Agustin Flores
Eduardo Quiles
Emilio García
Francisco Morant

J. Electrical Systems x-x (2010): x-xx

Regular paper

Novel Formulation using Artificial Neural Networks for Fault Diagnosis in Electric Power Systems – A Modular Approach

This work proposes a new method for fault diagnosis in electric power transportation systems based on neural modules. With this method, the diagnosis is performed by assigning a generic neural module for each type of element conforming a transportation system, whether it be a transportation line, bar or transformer. A total of three generic neural modules are designed, one for each type of element. These neural modules are placed in repeating groups in accordance with the element to be diagnosed, taking into consideration its circuit breakers and relays, both internal and backup. For the diagnosis of a transportation line, this method is further reinforced by taking into consideration the corresponding waveforms of fault voltages and currents as well as the frequency spectrums of these waveforms, through a neural structure, in order to verify if the line had in fact been subjected to a fault, and at the same time to determine which type of fault (LT, LLT, LL, LLL, LLLT). The most important and innovative aspect of this method is that only three neural modules will be used, one for each type of element, and these can be employed for a diagnosis as one function, the instant any change of status is detected in the internal and/or backup relays relating to the element subjected to diagnosis.

Keywords: Modular Neural Network, Fault Diagnosis, waveforms of fault voltages and currents, frequency spectrums of fault voltages and currents.

1. Introduction

At present, Control Center Operators for Generation and Transportation of Electric Power are increasingly overwhelmed by the huge amount of information that must be analyzed at any given moment in order to maintain the system in optimal operating conditions. Each time an event occurs in the system, based on the SCADA system alarms and the faulty elements, the operator must try to carry out a diagnosis as close as possible to the current status of the system in order to restore it without delay. A diagnosis in these conditions can become very complicated depending on the number of failed elements and protective devices in operation.

The aim of this work is to present a methodology for the implementation of a fault diagnostic system through the application of Artificial Neural Networks with a modular approach in Electric Power Transportation Systems, which will be used as an auxiliary tool in decision-making by operators in the Control Areas where a rapid and accurate diagnosis can facilitate a speedier reconnection of a collapsed power system.

Over the last few decades, a number of investigations have been developed dealing with fault diagnosis in electric power systems with different neural structures, such as Bayesian networks [1], Radial Base Function networks (RBF) [2][3][4], Backpropagation networks [10], SOM networks [17], all of which have given good results but with certain limitations. One of these limitations is the monolithic-type closed structure of these networks which,

Corresponding author: Agustin Flores. Área of Peninsular Control, CFE. Department of Electrical and Electronics Engineering, Technological Institute, Mérida México, agustin.flores@cfe.gob.mx
Eduardo Quiles, Emilio García, Francisco Morant . Department of Systems and Automatic Engineering , Thechnical University, Valencia Spain, equiles@isa.upv.es, egarciam@isa.upv.es

when applied to real power systems with greater dimensions, become more complicated to implement.
The diagnostic method proposed here comprises three levels of verification: the first two are connected in a series, in such a way that the first diagnostic level verifies if the fault was in the element under analysis through the correct operation of the internal and/or backup circuit breakers associated with the element. The second diagnostic level verifies if the fault was in the element under analysis through the correct operation of the internal and/or backup protection systems of the element. With the results of the two diagnostic levels previously established, a final validation is carried out, and only if the two diagnostic levels of verification prove to be true, will the fault be assigned to the element under analysis, otherwise the fault will not correspond to this element. The final validation for failed transportation lines by means of the two previous diagnostic levels, is reinforced by a third verification level, which processes the fault voltage and current waveforms the corresponding line, as well as the frequency spectrums of these waveforms, through a neural structure, in order to verify if the line was in fact subjected to a fault and at the same time to determine the type of fault (LT, LLT, LL, LLL, LLLT). This process can be carried out since every transportation line subjected to a fault will present fault currents and voltages before it is isolated from the system by the respective protection systems. A more reliable and accurate fault diagnosis system can be obtained therefore, if the results of the final validation obtained from the combination of discreet signals from breakers and protection devices is reinforced by processing the continuous signals from fault voltage and current waveforms, and the frequency spectrums of such signals, corresponding to each of the transportation lines. One important advantage of the proposed diagnostic system is that its implementation can be applied to one element alone, a specific area, or to the whole context of the power system.

2. Description of the Diagnostic Method

In order to provide a clear explanation of the proposed methodology, an example will be given using the Merida sub-station (MDA-115 Kv) at breaker and a half, belonging to the Merida zone of the Peninsular Area within the Mexican Power System, which interconnects with the MTO sub-station through line L, as shown in Fig. 1.1. The method will be applied exclusively to the transportation line L.

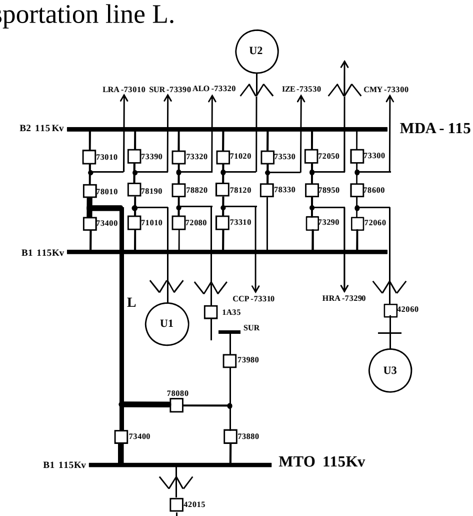

Figure 1.1 Interconnection topology of L

The transportation line (L) referred to is the LT MDA -73400- MTO, which connects at each end with substations at breaker and a half. The primary components (circuit breakers) through which line L is connected to both substations, MDA-115 and MTO-115, in accordance with figure 1.1 are: MDA INT-73400, MDA INT-78010, MTO INT-73400, MTO INT-78080.

Each element of a power network is characterized by a group of protections systems which guard it against short-circuit faults.

