

A HYBRID EXPERT SYSTEM BASED ON NEURAL NETWORKS AND FUZZY LOGIC FOR FAULT IDENTIFICATION IN ELECTRIC POWER SUBSTATIONS

Daniel da Silva Gazzana, Mario Orlando Oliveira, Arturo Suman Bretas
Federal University of Rio Grande do Sul, UFRGS, Porto Alegre, Brazil

Andre Lerm
Southern Federal Institute of Education and Technology, IFSUL, Pelotas, Brazil

Arlan Bettiol
A Vero Domino Consultoria e Pesquisa, Florianópolis, Brazil

Marcio A. Da S. Gonçalves
AES Uruguaiana, Uruguaiana, Brazil

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Abstract: This paper presents a novel approach for on-line fault identification in an Electric Power Substation (EPS). The proposed methodology is based on signal processing techniques allied with a Fuzzy Logic and Artificial Neural Network. The test electric system was rigorously built in an electromagnetic transient numerical simulator, named Alternative Transient Program (ATP), conformably to the needs presented by a Thermoelectric Generation Plant of 711 MW - 230 kV, located in southern Brazil. Simulated test cases demonstrate the generalization capability of the developed hybrid Expert System based on Neural Networks and Fuzzy Logic, now utilized in a Southern Brazilian Utility.

1 INTRODUCTION

The use of a rapid and efficient method for on-line fault detection in Electric Power Substations (EPS) helps both in maintenance tasks and in the prompt restoration of electrical system. The protection and substation control have undergone dramatic changes since the advent of powerful micro-processing and digital communication equipment.

In the Electric Power System the monitoring and control of substations are based generally on the computerized Energy Management System (EMS), Supervisory Control and Data Acquisition (SCADA) and Oscillography Digital Register (ODR). When faults occur in an automated substation, the faulted devices are isolated by the operation of corresponding protection relays and circuit breakers;

meanwhile, the SCADA system will issue alarm messages in a short time sending them into the operator's consoles. In this case, the operators in the control center are responsible for restoring the system and must use their judgment and experiences to determine the possible faulted elements and/or switches as the first step in the restoration procedures of the electric system (Chen *et al.*, 2000). In many cases, the fault location in EPS 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, obtained from system data

oscillography. Moreover, the evaluation of a greater number of variables leads to the necessity of using an Expert System (ES) to support decision making and fault diagnostic (Fukui and J. Kawakami, 1986; Tomsovic *et al.*, 1987; Kezunovic *et al.*, 1994; Protopapas *et al.*, 1991).

In this paper, it is presented a Fault Diagnosis Integrated System (FDIS) used in a substation of a Thermoelectric Generation Plant (TGP) located in the southern Brazil. The proposed approach was developed based on several simulations performed under Bonneville Power Administration Alternative Transients Program (BPA/ATP), Electromagnetic Transients Program (EMTP) and using a hybrid system based on Neural Networks and Fuzzy Logic. The results obtained show that the developed method is able to identify and locate the fault occurrence, even when subject to operational failures of circuit breakers.

2 FUZZY SETS AND NEURAL NETWORK IN FAULT DETECTION

Fuzzy Logic can systematically translate linguistic concepts to numbers and associate elements from a number set to concepts (Zadeh, 1965). This capability provides a simple method that can be used to detect and to qualify faults in Electric Power Substations. Fuzzy based algorithms and Fuzzy Logic are well adapted to situations where there is no clear distinction between the concept of true and false. Fuzzy Logic can handle situations where the answer lies somewhere in-between. This is the typical case of substation fault location. In general it is difficult to estimate the fault location between the several devices present in the electric power substation. However, it is more adequate to classify a fault in terms of the occurrence probability. Fuzzy Logic permits to infer about the fault location and to establish its certainty degree level of trust. An important feature of Fuzzy based systems is that the human knowledge and experience can be integrated into the systems in a systematic way, when the Fuzzy sets and Fuzzy rules have been defined.

In recent years, the use of Artificial Neural Networks (ANNs) presented it self as a potential solution to the on-line fault diagnosis in power substations (Ebron *et al.*, 1990; Yang *et al.*, 1994; Ranaweera, 1994). ANNs are computational techniques that try to obtain a performance similar to a human's performance when solving problems. An ANN can be seen as a union of simple processing

units, based on neurons that are linked to each other through connections similar to synapses. These connections contain the "knowledge" of the network and the patterns of connectivity express the objects represented in the network. The knowledge of the network is acquired through a learning process where the connections between processing units are varied through weight changes. ANN is an efficient alternative for problem solutions where it is possible to obtain data describing the problem behavior but a mathematical description of the process is impossible.

