1° Congresso Brasileiro de Redes Neurais

Escola Federal de Engenharia de Itajubá
Itajubá, 24 a 27 de outubro de 1994

APPLYING ASSOCIATIVE MEMORIES TO FAULT LOCATION IDENTIFICATION

A.P. Alves da Silva[1] A.H.F. Insfran[2]
P.M. da Silveira[1] G. Lambert-Torres[1]

1. Escola Federal de Engenharia de Itajubá - Brazil
2. Itaipú Binacional - Brazil/Paraguay

Abstract: Faults producing load disconnections or emergency situations have to be localized as soon as possible to start the electric network reconfiguration, restoring normal energy supply. This paper proposes the use of artificial neural networks (ANNs), of the associative memory type, to solve the fault localization problem. The main idea is to store measurement sets representing the normal behavior of the protection system into associative memories. Afterwards, these memories are employed on-line for fault location estimation from the protection system equipment status. The associative memories work correctly even in case of malfunction of the protection system. Although the ANNs are trained with single contingencies only, their generalization capability allows a good performance for multiple contingencies.

1 Introduction

In a power system substation, faults that produce load disconnections or emergency situations have to be localized as soon as possible. Fault localization is necessary to start the substation reconfiguration for restoring normal energy supply. However, the identification of the faulted points is not always an easy task, delaying the restoration procedures. This usually occurs when the protection system does not behave as expected.

Substations in commissioning phase or even the ones already in operation, but with complex constructive and operational natures, can have high indices of protection system failure. In these substations, fault localization can take a long time due to the great amount of information to be analyzed. Even visual inspection can be required.

The difficulty in identifying the faulted points significantly increases in non-conventional substations, as gas-insulated (GIS) ones [1].

This paper proposes the use of artificial neural networks (ANNs), of the associative memory type, to solve the fault localization problem in substations. The idea is to store, into associative memories, measurement sets representing circuit breaker and relay status (normal behavior) corresponding to possible single faults. Afterwards, these associative memories are used on-line to estimate fault locations (equipment, phase and compartment), even in case of misoperation of the protection system. Although the ANNs are trained with single contingencies only (stored cases), their generalization capability allows a good performance for multiple (simultaneous) faults.

2 Associative Memory ANNs

Intelligent systems have been successfully applied to the problem of fault diagnosis. Two approaches have been used to solve this problem: symbolic expert systems [2,3] and neural networks [4]. Expert systems have been criticized for requiring a great effort to build (knowledge acquisition) and maintain the knowledge base.

ANNs offer a simple and more robust solution to the fault diagnosis problem due to their noise suppression capacity, training power and adaptability. The noise suppression ability allows them to correctly localize faults, even in case of protection system misoperation. The capability of training using samples of solved cases (supervised training) reduces the development time very much. Finally, the ANNs adaptability makes the maintenance job trivial.

The proposed approach is an innovation compared with reference [4] where the ANNs are used as pattern recognizers, i.e., simple models are desirable. In [4], the ANNs training process is based on normal and abnormal operational conditions of the protection system, and not on the protection philosophy. As the numerous possibilities are not well defined, the limited number of cases used for training hardly produces good generalization.

The new approach utilizes the ANNs as associative memories, where models with redundancy are desirable. The novelty is related to the difference between the learning (pattern recognizers) and memorization (associative memories) concepts. The second concept is more useful when the population of interest is well defined.

The general characteristics required from an associative memory include the following abilities [5]:
- to store many associated stimulus/response signal pairs;
- to accomplish this storage through a self-organizing process;
- to store this information in a distributed, robust (highly redundant) manner;
- to generate the appropriate response signal on receipt of the associated stimulus signal;
- to regenerate the correct response signal although the input stimulus signal is distorted or incomplete; and
- to add to existing memory.

Associative memory models can be divided into two categories [6,7]:
1) information processing models, which employ programs for testing, comparing, analyzing, manipulating and storing information; and
2) ANN models, which implement the basic functions of a selective associative memory using a collection of relatively simple elements connected to one another.