In the case of transportation line (L) belonging to the substation MDA-115, the primary protection system is represented by a distance relay 21 for faults between phases, and a distance relay 21N for faults from phase to earth. This type of protection is typical for radial or long lines, therefore, in the case of grid or short lines, the primary protection system may be characterized by a differential relay 87L.

The secondary protection system is implemented by a directional over-current relay 67 for faults between phases and a directional over-current relay 67N for faults from phase to earth.

The secondary backup or additional protection system for this case comprises an instantaneous over-current relay 50FI, and is directly related to each breaker.

Based on the premise that ***each activation of a relay corresponds to an opening of a circuit breaker,*** if a fault should occur in line L, knowledge that must be learned by the neural module will be implemented in two levels:

a) Fault detection in line L by the correct opening of circuit breakers
b) Fault detection in line L by the correct activation of the protection systems.

- **By Circuit Beakers**

a) If the fault is in fact located in L, the primary breakers at both ends INT’s MDA-73400, 78010, INT’s MTO-73400, 78080 should open.
b) If the INT MDA-73400 fails, the secondary backup breakers that should open in order to avoid the propagation of the fault are in this case, MDA-71010, 72080, 73310, 78330, 73290, 72060.
c) If the INT MDA-78010 fails, the secondary backup breakers that should open in order to avoid the propagation of the fault are in this case, INT MDA-73010, INT LRA-73010.
d) If the INT MTO-73400 fails, the secondary backup breakers that should open in order to avoid the propagation of the fault are in this case, MTO-73980, 42015.
e) If the INT MTO-78080 fails, the secondary backup breakers that should open in order to avoid the propagation of the fault are in this case, MTO-73980, SUR-73980.

- **By relays**

a) If the fault is in fact located in L, at least one relay of both ends of the line should activate (in this case there are 3 protection systems at each end).

2.1 Breaker and Protection System Readings for the Neural Module of L

In order to achieve a more adequate management of the information regarding the status of breakers and protection relays corresponding to the element under analysis, Table 1.1 shows the database which will be applied to the data readings from SCADA relating to L.

LT MDA -73400- MTO

Inputs	1	2	3	4	5	6	7	8	9	10	11	
Int_PyR	INT MDA-73400	INT MDA-78010	INT MDA-72060	INT MDA-71010	INT MDA-73290	INT MDA-78330	INT MDA-73310	INT MDA-72080	INT MDA-73010	INT LRA-73010	*	Local End
States	1	1	1	1	1	1	1	1	1	1	2	
			INT MDA-73400					INT MDA-78010				
Relays	21	21N	67	67N	50FI	21	21N	67	67N	50FI		
States	0	0	0	0	0	0	0	0	0	0		
Inputs	1	2	3	4	5	6	7	8	9	10	11	
Int_PyR	INT MTO-78080	INT MTO-73400	INT MTO-73980	INT SUR-73980	*	*	*	*	INT MTO-73980	INT MTO-42015	*	Remote End
States	1	1	1	1	2	2	2	2	1	1	2	
			INT MTO-78080					INT MTO-73400				
Relays	21	21N	67	67N	50FI	21	21N	67	67N	50FI		
States	0	0	0	0	0	0	0	0	0	0		

Table 1.1 Database for the Transportation Line MDA -73400- MTO

2.2 Implementation of the Knowledge Base with which the Neural Module will be trained

The implementation of the knowledge base for the diagnostic neural module will be implemented in two levels:

a) **By Circuit breakers:** where the correct opening of the primary and secondary backup breakers will permit the location of a fault in the line.
b) **By Protection Systems:** where the correct activation of the protection systems will permit the location of a fault in the line.

a) By Circuit breakers

Using the Database corresponding to line MDA -73400- MTO we can obtain the following states for the primary breakers at one end of the element (Local End), Table 1.2.

BREAKERS (S.E Breaker and a Half)											
1	2	3	4	5	6	7	8	9	10	11	
INT MDA-73400	INT MDA-78010	INT MDA-72060	INT MDA-71010	INT MDA-73290	INT MDA-78330	INT MDA-73310	INT MDA-72080	INT MDA-73010	INT LRA-73010	*	YInt_e
0	0	1	1	1	1	1	1	1	1	1	1
0	1	1	1	1	1	1	1	0	0	0	1
1	0	0	0	0	0	0	0	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	0
1	0	1	1	1	1	1	1	1	1	1	0
0	1	1	1	1	1	1	1	1	1	1	0

Table 1.2 Logical states of the Primary breakers at one end of L (Local End)

Based on the previous patterns and the different combinations that contemplate a fault in the secondary backup breakers, 250 training patterns are generated with which a Perceptron Neural Network will be trained, having the previously mentioned patterns as input and the activation indicating that the fault was in fact in the line being diagnosed as the output, taking into consideration only the opening of breakers at one end (Local End). The structure of this neural network is shown in Figure 1.2. It is important to mention that this diagnosis is located only at one end of the line (Local End), therefore, another similar neural network with the same patterns and the same output must be located at the other end of the line (Remote End), since the line is connected at both ends to substations with breaker and a half.

The combination of results from the neural networks at both ends (Local and Remote Ends) will provide the final diagnosis on the element, in this case line L. This combination will be based on the logic rules shown in Table 1.3. The neural network is shown in Figure 1.3.

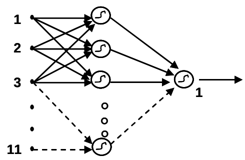

Figure1.2 Neural Structure Local End of the line

YInte	YIntr	F_LT_Int
1	1	**1**
1	0	**1**
0	1	**1**
0	0	**0**

Table 1.3 Final Diagnostic Logic for the line by Breakers

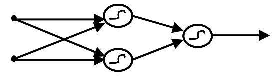

Figure 1.3 Final Diagnostic Neural Network for a fault in the line by break

Table 1.3 indicates that a fault will exist in line L, determined by the breaker statuses, only if there is activation at one or both ends of the line. The complete modular structure can be seen in Figure 1.4.

