Alarm Processing in Electrical Power Systems Through a Neuro-Fuzzy Approach

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***Abstract*—This work presents a methodology that combines the use of artificial neural networks and fuzzy logic for alarm processing and identification of faulted components in electrical power systems. Fuzzy relations are established and form a database employed to train artificial neural networks. The artificial neural networks inputs are alarm patterns, while each output neuron is responsible for estimating the degree of membership of a specific system component into the class of faulted components. The proposed method allows good interpretation of the results, even in the presence of difficult corrupted alarm patterns. Tests are performed with a test system and with part of a real Brazilian system.**

***Index Terms*—Alarm processing, fuzzy logic, neural networks, pattern recognition, power system protection.**

I. Introduction

In modern control centers, system operators usually have to handle a large number of alarms and messages in real time, and to take decisions on power system operation. These alarms may be related to fault occurrences, protection devices misoperations, etc. In many cases it is very difficult and time-consuming to draw conclusions about what has happened, particularly when protection schemes does not operate properly, communication failures occur, corrupted data are processed, etc. Following fault occurrences or other disturbances, it is crucial to restore system normal operating conditions as soon as possible. Then, alarm processing and diagnosis, including the identification of faulted devices, becomes a very important task to be addressed in real-time.

Many applications of intelligent systems techniques for alarm processing and fault diagnosis have been proposed in the technical literature. Most of them use expert systems [1]–[7], in which a set of alarm patterns is employed for the construction of a knowledge base. Human expertise is explored to build a set of rules that form the inference engine for diagnosis in a real-time environment. When a disturbance occurs, the alarm pattern transmitted to the control center is evaluated through the set of rules and a diagnosis is produced. However, expert systems perform satisfactorily only for those situations that have been previously considered during the development of the knowledge base. The major drawback of these methods is the difficulty to deal with new or corrupted alarm patterns. Alternatively, some methods based on the application of artificial neural networks (ANN) have also been proposed [8]–[15]. ANN-based methods overcome some drawbacks of expert systems approaches, but still may present some difficulties to achieve correct classifications, e.g., when the protection system fails to operate. In such cases, it may be difficult to interpret the results obtained at the ANN's outputs. Applications of fuzzy logic methods have been proposed in [16], [17]. However, those methods are not capable of performing well in the presence of corrupted/lost data.

This work extends the ideas presented in [10] and [17] and proposes a new methodology based on ANN and fuzzy logic for alarm processing and identification of faulted components in power systems. Fuzzy logic allows one to take into account qualitative information provided by human experts, such as experienced operators. On the other hand, ANNs are fault tolerant and present generalization capability, responding well for new unseen patterns. Fuzzy relations are constructed and form a database that is employed to train artificial neural networks. The artificial neural networks have alarm patterns as inputs and each output neuron is responsible for estimating the degree of membership of an specific system component into the class of faulted components. Thus, rather than simply trying to classify each system component as faulted or nonfaulted, the ANN estimate degrees of membership, allowing better interpretation of their outputs even under adverse circumstances, such as protection devices failures and/or data loss. Test results with a 7-bus system and part of a real Brazilian system are presented to illustrate the proposed methodology.

II. Alarm Processing and Faulted Section Identification

Power systems are subject to the occurrence of faults or other disturbances during their operation. Protection systems are designed to isolate power system faulted components whenever a fault occurs. This has to be done very quickly in order to reduce the risk of damage in system electrical devices. Besides, the interruption of energy supply must be minimized, or, whenever possible, avoided. Quickness, selectivity and coordination are among the most desirable features of a protection system. Then, protection devices should operate in a coordinated scheme to guarantee that only the faulted components will be disconnected. These devices also provide backup protection, i.e., if the protection device responsible for isolating the faulted component does not operate properly, other protection devices

Manuscript received November 6, 2002. This work was supported by CNPq and FAPERJ under Grant E-26/171.384/2001.