Optimal Associative Memories

The optimal nonlinear associative memory (ONAM), an ANN paradigm introduced by Kohonen [8], is selected because of its interpolative response, its least-squares storage degradation, and its well-understood mapping. The ANN models for associative storage based on feedback networks [9-11] are not suitable for the fault localization problem. In addition to the low storage capacity, their nearest-neighbor response (besides the difficulty to control the "attractors", which can generate responses not related to the nearest-neighbor) does not allow the localization of simultaneous faults without explicitly storing them. The interpolative response of an optimal associative memory allows that.

The purpose of an optimal associative memory is to obtain optimal transformations such that, with respect to a wanted input-output transfer relation, the effect of noise or other imperfections on the input signals would be minimized. As the ONAM is a simple extension of the optimal linear associative memory, the latter is described first.

The Optimal Linear Associative Memory

Let $\underline{x}_1=(x_1,x_2, \dots , x_m)^t$, $\underline{x}_2, \dots , \underline{x}_r$ be an ensemble of input signals (status of circuit breakers and protection relays) in a representation space $\Re^m$, and $\underline{y}_1=(y_1,y_2, \dots , y_n)^t$, $\underline{y}_2, \dots , \underline{y}_r$ their associated output signals (fault location) in $\Re^n$. The signals are assumed to be linearly transformed by the following transfer relation (recall procedure):

$$Y = X.W \tag{1}$$

where $X = [\underline{x}_1 \ \underline{x}_2 \ \dots \ \underline{x}_r]^t$, $Y = [\underline{y}_1 \ \underline{y}_2 \ \dots \ \underline{y}_r]^t$ and W is an m x n matrix. The components of W, w_{ij}'s , represent the interconnection weights leading from element "i" to element "j" in the corresponding two-layer feed-forward ANN (Figure 1).

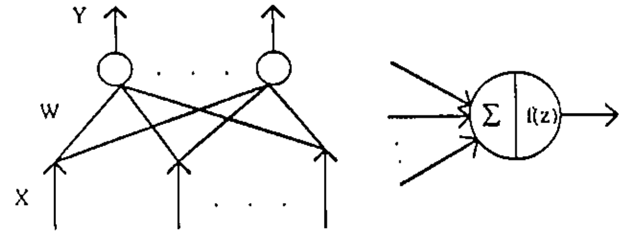


Figure 1 - ANN of the optimal associative memory type, where f(z) = z.

The following analysis is developed considering an autoassociative recall (Y=X). The vectors $\underline{x}_1, \underline{x}_2, \dots , \underline{x}_r \in \Re^m$ span a subspace $L \subset \Re^m$. An arbitrary vector $\underline{x} \in \Re^m$ is uniquely described as the sum of two vectors $\hat{\underline{x}}$ e $\tilde{\underline{x}}$, i.e., the orthogonal projections of $\underline{x}$ on L and on the orthogonal complement of L, respectively. Therefore, $\hat{\underline{x}}$ is the best linear combination of the input signals $\underline{x}_k (k=1, \dots , r)$ that approximates $\underline{x}$ in the sense of least-squares

Orthogonal projection operations have the property of correcting noisy and/or incomplete input signals towards the stored ones. If an input signal is a noisy version of one of the stored signals $\underline{x}_k$, $\underline{x} = \underline{x}_k + \underline{\varepsilon}$, where $\underline{\varepsilon}$ is a random error, then in general, $\hat{\underline{x}}$ is a better approximation of $\underline{x}_k$. It can be shown that for the case in which $\underline{\varepsilon}$ has a symmetrical multivariable Gaussian radial distribution in $\Re^m$, its orthogonal projection on L, $\hat{\underline{\varepsilon}}$, has a distribution with the following standard deviation:

$$\delta(\|\hat{\underline{\varepsilon}}\|_2 = \|\hat{\underline{x}} - \underline{x}_k\|_2) = (r/m)^{1/2} . \|\underline{x} - \underline{x}_k\|_2 \tag{2}$$

The input signal noise is attenuated by the orthogonal projection if $r < m$. Although the analysis above is related to an autoassociative memory, the same noise attenuation factor, $(r/m)^{1/2}$, can be applied to the output vectors of a heteroassociative memory ($Y \neq X$) [8].