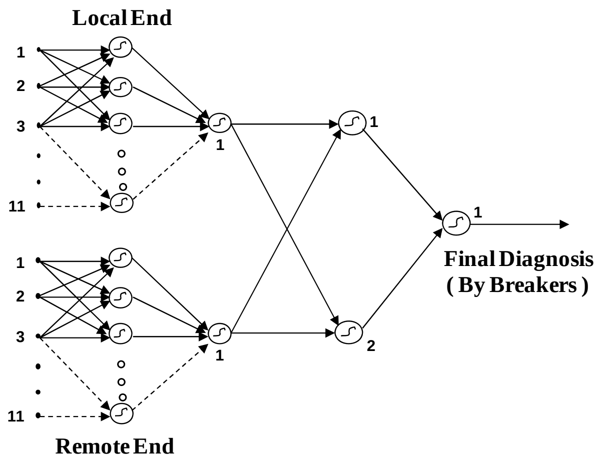

Figure 1.4 Modular Network for Fault Diagnosis by breakers in Line L

b) By Protection Systems

With the neural module described above, the existence of a fault in line L is determined exclusively by opening the primary and secondary backup breakers which are directly related to line L. In some cases, the breaker status alone may not provide enough information to determine if the fault is in fact in the line, therefore, this diagnosis must be reinforced through the validation of the protection systems directly relating to line L. In this case there are three protection systems for each primary breaker associated with the line, and keeping in mind always that; if the fault is in fact in L, at least one relay at both ends of the line should activate.

The logic for determining the activation of the protection systems for each primary breaker is shown in Table 1.4. This logic table will be implemented by a perceptron neural network, with the activations of each protection system pertaining to each breaker as input. The structure of this network is shown in Fig. 1.5.

Local End					
21	21N	67	67N	50FI	Yrel_e
1	1	1	1	1	1
1	1	1	1	0	1
1	1	1	0	1	1
1	1	1	0	0	1
1	1	0	1	1	1
1	1	0	1	0	1
1	1	0	0	1	1
1	1	0	0	0	1
1	0	1	1	1	1
1	0	1	1	0	1
1	0	1	0	1	1
1	0	1	0	0	1
1	0	0	1	1	1
1	0	0	1	0	1
1	0	0	0	1	1
1	0	0	0	0	1
0	1	1	1	1	1
0	1	1	1	0	1
0	1	1	0	1	1
0	1	1	0	0	1
0	1	0	1	1	1
0	1	0	1	0	1
0	1	0	0	1	1
0	1	0	0	0	1
0	0	1	1	1	1
0	0	1	1	0	1
0	0	1	0	1	1
0	0	1	0	0	1
0	0	0	1	1	1
0	0	0	1	0	1
0	0	0	0	1	0
0	0	0	0	0	0

Table 1.4 Logic states of the Protection Systems for each Primary Breaker

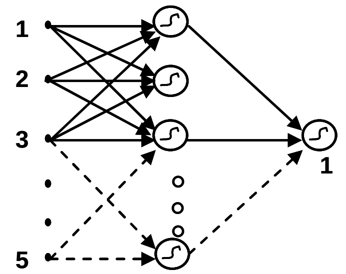

Figure 1.5 Neural Network for detecting the Activation of Relays in the Breaker

This neural network will be applied for each primary breaker at both ends of line L, and in this way, the combined results from these neural networks will provide the final diagnosis on the element, in this case line L. This combination will be carried out based on the following logic rules, shown in Table 1.5. Figure 1.6 presents the neural network in question, where the inputs will be the outputs from the neural networks assigned to each primary breaker at each end of line L, and the output will be the final diagnosis for line L, in relation to the logic state of the protection systems for each breaker.

YRele1	YRele2	YRelr1	YRelr2	F_LT_Rel
1	1	1	1	**1**
1	1	1	0	**1**
1	1	0	1	**1**
1	1	0	0	**0**
1	0	1	1	**1**
1	0	1	0	**1**
1	0	0	1	**1**
1	0	0	0	**0**
0	1	1	1	**1**
0	1	1	0	**1**
0	1	0	1	**1**
0	1	0	0	**0**
0	0	1	1	**0**
0	0	1	0	**0**
0	0	0	1	**0**
0	0	0	0	**0**

Table 1.5 Final Activation Logic of the Element by Relays

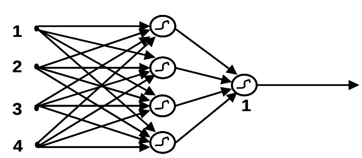

Figure 1.6 Neural Network for fault detection in the line by Relays

The entire neural structure for fault diagnosis, taking into consideration only the activation states of the protection systems for line L, is shown in Figure 1.7.
In order to carry out a validation of the fault, taking into account the diagnoses, by breakers and by protection systems, the logic rules shown in Table 1.6 will be taken.

We can see in Table 1.6 that, before a fault in the line can be validated, there must be confirmation of the validation by breakers and by protection systems; otherwise the possibility of a fault in line L must be dismissed. The neural network representing the logic states in Table 1.6 is shown in Figure 1.8.

Figure 1.9 presents the entire neural structure for fault diagnosis in line L, by breakers and by protection systems.