The basic idea of uniting these two techniques is to use the qualitative analysis supplied by Fuzzy Logic, allied to the learning ability of Neural Networks. Hybrid systems Neuro-Fuzzy can be used to resolve this kind of problems with good accuracy and robustness, joining the advantages of these methodologies (Kezunovic, 2004).

3 FAULT DETECTION METHODOLOGY

The proposed methodology is based on the three integrated subsystems: Pre-Processing Data System, Fault Identification System and Expert System. The main structure of the proposed automated disturbance analysis system can be seen in Figure 1.

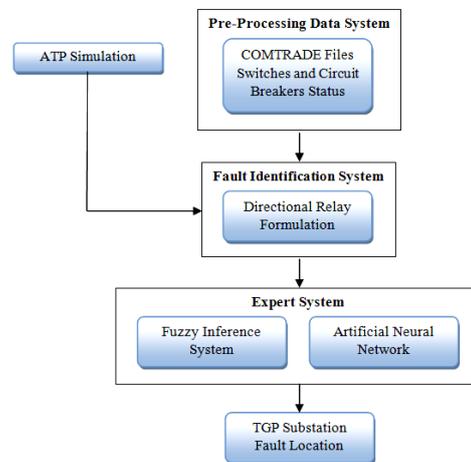


Figure 1: General structure of the proposed scheme.

3.1 Pre-Processing Data System

The first procedure of the Pre-Processing Data System is related to phasors extraction from COMTRADE files (IEEE Standard C37.11.1.1999, 1999) and the evaluation of the state of switches and

circuit breakers from SCADA system. This study used the Discrete Fourier Transform (DFT) and signal processing techniques to process and evaluates the signals (Phadke and Thorp, 1999). Figure 2 presents a basic flow chart for the signal processing.

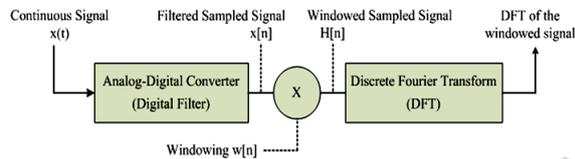


Figure 2: Pre-Processing Data System.

The development of fault identification algorithm is based on the module (amplitude) and the angular difference between voltage and current phasors measured at the site of installation of the protective relay.

3.2 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 detected and the direction of failure is indicated by the relay (Suonan *et al.*, 2004). Figure 3 shows the basic installing scheme of a directional relay.

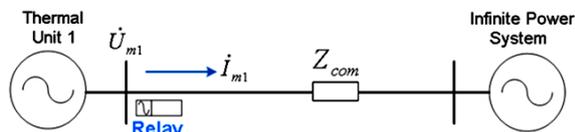


Figure 3: Fault Identification System.

Here, the voltage at the relay location is given by:

$$U'_{m1} = U_{m1} - I_{m1} \cdot Z_{com} \quad (1)$$

where U_{m1} is the voltage phasor positive sequence in the protection point; I_{m1} is the current phasor positive sequence from the protection point to the line; Z_{com} is the impedance compensating of the circuit.

The direction of a backward or forward fault is determined by comparing the angle between of the voltage and current phasors positive sequence. Thus, the criterion for detecting a backward fault of the directional relay is given by:

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

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 (Infinite Power System), in other words, the source (TGP) provides power. However, when a fault happens backward of directional relay, the current I_{m1} changes of direction changing the value of the angle between the voltage and current phasors.

4 EXPERT SYSTEM (ES)

The developed ES is composed by a hybrid system based on Neural Networks and Fuzzy Logic. 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. The Fuzzy Logic system runs independently of the ANN.

4.1 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 1.

Table 1: Fuzzy inference system variables.

Fuzzy Input Variables	Fuzzy Output Variables
Angle directional relay 1	Fault on line L1
AP directional relay 1	Fault on Bus A or TR SAT-2
Angle directional relay 2	Fault on Bus B or TR SAT-1
AP directional relay 2	Fault on the CT1 generator
Angle directional relay 3	Fault on the CT2 generator
AP 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, $-360^\circ \leq \text{input} \leq 0^\circ$ and the second one related to the positive angle, $0^\circ < \text{input} \leq 360^\circ$. The Apparent Power (AP) variables were composed for one triangular-shaped membership function corresponding to the positive values of power, $0 \leq \text{input} \leq 40 \text{ MVA}$. 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 composed by one triangular membership function for each fault, as presented in Table 1. The range of output membership function is in the interval $0 \leq \text{output} \leq 2$, 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, $0 < \text{output} < 2$ represent intermediary values of fault probability.