With regard to Eq.1, the optimal least-squares correlation of X and Y (training procedure) is defined as

$$W = X^{\dagger} . Y \quad (3)$$

where

i) $X^{\dagger} = X^{-1}$ (4)

if m = r and X is nonsingular,

ii) $X^{\dagger} = X^{t} (X X^{t})^{-1}$ (5)

if the rank of X is equal to r, i.e., the input signals to be memorized are linearly independent (r < m), and

iii) $X^{\dagger} = (X^{t} X)^{-1} X^{t}$ (6)

if the rank of X is equal to m, i.e., the input channels are linearly independent (m < r).

When exact solutions to Eq.3 exist, i.e., Eqs. 4 and 5, then W is the particular solution that supplies the associative mapping with the best error tolerance. When exact solutions do not exist, Eq.6, W is the best approximate solution in the least-squares sense.

With this encoding scheme, the strong condition of orthogonality among stored signals is not required to get perfect recall (when an exact solution is possible), as would be the case for an encoding scheme based on the Hebb's rule [12].

The Optimal Nonlinear Associative Memory

For linear associative mappings, a necessary condition for an exact solution to exist is the linear independence of the signals to be memorized (rows of X($\underline{x}_k^t$'s)). When the number of signals is greater than their dimensionality, this condition is necessarily violated and no exact solution exists. It is possible to overcome this limitation by using nonlinear transformations to enhance the original input signal representation. With a nonlinear preprocessing transformation, the dimensionality of the $\underline{x}_k$'s is increased; consequently, the probability for the transformed vectors to become linearly independent (distinguishable) also increases. Another desirable effect produced by an enlargement of the dimensionality of the signals is the improvement of the noise attenuation factor $(r/m)^{1/2}$.

The selected nonlinear transformation is a polynomial one. Polynomial transforms belong to a class of least-squares problems that are linear in the parameters and nonlinear with respect to the input vectors. The chosen polynomial transform is as follow:

$$\underline{x}_k = (x_1, x_2, \ldots, x_m)^t \rightarrow$$
$$\rightarrow \underline{p}_k = (x_1, x_2, \ldots, x_m, x_1x_2, x_1x_3, \ldots, x_{m-1}x_m, x_1x_2x_3, \ldots, x_{m-2}x_{m-1}x_m)^t \quad (7)$$

The name ONAM does not imply that the nonlinear transformation is optimal in an absolute sense. The optimality criterium is applied to estimate the parameters, given a certain nonlinear transformation.

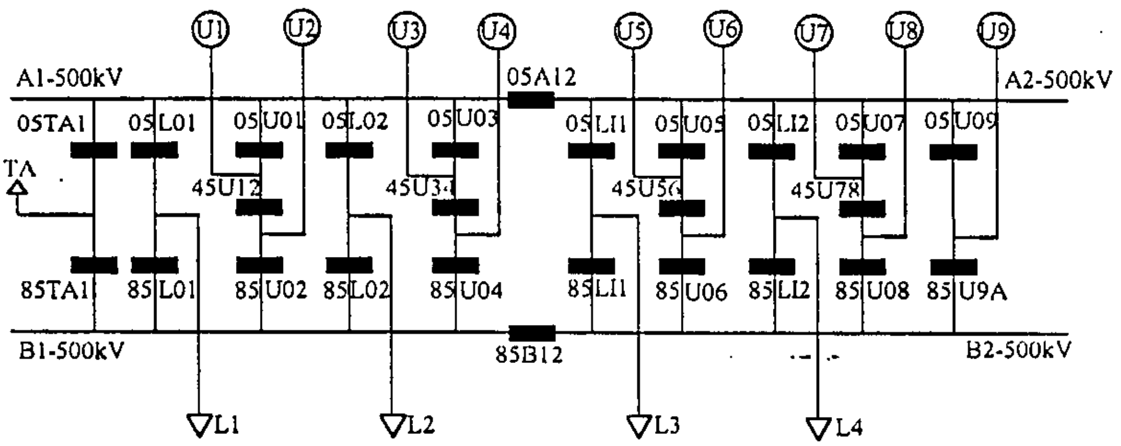


Figure 2 - 500 kV Gas-Insulated Substation.

3 The Proposed Approach

The proposed scheme was idealized for the 500 kV, 50 Hz, Itaipú gas-insulated substation, which used to present difficulties in fault localization due to its large number of compartments (321). This substation is represented in Figure 2, where there are 9 generation units, 4 transmission lines, 4 buses, 1 auxiliary transformer and 26 circuit breakers. The protection system has 66 relays. There are 18 generator differential relays, 8 bus differential relays, 2 transformer differential relays, 8 distance relays, and 30 circuit breaker failure relays.