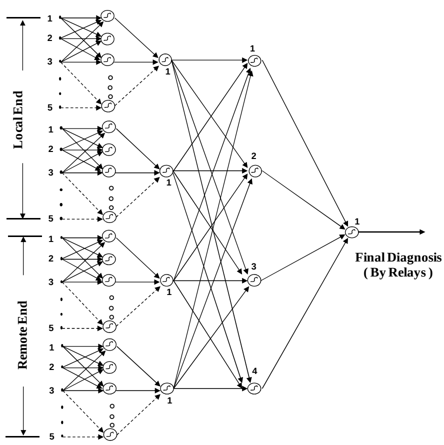

Figure 1.7 Modular Network for Fault Diagnosis by Protection Systems

F_LT_Int	F_LT_Rel	F_LT_Final
1	1	**1**
1	0	0
0	1	0
0	0	0

Table 1.6 Logic states for total fault diagnosis in the Line

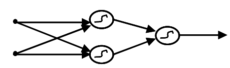

Figure 1.8 Final fault diagnosis in the line by Breakers and Protection Systems

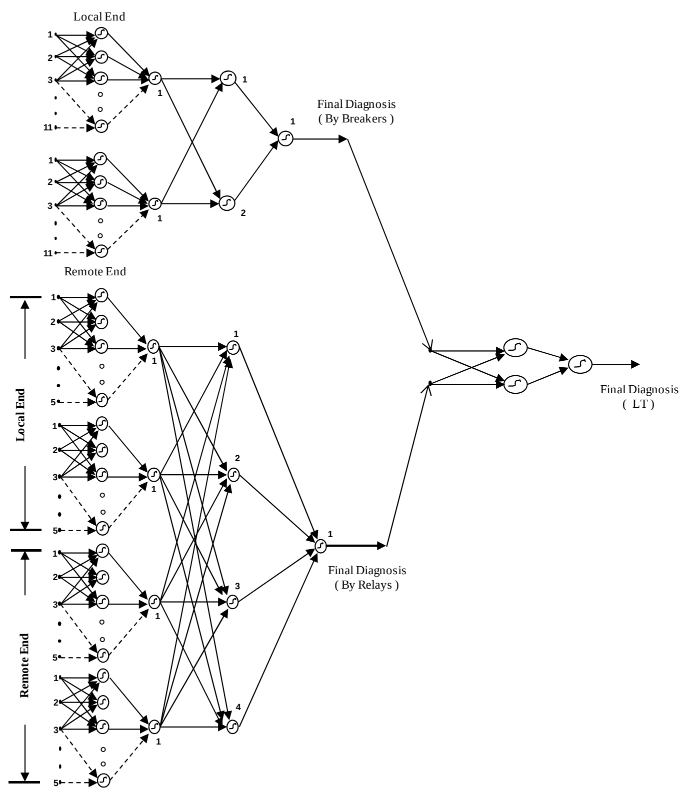

Figure 1.9 Total neural structure for Fault Diagnosis in Lines by Breakers and Protection Systems

It is important to mention that the same implementation procedure is used for bars and transformers.

2.3 Example of a test with real-time historic information

Simple fault

On March 4th 2008, a fault occurred in the transportation line NCM -73870- KNP at 4:01:46 Hrs. Information from SCADA which is grouped in the database corresponding to the failed element is shown in Table 1.7. The report generated for this event is shown below. The results obtained from the application of the diagnostic system, using in this case data taken from the historic database, are presented in Figure 1.10.

LT KNP -73870- NCM II

Inputs	1	2	3	4	5	6	7	8	9	10	11	Local End
Int_PyR	INT KNP-73870	INT KNP-73560	INT KNP-72020	INT KNP-77000	*	*	*	*	*	*	*	
States	0	1	1	1	2	2	2	2	2	2	2	
			INT KNP-73870					*				
Relays	PR-PRIM1	PR-PRIM2	67	67N	50FI	21	21N	67	67N	50FI		
States	1	0	0	0	0	2	2	2	2	2		
Inputs	1	2	3	4	5	6	7	8	9	10	Remote End	
Int_PyR	INT NCM-73870	INT NCM-72060	INT NCM-72090	INT NCM-73370	INT NCM-73360	INT NCM-77000	INT NCM-71010	INT NCM-71030	*	*		
States	0	1	1	1	1	1	1	1	2	2		
			INT NCMII-73870					*				
Relays	PR-PRIM1	PR-PRIM2	67	67N	50FI	21	21N	67	67N	50FI		
States	1	0	0	0	0	2	2	2	2	2		

Table 1.7 Database corresponding to the LT KNP -73870- NCM II

04/MAR/2008 04:01:45 08 NCM IN-73870 KNP Cambio No Comandado Abiert
04/MAR/2008 04:01:45 08 NCM PR-PRIM1 73870 KNP Cambio No Comandado Operad
04/MAR/2008 04:01:45 08 NCM IN/73870 KNP Cambio No Comandado Abiert
04/MAR/2008 04:01:45 08 NCM PR/PRIM1 73870 KNP Cambio No Comandado FALLAD
04/MAR/2008 04:01:46 08 CCP B -01 230 KV Límite alto 4 violado. Valor= 240.83KV
04/MAR/2008 04:01:46 08 CCP B -01 230 KV Límite de emergencia alto. Valor= 240.83KV
04/MAR/2008 04:01:46 08 KNP PR-85L 73870 NCM Cambio No Comandado Operad
04/MAR/2008 04:01:46 08 KNP IN-73870 NCM Cambio No Comandado Abiert
04/MAR/2008 04:01:46 08 KNP PR-85L 73870 NCM Cambio No Comandado Normal RTN
04/MAR/2008 04:01:46 08 CCP B -02 230 KV Límite alto 1 violado. Valor= 240.60KV
04/MAR/2008 04:01:46 08 NTE B -01 230 KV Límite alto 4 violado. Valor= 238.04KV
04/MAR/2008 04:01:46 08 TIC AL-27 44070 RE 07 Cambio No Comandado Operad
04/MAR/2008 04:01:47 08 TIC AL-27 44070 RE 07 Cambio No Comandado Normal RTN
04/MAR/2008 04:01:47 08 NCM PR-PRIM1 73870 KNP Cambio No Comandado Normal RTN
04/MAR/2008 04:01:47 08 NCM AL-73870 RX DTD Cambio No Comandado BLOQ
04/MAR/2008 04:01:48 08 CCP B -01 230 KV Límite de emergencia alto. Valor= 238.94KV RTN
04/MAR/2008 04:01:48 08 CCP B -01 230 KV Límite alto 4 violado. Valor= 238.94KV RTN
04/MAR/2008 04:01:48 08 NCM PR/PRIM1 73870 KNP Cambio No Comandado NORMAL RTN
04/MAR/2008 04:01:48 08 NTE B -01 230 KV Límite alto 4 violado. Valor= 236.43KV RTN
04/MAR/2008 04:01:48 08 NCM AL-73870 RX DTD Cambio No Comandado NORMAL RTN
04/MAR/2008 04:01:49 08 MTO AL-TI FVCA CDBC Cambio No Comandado FALLAD
04/MAR/2008 04:01:49 08 CCP B -02 230 KV Límite alto 1 violado. Valor= 238.29KV RTN
04/MAR/2008 04:01:49 08 MTO AL-TI FVCA CDBC Cambio No Comandado NORMAL RTN
04/MAR/2008 04:01:50 08 NCM AL-SUBES FVCA TSP Cambio No Comandado FUERA
04/MAR/2008 04:01:50 08 NCM AL-SUBES FVCA TSP Cambio No Comandado DENTRO RTN
04/MAR/2008 04:01:50 08 MDN B -01 115 KV Límite bajo 4 violado. Valor= 111.33KV
04/MAR/2008 04:01:50 08 MDN B -01 115 KV Límite de emergencia bajo. Valor= 111.33KV
04/MAR/2008 04:01:51 08 MDN B /01 115 KV Límite bajo 4 violado. Valor= 111.33KV
04/MAR/2008 04:01:52 08 CNR B -01 115 KV Límite de emergencia bajo. Valor= 113.75KV RTN
TUE 4 MAR '08 04:01:53
COLA DE BITACORA DE EVENTOS 1

