

MODEL OF RESTORATION OF DISTRIBUTION NETWORK OF ELECTRICAL ENERGY USING ARTIFICIAL NEURAL NETWORKS

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Abstract. A computational model for self-recovery of electricity distribution network was developed to simulate it, emulated by the IEEE 123 nodes model. The electrical system considered has automatic switches capable of identifying a momentary fault in the line and finding the best reconfiguration for its reclosing. An artificial neural network (ANN), backpropagation, was used to classify the type of failure and determine the best reconfiguration of the distribution network. Initially, five power failure scenarios were simulated in certain different parts of the power grid, and power flow analysis via OpenDSS was performed. Following, the most suitable switching was observed within the shortest time interval to restore the power supply. In this way it is possible to identify the faulted segment in order to isolate it, leaving the smallest number of consumers in the shortest possible time without power supply. With the results of the simulations, tests and analyzes were performed to verify their robustness and speed, in the expectation that the model developed, be faster than an experienced Operator of a Distribution Center.

Key words

Distribution Networks, Optimization, Self-recovery of networks, Smart Grid.

1. Introduction

The availability of electric energy represents an increase in the quality of life of the population. At the first moment in which an electric energy distribution system is implanted, the local population immediately has countless benefits, both from the point of view of greater domestic comfort and better possibilities of employment, production towards more equipment and machines in operation, associating this with a higher production [1].

In this context, the constant search for the improvement in the quality of electricity distributed to consumers has been a motivating factor for a series of changes, both in the

legal and regulatory instruments, and in the organization of companies in the direction of their strategies [2].

According to [3] self-healing is a system capable of detecting, analyzing, responding and restoring faults in the electrical energy network (EE) automatically (and in some cases instantaneously). This system uses real-time information, generated by sensors arranged in the distribution network to respond reactively (when service has already occurred) or proactive (still without restriction to the contracted service) to network problems, automatically avoiding or mitigating drops or problems with the quality of energy and the discontinuity of services.

As one of the features of the smart grid, self-healing aims to improve network reliability and have a rapid response when a Distribution Network (RD) failure occurs, isolating it and reducing the period of power failure in the network. network [4].

The benefits of applying the concept of self-healing in electrical systems include: (i) rapid restoration of the system to the operating mode; (ii) restoration of more loads and (iii) less need to send field teams to reconfigure the network [5].

Therefore, knowing the potential of the smart grid and its functionalities, such as self-healing, it is possible to solve the problem of disconnection of electricity distribution networks. For this, an artificial neural network, backpropagation, was applied to reconfigure an electrical energy distribution network in an adequate time. The purpose of this work is to restore an electricity distribution network, represented by the IEEE model 123 nodes, according to the National Electric Energy Agency.

The modern power grid has evolved into a highly interconnected, complex and interactive system. The growing demand for energy independence, modernization of old infrastructure with new technologies, integration of multiple renewable energies and storage, more efficient use of energy, self-healing and resilience to natural disasters and attacks, coupled with the pressure for sustainable development, has motivated the development of intelligent network in the 21st century [6].

2. Methods

This article has the character of experimental bibliographical. It is based on information from the IEEE Xplore Magazine regarding self-recovery in the areas of electricity distribution network and information from COPEL (Local Electric Power Concessionaire) and ANEEL (National Electric Energy Agency).

2.1 Artificial Neural Network (ANN)

ANN is a distributed and parallel system, which can be divided into several simple processing units, which are capable of processing the information obtained from the database. With this definition, it is observed that there are similarities between an ANN system and the nervous system, among them the ability to process information in several simple units, called artificial neurons, the interconnection capacity between these units, establishing ANN and the transmission of information (signals), through connections between the elements.

With respect to the storage of information, it can be emphasized that each interaction between the simple units is represented by an associated weight, varying according to the efficiency of the connection. The assessment of the environment provides information to build a knowledge base and is part of the learning process, and this process is basically responsible for adapting weights to the connections made in response to environmental stimuli [7].