The status of circuit breakers and protection relays can be used to localize faults in a substation. The status of these equipment can be represented by binary signals in which the "0" characterizes a closed circuit breaker or a non-operating relay, while "1" characterizes an open/tripped circuit breaker or an operating relay. A typical training set is presented in Table 1. The 26 first input channels represent the circuit breaker status, while the other 40 channels represent the relay status. For example, in case of a fault in bus B2, the value "1" for channels 14, 22, 23, 24, 25 and 26 shows that the circuit breakers 85B12, 85LI1, 85U06, 85LI2, 85U08 and 85U09A have opened. The value "1" for channels 33, 34 and 38 shows that the relays 87B2/P, 87B2/A and BF/B2 have operated. The value "0" for the other channels represents closed circuit breakers and relays that have not operated. The output channels indicate a single fault in bus B2. The number of output channels is the same as the number of equipment. In this example, the output signal generated by the ANN that identifies the faulted equipment activates the ANN responsible for bus B2, which is utilized to localize the faulted phase and compartment.

In this way, the fault localization problem is decomposed as shown in Figure 3. Based on the states of relays and circuit breakers, 66 and 92 input binary channels feed the EQUIP and CB's ANNs, respectively. CB's is responsible for detecting defective circuit breakers. EQUIP and CB's form the ANNs main group. These ANNs input channels contain information about which equipment are defective and the post-fault substation topology. No information is supplied regarding the faulted phase and compartment. A second group of ANNs is used for that. The input channels for this new group contain information of distance relays situated in the GIS (24 = 4 lines x 3 phases x 2 (double primary protection system)) and in a neighbor substation (12 = 2 lines x 3 phases x 2), of bus differential relays of the GIS (12 = 4 x 3), and of pressure drop relays (107 = 321 / 3; only one alarm for the three phases) also situated in the GIS. Therefore, there are 155 inputs to the second group of ANNs. The number of input channels for each of these ANNs, and the number of ANNs for each type of equipment, including circuit breakers, are shown in Figure 3.

All the ANNs are trained considering normal operation of the primary protection system. The basic idea behind the problem decomposition is to reduce the number of cases that should be memorized if a single ANN were employed. With the reduction on the number of cases to be memorized by each ANN of the proposed approach, smaller ANN architectures can be used for the same noise attenuation factor (significantly reducing the training time).

4 Tests

The ANNs performance is verified using 21 historical cases. There are 17 single contingencies and 4 multiple contingencies. Relay and/or circuit breaker misoperations occur in the 21 faults. All historical cases are correctly solved by the ONAMs (Kohonen nets).

Figure 4 is related to the behavior of the EQUIP ANN with respect to the number of auxiliary input variables (generated by the nonlinear transformation defined by Eq.7). The graph vertical axis shows the difference between the largest and the second largest value of the output channels of the trained ANN. The reliability of a certain output signal is as large as this difference is closer to 1. Figure 4 is built based on the average result for 6 (randomly chosen) of the 17 single faults mentioned before. The best performance happens when the number of auxiliary input variables is equal to 2000. From now on, all the results from EQUIP are obtained using 66 original input channels plus 2000 auxiliary channels (m=2066).

