An Expert System for Substation Fault Detection in Thermoelectric Generation Plants

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Abstract— **This paper presents a methodology to develop a Fault Diagnosis Integrated System in a Thermoelectric Generation Plant (TGP). The proposed methodology is based on three methods: Discrete Fourier Transform (DFT), Fuzzy Logic and Artificial Neural Network (ANN). The test electric system was built in BPA's ATP/EMTP software, conformably to the needs presented by a Thermoelectric Generation Plant (TGP) of 711 MW - 230 kV, located in southern Brazil. Simulated test cases demonstrate the generalization capability of the protection system developed, now used in a Southern Brazilian Utility.**

Keywords - Faults Diagnosis; Thermoelectric Generation Plants; Alarm Processing; Expert System.

I. INTRODUCTION

The complexity of power system configurations requires improved performance of protection schemes. The protection and substation control have undergone dramatic changes since the advent of powerful micro-processing and digital communication equipment. TGPs are an important part of the Electric Power Systems (EPS). These plants are composed by generation equipment, switches, transformers, substation (EES) and other machinery that must be constantly monitored and protected.

Oscillography data analysis, generated by faults and/or disturbances can be a valuable strategy to assure a reliable EPS operation. This task usually is executed by the protection and monitoring system as Supervisory Control and Data Acquisition (SCADA), Energy Management System (EMS) and Oscillography Digital Register (ODR). The ODR has been widely used by energy companies for a more rigorous analysis of the disturbances that occur in the EPS. These devices register samples of current and voltage signals, beyond registering the digital relays state. One of the main difficulties related to the data analysis is the waste of time in the data verification that does not represent fault situations [1]-[2]. On the other hand, the events sequence registered by SCADA system can be used in comparison with the data recorded by oscilography digital register, in order to detect incoherences between the two information sources [3]-[6].

In many cases, the fault location in one Thermoelectric Generation Plant (TGP) is performed only with base on data assessment from the monitoring system, as for example, the state of switches and circuit breakers. However, this procedure can lead to misidentification of the fault component, especially when the substation is large. Accordingly, it should be taken into account other variables such as the magnitude and phase of voltages and currents as well as data oscillography of the involved system. Moreover, the evaluation of a greater number of variables leads to the need of using an Expert System (ES) to support decision making.

In this context, the aim of this paper is to present a Fault Diagnosis Integrated System (FDIS) for a TGP located in the southern Brazil. In this work, all algorithms were developed in MATLAB® platform [7] and several simulations were performed under BPA's ATP/EMTP software (Alternative Transients Program/Electro-Magnetic Transient Program) [8]. The results obtained in the cases tested show the high performance of the FDIS proposed.

II. FAULT DETECTION SYSTEM PROPOSED

The proposed FDIS is based on three integrated subsystems: Pre-Processing Data System, Fault Identification System and Expert System:

- The Pre-Processing Data System consists of a subsystem responsible for phasor extraction from COMTRADE files [9] and the switches and circuit breakers status acquisition from SCADA system. This important information is then used for identification and classification of fault equipment.
- The Fault Identification System was developed based on the directional relay formulation. Thus, when a pre-determined threshold value is exceeded by the fault current, a fault condition is detected and the direction of failure is indicated by the subsystem. The decision criterion of the developed directional relay in this work is based on the angular difference between the positive sequence voltage and current phasors.
- The Expert System uses the processed data from directional relay and the states of circuit breakers and

switches to estimate the fault location. In this subsystem, Fuzzy Logic and Artificial Neural Network (ANN) were used to estimate the fault location [10]-[11].

The main structure of the proposed FDIS can be seen in Fig. 1.

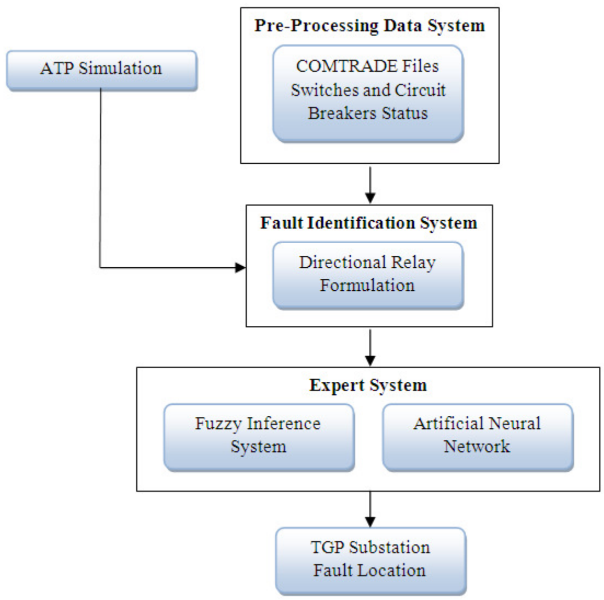

Figure 1. General structure of the proposed scheme.