Figure 1.10 Diagnosis provided by the Simulator on the event occurring in the LT KNP -73870- NCN II

3. Fault detection in Transportation Lines through Fault Current and Voltage Waveforms

In order to obtain a more accurate and reliable fault diagnosis system, the diagnosis obtained from the final validation is reinforced with the two previously established diagnostic levels, for failed transportation lines, by means of a third verification level which processes the fault voltage and current waveforms in the corresponding line, as well as the frequency spectrums of these waveforms, through a neural structure, to verify if the line was in fact subjected to a fault and at the same time to determine what type (LT, LLT, LL, LLL, LLLT). This process is possible, since each transportation line subjected to a fault will present fault currents and voltages before the fault is isolated from the system by its respective protection systems.

3.1 Transportation line model for obtaining fault types

The database representing the training patterns for the proposed neural structure pertaining to the third diagnostic level will comprise the characterization of each one of the dynamics involved in the different fault types that may occur in a transportation line (LT, LLT, LL, LLL, LLLT). These dynamics are obtained from simulations carried out in the PowerSys Blockset of MatLab with the characteristic parameters of the previously mentioned transportation line, corresponding to a 13 Km TL at an operative nominal voltage of 115 Kv.

Each of the fault types will be characterized by their transitory response waveforms corresponding to each phase. The database will take the voltage and current waveforms as training patterns from each fault type occurring at the local end of the line, at the middle and at the remote end. In order to explain the procedure, the voltage and current waveforms at the local end of the transportation line (at 3 Km) will be simulated for a fault in phase A to earth, the objectives being to observe the corresponding graphs and to be able to represent them in a database for training the neural structure which will classify the type of fault present in the line, and also to determine if the line had in fact experienced a fault.

3.2 Calculation Methodology

In order to simulate fault voltage and current waveforms for each fault type in the line model represented in the PowerSys MatLab's Blockset, a frequency of the signal 28.8 KHz [21], [22] will be used. This signal frequency guarantees a good simulation for the analogical current and voltage signals that take place in the event registers located at the ends of the transportation lines.

Reproduction of the signals for simulation, at a frequency of 28.8 KL and with a simulation time of 0.1 seconds, corresponds to an integration time of 34.722 µsec, and to 2880 points for each of the simulated signals.

The simulation time will be 0.1 seconds, since this time corresponds to 6 cycles of the current or voltage signal, where the first two cycles correspond to the dynamics of the signal previous to the fault, the following three cycles correspond to the dynamics of the fault, and the last cycle corresponds to the dynamics once the fault is liberated. The classification of the signal by sectors can be seen in Figure 1.11, corresponding to the dynamics of the current signal for a fault from phase A to earth.

Fault Current Dynamics from phase A to earth.

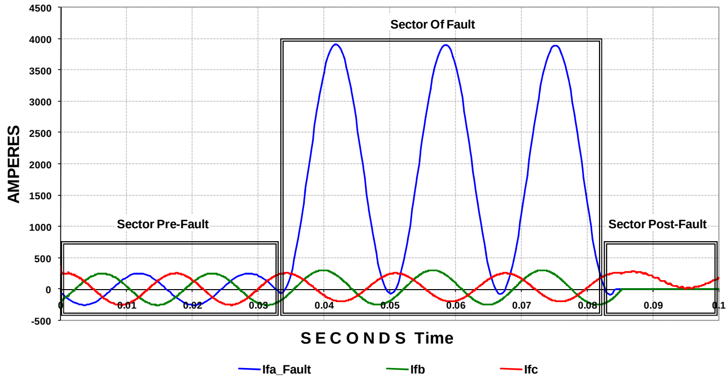

Figure 1.11 Classification of Fault Current Dynamics by Sectors

3.3 Filtering and Sampling Process

It has been demonstrated that with the use of a frequency of 28.8 KHz for the fault current and voltage signals, it is possible to reproduce, through simulations, the different fault types that can occur in a transportation line. In order to condition the analogical voltage and current signals, a second order low-pass filter is included in the model represented in the PowerSys MatLab’s Blockset to eliminate high frequencies, and in this way to avoid the problem of aliasing during the sampling process [24]. To obtain sample signals of fault voltage and current which represent the original fault voltage and current signals accurately, a decimation to the order of 120 is carried out, in other words, one sample point will be taken each 120 points of each cycle, giving 4 points (samples) for each cycle of the voltage and current signals, thus the dynamics of fault voltage and current signals are characterized by 6 cycles, giving a total of 24 samples which will reproduce the original signals accurately [24].

3.4 Training database structure

The way in which the data used in the elaboration of the training patterns for the neural structure are classified, is illustrated below. The input patterns will be obtained from the simulations corresponding to the fault type.
The database is represented as follows: For a fault from phase A to earth, the information pertaining to currents and voltages from the different phases is shown in Figures 1.12 and 1.13, and in this particular case, at 3 kilometers from the local end bar of the previously mentioned transportation line.