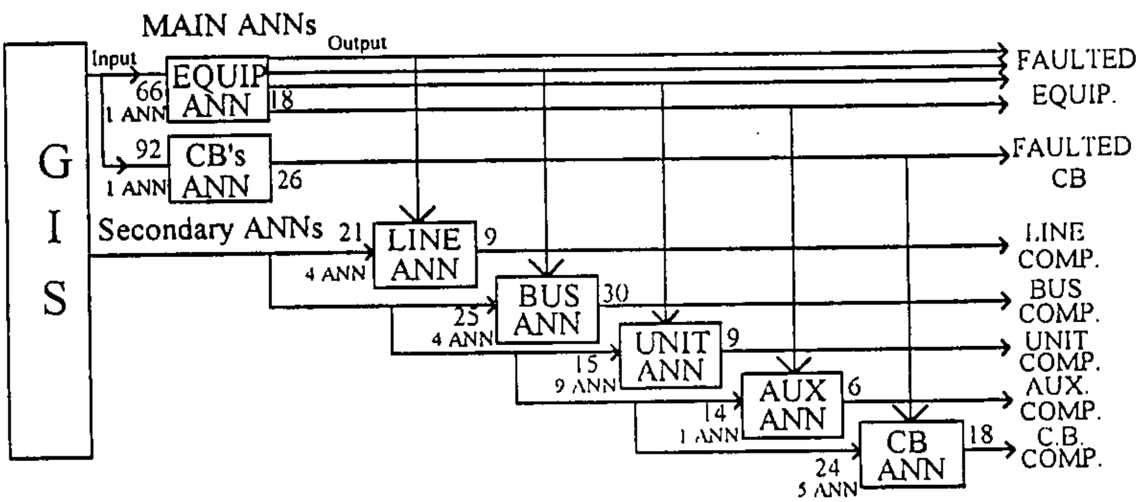


Figure 3 - Decomposition of the Fault Localization Problem.

Table 1 - Training Set for Identifying Faulted Equipment.

	Input	FAULT LOCATION																		
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
			A1	A2	B1	B2	L1	L2	L3	L4	U1	U2	U3	U4	U5	U6	U7	U8	U9	A7
C	05TA1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
.	05L01	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
B	05U01	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
.	05L02	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	05U03	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	05A12	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	45U12	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
	45U34	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
	85TA1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	85L01	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	85U02	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	85L02	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	85U04	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	85B12	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	05L11	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	05U05	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	05L12	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	05U07	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	05U09	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	45U56	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
	45U78	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
	85L11	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	85U06	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	85L12	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	85U08	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	85U09A	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
R	87A1/P	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	87A1/A	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	87B1/P	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	87B1/A	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Y	87A2/P	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	87A2/A	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	87B2/P	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	87B2/A	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	BF/A1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	BF/A2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	BF/B1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	BF/B2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	21P/L1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	21A/L1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	21P/L2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	21A/L2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	21P/L3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	21A/L3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	21P/L4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	21A/L4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	87V/U1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	87TR/U1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	87V/U02	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	87TR/U2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	87V/U03	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	87TR/U3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	87V/U04	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	87TR/U4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	87V/U05	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	87TR/U5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	87V/U06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	87TR/U6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	87V/U07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	87TR/U7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	87V/U08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	87TR/U8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	87V/U09	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	87TR/U9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	87	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	87TA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

	Output	FAULT LOCATION																		
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
			A1	A2	B1	B2	L1	L2	L3	L4	U1	U2	U3	U4	U5	U6	U7	U8	U9	A1
E	BUS A1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Q	BUS A2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	BUS B1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	BUS B2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P	LINE 1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
.	LINE 2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	LINE 3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	LINE 4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	UNIT 1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	UNIT 2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	UNIT 3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	UNIT 4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	UNIT 5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	UNIT 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	UNIT 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	UNIT 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	UNIT 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	AUX.TR.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

