combined in an appropriate way to give the best performance.

B. Neural Network Learning

Supervised learning is also known as learning with a teacher. During the training process, the desired set of outputs is presented together with the associated set of inputs. Unsupervised learning is the technique in which the desired output is not known, but the network performs classification based on identified similarity between actual inputs. Classifiers that use combined unsupervised/supervised learning firstly use unsupervised learning with unlabeled data to form internal clusters and labels are then assigned to the clusters during the supervised learning stage.

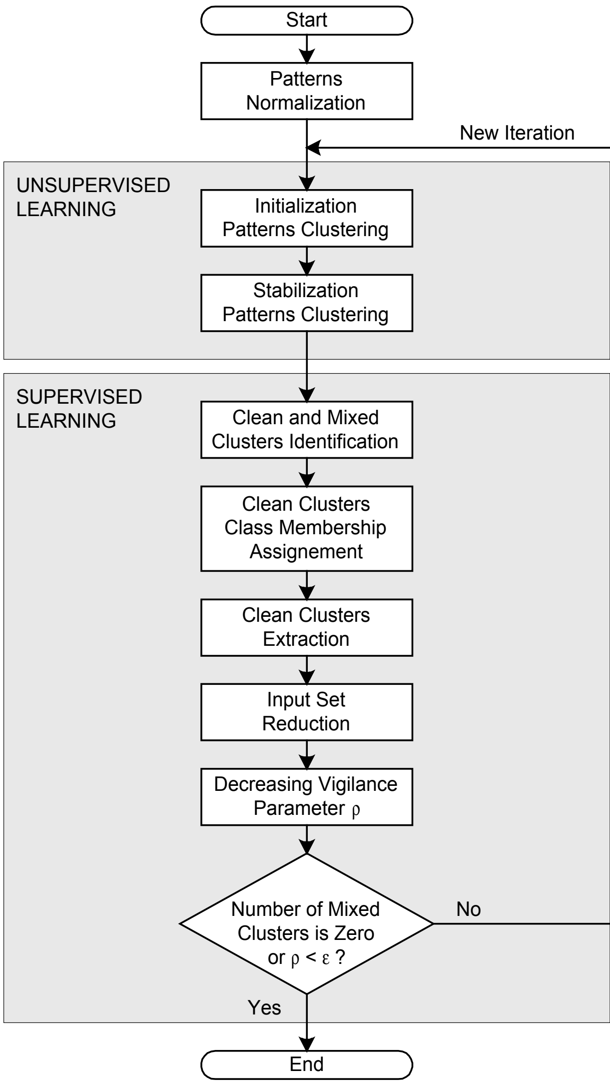

Fig. 1. Neural network clustering algorithm

In the learning phase, the initial data set containing all the patterns is processed using unsupervised clustering algorithm (Fig. 1). This algorithm is a modified ISODATA clustering algorithm. It does not require either the initial guess of the cluster center coordinates, or the initial number of clusters. The characteristic patterns or prototypes are identified as cluster centers. The first pattern is selected as the center of the first cluster. Then the next pattern is compared to the first cluster center. If the Euclidean distance between the pattern and the cluster center is smaller than the radius of that cluster (vigilance parameter) it is assigned to the first cluster. Otherwise, it is selected as a center of a new cluster. This process is repeated for all patterns (initialization clustering). Once all the patterns are processed, the algorithm is reiterated until a stable cluster formation occurs when no pattern changes its cluster membership during the iterations (stabilization clustering). The outcome is a stable family of clusters, formed as hyperspheres in n dimensional space, where n denotes the number of input features. Then supervised learning separates non-homogenous or mixed clusters (having patterns with different class memberships) from the homogeneous or clean ones (having patterns with the same class membership). Class membership is assigned to the homogeneous clusters, and then the training data set is reduced to contain only patterns from the non-homogeneous clusters. The vigilance parameter is decreased and the whole procedure, including unsupervised and supervised learning, is reiterated. The learning is done until only the homogenous clusters exist or current value of vigilance parameter is less then specified value ε. Simplified example in two dimensions is given in Fig. 2. In this case learning is less complex than in the standard supervised learning, because there is only one tuning parameter consecutively decreasing in each iteration.