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Digital Object Identifier 10.1109/TPWRD.2003.823205

must operate in order to eliminate the fault. When this happens, a larger area in the system is usually disconnected, which may impose difficulties for the identification of faulted devices.

The most commonly used power systems protection devices/schemes are as follows.

- *Differential protection relays (DP)*—the main characteristic of a differential relay is selectivity. It is designed to operate only for faults in the protected zone. It is usually employed for busbar protection, transformers protection, generation protection, and short transmission lines protection.
- *Distance relays*—these relays are mainly used for transmission line protection in meshed networks. It usually consists of three protection zones:
  main protection zone (MP)—responsible for detecting and eliminating faults in 100% of the transmission line, must operate without any time delay, using teleprotection schemes;
  first zone backup protection (Z1)—responsible for protecting about 80% of the transmission line, it serves as an instantaneous backup protection for the main protection zone;
  second zone backup protection (Z2)—usually set to 120–150% of the length of the line, it serves as backup protection for adjacent transmission lines.
- *Breaker failure protection (BF)*—this protection scheme is employed to operate whenever a breaker failure is detected. When this happens, a tripping command is sent to remote breakers without any time delay. This prevents electrical devices damages due to a sustained faulted condition.
- *Circuit breakers (CBs)*—the circuit breakers effectively change network topology through their operation, usually following a tripping command sent by a protection relay.

Other protection devices such as overcurrent relays, ground fault relays, etc. are also employed in the protection system [18].

Following the operation of a protection relay, a tripping command is sent to circuit breakers, which will isolate part of the system. Alarms and messages are also transmitted to the control center. There, the incoming alarms must be analyzed by system operators, which have to draw conclusions and take decisions about system maintenance and restoration. The large amount of information to be addressed and other problems such as loss of important information, protection system failures, etc. can make the faulty system analysis a very difficult task, particularly when real-time actions are needed.

III. Fuzzy Logic and Neural Networks

Imprecision and uncertainty are two major characteristics that may be found in the information to be processed during the solution of a given problem. Probability theory has been largely employed to represent uncertainty in mathematical models. Data uncertainty has been modeled and handled using statistical models, probability theory and random processes. Although very useful, these theories and models may be not able to perceive and represent many aspects of the information provided by human experts.

Fuzzy set theory [19] has been developed to deal with imprecision, ambiguity, and vagueness in information. It can be seen as a theory of classes of objects with nonsharp boundaries and, being less restrictive than the conventional sets theory, is more adequate to represent information provided by human experts.

Fuzzy set theory is suitable to deal with processes that present one or more of the following characteristics [20]:

- human interaction is involved;
- an expert is available to specify the rules underlying system behavior and the fuzzy representations;
- a mathematical model of the process does not exist or is difficult to encode;
- the process involves continuous phenomena, not easily broken down into discrete segments; or
- noisy data are present.

Fuzzy variables have the property of mapping gradual state transitions. A fuzzy set element may both belong to a fuzzy set A and a fuzzy set B. The degree of vagueness, ambiguity or imprecision concerning the association of the element with a fuzzy set can be described by its membership function in the fuzzy sets A and B. Classification tasks, instead of trying to associate each pattern to a single class, may involve the evaluation of the associated membership functions. This allows handling with more complex mapping problems and the class identification may be achieved through the analysis of the computed degrees of membership. The mathematical foundations of fuzzy sets have been extensively covered by the technical literature [21].

ANNs have the ability to acquire knowledge about a problem, learning from historical or simulated data. They are able to process a large amount of information and present execution times that are compatible with real-time requirements. Besides, ANN are fault tolerant and present excellent generalization capability, being able to deal with unseen alarm patterns.

Many ANN models have been proposed in the technical literature [22]. These models differ basically on the network topology, neuron model, and training strategy. In this work, multilayer perceptron (MLP) model is employed in the construction of ANN classifiers.

The MLP model uses supervised learning and is capable of approximating any decision region. The training strategy usually employs the Backpropagation error-correction algorithm. This model has been extensively adopted for the solution of pattern recognition problems. More details about the MLP model and the Backpropagation algorithm can be easily found in the technical literature [22].