The base rule is composed for 37 rules that represent faults proceedings from 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. Figure 4 illustrates the Fuzzy inference process.

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

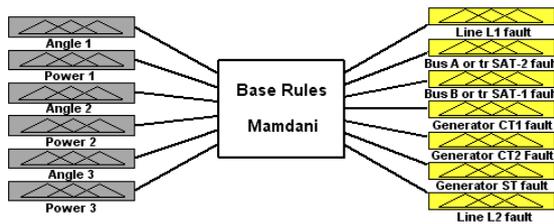


Figure 4: Fuzzy Inference Process.

4.2 Artificial Neural Network (ANN)

The second stage in the Expert System is composed by a Multilayer Perceptron (MLP) Feedforward Artificial Neural Network (Haykin, 1998). 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. In the Table 2 can be seen the ANN performance, in training stage, to classify substation faults considering different number of neurons in hidden layer. Table 3 shows the same faults in test stage.

Figure 5 presents the MLP Feedforward used in the developed Expert System.

Table 2: ANN error in training process.

Type of fault	ANN Classification Error (%)		
	Neurons in hidden layer		
	20	50	80
Outage of line L1 for temporary defect	8.83	0	0
Defect on bus A or transformer SAT-2	25	0	0
Defect on bus B or transformer SAT-1	50	0	0
Defect on CT1 generator with fault on the circuit breaker 52-1	0	0	0
Defect on CT1 generator with fault on the circuit breaker 52-2	25	0	0
Defect on CT2 generator with fault on the circuit breaker 52-4	0	0	0
Defect on CT2 generator with fault on the circuit breaker 52-5	0	0	0
Defect on ST generator with fault on the circuit breaker 52-7	0	0	0
Defect on ST generator with fault on the circuit breaker 52-8	0	0	0
Defect on line L1 with fault on the circuit breaker 52-2	0	0	0
Defect on line L1 with fault on the circuit breaker 52-3	25	0	0
Fault on CT1 generator with circ. breaker 52-1 in maintenance	0	16.7	0
Fault on line L1 with circuit breaker 52-2 in maintenance	0	0	0
Fault on bus A or tr. SAT-2 with circ. bre. 52-1 in maintenance	0	0	0
Defect on line L2 with open. of the circ. break. 52-5 and 52-6	33.3	0	0
Defect on line L2 with fault on the circuit breaker 52-5	16.7	0	0
Defect on line L2 with fault on the circuit breaker 52-6	0	0	0
Global error (%)	10.8	0.98	0

The Feedforward Backpropagation Network is composed by 6 and 17 perceptrons in the input, and output layer respectively. For the hidden layers, different number of neurons was tested and the convergence results were presented in the following.

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.

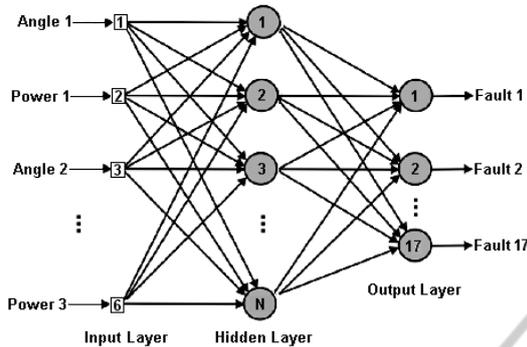


Figure 5: MLP structure used in the Expert System.

Table 3: ANN error in test process.

Type of fault	ANN Classification Error (%)		
	Neurons in hidden layer		
	20	50	80
Outage of line L1 for temporary defect	16.7	0	0
Defect on bus A or transformer SAT-2	50	16.7	33.3
Defect on bus B or transformer SAT-1	33.3	50	50
Defect on CT1 generator with fault on the circuit breaker 52-1	16.7	0	16.7
Defect on CT1 generator with fault on the circuit breaker 52-2	16.7	0	33.3
Defect on CT2 generator with fault on the circuit breaker 52-4	16.7	16.7	50
Defect on CT2 generator with fault on the circuit breaker 52-5	0	0	16.7
Defect on ST generator with fault on the circuit breaker 52-7	0	0	0
Defect on ST generator with fault on the circuit breaker 52-8	0	0	0
Defect on line L1 with fault on the circuit breaker 52-2	16.7	0	16.7
Defect on line L1 with fault on the circuit breaker 52-3	16.7	33.3	33.3
Fault on CT1 generator with circ. breaker 52-1 in maintenance	33.3	16.7	16.7
Fault on line L1 with circuit breaker 52-2 in maintenance	16.7	0	0
Fault on bus A or tr. SAT-2 with circ. bre. 52-1 in maintenance	33.3	33.3	50
Defect on line L2 with open. of the circ. break. 52-5 and 52-6	33.3	33.3	16.7
Defect on line L2 with fault on the circuit breaker 52-5	0	0	0
Defect on line L2 with fault on the circuit breaker 52-6	0	0	0
Global error (%)	17.6	11.8	19.6