In this paper we used an artificial neural network (ANN), backpropagation, which considers five different types of failure to solve the reclose restoration problem.

3. IEEE 123 nodes test feeder and tools used

In this work the proposal is a self-healing and restoration technique, in an IEEE 123 nodes test feeder model [8], because it is widely used and diffused in the academic environment, using Artificial Neural Network (ANN).

Firstly, a study was performed on the power flow in the model through OpenDSS software. Using the software information provided by the simulations, a database was built, consisting of more than two thousand information per failure. From the possession of the values of the

currents in the branches of the electric network were built 5 scenarios of failures in this network. These scenarios were then simulated by OpenDSS.

This database was then used to train ANN, which once trained, several tests were performed to obtain the desired information, thus evaluating the classification of the resulting failure type.

3.1 IEEE 123 nodes test feeder model

The IEEE 123 nodes test feeder model was chosen because it is an already consolidated model, operating at a nominal voltage of 4.16 kV. Although this is not a popular voltage level, it provides voltage drop problems that must be solved with the application of voltage regulators and shunt capacitors [8].

This circuit is characterized by aerial and underground lines, unbalanced load with constant current, impedance and power, four voltage regulators, shunt capacitor banks and multiple switches. The model used [8], presents minimal problems of convergence with respect to its equilibrium and it is shown in Figure 1.

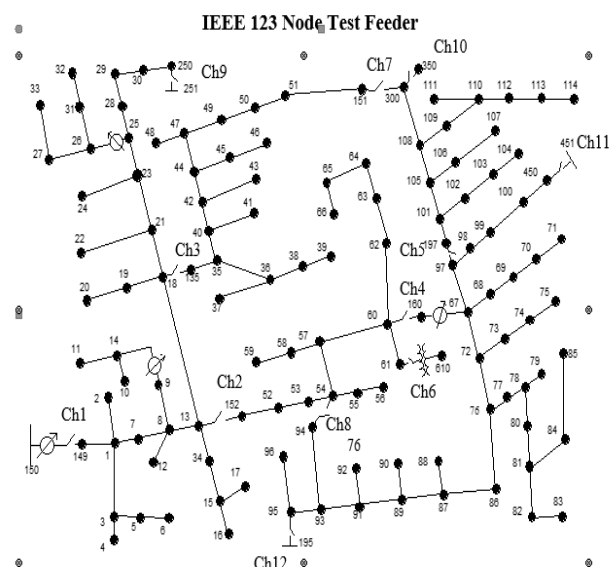


Figure 1: IEEE 123 nodes test feeder model.

3.2 The Open Distribution System Simulator

The Open Distribution System Simulator (OpenDSS, or simply DSS) is a simulation tool for electricity distribution systems.

OpenDSS refers to the open source DSS implemented as a standalone executable program for the in-process Dynamic Link Library (DLL) server designed to be moved from a variety of existing software platforms. The executable version has a basic user interface .

Figure 2 represents the IEEE 123 nodes test feeder model in OpenDSS. In it there is a main power impeded to

supply the electric circuit loads, due to a fault in the region where the substation is located.

To solve this problem, alternative feeders have been made available which will be able to re-connect as many consumers as possible, leaving only the defective sector isolated. After the maintenance sector solves the problem the faulty sectors will be reconnected.