IV. Proposed Methodology

As discussed in Section III, fuzzy models are capable of dealing with qualitative and uncertain information provided by human experts based on their knowledge and experience in the solution of a given problem. On the other hand, ANN models, which may have difficulties to represent some qualitative information, present characteristics such as generalization capability and fault tolerance, which are highly desirable for performing complex mappings, particularly when the problem domain cannot be completely covered and represented by human expertise.

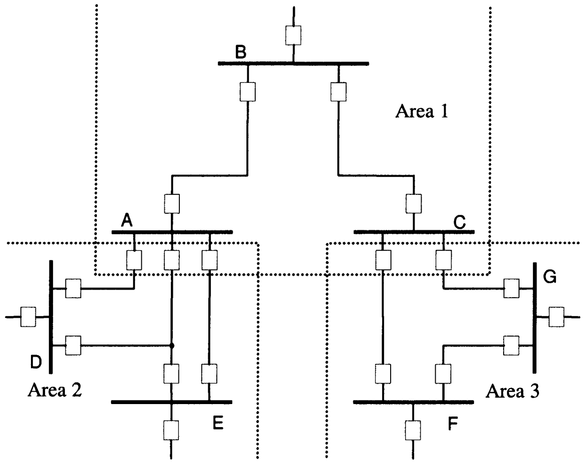

Fig. 1. Seven-bus electrical power system.

In this section, a neuro-fuzzy based approach is proposed for alarm processing and faulted sections identification in power systems. In a first step, fuzzy relations representing the relationship among many different alarm patterns and possibly faulted system components are obtained. Then, in a second step, databases containing the fuzzy associations serve as training sets for ANN that are trained to estimate the degrees of membership of each system component into the class of faulted components. The proposed method is detailed as follows.

A. Construction of the Fuzzy-Based Training Set

A fuzzy relation can be represented by a sagittal diagram [16]. Three sets of nodes are considered for representing system components, relays and circuit breakers. The sagittal diagrams are built considering the causal operations of relays and circuit breakers in the occurrence of a fault and the causality is denoted by arrows. Considering the test system presented in Fig. 1, a sagittal diagram may be constructed for each component. Fig. 2 illustrates the sagittal diagram for transmission line A–B.

In Fig. 2, each node designation is associated with a specific protection device and its location in the network. The label on each line connecting two nodes is determined with the aid of experienced protection engineers, which are able to adequately weight the associations between components, relays, and circuit breakers. This is done according to their knowledge and/or through the analysis of historical data from protection systems operation. The protection devices considered in this paper are those previously presented in Section II. Then, the adopted labels reflect the strength of the associations among relays operation and faults involving a specific system component. For example, for a transmission line the first zone protection is closely related, due to its selectivity, while the association with the second protection zone is weaker as it may operate in case of faults involving adjacent components. The associations among relays and circuit breakers can be established in the same manner. These associations can be seen in the sagittal diagram of Fig. 2.

The fuzzy associations between alarm patterns and system components can be determined with the help of the sagittal diagrams by performing two steps:

