NEURAL NETWORKS APPLICATION TO FAULT DETECTION IN ELECTRICAL SUBSTATIONS

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Abstract: This paper proposes an application of neural networks to fault detection in electrical substations, particularly to the Parada Angélica Electrical Substation, part of the AMPLA Energy System provider in Rio de Janeiro, Brazil. For research purposes, that substation was modeled in a *bay oriented* fashion instead of component oriented. Moreover, the modeling process assumed a substation division in five sectors or set of bays comprising components and protection equipments. These five sectors are: 11 feed bays, 2 capacitor bank bays, 2 general/secundary bays, 2 line bays and 2 backward bays. Electrical power engineer experts mapped 291 faults into 134 alarms. The employed neural networks, also bay oriented, were trained using the Levenberg-Marquardt method, and the AMPLA experts validated training patterns, for each bay. The test patterns were directly obtained from the SCADA (Supervisory Control And Data Acquisition) digital system signal, suitably decoded were supplied by AMPLA engineers. The resulting maximum percentage error obtained by the fault detection neural networks was within 1.5 % which indicates the success of the used neural networks to the fault detection problem. It should be stressed that the human experts should be the only ones responsible for the decision task and for returning the substation safely into normal operation after a fault occurrence. The role of the neural networks fault detectors are to support the decision making task done by the experts.

1 INTRODUCTION

Electrical substations evolved rapidly in time not only in their conception but also in their protection equipment that are now fully electronic instead of electromechanical, in the digital substation *age*. The Standard IEC (International Electromechanical Commission) 61850 and the possibility of using high speed and reliable Ethernet LAN networks brought new developments to the area. Such developments include sharing information among several IEDs (Intelligent Electronic Devices) as well as the capability of providing these information to several Electrical Energy Companies users or industrial heavy consumers (Cascaes et alli., 2007) As a natural consequence, the current supervision, automation, and control systems are gradually being adapted to that new reality that is present in the Brazilian electrical sector. Nowadays, the main facility to aid the operator in the supervision system system comprised by multiple alarms having the purpose of making the operator aware of the problems that is afflicting the electrical sector (Chan, 1990). The operator must detect the fault based on the set of fired alarms and proceed to the corrective action towards a quick recover of the system and to normal operation conditions. So all the responsibility to return the system to normal operation lies on the shoulders of the operator which can suffer a lot of stress and pressure. Due to

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operator fatigue and inexperience, and an excessive number of simultaneous fired alarms, usually a significant number of wrong diagnostics occur which seriously affects security and efficiency in electrical systems (Kwang-Ho et alli., 1993).

Modern techniques (Biondi et alli., 2007) such as Neural Networks can help in the solution of the problem, leaving the operator focused on the corrective action in which his or her participation is very important. The investigated substation is part of the AMPLA system and is called **Parada Angélica** (PAR) which diagram is shown in Figure 1.

The susbstation comprises 19 BAY’s as indicated in Table 1 and shown in Figure 1.

Table 1: BAY's Distribution in the substation.

Type of BAY	Quantity
Feeder	11
Capacitor Bank	02
General/Secondary	02
Line	02
Backward	02
TOTAL	**19**

- **Feeder** BAY’s are the following: PAR 5, PAR 22, PAR 17, PAR 11, PAR 14, PAR 8, PAR 6, PAR 15, PAR 9, PAR 7, and PAR 10.
- **Capacitor Bank** BAY’s are: BCO 3 and BCO 4.
- **General/Secundary** BAY’s are: General T3 and General T4.
- **Line** BAY’s are: LI ALC/ADR # 3 and LI ALC/ADR # 1.
- **Backward** BAY’s are: all other BAY’s. diferindo apenas, relativamente às linhas LI #3 e LI #1.

The substation in study has two (138/13.8 KV) three-phase transformers (TRAFO), and a high and a low Bus (BUS), subdivided in two, connected by a link disconnector.