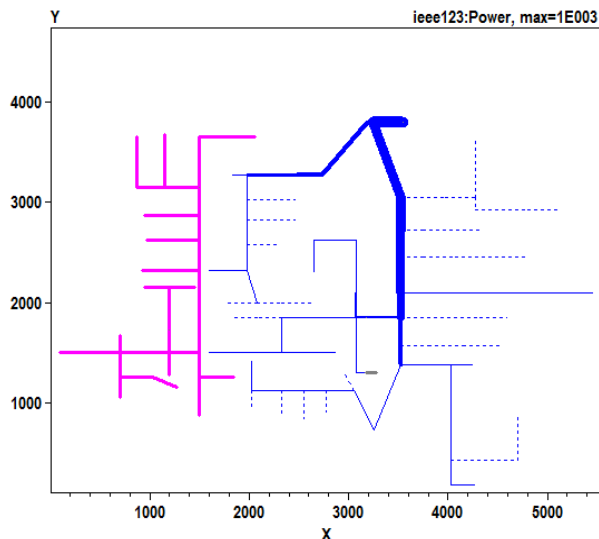


Figure2: OpenDSS Simulation – Failure 1.

Figure 3 demonstrates a case where the fault occurred in a region where the main power continues to supply the demand of the circuit, being maneuvered the faulty part so that it does not affect the others.

This is an ideal situation where the main feeder itself maintains its consumers with energy. The key needed was the detection of the short circuit and the opening of key number 3.

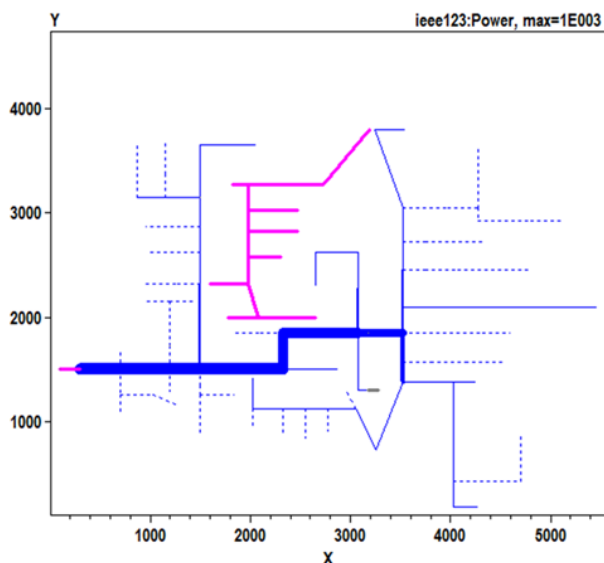


Figure3: OpenDSS Simulation – Faliture 2

Figure 3 shows the currents in the section between posts 108 and 300, see Figure 1, in each phase after the power flow, with the current remaining 314.872 A in phase A, 241.11 A in phase B and 252,095 A in phase C this seen

by the post 108 seen by the post 300 there is a small difference, usually at the angles, with the three-phase current being 62.4182, the same as was considered later in ANN training.

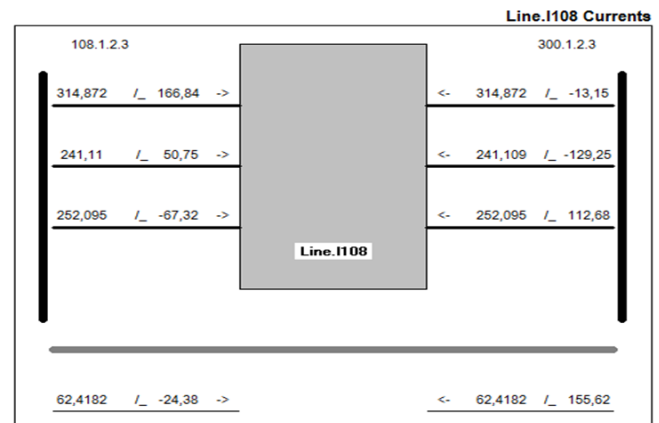


Figure4: OpenDSS Simulation – Currents

Table I shows the failures of the IEEE model and OpenDSS solutions. The normal line represents the default configuration of the software. Within a fault there are alternatives to reestablish electric power, depending on where it is located. The letters "a, b, c, d and e" are the possible alternatives without a simultaneous failure, and the numbers 0 and 1 represent the open and closed key, respectively.