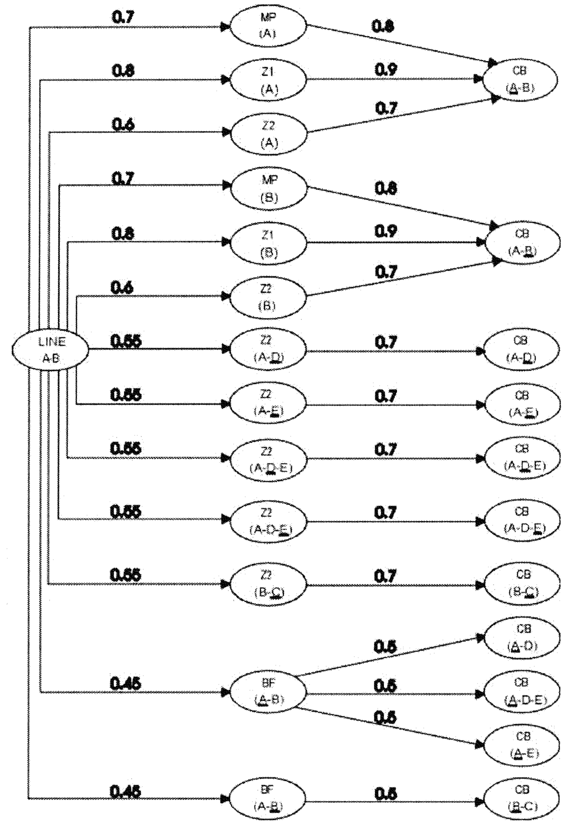

Fig. 2. Sagittal diagram for transmission line A–B.

1) intersection of the labels of the line that make a path through the node that represent the system component and those representing relays and circuit breakers that have operated;
2) union of the results obtained in step 1) for the paths connected to one component.

The result of step 2) yields the degree of membership of system components in the class of faulted components.

The *min* and *max* operators have been usually adopted to represent the intersection and union of fuzzy sets, respectively. Alternative operators have also been proposed. These proposals vary with respect to the generality or adaptability of the operators as well as to the degree to which and how they are justified [20]. Adaptability may be achieved through the use of parameterized families of operators, which may be very useful for obtaining membership functions in a variety of problems. In [17], a simulation study has been carried out to compare four families of operators with respect to their capability of obtaining fuzzy relations among alarm patterns and possibly faulted system components. Among the tested families, the Hamacher's model [20], with parameter $\gamma = 5$, was found to be the most adequate. In this model, the intersection and union of two fuzzy sets A and B are defined in terms of the parameter γ as follows:

$$\mu_{A\cap B}(x) = \frac{ab}{\gamma + (1-\gamma)(a+b-ab)} \quad (1)$$

$$\mu_{A\cup B}(x) = \frac{a+b+(\gamma'-1)ab}{1+\gamma' ab} \quad (2)$$

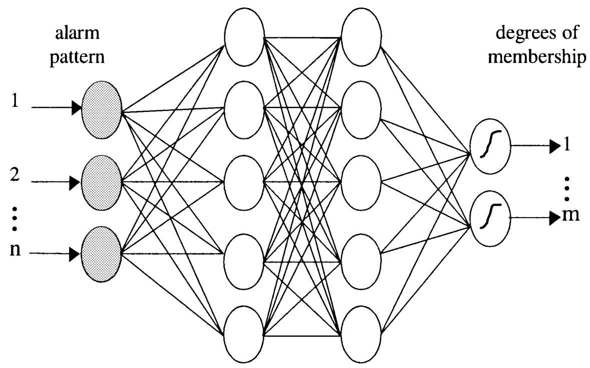

Fig. 3. ANN model.

where $\mathrm{a} = \mu_{\mathrm{A}}(\mathrm{x}), \mathrm{b} = \mu_{\mathrm{B}}(\mathrm{x}), \gamma \geq 0, \gamma' \geq -1$, and $\gamma' = \gamma - 1$. $\mu_{\mathrm{A}}(\mathrm{x})$ and $\mu_{\mathrm{B}}(\mathrm{x})$ are the membership functions of A and B, respectively, and x is an element of the universe of discourse.

Then, many different alarm patterns may be evaluated and the degrees of membership associated with system components may be computed. A database containing the fuzzy associations is then constructed and may serve as training set for ANNs, as will be detailed in the next section.

B. Construction of ANN Classifiers

The ANN construction explores the fact that it is possible to identify a faulted component based only on information from alarms that come from a restricted area of the system. Thus, a local strategy is adopted to reduce the problem dimension. This is done by employing several ANNs, each of them responsible for estimating the degree of membership of system components of the corresponding area into the class of faulted components. This can be illustrated for the seven-bus test system shown in Fig. 1. The system is arbitrarily divided into three different areas that enclose different components. In this case, three different ANN are employed, each of them being responsible for monitoring system components in a specific area.