A. *Pre-Processing Data System*

The first procedure of the Pre-Processing Data System is related to phasor extraction from COMTRADE files, and state of switches and circuit breakers analysis from SCADA system. When the objective is to store the signals generated by an electrical event, it is necessary to design a system that can interact with the event as a result of obtaining a representation of these signals in analog form. However, this form of representation undermines its computational treatment. Therefore, the proposed method used the Discrete Fourier Transform (DFT) and signal processing techniques to process and evaluates the signals [12]. Fig. 2 shows a basic flow chart.

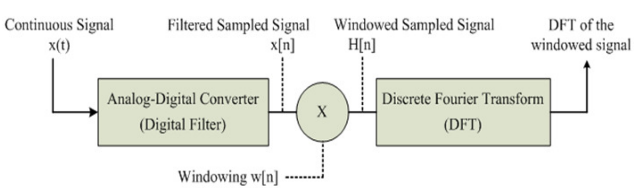

Figure 2. Pre-Processing Data System.

These events can be simulated in BPA's ATP/EMTP (ATP). The sampling rate chosen for this study was 960 Hz (rate of conventional operation of the majority of digital protective relays).

The development of fault identification algorithm is based on the amplitude and the angular difference between voltage and current phasors measured at the site of installation of the protective relay. Thus, starting from the signals of oscillography, voltage and current phasors are calculated at a given instant of time through a DFT. The value of the angle difference phasors is then used by the directional relay algorithm for identification of the direction (forward or backward) of the fault.

B. *Fault Identification System*

Aiming to detect faults in respect to the TGP, it was developed a directional relay whose main characteristic is to determine the direction of a failure from its installation location. Thus, when a pre-determined threshold value is exceeded by the current fault, a fault condition is identified and the direction of failure is indicated by the relay. Fig. 3 illustrates the basic scheme of a directional relay.

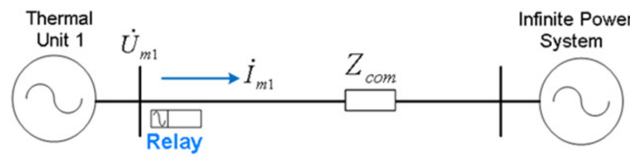

Figure 3. Fault Identification System.

Here, the voltage at the point of installing the relay is given by:

$$\dot{U}'_{m1} = \dot{U}_{m1} - \dot{I}_{m1} \cdot Z_{com} \tag{1}$$

where $\dot{U}_{m1}$ is the positive sequence voltage phasor at the protection point; $\dot{I}_{m1}$ is the positive sequence line current phasor at the protection point; Z_{com} is the equivalent impedance of the circuit.

The direction of a backward or forward fault is determined by comparing the angle between of the voltage and current phasors. Thus, the criteria for identifying a backward fault is given by:

$$90° \leq tg^{-1}(\dot{U}'_{m1} / \dot{I}'_{m1}) \leq 270° \tag{2}$$

When the above condition is satisfied, a backward fault is detected. During normal operation or forward faults, the power flow is always toward the load (Substation), in other words, the source (TGP) provides power. However, when a fault happens backward of directional relay location, the current I_{m1} changes of direction changing the value of the angle between the voltage and current phasors.

C. *Expert System (ES)*

The developed ES is composed by a hybrid Fuzzy-Neuro System. In a first stage, decision rules based on Fuzzy Logic indicate the local in the substation where a possible fault occurred (bus, lines, generators, transformers), supplying a probability index associated with the disturbance. In a second stage, an ANN classifies the fault on a more specific manner, estimating the site of the fault and the associated circuit breaker.

1) *ATP Simulations*

The first step for the ES construction is related to the Fuzzy Data Sets creation, as well as, to the ANN training. In such a way, a representative substation model was modeled in ATP [10]. The simulated system was built, rigorously, conformably to the needs presented by a TGP of 711 MW, 230 kV, located at southern Brazil. Fig. 4 illustrates the electric circuit used in the simulations.