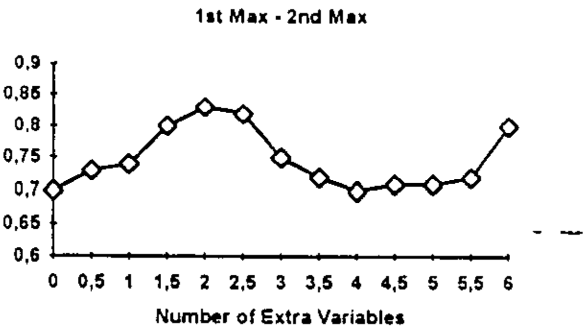
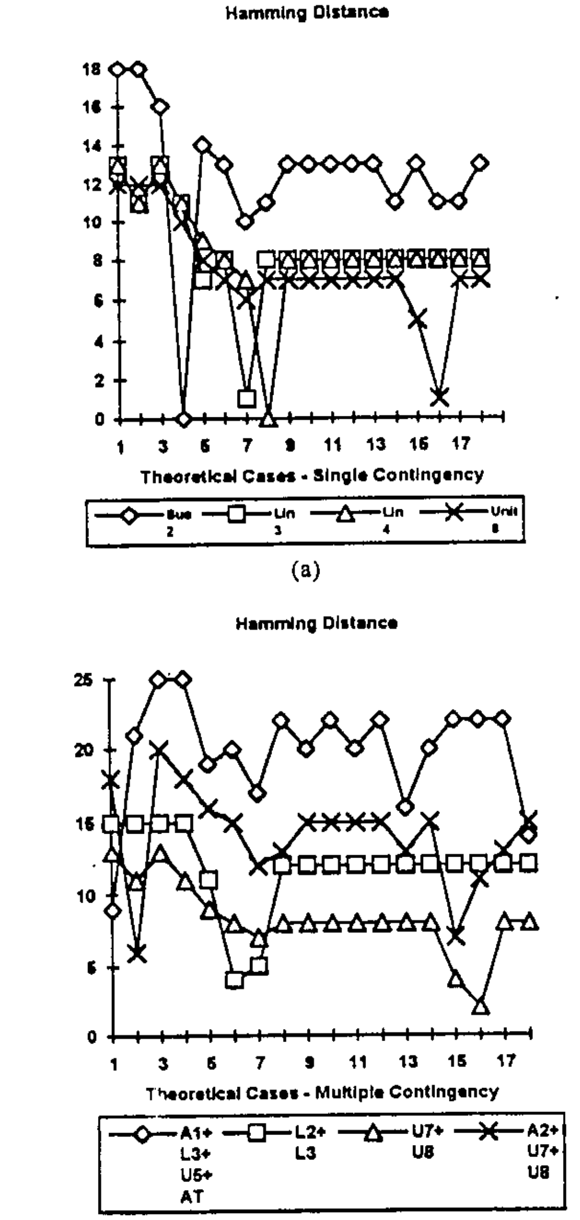


Figure 4 - EQUIP Performance with respect to the Number of Input Variables.

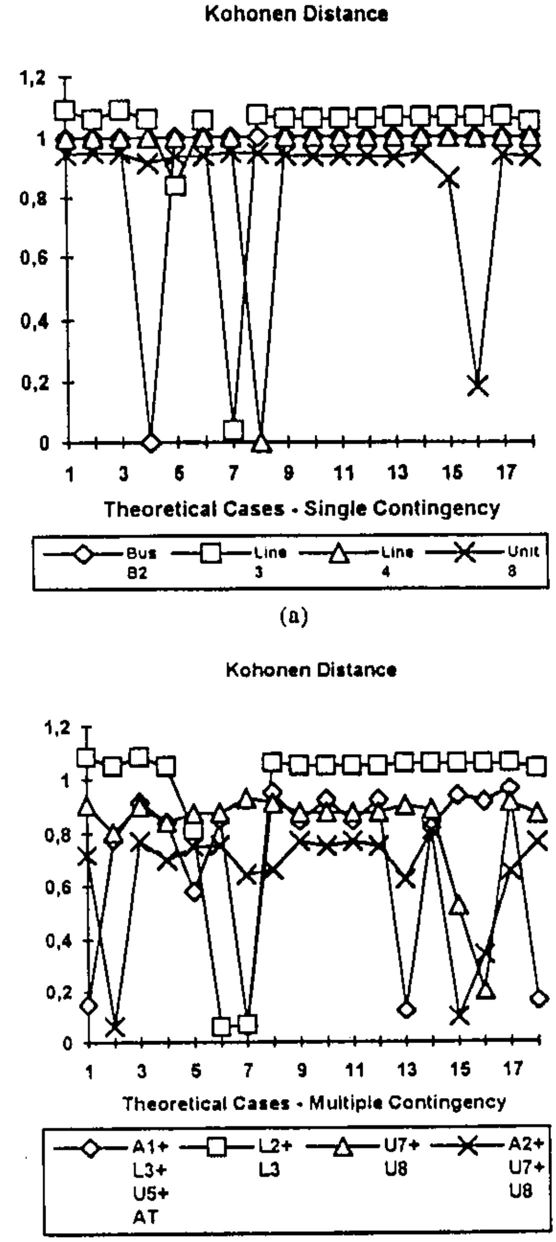
For comparison, Figures 5(a) and 5(b) present the performance of an associative memory based on the Hamming distance with the same objective of EQUIP. The faults are identified by the smallest Hamming distances (nearest-neighbors) between the vector representing the current states of circuit breakers and relays, and the 19 stored vectors. There is one stored vector for each of the 18 equipment of interest, plus one vector associated to the condition of non activation of the protection system.