The training sets are constructed considering alarm patterns associated with different fault conditions involving different system components. For each ANN the input variables consist of alarms from relays and circuit breakers that may operate in case of faults involving components in the monitored area. Each input variable is binary, being equal to 1 if it represents an alarm that has been received or equal to 0 if the corresponding alarm has not been received. The number of output variables corresponds to the number of components being monitored. Each training pattern is then formed by an input/output pair, where the input vector represents an alarm pattern for a given fault condition, while each desired output contains the degree of membership of each monitored component in the set of faulted components. The fuzzy associations that form the training set are obtained using the procedure described in the last section.

The ANN model adopted is the MLP, which is illustrated in Fig. 3 for n input variables and m outputs (monitored components).

C. Real-Time Diagnosis

In real time, the alarm pattern received at the control center after a disturbance may be evaluated using the off-line trained ANNs. The selection of the ANNs to be tested for a given alarm pattern depends on the incoming alarms. An ANN is selected whenever there is, among its input variables, at least one of the alarms received. Then, due to the criterion described in Section IV-B for choosing input variables for each ANN, the faulted component will certainly be inside one of the areas monitored by the selected ANNs. The following steps are employed for producing a final diagnosis:

(i) select the ANNs for which at least one of the incoming alarms is an input variable;
(ii) present the input pattern for each selected ANN and compute the degrees of membership of system components at the ANN outputs;
(iii) produce a final diagnosis based on the analysis of the estimated degrees of membership.

In step (iii), the final diagnosis is achieved by observing all computed outputs and assuming as faulted the system component with the highest degree of membership.

The fuzzy mapping employed allows good interpretation of the computed outputs for producing correct diagnoses even in difficult situations, where corrupted or incomplete alarm patterns are observed. This would not be the case if, instead of fuzzy associations, binary associations were constructed in the training set. In such case, neuron outputs would be trained to simply classify system components as faulted or not faulted (desired output equal to 1 or 0, respectively). Difficult alarm patterns would cause two or more neuron outputs to be very close and/or lying in the midrange between 1 and 0, not allowing a reliable interpretation of the results.

V. Test Results

Many tests have been performed to evaluate the proposed methodology. The alarm patterns employed to train the ANN classifiers correspond to many different fault conditions. The desired outputs for each training pattern are degrees of membership obtained using the relations presented in Section IV, where sagittal diagrams are constructed for system components and a fuzzy inference is performed using the Hamacher's model with parameter $\gamma = 5$. Once trained, the ANNs are tested using new, unseen alarm patterns, including cases in which there are misoperations of the protection system, protection devices failure, missing data, etc. The simulations have been carried out for the test system of Fig. 1 and for part of a real Brazilian system (LIGHT, Brazilian utility responsible for energy supply in the Rio de Janeiro area), shown in Fig. 4. The ANN model adopted was the MLP, trained with the Backpropagation algorithm. The best architectures for each ANN are presented in Tables I and II for the 7-bus test system and the LIGHT system, respectively. The number of training patterns (TP) is also shown. Note that the choice of input and output variables for each ANN followed the strategy presented in Section IV-B.

In the following sections, some test cases are presented to illustrate the proposed methodology.

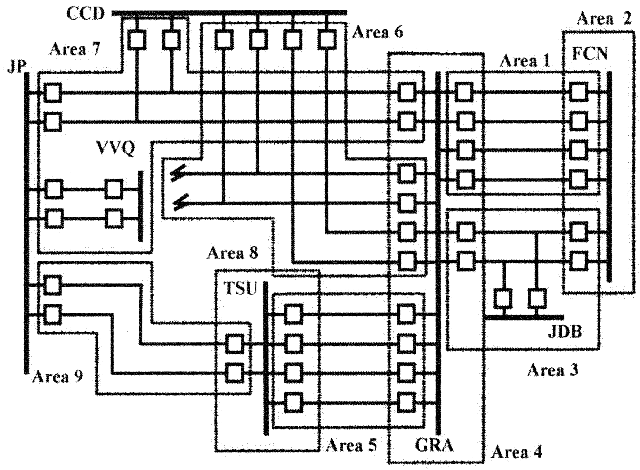

Fig. 4. Part of a Brazilian system (LIGHT system).