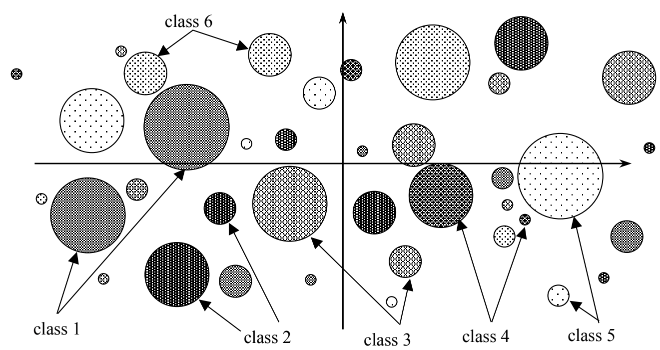

Fig. 2. Homogeneous family of clusters

C. Neural Network Implementation

General clustering method presented here should be able to adaptively determine the number of clusters based on the distribution of the given data and the nature of the clusters present. The number of clusters is not specified, but a strong interclass distance measure is specified.

In the testing phase, input to the neural network is in the form of the “sliding” data window containing samples of phase currents and/or voltages [4,5]. Input pattern is classified by using K-Nearest Neighbors (K-NN) classification algorithm, where each pattern is classified according to most frequent class label of k nearest clusters. If input pattern belongs to the “normal-state” cluster then the input window is "moved" for one sample and the comparison is performed again. If input pattern does not belong to the “normal-state” cluster then fault is detected and execution of the fault classification logic is initiated. The parameter used to force the neural network to make the final decision is the time. After decision time has expired, if pattern still does not come back to the normal state, neural network will classify fault event according to the fault type detected in that instance.

Protective relaying algorithm, once the development is completed, will need to be thoroughly tested to demonstrate the silent features of the new approach. The existing protective relaying algorithms are quite good in many applications. Demonstrating the benefits of the new approach will require an extensive study of the most interesting and relevant comparison cases.

IV. Evaluation of the New Protective Relaying Approach

The simulation environment should include software tools for: power system modeling and simulation, protective algorithm training and testing, and interfacing between different simulation packages. Considering everything, a new interactive simulation environment is proposed for protective algorithm design and evaluation.

MATLAB is the main software environment for implementing the neural network algorithm [8]. Other programs can be connected with MATLAB and used for power network simulation (Fig. 3). The unique feature is the capability of implementing the models of the controllers (relays) using programming tools provided in MATLAB. In this environment various scenarios may be implemented and both, open-loop and closed-loop simulation features are available.

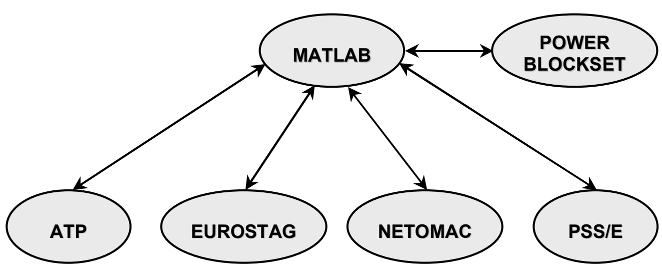

Fig. 3. MATLAB as the main software environment for interfacing other software packages

The standard programs such as ATP [7] for electromagnetic transient simulation, PSS/E [14] for load flow and short circuit study, EUROSTAG [15] for simulating the network stability dynamics, and NETOMAC [16] and Power System Blockset [17] for simulating electromagnetic and electromechanical phenomena, may be interfaced to the MATLAB environment. This approach allows the simulations to be split into the time domains of interest and they correspond to well-known power system conditions: load flow, fast electromagnetic transients, steady state unbalanced operation, and fast and slow stability dynamics.

Interaction between these programs and MATLAB leads to better design and performance evaluation of the protection algorithm for many real situations in power networks. MATLAB can be used to change network topologies and parameters in the models developed in other programs, to initiate the simulation in the overall environment and to extract output data for neural network training and testing implemented in MATLAB.

Design approach implemented in this work utilizes ATP program as a signal generator for protection algorithm training and testing. Specially developed complex MATLAB program interface enables running simulations for a large number of different scenarios by changing network topologies and parameters. This interaction is shown in Fig. 4. Combining this approach with the one proposed in [9], the closed-loop relay simulation for a large number of scenarios can be achieved.

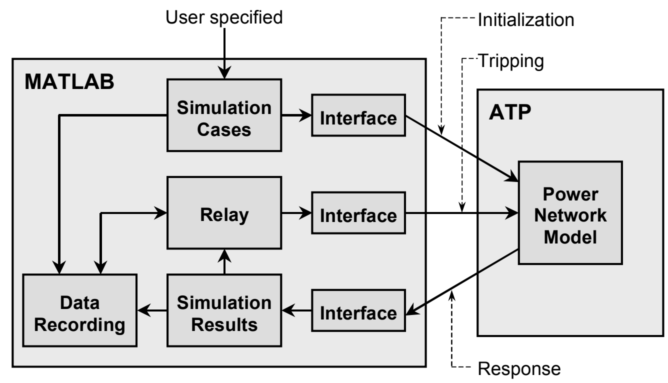

Fig. 4. Integrated simulation tools for protective relaying by using MATLAB and ATP