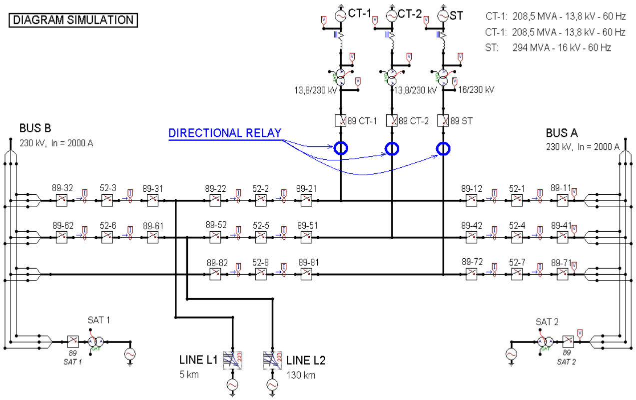

Figure 4. Subestation Model.

In ATP, three-phase faults were simulated with base on operative sequence of closing and synchronism of 230 kV circuit breakers from the TGP substation. The simulation faults are listed in Table I.

TABLE I. TYPE OF THE FAULT SIMULATED IN ATP

Fault Type
Outage of line L1 for temporary defect
Defect on bus A or transformer SAT-2
Defect on bus B or transformer SAT-1
Defect on CT1 generator with fault on the circuit breaker 52-1
Defect on CT1 generator with fault on the circuit breaker 52-2
Defect on CT2 generator with fault on the circuit breaker 52-4
Defect on CT2 generator with fault on the circuit breaker 52-5
Defect on ST generator with fault on the circuit breaker 52-7
Defect on ST generator with fault on the circuit breaker 52-8
Defect on line L1 with fault on the circuit breaker 52-2
Defect on line L1 with fault on the circuit breaker 52-3
Fault on CT1 generator with circuit breaker 52-1 in maintenance
Fault on line L1 with circuit breaker 52-2 in maintenance
Fault on bus A or transformer SAT-2 with circ. breaker 52-1 in maintenance
Defect on line L2 with opening of the circuit breaker 52-5 and 52-6
Defect on line L2 with fault on the circuit breaker 52-5
Defect on line L2 with fault on the circuit breaker 52-6

For all fault types presented in the Table I, faults resistance values of 0.01 Ω until 1000 Ω had been considered, totalizing 204 types of different fault conditions. For each fault resistance, the current and voltage of the three phases were collected and 612 data sets were obtained. Part of this data was used to compose the Fuzzy Sets and training the ANN. The other data was used to test the ES.

Finally, the apparent power and the angular difference calculated for each one of the directional relays connected in the three generator units of the TGP are used as input variables for the Fuzzy-Neuro Expert System. It was constructed also a graphical interface in MATLAB® environment with the purpose of the better user interface. This interface is illustrated in Fig. 5.

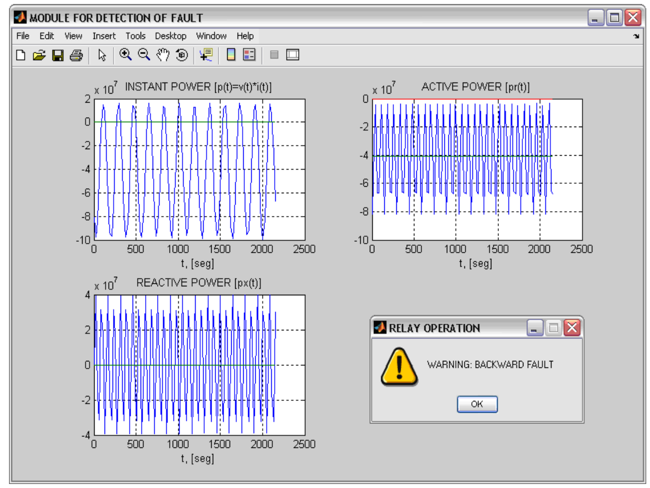

Figure 5. Graphical Interface.

2) Fuzzy Inference System

The developed Fuzzy Inference System is composed by six input variables (apparent power and angle of each directional relay output) and for seven output variables that estimate the fault location. The related variables can be seen in Table II.