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.

Analysing Table 2 and Table 3 it can be seen that the best ANN response is obtained with a MLP structure composed by 50 perceptrons in hidden layer. A major number of neurons in hidden layer not represent significant improvements in ANN classification process.

The Table 4 presents the number of epochs and MSE obtained for the previously MLP structures. The MLP structure with 6, 50 and 17 perceptrons in the input, hidden and output layer respectively was implemented in the developed system.

Table 4: ANN performance.

Neurons in hidden layer	Epochs	MSE
20	200	0.0195
50	150	0.0057
80	300	0.0003

5 SIMULATION AND RESULTS

To illustrate the results obtained with the Fault Diagnosis Integrated System two cases of disturbances in the Thermoelectric Generation Plant substation are presented below. The simulated system was built, rigorously, conformably to the needs presented by a TGP of 711 MW, 230 kV, located in southern of Brazil. Figure 6 illustrates the electric circuit used in the simulations of the faults in the EPS.

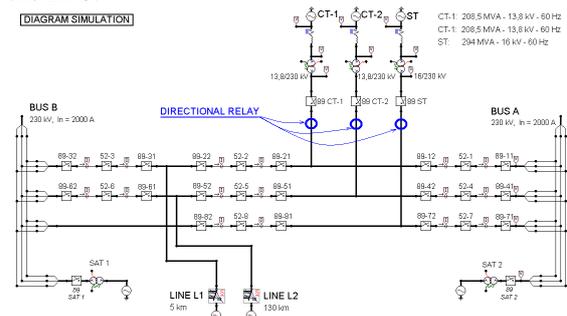


Figure 6: Substation model used in the simulation faults.

5.1 Defect on Line L1 with Fault on the Circuit Breaker 52-2

The Figure 7 shows the behaviour of three-phase voltages and currents in the occurrence of a defect in line L1 with fault on the circuit breaker 52-2. In the

presented case, the defect is a three-phase short-circuit with fault resistance (R_f) of 50Ω . In this case the angle and power used as input variable for the Expert System are: angle 1 = 73.4° ; power 1 = 10.1 MVA; angle 2 = 70.4° ; power 2 = 30.7 MVA; angle 3 = 71.7° ; power 3 = 33.2 MVA. The Figure 8 illustrates the software interface with the information of the fault identification.

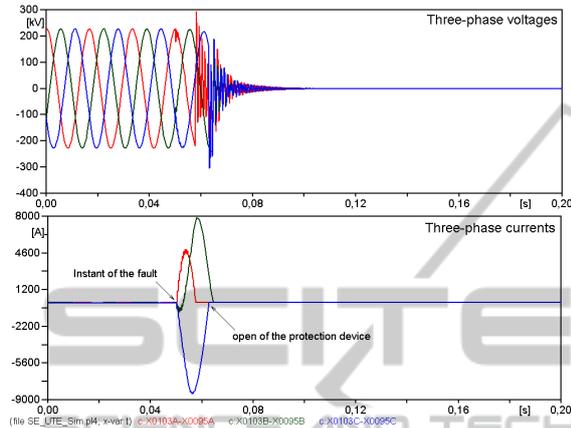


Figure 7: Voltage and currents on Line L1 due three-phase short-circuit with fault resistance $R_f = 50\Omega$.