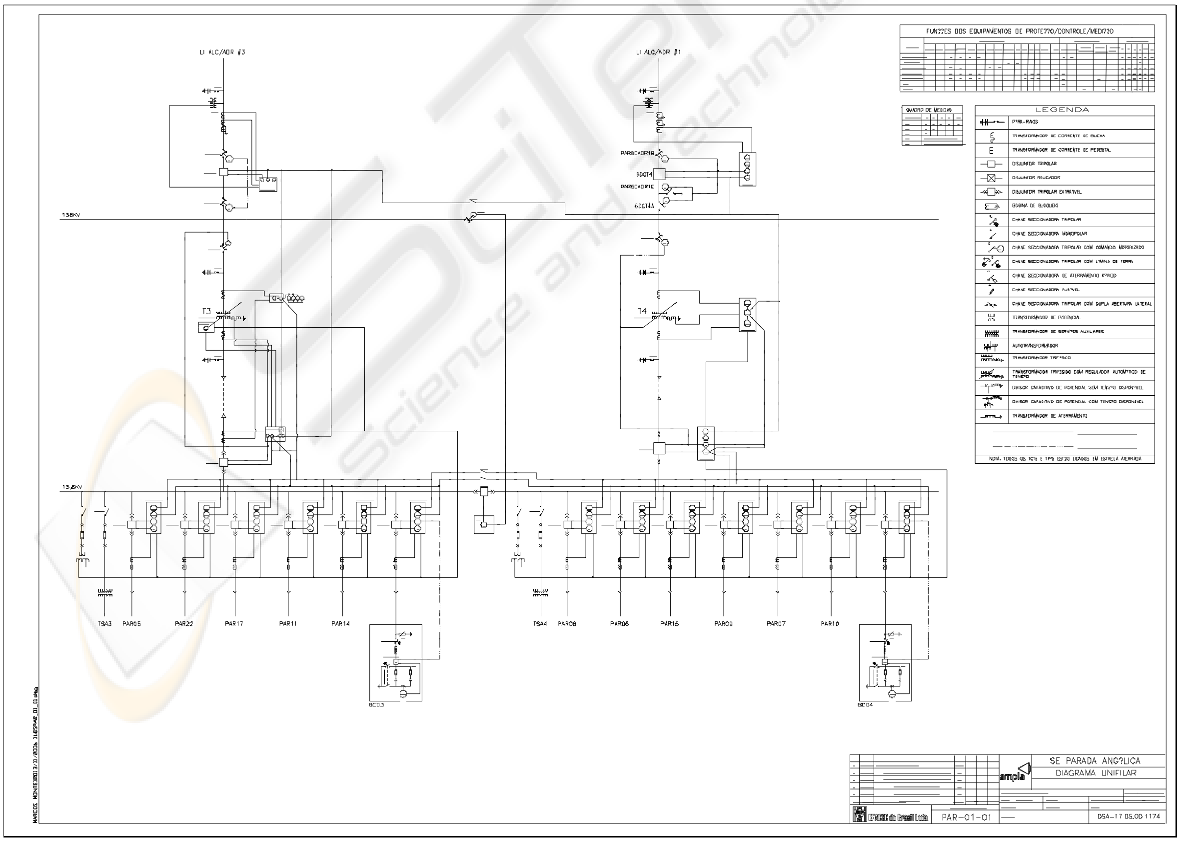

Figure 1: Parada Angélica Substation Diagram.

2 DATA PREPROCESSING

The AMPLA data base concerning the mapping of alarms into faults characterizes, in a reliable way, the Parada Angélica substation operation in respect of alarms processing. The dimension of the matrix which maps alarms into faults, for each bay, is shown in Table 2, for 291 faults.

Table 2: Mapping Dimension.

BAY	Alarms X Faults
Feeder	16 x 20
Capacitor Bank	19 x 20
General/Secondary	19 x 62
Line	13 x 32
Backward	67 x 157

Table 3 shows the mapping of alarms into faults, only for the line Bay. The mappings concerning the other neural networks were not shown here due to the oversize of such Tables. As seen in Table 3, each fault is defined by the set of fired alarms and that behavior is trained by 5 neural networks, one for each substation Bay.

Table 3: Line BAY Mapping.

	A01	A02	A03	A04	A05	A06	A07	A08	A09	A10	A11	A12	A13
F1	0	1	1	0	0	0	0	0	0	0	0	0	0
F2	1	1	1	0	0	0	0	1	0	0	0	0	0
F3	1	1	1	0	0	0	0	1	1	0	0	0	0
F4	1	1	1	0	0	0	0	1	0	1	0	0	0
F5	1	1	1	0	0	0	0	1	0	0	1	0	0
F6	1	1	1	0	0	0	0	1	0	0	0	1	0
F7	0	1	1	0	0	0	0	0	0	0	0	0	1
F8	1	1	1	0	0	0	0	1	0	0	0	0	1
F9	0	0	0	1	1	0	0	0	0	0	0	0	0
F10	1	0	0	1	1	0	0	1	0	0	0	0	0
F11	1	0	0	1	1	0	0	1	1	0	0	0	0
F12	1	0	0	1	1	0	0	1	0	1	0	0	0
F13	1	0	0	1	1	0	0	1	0	0	1	0	0
F14	1	0	0	1	1	0	0	1	0	0	0	1	0
F15	0	0	0	1	1	0	0	0	0	0	0	0	1
F16	1	0	0	1	1	0	0	1	0	0	0	0	1
F17	0	0	1	0	0	1	0	0	0	0	0	0	0
F18	1	0	1	0	0	1	0	1	0	0	0	0	0
F19	1	0	1	0	0	1	0	1	1	0	0	0	0
F20	1	0	1	0	0	1	0	1	0	1	0	0	0
F21	1	0	1	0	0	1	0	1	0	0	1	0	0
F22	1	0	1	0	0	1	0	1	0	0	0	1	0
F23	0	0	1	0	0	1	0	0	0	0	0	0	1
F24	1	0	1	0	0	1	0	1	0	0	0	0	1
F25	0	0	0	0	1	0	1	0	0	0	0	0	0
F26	1	0	0	0	1	0	1	1	0	0	0	0	0
F27	1	0	0	0	1	0	1	1	1	0	0	0	0
F28	1	0	0	0	1	0	1	1	0	1	0	0	0
F29	1	0	0	0	1	0	1	1	0	0	1	0	0
F30	1	0	0	0	1	0	1	1	0	0	0	1	0
F31	0	0	0	0	1	0	1	0	0	0	0	0	1
F32	1	0	0	0	1	0	1	1	0	0	0	0	1