TABLE I
TRAINING DATA (7-BUS SYSTEM)

ANN	Number of TP	Input Layer	Hidden Layer	Output Layer
ANN_1	82	34	20	5
ANN_2	137	40	20	5
ANN_3	111	35	20	5

TABLE II
TRAINING DATA (LIGHT SYSTEM)

ANN	Number of TP	Input Layer	Hidden Layer	Output Layer
ANN_1	176	48	24	4
ANN_2	15	8	4	1
ANN_3	152	38	20	2
ANN_4	152	18	10	1
ANN_5	33	48	25	4
ANN_6	182	48	25	4
ANN_7	175	62	30	4
ANN_8	14	8	4	1
ANN_9	84	28	15	2

A. Tests Using the 7-Bus Test System

Table III illustrates some of the test cases employed for testing the 7-bus system. Note that these test samples were not presented during the ANN's training phase and correspond to situations where protection devices malfunctions or data loss are present. The ANNs tested during the classification phase, selected automatically as described in Section IV, are also presented. Table IV shows the obtained results. The results obtained for each test case are presented in each column of Table IV.

The computed outputs are estimates of the degree of membership of each system component in the class of faulted components. The largest degree of membership obtained for each test case is highlighted in Table IV. According to the proposed methodology the system component associated with the larger degree of membership is classified as faulted. It can be seen that in all cases the faulted components have been correctly identified.

TABLE III
SOME TEST CASES FOR THE 7-BUS SYSTEM

Test cases	Incoming alarms	ANNs Tested
1- Fault at line A-B	Terminal A - Z1, CB Terminal B - Z2, CB	ANN1 ANN2
2- Fault at bus A, missing information from breaker operation at line A-E, terminal A	Bus A - DP, CBs associated with bus A (except the one in line A-E)	ANN1 ANN2
3- Fault at bus C with breaker failure at line C-F, terminal C	Bus C - DP, CBs (except C-F) Terminal F - Z2, CB (Line C-F)	ANN1 ANN3
4- Fault at line B-C with protection failure at terminal C	Terminal B - MP, CB (Line B-C) Terminal F - Z2, CB (Line C-F) Terminal G - Z2, CB (Line C-G)	ANN1 ANN3
5- Fault at line C-F, missing information from breaker operation at terminal C	Terminal C - MP Terminal F - Z1, CB	ANN3

TABLE IV
OBTAINED RESULTS (7-BUS SYSTEM)

	System components	Test Cases (Degrees of Membership)				
		1	2	3	4	5
ANN_1	A-B	**0,8732**	0,1195	0,0704	0,0000	-
	B-C	0,0000	0,0327	0,0789	**0,8734**	-
	A	0,2349	**0,9713**	0,0000	0,0000	-
	B	0,0000	0,0161	0,0000	0,0000	-
	C	0,0000	0,0000	**0,9637**	0,4232	-
ANN_2	A-D	0,2137	0,0807	-	-	-
	A-E	0,2169	0,2224	-	-	-
	A-D-E	0,2016	0,0212	-	-	-
	D	0,0000	0,2132	-	-	-
	E	0,0000	0,0000	-	-	-
ANN_3	C-F	-	-	0,1358	0,4273	**0,6986**
	C-G	-	-	0,1700	0,4923	0,0000
	F-G	-	-	0,0000	0,0000	0,0000
	F	-	-	0,0000	0,0000	0,1404
	G	-	-	0,0000	0,0045	0,0561

B. Tests Using the LIGHT System

Table V illustrates some of the test cases employed for testing the LIGHT system. Again, the test samples were not presented during the ANN's training phase and correspond to situations where protection devices malfunctions or data loss are present. The ANNs tested during the classification phase are also presented. Note that, according to the procedures for real-time diagnosis presented in Section IV, only the ANNs associated with areas 1, 2, 3, and 4 are selected and tested for the incoming alarms shown in Table V. Table VI shows the obtained results.