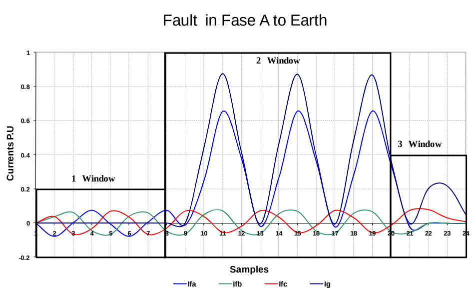

Figure 1.12 Fault Currents in the different Phases and Neutral

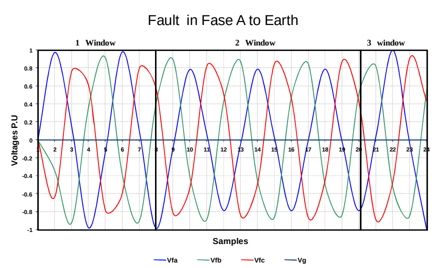

Figure 1.13 Fault Voltages in the different Phases and Neutral

The values of each voltage and current signal sample are classified as shown in Table 1.8. The first eight columns represent the voltage and current values of each phase, where, in this case in particular, the values correspond to a fault in phase A to earth, and at 3 kilometers from the local end node of the transportation line. The last four columns represent the type of fault referred to above, in binary form.

									OUTPUT			
	Vfa	Ifa	Vfb	Ifb	Vfc	Ifc	Vg	Ig	Ffa	Ffb	Ffc	Ft
Fa_n	-0.000641908	-3.89106E-05	-0.001196387	-0.000115793	0.001838295	0.000154704	-2.99652E-17	4.00104E-17	0	0	0	0
	0.973500712	-0.076403231	-0.341666582	0.038534072	-0.63183413	0.037869159	-5.32196E-14	-1.98263E-14	0	0	0	0
	0.156566311	0.002872043	-0.922627157	0.062640411	0.766060845	-0.065512454	-2.41759E-15	-3.23525E-14	0	0	0	0
	-0.977512088	0.075485482	0.364054269	-0.043151615	0.613457819	-0.032333866	5.32906E-14	2.06067E-14	0	0	0	0
	-0.130876155	-0.00568791	0.913496633	-0.06454914	-0.782620478	0.07023705	1.00613E-15	3.18474E-14	0	0	0	0
	0.980883709	-0.076176568	-0.388121211	0.04180751	-0.592762498	0.034369058	-5.33092E-14	-2.14547E-14	0	0	0	0
	0.105208914	0.006837681	-0.903372184	0.060413037	0.798163271	-0.067250718	3.89477E-16	-3.12883E-14	0	0	0	0
	-0.983615105	0.075157806	0.411821	-0.046420056	0.571794105	-0.02873775	5.3296E-14	2.22791E-14	0	0	0	0
	-0.084428121	-0.009384517	0.8933021	-0.062235359	-0.812343335	0.071862616	-5.63733E-16	0.000560452	1	0	0	1
	0.785338106	0.252445204	-0.412101195	0.052060412	-0.527445441	0.037764918	-1.96769E-15	0.446483296	1	0	0	1
	0.061426056	0.653656118	-0.881909575	0.0718723	0.826727144	-0.054967353	3.81939E-15	0.874263066	1	0	0	1
	-0.786536083	0.376808956	0.434929598	-0.043067483	0.505593599	-0.018576869	4.41506E-15	0.411179379	1	0	0	1
	-0.040861463	-0.01785839	0.870712965	-0.059906312	-0.839768851	0.073163383	-1.38021E-15	-0.005481148	1	0	0	1
	0.787895309	0.26860398	-0.457829728	0.055467059	-0.483751951	0.034358295	-1.83306E-15	0.467503931	1	0	0	1
	0.02042229	0.655089309	-0.858742147	0.069252068	0.852422573	-0.056409937	3.97365E-15	0.87082301	1	0	0	1
	-0.788250148	0.357809874	0.480280097	-0.046489329	0.461442524	-0.015245042	4.27146E-15	0.386294464	1	0	0	1
	0.000417809	-0.021588699	0.846125226	-0.057278473	-0.864545281	0.074407237	-1.5466E-15	-0.00532429	1	0	0	1
	0.788384361	0.284914777	-0.502392656	0.058730449	-0.438803196	0.030875186	-1.69366E-15	0.488462146	1	0	0	1
	-0.020807539	0.65560237	-0.83305111	0.066460405	0.875958271	-0.057670046	4.12372E-15	0.866187124	1	0	0	1
	-0.787684823	0.338706734	0.524195355	-0.049770838	0.415902088	-0.011849112	4.11727E-15	0.361540869	1	0	0	1
	0.041626187	-0.024385659	0.819290543	-0.054480727	-0.886883623	0.075469907	-1.70391E-15	-0.003961415	0	0	0	0
	0.99835352	-2.45489E-05	-0.532056568	8.18855E-06	-0.460298573	0.078953834	-6.64625E-16	0.203294914	0	0	0	0
	-0.052759969	-3.43371E-07	-0.842990684	-1.9136E-05	0.911537409	0.030209745	3.4266E-15	0.216551411	0	0	0	0
	-0.997024536	-1.97775E-05	0.554676551	8.12295E-06	0.436288758	0.008014495	1.34953E-15	0.0483473	0	0	0	0

Table 1.8 Training Database Structure

The data structures for faults in phase A to earth are placed in descending order, at the middle of the line (6.5 Km), and at the remote end. A total of 72 training patterns are obtained which characterize a fault from line to earth, in this case in phase A, at three different positions in the line: at the local end (3Km), at middle of the line (6.5Km), and at the remote end (3 Km). The management of three possible positions of the fault on line provides the neural structure with an optimal capacity of generalization, since with these three possible locations of the fault, the neural structure is able to classify adequately the type of fault the line has been subjected to. This entire clustered structure is repeated for each fault type, thus, 10 clusters of 72 patterns are obtained with a total of 720 training patters. The outputs of each structure, as with the first, represent in binary form, the fault type to which the cluster refers to.