TABLE II. FUZZY INFERENCE SYSTEM VARIABLES

Fuzzy Input Variables	**Fuzzy Output Variables**
Angle directional relay 1	Fault on line L1
Apparent power directional relay 1	Fault on Bus A or transformer SAT-2
Angle directional relay 2	Fault on Bus B or transformer SAT-1
Apparent power directional relay 2	Fault on the CT1 generator
Angle directional relay 3	Fault on the CT2 generator
Apparent power directional relay 3	Fault on the ST generator
	Fault on line L2

In the input variables, the angle is composed for two triangular-shaped membership functions. The first one is related to negative angles, $-360^{o} \leq$ input $\leq 0^{o}$ and the second one related to the positive angle, $0^{o} <$ input $\leq 360^{o}$. The apparent power variables were composed for one triangular-shaped membership function corresponding to the positive values of power, $0 \leq$ input ≤ 40 MVA. The range of the input membership functions was obtained with base on angle and power data groups that represent each kind of fault. The output variables also are compound for one triangular membership function for each fault, as presented in Table 2. The range of output membership function is in the interval $0 \leq$ output ≤ 2, so: output values in the mid of interval, output = 1, correspond 100% of probability of the related fault to have occurred; values in the threshold of the range, output = 0 or output = 2, correspond 0% of probability of the related fault to have occurred and output values inside of the range, 0 < output < 2 represent intermediary values of fault probability.

The base rule is composed for 37 rules that represent faults obtained from ATP simulations. In the inference process the Method of Mamdani was used and the smallest (absolute) value of maximum was applied in defuzzification process. In such a way, some rules can be activated for a same group of input data. In this case, each fault has its probability value of occurrence. In the second step, the ANN can classify more exactly which fault occurred. Fig. 6 illustrates the Fuzzy inference process.

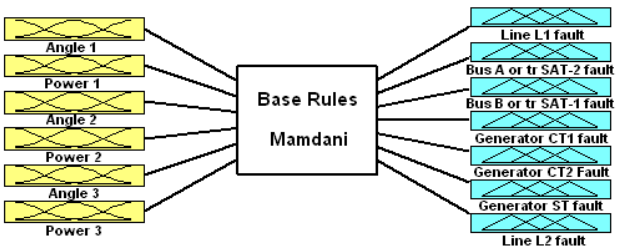

Figure 6. Fuzzy Inference Process

Additionally, others types of membership functions as gaussian and trapezoidal shapes were testes, but the best results were obtained with triangular shape.

3) Artificial Neural Network (ANN)

The second stage in the Expert System is composed by a Multilayer Perceptron (MLP) Feedforward Artificial Neural Network. This ANN maps input angle and power data in an appropriate output fault location estimate. As well as the Fuzzy System, the input variables of ANN are the angle and apparent power of each directional relay output. On the other hand, the ANN fault identification is more specific than Fuzzy inference. Beyond the fault location, the MLP structure can identify the involved circuit breaker. So, six input variables are mapped in 17 kinds of faults, presented previously in Table I. Fig 7 presents the MLP Feedforward used in the developed Expert System.

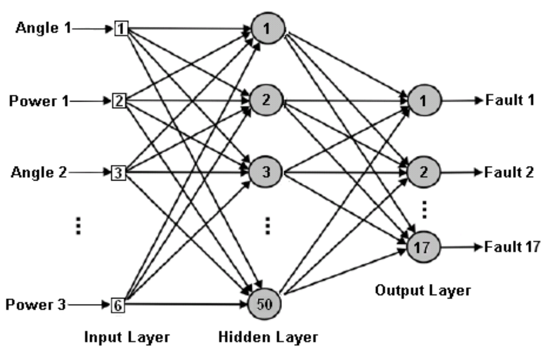

Figure 7. MLP structure used in the Expert System

The Feedforward Backpropagation Network is composed by 6, 50 and 17 perceptrons in the input, hidden and output layer respectively. Other number of neurons in the hidden layer was utilized in the simulations, but the best convergence was obtained with this configuration. To calculate a layer's output from its net input the hyperbolic tangent sigmoid transfer function (hidden layer) and linear transfer function (output layer) were used. The Levenberg-Marquardt optimization was adopted as training function, because it is a fast backpropagation algorithm. The mean squared normalized error (MSE) was used as performance function. The input data was divided in two groups, the first one corresponding a 2/3 of total data was used in the ANN training process and remaining data was used in ANN tests. Several simulations of different values of epochs were performed in network training process and the best results were attainment with 500 epochs converging to a MSE = 0.004. In the Table III can be seen the ANN performance to classify different fault types in the test process.