Once more, the largest degree of membership estimated for each test case is associated with the faulted component.

TABLE V
SOME TEST CASES FOR THE LIGHT SYSTEM

Test cases	Incoming alarms	ANNs Tested
1- Fault at line FCN-GRA-2	Terminal GRA - Z2, CB Terminal FCN - MP, CB	ANN1 ANN2 ANN3 ANN4
2- Fault at bus FCN with breaker failure at line FCN-GRA-2, terminal FCN	Bus FCN - DP, CBs associated with bus FCN Terminal GRA - Z2, CB (Line FCN-GRA-2)	ANN1 ANN2 ANN3 ANN4
3- Fault at line FCN-GRA-JDB-1 with protection failure at terminal FCN	Terminal GRA - MP, CB (Line FCN-GRA-JDB-1) Terminal JDB - Z1, CB (Line FCN-GRA-JDB-1) Terminal GRA - Z2, CB (Lines FCN-GRA-1,2,3 and 4) Terminal GRA - Z2, CB (Line FCN-GRA-JDB-2)	ANN1 ANN2 ANN3 ANN4
4- Fault at line FCN-GRA-4 missing information from relay operation at terminal GRA	Terminal FCN - Z1, CB Terminal GRA - CB	ANN1 ANN2 ANN3 ANN4
5- Fault at line FCN-GRA-1 with misoperation of the protection relay of line FCN-GRA-2	Terminal FCN - MP, CB Terminal GRA - Z1, CB Terminal GRA - MP, CB (Line FCN-GRA-2)	ANN1 ANN2 ANN3 ANN4

TABLE VI
OBTAINED RESULTS (LIGHT SYSTEM)

	System components	Test Cases (Degrees of Membership)				
		1	2	3	4	5
ANN_1	FCN-GRA-1	0,0027	0,3038	0,7962	0,0000	**0,8536**
ANN_1	FCN-GRA-2	**0,7485**	0,3388	0,8463	0,0000	0,3525
ANN_1	FCN-GRA-3	0,0002	0,3021	0,6049	0,1081	0,0000
ANN_1	FCN-GRA-4	0,0051	0,3052	0,7489	**0,8942**	0,0000
ANN_2	FCN	0,3747	**0,9750**	0,3263	0,3664	0,4476
ANN_3	FCN-GRA-JDB-1	0,0240	0,0577	**0,9765**	0,1024	0,0435
ANN_3	FCN-GRA-JDB-2	0,0523	0,0766	0,7533	0,0000	0,0284
ANN_4	GRA	0,0583	0,0583	0,4467	0,5724	0,2915

TABLE VII
GLOBAL RESULTS

	7-bus system	LIGHT system
Tested samples	92	140
Correct Classifications (%)	96.8	95.0
Incorrect Classifications (%)	3.2	5.0

C. Global Results

Besides the test cases presented in Tables III and V, many other new alarm patterns have been evaluated using the proposed methodology. Most of them consisted of alarms obtained for situations where protection devices failures and/or data loss are present. Table VII illustrates the global results for classifications performed with the 7-bus system and with the LIGHT system.

The results in Table VII show that the proposed method presented excellent performance, providing good interpretation of corrupted alarm patterns. Many of these patterns involve multiple protection devices failures and/or data loss. Besides, it has been observed that correct classifications are always achieved when the protection system operates properly. The computational burden involved in testing the selected ANNs can be considered negligible.

It is important to emphasize that incorrect classifications were obtained for very corrupted alarm patterns, usually due to the combination of multiple noncorrelated protection devices failures and/or data loss. Although employed for testing the proposed method under severe scenarios, many alarm patterns are not likely to happen, particularly those that were not correctly classified.