3.5 Neural structure

The neural structure will comprise an input layer with 8 inputs, a hidden layer with 14 neurons and the output layer with 4 neurons. This was the structure that presented a greater capacity of generalization using the back-propagation algorithm, for the classification of patterns for which the neural structure was not trained. The neural structure can be seen in Fig. 1.14.

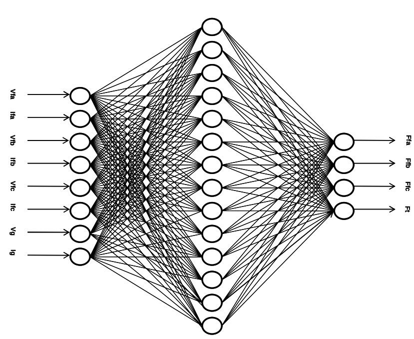

Figure 1.14 Classifying Neural Structure

3.6 Implementation of the proposed neural structure through the use of the FFT

In order to design the proposed neural structure, taking into consideration the frequency spectrums for each fault type for the third diagnostic level, samples of analogical voltage and current fault signals will be taken and the respective frequency spectrums for each one will be obtained by applying the FFT (Fast Fourier Transform).These frequency spectrums will be taken as input patterns in order to implement the knowledge base with which the neural structure will be trained.

3.7 Training Database Structure

The input patterns will be obtained from the frequency spectrums corresponding to the fault type. The database will be represented as follows: For a fault in phase A to earth, the information pertaining to the frequency spectrums corresponding to the fault is shown in Figure 1.15.

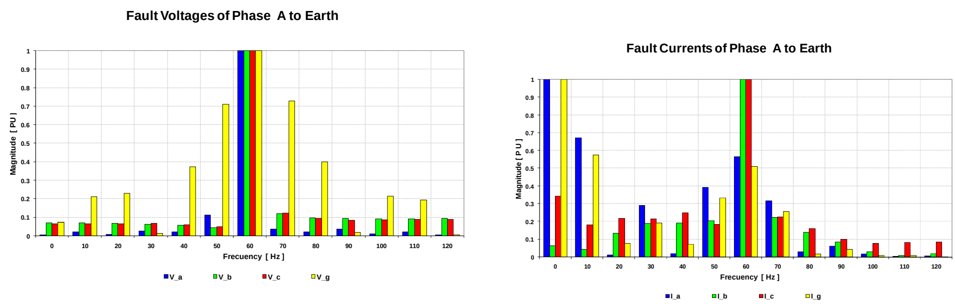

Figure 1.15 Frequency spectrums of fault Currents and Voltages. Phase A to earth

These spectrums represent the fault currents and voltages of phase A to earth, and at a distance of three kilometers from the local end bar of the transportation line mentioned above.

The values of each frequency spectrum sample from the fault current and voltage signals are classified as shown in Table 1.9. The first eight columns represent the frequency spectrum values of the fault voltage and current of each phase, in this case in particular, these values correspond to a fault in phase A to earth, and at a distance of three kilometers from the local end node in the transportation line. The last four columns represent the fault type referred to previously, in binary form.

	1	2	3	4	5	6	7	8	OUTPUT				
	Vfa	Ifa	Vfb	Ifb	Vfc	Ifc	Vg	Ig	Ffa	Ffb	Ffc	Ft	Frecuency
Fa_n	0.004605038	1	0.069542277	0.063107352	0.064673373	0.342182128	0.073259826	1	1	0	0	1	0
	0.020386201	0.672185004	0.070647701	0.041720784	0.064018901	0.180145743	0.210884802	0.57343144	1	0	0	1	10
	0.006834834	0.010788749	0.068941921	0.132129325	0.065735503	0.215406216	0.23030578	0.07606745	1	0	0	1	20
	0.027297671	0.290069577	0.062940584	0.188294074	0.06774174	0.214743007	0.012966676	0.191934521	1	0	0	1	30
	0.021189475	0.019199074	0.057696463	0.189617753	0.059659392	0.249206812	0.372151259	0.069859712	1	0	0	1	40
	0.112615895	0.390391659	0.043370754	0.204928413	0.049608892	0.183051838	0.710055137	0.332893109	1	0	0	1	50
Fault local End	1	0.564840942	1	1	1	1	1	0.510033295	1	0	0	1	60
	0.03614176	0.316556091	0.120175688	0.223208735	0.123449473	0.224260855	0.728391712	0.25588512	1	0	0	1	70
	0.021404483	0.029407374	0.097651898	0.139173491	0.093331105	0.159480022	0.400070482	0.016269979	1	0	0	1	80
	0.035348827	0.058877968	0.094455718	0.083029994	0.083881301	0.099234976	0.019220911	0.041634805	1	0	0	1	90
	0.009806449	0.015211322	0.091665774	0.02941833	0.086296543	0.076411632	0.214557387	0.008346485	1	0	0	1	100
	0.02035394	0.003453443	0.0923732	0.009093577	0.088649187	0.080884693	0.193210675	0.007231055	1	0	0	1	110
	0.005782392	0.004719622	0.094224469	0.01817884	0.088229176	0.084830098	0.00446349	9.09783E-05	1	0	0	1	120

Table 1.9 Training Database Structure

The frequency spectrums for the faults in phase A to earth are placed in descending order, at the middle of the line (6.5Km), and at the remote end (3 Km). A total of 39 training patterns are obtained which characterize a fault from line to earth, in this case in the phase A, at three different positions in the line: at the local end (3Km), at the middle of the line (6.5 Km), and at the remote end (3 Km). The management of three possible positions of the fault on line provides the neural structure with an optimal capacity of generalization, since with these three possible locations of the fault, the neural structure is able to classify adequately the type of fault the line has been subjected to.

This entire clustered structure is repeated for each fault type, resulting in 10 clusters with 39 patterns and a total of 390 training patterns.

The neural structure will comprise an input layer with 8inputs, a hidden layer with 14 neurons and the output layer with 4 neurons. This structure is also used in the case of analogical signals. In contrast with the previous case, this neural structure will be trained with the frequency spectrums of the analogical signals from fault voltages and currents as inputs.