TABLE III. ARTIFICIAL NEURAL NETWORK PERFORMANCE

Fault	Error (%)
Outage of line L1 for temporary defect	5.5
Defect on bus A or transformer SAT-2	16.6
Defect on bus B or transformer SAT-1	44.4
Defect on CT1 generator with fault on the circuit breaker 52-1	5.5
Defect on CT1 generator with fault on the circuit breaker 52-2	38.8
Defect on CT2 generator with fault on the circuit breaker 52-4	5.5
Defect on CT2 generator with fault on the circuit breaker 52-5	33.3
Defect on ST generator with fault on the circuit breaker 52-7	38.8
Defect on ST generator with fault on the circuit breaker 52-8	0
Defect on line L1 with fault on the circuit breaker 52-2	5.5
Defect on line L1 with fault on the circuit breaker 52-3	27.7
Fault on CT1 generator with circ. breaker 52-1 in maintenance	0
Fault on line L1 with circuit breaker 52-2 in maintenance	5.5
Fault on bus A or tr. SAT-2 with circ. bre. 52-1 in maintenance	44.4
Defect on line L2 with open. of the circ. break. 52-5 and 52-6	22.2
Defect on line L2 with fault on the circuit breaker 52-5	0
Defect on line L2 with fault on the circuit breaker 52-6	5.5

III. SIMULATION AND ANALYSIS OF DISTURBANCES

To illustrate de results obtained with the Fault Diagnosis Integrated System two cases of disturbances in the Thermoelectric Generation Plant substation are presented below.

A. Defect on line L1 with fault on the circuit breaker 52-3

The Fig. 8 shows the behavior of three-phase voltages and currents in the occurrence of a defect in line L1 with fault on the circuit breaker 52-3. In the presented case, the defect is a three-phase short-circuit with fault resistance = 80Ω. In this case the angle and power used as input variable for the Expert System are: angle 1 = 17.3º; power 1 = 29,6 MVA; angle 2 = 68.3º; power 2 = 29.8 MVA; angle 3 = 71.2º; power 3 = 32.2 MVA. Fig. 9 illustrates the software interface with the fault information.

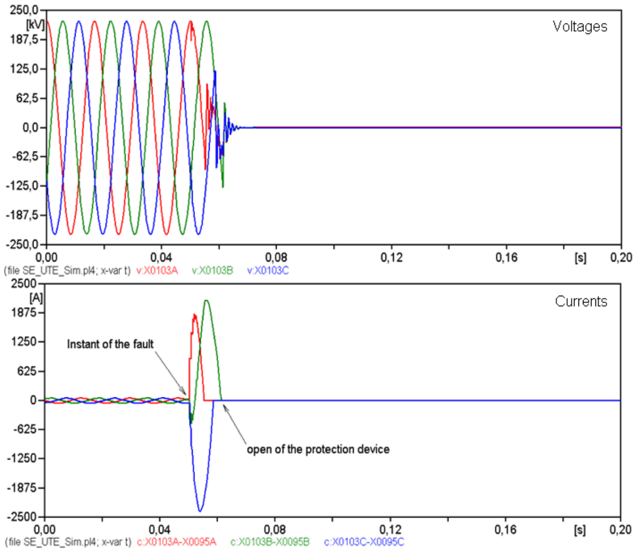

Figure 8. Voltages and currents on Line L1 due three-phase short-circuit.

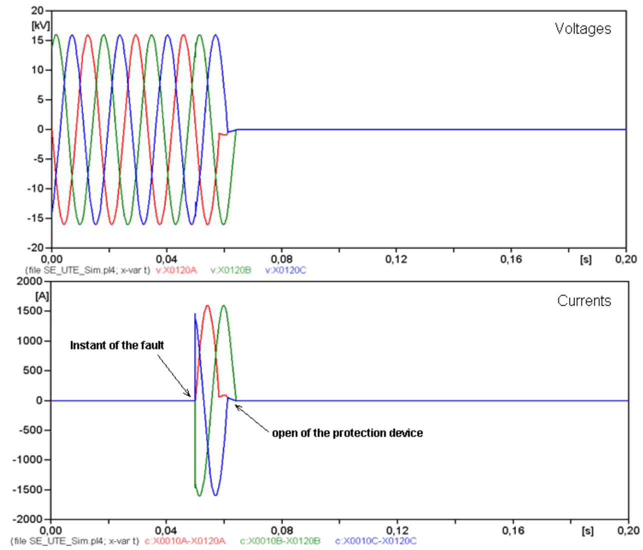

Figure 10. Voltages and currents on out ST generator with fault (no open) of the circuit breaker 52-7.