V. Power System Model

The network model developed for this study is unique since it has the configuration that can exercise many normal as well as fault conditions that are rather difficult for the traditional relaying to deal with. The specially developed power network model of actual power system section, selected as an example in this paper, is the Reliant Energy (RE) HL&P STP-SKY, nine-bus model (Fig. 5). The electrically remote parts of the system were modeled using Thevenin equivalent circuits, while other components in the reduced system were modeled in detail. This model was implemented using calculations based on short-circuit data available from RE HL&P company. The simulation accuracy is "calibrated" using recordings captured during actual fault events in the system.

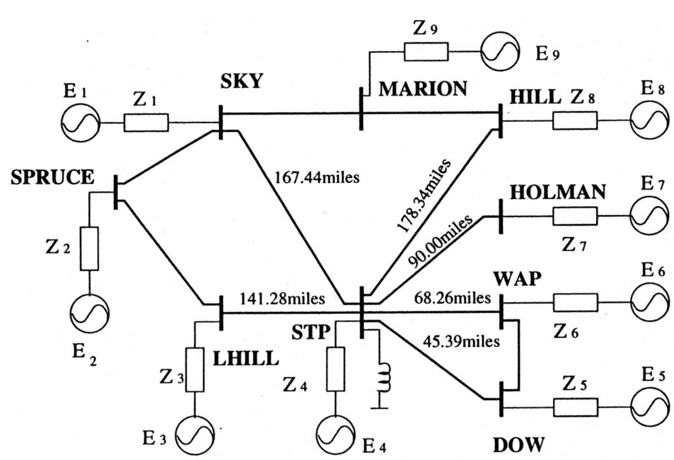

Fig. 5. RE HL&P STP-SKY power system model

This reduced system is to be used for simulation of various fault events and operating states, and appropriate transient signals will be utilized for performing relay design evaluation and testing. Reliable and fast execution of all relaying functions is expected in all cases. Many scenarios including faults and no-fault events should be investigated, and they are given in Table I.

TABLE I
GENERAL SCENARIOS FOR POWER NETWORK PROTECTIVE RELAYING

Group of events	Specific event
General fault events	All types of fault; Fault location variation; Fault impedance variation; Fault inception angle variation; Infeed/outfeed;
Special fault events (Dependability)	Faults in reverse direction; Evolving faults; Cross-country faults; Unsymmetrical faults; Time variant fault impedance; The parallel line out of service or faulted; Sympathetic trip on parallel lines;
Events in the normal state (Security)	Source voltage variation; Load variation; Line switching; Line parameters variation; System frequency variation; Power swings; Inaccuracies in the relay measurement system.

VI. SIMULATION RESULTS

In this particular case, the proposed network has been used to achieve real time transmission line fault detection and classification in a short time (1 cycle). Thousands of fault and normal training and testing cases with different parameters were generated.

MATLAB has been used for initiating power network simulations and for protection algorithm design. STP-SKY power network model has been implemented in ATP program. This model is used for simulating many fault scenarios on its STP-SKY line by varying fault parameters. Protective relaying algorithm is located on STP bus, and it takes voltage and current samples from that end of STP-SKY transmission line. It has to be trained to recognize the type and zone of fault on selected line. Values of fault parameters used in the learning phase uniformly cover input space of possible events and their appropriate selection is important to later avoid misclassification in the testing phase. Examples of training patterns for different values of fault type are shown on Fig. 6.

Parameters used for generation of the training patterns are: all 11 types of fault and normal state; fault distances 5 to 95 % in increments of 10%; fault resistance (for grounded faults) 0, 10, 20 Ohms; fault angle 0 to 330 degrees. Fault angle is transformed into corresponding fault incident time where 0 deg is equal to the initial fault incident time, and 360 deg is equal to the initial fault incident time shifted by 1 cycle. Total number of training patterns is 2652.

Parameters used for algorithm training are: 3 phase currents selected as data for training; time window for taking patterns of 16.7 ms (1 cycle); sampling frequency of 2 kHz (33 samples per cycle). Features of the training patterns are extracted by using simulation data obtained in a desired time window and with selected sampling frequency. Phase A, B, C currents sampled during one cycle after the fault occurs are extracted and placed together in one row (Fig. 6) to form feature vector of 99 components (3 phases with 33 samples each). Also, data are normalized, and this scaling value has to be used later for normalization of the testing patterns. Two types of classifications were implemented. Training I was performed for establishing the cluster structure capable of recognizing only the type of fault. Training II was performed for establishing the cluster structure capable of recognizing type of fault and zone of fault. Boundary distance between the first and second zone is 80% of line length.