D. Final Comments

The neuro-fuzzy approach proposed in this paper is more powerful than the neural approach presented in [10]. Improvements in the ANN classifications are particularly noted for situations where protection systems failures occur. This happens because binary associations are constructed in the neural approach [10] and neuron output values in the midrange between 0 and 1 do not provide reliable interpretation for correct classification and diagnosis. On the other hand, fuzzy associations are constructed in the proposed model. The ANNs are trained to produce output values that are real numbers in the range 0–1. These output values are estimated degrees of membership, and can always be interpreted for classification and diagnosis. It is important to remark that, using the proposed neuro-fuzzy approach, correct diagnoses have been achieved for 100% of the situations that have been considered on [10] for testing the neural model. In [10] the correct diagnoses rate was 91.22%. Besides, the proposed model does not produce undetermined diagnoses, which might occur if the model proposed in [10] is used. Incorrect diagnoses observed in this paper also occur when the neural model of [10] is adopted.

The proposed model is capable of dealing with corrupted alarm data, protection devices failure and, in many cases, also with the combination of these situations. Many of them have been considered for testing the adopted methodology and incorrect classifications related in Table VII were achieved only for rare and difficult combination of those situations. It is also important to observe that in the presence of multiple faulted components, more than one output neuron of the tested ANNs will present large and close values for the estimated degree of membership of the corresponding elements, flagging that these are faulted. Also, to some extent, the proposed model is capable of dealing with different network topologies without need of retraining. This is due to ANN's generalization capability. For example, test case 2 of Table III represents a situation in which the circuit breaker operation at line A–E is not among the incoming alarms either because a communication failure has occurred or because line A–E is out of service. Although this represents a topology condition different from the one considered during the training phase, the ANN classifiers performed correctly. It should be noted, however, that for major topology changes it may be necessary to retrain the ANN that monitors components in the area where system reconfiguration took place.

The design of the proposed hybrid system allows the incorporation of some qualitative aspects of the problem to be solved. This is one of the main advantages of the neuro-fuzzy approach, as not only general knowledge on protection systems theory, but also specific knowledge on the power system and protection system under consideration can be easily represented. This is achieved by properly constructing and weighting the associations among components, relays and circuit breakers in the sagittal diagrams described in Section IV. Besides, ANN's robustness makes it possible to carry out correct diagnosis even for difficult and/or unseen situations. It is also worthy mentioning that the maintenance of the proposed model is not difficult to address. As the employed ANNs act as almost independent classifiers, each of them monitoring different system components, in specific areas of the system, only one or a few ANNs may need to be retrained if the system experiences significant changes, such as network expansion, in a specific area.

Due to the local strategy adopted, the proposed model can be easily used to cover more areas in a larger power system. This is done by constructing more ANN classifiers, which would be responsible for monitoring more areas in the system. Also, the classification accuracy would not be influenced by the system size.

A prototype system based on the proposed model is under development to be implemented in the LIGHT control centre. Practical aspects of implementation and the experience with the prototype in an actual control centre will be subject of a future paper.

VI. Conclusion

This paper presented a neuro-fuzzy approach for alarm processing and identification of faulted components in electrical power systems. Fuzzy relations among alarm patterns and possibly faulted system components are established and employed as training sets for artificial neural networks. The ANNs are trained to produce online estimates of the degrees of membership of system components into the set of faulted components whenever a new alarm pattern is received at the control center. The methodology has been tested using a 7-bus system and part of a real Brazilian system. Test results show that correct diagnoses have been achieved from the analysis of the fuzzy inferences produced at the neural networks outputs. Even difficult corrupted alarm patterns have been correctly classified. The ability of producing good estimates for degrees of membership and correct diagnoses for the incoming alarms is due to the ANN's generalization capability and to the fact that using fuzzy inferences as desired outputs allows a better interpretation at the class boundaries, where corrupted alarm patterns may be difficult to interpret.

Acknowledgment

The authors acknowledge M. A. P. Rodrigues, Senior Protection Engineer, from Light Electricity Services Company, for his support.

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