The vertical axes of the graphics show the Hamming distances from historical contingencies to each stored case, represented in the horizontal axes. In Figure 5(a), curves related to 4 single contingencies (fault in bus 2, fault in line 3, fault in line 4, and fault in generator 8) are shown. The minimum Hamming distance correctly indicates the faulted equipment for the 4 cases, and consequently the number of relays and circuit breakers, among those that serve as input to EQUIP, that have not operated as expected.



(a) (b)

Figure 5 - Associative Memory based on the Hamming Distance



(b)

Figure 6 - Kohonen Net (ONAM) Results.

A graph analogous to 5(a) is displayed in Figure 5(b). This time, the curves are related to multiple contingencies. Once more, the l smallest Hamming distances, where l is the contingency order are correctly associated to the faulted equipment. For example, for the multiple contingency A2+U7+U8 the points 2, 15 and 16 represent the corresponding equipment. However, the difference between the forth and the third smallest Hamming distance does not appropriately characterize the contingency order (previously unknown). Analogously, in Figure 5(a) the difference between the second smallest and the minimum Hamming distance does not characterize single faults. For example, the single fault in the generation unit 8 (Figure 5(b)) has value 4 for this difference, while the multiple fault A1+L3+U5+AT has value 5 for the same difference (second smallest minus minimum).

The same conclusions are reached with the Euclidean distance instead of the Hamming distance. Figures 6(a) and 6(b) show graphics analogous to the ones presented in Figures 5(a) and 5(b), employing the Kohonen net this time.

It can be observed that the contingency order is much better defined by the Kohonen net. This becomes clear in Figure 7, where the dispersion that characterizes the contingency order is displayed in a normalized scale for 6 randomly selected historical cases. As the dispersion value 1 is the best characterization of the contingency order, it is clear that the Kohonen net has a superior performance compared with the nearest-neighbor associative memories based on the Hamming and Euclidean distances.

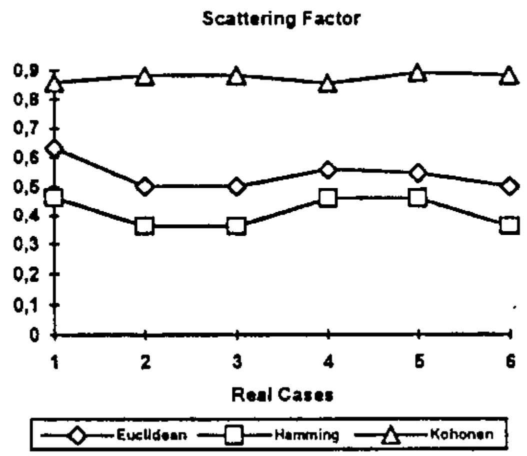


Figure 7 - Dispersion Factor for the Three Associative Memories.

Finally, Figure 8 exhibits results from one of the ANNs belonging to the second group. After EQUIP has identified bus B1 as the defective equipment, the fault location, i.e. the defective compartment, is indicated by the ANN responsible for B1 (bus B1 has 30 compartments; 10 compartments/phase). Once more the results are excellent. The training process of each ANN takes a few seconds in a 486-DX2 66 MHz microcomputer.

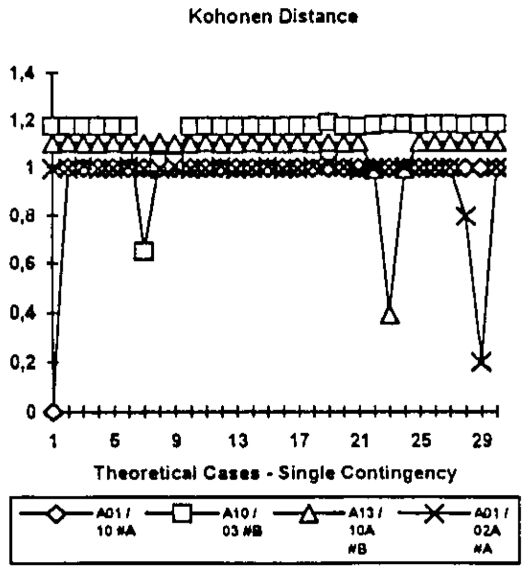


Figure 8 - Results of the ANN responsible for Bus B1.