The Levenberg-Marquardt backpropagation algorithm was used for the neural networks training.

3 MODELING, TRAINING AND RESULTS

The neural network for the feeder BAY had two hidden layers with 45 and 35 neurons and was trained with the 16 input alarms and had 20 output neurons. (16-45-35-20).

The training 16 x 20 matrix was validated by the correlation statistics technique in order to avoid the mapping of the same set of alarms into different faults. The neural network general model that is the basis for all neural networks used in this paper is shown in Figure 2 for the feeder BAY. The best neural network architecture was the (16-45-35-20) one, that is the neural network with 16 input neurons, 45 and 35 neurons in the hidden layers and 20 output neurons.

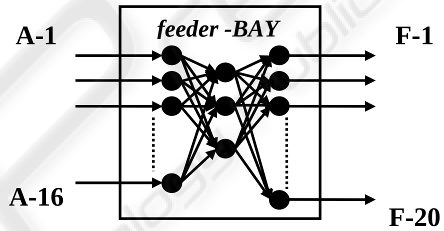

Figure 2: Neural Net Model - feeder BAY.

The cross-validation technique entitled to train, validate, and test all the neural networks during training. The training results for training and tests and, the percentage error curve are shown in Figure 3 and, Figure 4 respectively.

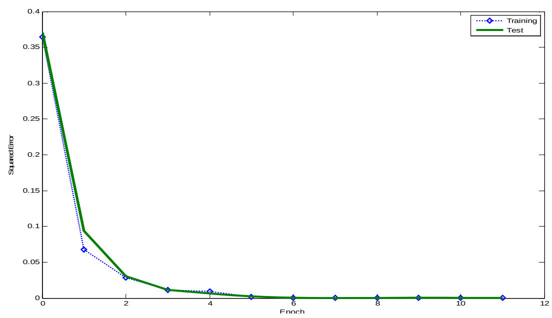

Figure 3: Test and Training - feeder BAY.

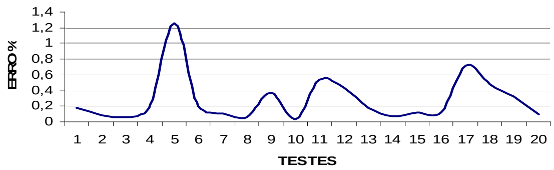

Figure 4: Error Percentage - feeder BAY.

The neural network for the Capacitor bank BAY was trained for 19 input alarms and had two hidden layers with 46 and 33 neurons, and an output layer with 20 neurons resulting in a (19-46-33-20) architecture. The neural network for the General/Secundary BAY was trained for 19 input alarms and had two hidden layers with 78 and 44 neurons, and an output layer with 62 neurons resulting in a (19-78-44-62) architecture. The neural network for the line BAY was trained for 13 input alarms and had two hidden layers with 65 and 46 neurons, and an output layer with 32 neurons resulting in a (13-65-46-32) architecture.

Finally, the neural network for the backward BAY was trained for 67 input alarms and had two hidden layers with 410 and 220 neurons, and an output layer with 157 neurons resulting in a (67-410-220-157) architecture. For all neural networks used, the activation functions were of the sigmoid type and the training algorithm was the Levenberg-Marquardt method. Over 5000 tests proposed by the AMPLA experts were carried out and validated the mapped faults in Parada Angélica substation and the results were within the quality standards required by the AMPLA energy provider group. Table 4 shows the maximum percentage error found for each BAY.

Table 4: Maximum Percentage Error.

BAY	Maximum Percentage Error
Feeder	1.2610 %
Capacitor Bank	0.6450 %
General/Secondary	0.4679 %
Line	0.8385 %
Backward	1.4493 %

4 CONCLUSIONS

The results indicate the success of BAY oriented application of fault detection in electrical substations. Table 4 shows that the highest percentage error found in all BAYs is less than 1.5%. According to AMPLA experts, the application produces faster and more reliable responses compared to traditional procedures of fault detection which are completely dependent on human beings empirical analysis. Due to the good results so far, the authors of this paper are pursuing an ongoing action for a man-machine interface to be imbedded in an expert system in order to explain each occurred fault and also in the concept modeling of a knowledge base for that project.

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