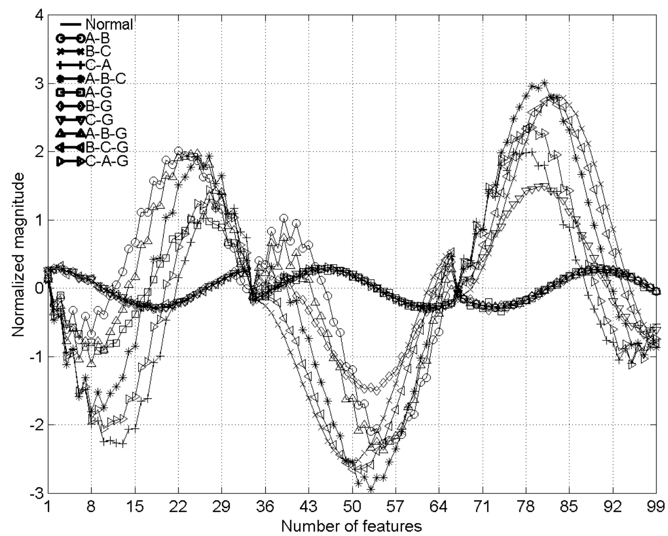

Fig. 6. Example of training patterns for all types of fault

Simulation output of the training I is the cluster structure with 269 clusters, and of training II is the cluster structure with 706 clusters.

The set of test patterns is different from the training set, and corresponds to a new set of simulation events, previously unseen by the classification algorithm. Generation of testing patterns is based on random setting of all fault parameters selected by the user.

Parameters used for generation of testing patterns are uniformly random selection of fault type, distance (0 to 100%), angle (0 to 360 deg), and normally random selection of fault resistance. Total number of testing patterns is 5000.

Classification error (for the entire set of test patterns) for selected values of the nearest neighbors from 1 up to 12 is shown on Fig. 7. This is necessary for finding an optimal value for parameter *K*. It is obvious that algorithm gives the lowest error of 0.10% for the optimal value *K*=1 in the first case and 3.48% for the optimal value *K*=1 in the second case. The results show that classifying the zone of fault is much more difficult task then classifying the type of fault.

It can be observed that the proposed approach assures very good detection of the faults in power system networks and satisfactory detection of the fault zone. This is the most important requirement for proper action to protect the network against faults in the system.

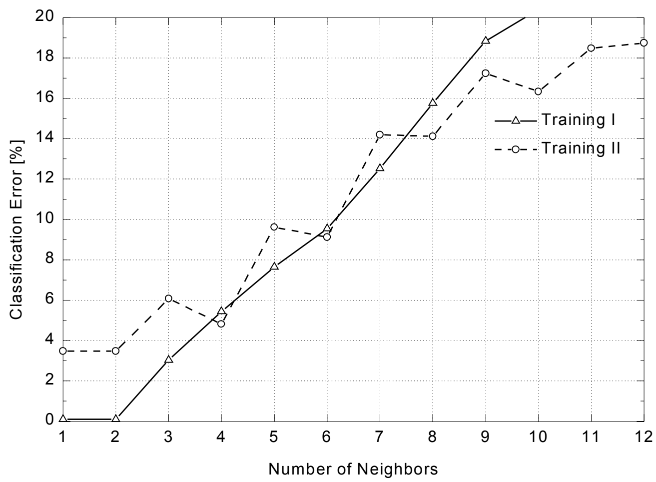

Fig. 7. Classification error vs. number of used nearest neighbors

VII. CONCLUSION

In this paper, a novel context-dependent protective relaying strategy as well as advanced design evaluation environment have been proposed, implemented, and demonstrated.

Neural network based protective relaying algorithm is characterized with unique relationship between unsupervised and supervised learning strategies that guarantees well tuned pattern recognition capabilities to the prevailing operating conditions. Its outcome is family of homogenous clusters defined as pattern prototypes, and representing various classes of input data set. Simulation results show satisfactory behavior of the new algorithm. With this new approach where the patterns of voltages and currents are used to make the relaying decision, one avoids the ambiguities of the setting validity for the prevailing operating conditions. This neural network algorithm is very flexible for further modifications.

MATLAB based software environment, which enables training and testing of the neural network based protective relaying algorithm as well as interfacing various software modules specialized for particular power system operating conditions has been established. The environment allows evaluation of both individual relays as well as the interactions among relays incorporated into a protective relaying system under a variety of power system operating conditions.

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IX. BIOGRAPHIES

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