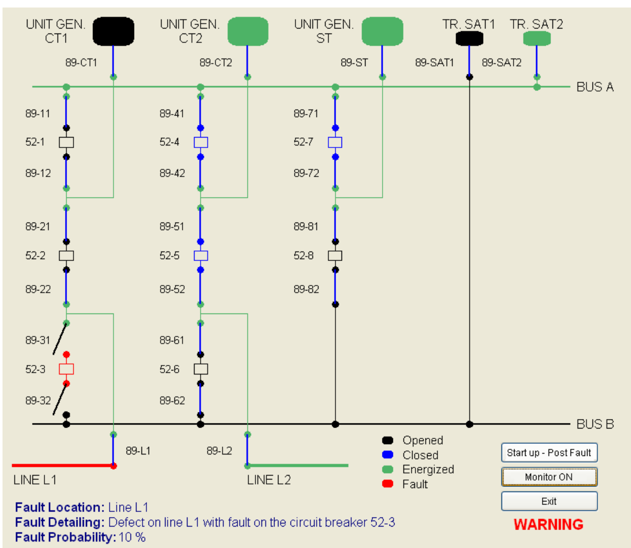

Figure 9. Software interface shows defect in line L1

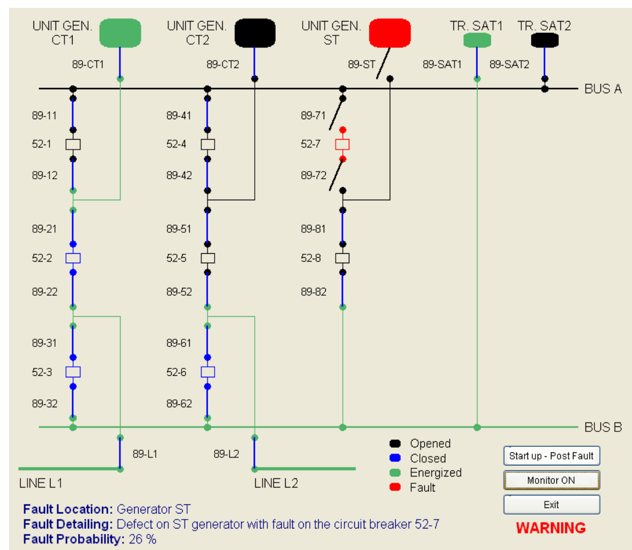

Figure 11. Software interface shows defect in generator ST

B. Defect on ST generator with fault on the circuit breaker 52-7

In Fig. 10 it can be seen the behaviour of three-phase voltages and currents in the occurrence of a defect in generator ST with fault on the circuit breaker 52-7. In this case, the defect is a three-phase short-circuit with fault resistance = 325Ω. The calculated angle and power used as input variable for the Expert System are: angle 1 = 66.8º; power 1 = 30.1 MVA; angle 2 = -26.5º; power 2 = 12.5 MVA; angle 3 =-177.9 º; power 3 = 13.8 MVA.

The results of this test case can be seen in Fig. 11.

IV. CONCLUSIONS

This paper presented a FDIS for fault location in a Thermoelectric Generation Plant. The proposed study combined signal processing techniques with intelligent systems to detect and estimate the fault location.

The use of oscillography data associated with the state of switches and circuit breakers showed to be an appropriate strategy to attain reliable information that can be used as input data source of the proposed scheme.

The developed ATP model allows the simulation of diverse disturbances inside the substation, which was used for compose Fuzzy Sets, training the ANN and test the hybrid Fuzzy-Neuro Expert System. The model was built, conformably to the needs presented. Additionally, the ATP model can be used to test others kind of faults with difference sequence of closing and synchronism of circuit breakers from the TGP.

The Expert System classifies the fault in two levels of details. The Fuzzy System is more generalist and identifies only the local of fault, whereas, the ANN is qualified to indicate the related circuit breaker. For this reason, the fact that the net is very specialist, a level of classification error can occur. In some ANN tests, the error is allied with the wrong of circuit breaker and not with the local of fault as bus, transformer, line or generators. It is important to highlight that the ES input data are very close and the classification process is not a trivial task.

Currently, the system is being tested in the TGP.

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