4.Conclusion

The application of this new method facilitates the diagnosis at an element level, since three generic modules are available which can be called upon, depending on the function of the type of element to be diagnosed, thereby allowing the diagnosis to be carried out on each element, each zone, or on the whole power system. The method is further reinforced by taking into consideration, for the diagnosis of the corresponding transportation line, the fault voltage and current waveforms, as well as the frequency spectrums of these waveforms, by means of a neural structure, to verify if the line was in fact subjected to a fault and at the same time to determine the type of fault (LT, LLT, LL, LLL, LLLT). This can be done by calling upon each of the generic modules every time an element is found in the system (lines, transformers, bars).

It is also clear that this modular neural structure can be used as a tool by control center operators.

References

[1] Zhu Yongli, Huo Limin, Lu Jinling, Bayesian Networks-Based Approach for Power System Fault Diagnostic, IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 21 No. 2, April 2006.

[2] Nuno Malheiro, Zita Vale, Carlos Ramos, Albino Marques, Vieira Couto, On-line Fault Diagnosis with Incomplete Information in a Power Transmission Network, GECAD - Knowledge Engineering and Decision Support Group Instituto Superior de Engenharia do Porto. REN - Rede Eléctrica Nacional, S.A Portuguese Electricity Transmission.

[3] Michael Negnevitsky, Vsevolod Pavlovsky, Neural Networks Approach to Online Identification of Multiple Failures of Protection Systems, IEEE TRANSACTIIONS ON POWER DELIVERY, VOL. 20 No. 2, April 2005.

[4] Jiang Huilan, Guan Ying, Li Dongwei, Xu Jianquiang, Self – adaptive Clustering Algorithm Based RBF Neural Network and its Application in the fault Diagnosis of Power Systems, IEEE/PES Transmission and Distribution Conference & Exhibition: Asia and Pacific Dalian, China, 2005.

[5] Jing Sun, Shin-Yin Qin, Yong-Hua Song, Fault Diagnosis of Electric Power Systems Based on Fuzzy Petri Nets, IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 19, No. 4, November 2004.

[6] S.D.J. McArthur, E. M. Davidson, J. A. Hossack, J. R. McDonald, Automatic Power System Fault Diagnosis through Multi-Agent System Technology, Proceedingsof the 37th Hawaii International Conference on System Sciences- 2004.

[7] Raj Aggarwal and Yonghua Song. “Artificial Neural Networks in power Systems” Part 1 General Introduction to Neural Computing. Power Engineering Journal. June 1997.

[8] Raj Aggarwal and Yonghua Song. “Artificial Neural Networks in power Systems” Part 2 Types of Artificial Neural Networks. Power Engineering Journal. February 1998.

[9] Raj Aggarwal and Yonghua Song. “Artificial Neural Networks in power Systems” Part 3 examples of Applications in power Systems. Power Engineering Journal. December 1998.

[10] A. Sittithumwat and K. Tomsovic " Dynamic Security Margin Estimation with Preventive Control Using Artificial Neural Networks " School of Electrical Engineering and Computer Science, Washington State University. Electricity Supply Industry in Transittion: Issues and Prospect for Asia. 14-16 January 2004.
[11] Albrecht Schmidt and Zuhair Bandar. " A Modular Neural Network Architecture with Additional Generalization Abilities for Large Input Vectors ". The Intelligent Systems Group Department of Computing. The Manchester Metropolitan University.
[12] T.Yalcinoz, M.J Short and B.J. Cory " Security Dispatch Using The Hopfield Neural Network". IEE Proc. Gener. Transm. Distrib., Vol 146, No. 5, September 1999.
[13] Yann-Chang Huang, Abductive Reasoning Network Based Diagnosis Systemfor Fault Section Estimation in Power System, IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 17, No. 2, Abril 2002.
[14] Tianshu Bi, Yixin Ni, Felix F. Wu y Qixu Yang, Novel Distributed Fault Section Estimation System for Large Scale Power Networks, Power System and Communications infrastructures for the future, Beijing, Septiembre 2002.
[15] Yann-Chang Huang, A Novel Model for Fault Diagnosis in Electric Power Systems, Cheng Shiu Institute of Tecnology.
[16] El_Fergany, M. T. Yousef, y A. A. El_Alaily, Fault Diagnosis of Power System Using Binary Information of Breakers and relays Through DPNs.
[17] Jun-Fen Wu, Nian-Su Hu, Sheng Hu, y Yu Zhao, Application of som Neural Network in Fault Diagnosis of the Steam Turbine Regenerative System, Proceedings of the First International Conference on Machine Learning and Cybernetics, Beijing, 4-5 noviembre 2002.
[18] Juhwan Jung, Chen-Ching Liu, Mingguo Hong, Massimo Gallanti, y Giorgio Tornielli, Multiple Hypotheses and Their Credibility in On-Line Fault Diagnosis, IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 16, No. 2, April 2001.
[19] El_Fergany, M. T. Yousef, y A. A. El_Alaily, Fault Diagnosis in Power System –Substation Level– Through Hybird Artificial Neural networks and Expert System.
[20] Jia-Zhou He, Zhi-Hua Zhou, Zhi-Hong Zhao, y Shi-Fu Chen, A General Desing Technique for Fault Diagnosis Systems, Washington, DC, 2001, vol. 2, pp. 1307-1311.
[21] TAHAR BOUTHIBA, FAULT LOCATION IN EHV TRANSMISSION LINES USING ARTIFICIAL NEURAL NETWORKS, Int. J. Appl. Math. Comput. Sci., Vol. 14, No. 1, 2004.
[22] Ernesto Vazquez, Oscar L. Chacon, Hector J. Altuve, NEURAL NETWORK-BASED FAULT DETECTOR FOR TRANSMISSION LINE PROTECTION, ITESM, 1996.
[23] S. M. El Safty, H. A. Ashour, H.El Dessouki, and M. El Sawaf, On-line Fault Detection of Transmission Line Using Artificial Neural Network, POWERCON, 21-24 November 2004.
[24] M. Sanaye-Pasand, y H. Khorashadi-Zadeh, Transmission Line Fault Detection & Phase Selection using ANN, Iternational Conference on Power System Transients, IPST, 2003.