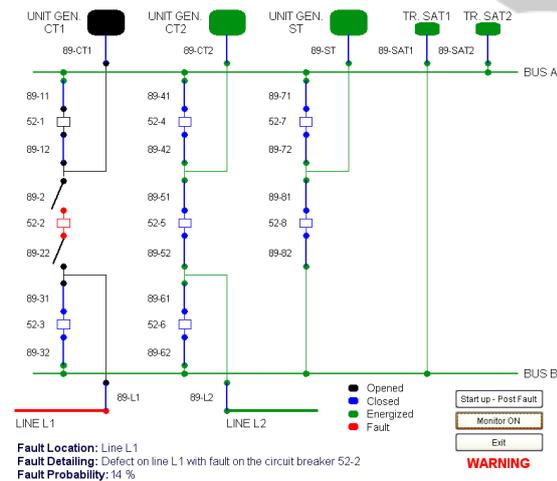


Figure 8: Software interface shows fault at Line L1.

5.2 Defect on CT2 Generator with fault on the Circuit Breaker 52-4

In Figure 9 it can be seen the behaviour of three-phase voltages and currents in the occurrence of a defect in generator CT2 with fault on the circuit breaker 52-4. In this case, the defect is a three-phase short-circuit with low fault resistance of 0.5Ω . The calculated angle and power used as input variable for the Expert System are: angle 1 = -273.3° ; power 1 = 30.2 MVA; angle 2 = -204.7° ; power 2 = 19.3

MVA; angle 3 = -273.4° ; power 3 = 32.6 MVA. The developed software interface with the fault location can be seen in Figure 10.

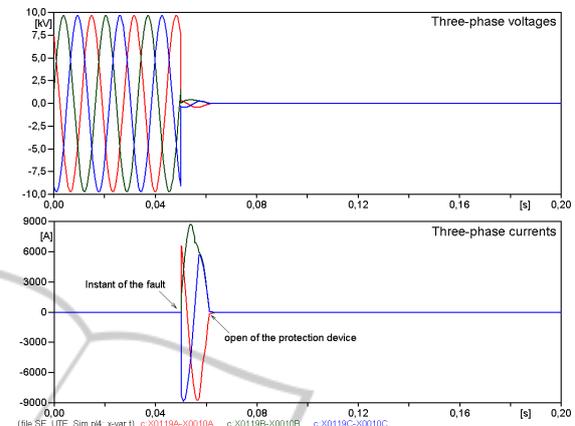


Figure 9: Voltage and currents on out CT2 generator with fault of the circuit breaker 52-4.

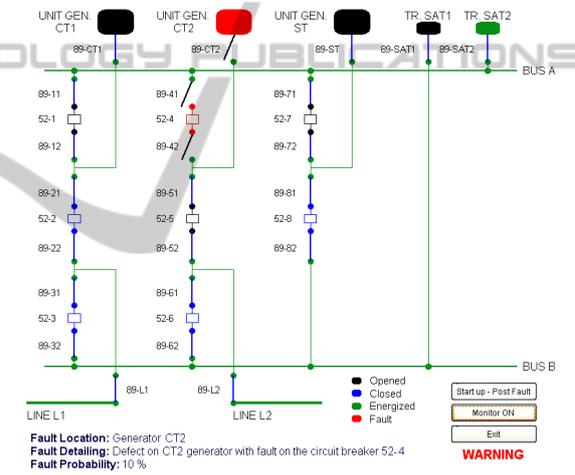


Figure 10: Software interface shows defect in generator CT2.

6 CONCLUSIONS / DISCUSSION

This paper presented a methodology for fault location in power electric substation with base on Fuzzy Sets and Artificial Neural Networks. The proposal study combine signal processing techniques with intelligent systems to detect the local and the related device in a fault occurrence.

This methodology starts with the extraction data from oscillography files and with base on the state of circuit breakers in the substation. In the development stage, this task is replaced by simulation of the substation operational conditions using the Alternative Transients Program (ATP). After, the

signal processing techniques are implemented supplying input data to the Fuzzy-Neuro Expert System that classify a possible fault.

The directional relay shows to be a robust method to provide an indication of the fault direction, beyond supplying angle information that is used as input to the ES with satisfactory results.

The developed ATP/EMTP 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 Fuzzy-Neuro 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.

Several simulations of different values of epochs was performed in network training process and the best results were attainment with 150 epochs converging to a MSE = 0.0057, ANN global test error = 11.8% considering 6, 50 and 17 perceptrons in the input, hidden and output layer respectively. With this configuration the best results was obtained and this structure was implemented in the fault detection expert system.

The developed integrated system can become the management maintenance activities more efficient. Moreover, such system contributes for the increase of the reliability, having as one of its benefits, the reduction of involved time to detect and localize a possible fault, optimizing the maintenance practices.

Currently, the system is being tested in the TGP in the Southern Brazilian, but this methodology can be used to detect and localize faults in similar energy electric substations.

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