5 Conclusions

A new approach to the fault localization problem is introduced. In a previous project the authors participated in the development of an expert system to solve the same problem for the Itaipú system [13]. The advantages of the ANN approach are the following:

- The development time of the fault localization system based on ANNs is about 10 times less than one required by the expert system approach. The expert system maintenance takes more time also, because of the necessity of knowledge base consistency checking.

- In general, the great disadvantages of an ANN compared with an expert system is the mapping "opacity" of the ANN. However, for the fault localization problem, the expert system explanation capability does not supply relevant information that cannot be obtained from ANNs, too. This is because solution justification is more useful when the protection system does not behave as expected. In these situations, besides fault localization, it is important that the operator be aware of which relays and/or circuit breakers have not correctly operated. This information can also be obtained via ANNs, comparing the current input signal with the stored input signal corresponding to the current output signal.

- Nevertheless, the ANNs have been more robust than the expert system in situations of protection system misoperation.

Although the proposed approach has been used for a GIS, it can be applied to power system operation centers.

ACKNOWLEDGEMENTS

This work was supported by Itaipú Binacional and the Brazilian National Research Council (CNPq).

REFERENCES

[1] R. Fragiacomo, R. Pani, and A. Tomassi: "Problems Relating to Protection of HV Metal-Enclosed Gas-Insulated Substations (GIS)", Second International Conference on Developments in Power-System Protection, London, June 1980, pp. 6-9.

[2] C. Fukui and J. Kawakami: "An Expert System for Fault Section Estimation using Information from Protective Relays and Circuit Breakers", IEEE Transactions on Power Delivery, Vol. PWRD-1, No. 4, October 1986, pp. 83-90.

[3] T. Kimura, S. Nishimatsu, Y. Ueki, and Y. Fukuyama: "Development of an Expert System for Estimating Fault Section in Control Center based on Protective System Simulation", IEEE Transactions on Power Delivery, Vol. 7, No. 1, January 1992, pp. 167-172.

[4] K.S. Swarup and H.S. Chandrasekharaiah: "Fault Detection and Diagnosis of Power Systems using Artificial Neural Networks", First International Forum on Applications of Neural Networks to Power Systems, Seattle, July 1991, pp. 102-106.

[5] Y.-H. Pao: *Adaptive Pattern Recognition and Neural Network*, Addison Wesley, 1989.

[6] A.P. Alves da Silva, V.H. Quintana, and G..K.H. Pang: "Associative Memory Modelsfor Data Processing", International Journal of Electrical Power & Energy Systems, Vol. 14, No. 1, February 1992, pp. 23-32.

[7] A.P. Alves da Silva, V.H. Quintana, and G.K.H. Pang: "A Probabilistic Associative Memory and Its Application to Signal Processing in Electrical Power Systems", Engineering Applications of Artificial Intelligence Journal, Vol. 5, No. 4, 1992, pp. 309-318.

[8] T. Kohonen: *Self-Organization and Associative Memory*, Springer-Verlag, 1989.

[9] J.J. Hopfield: "Neurons with Graded Response have Collective Computational Properties like those of Two-State Neurons", Proceedings of the National Academy of Sciences (USA), Vol. 81, May 1984, pp. 3088-3092.

[10] B.Kosko: "Bidirectional Associative Memories", IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-18, No. 1, January/February 1988, pp.49-60.

[11] A. Atiya and Y. Abu-Mostafa: "A Method for the Associative Storage of Analog Vectors", in *Advances in Neural Information Processing Systems 2*, D.S. Touretzky (Ed.), Morgan Kaufmann, 1990, pp. 590-595.

[12] J. Hertz, A. Krogh, and R.G. Palmer: *Introduction to the Theory of Neural Computation*, Addison-Wesley, 1991.

[13] R. de Lepeleire, S.M. Francsak, F.M. Vargas, R.D. Siqueira, W.L. Pagliuca, e G. Lambert Torres: "Study of the Use of an Expert System for Post-Fault Disturbance Analysis in Substations", V ERLAC - CIGRÉ Latin-American Meeting, Cidade del Este, Paraguay, May 1993 (in Portuguese).