3.3 Treatment of power flow results with artificial intelligence

With the results of the OpenDSS simulations, a spreadsheet with the electric currents was elaborated in each part of the system, that is, each piece between two consecutive posts.

In order to apply the neural network, the spreadsheet was divided into three parts, one for ANN training, the other for choosing the type of failure (five options) and the third and last one, the actual test of them.

Figure 5 shows that it took seven epochs for the training error to be below 0.0001%, with a pitch of 0.1. The chosen network was of backpropagation, being the architecture two entrances tansig and exit purelin. With this performance it required fifteen neurons for each layer, being two layers.

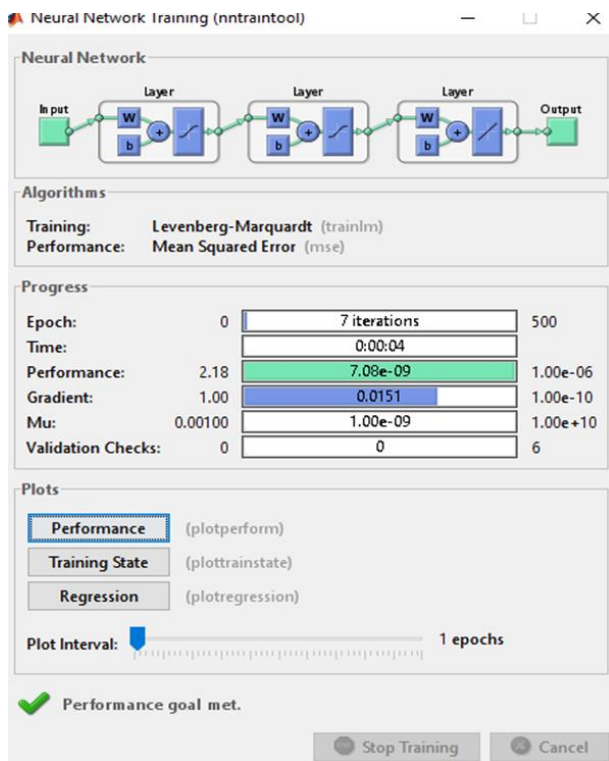


Figure5: Simulation – ANN

Table I. - Switching according to failure.

Failure	ch1	ch2	ch3	ch4	ch5	ch6	ch7	ch8	ch9	ch10	ch11	ch12
Normal	1	1	1	1	1	1	0	0	0	0	0	0
Failure 1	a	1	0	0	1	1	1	1	0	0	1	0
	b	1	0	0	1	1	1	1	0	0	0	1
	c	1	0	0	1	1	1	1	0	0	0	1
Failure 2	a	1	1	0	1	1	1	0	0	0	0	0
	b	1	1	0	1	1	1	0	0	1	0	0
	c	1	1	0	1	1	1	0	0	0	1	0
	d	1	1	0	1	1	1	0	0	0	0	1
	e	1	1	0	1	1	1	0	0	0	0	1
Failure 3	a	1	0	1	0	1	1	1	0	0	0	0
	b	0	0	1	0	1	1	1	0	1	0	0
	c	0	0	1	0	1	1	1	0	0	1	0
	d	0	0	1	0	1	1	1	0	0	0	1
	e	0	0	1	0	1	1	1	0	0	0	1
Failure 4	a	1	1	1	0	0	1	1	0	0	0	0
	b	0	1	1	0	0	1	1	0	1	0	0
	c	0	1	1	0	0	1	1	0	0	1	0
Failure 5	a	1	1	1	1	0	1	0	0	0	0	0
	b	0	1	1	1	0	1	0	0	1	0	0
	c	0	1	1	1	0	1	0	0	0	0	1
	d	0	1	1	1	0	1	0	0	0	0	1

Figure 6 shows the graph of performance in training. It is verified that before reaching the seventh epoch the mean square error is reached within the established limits.

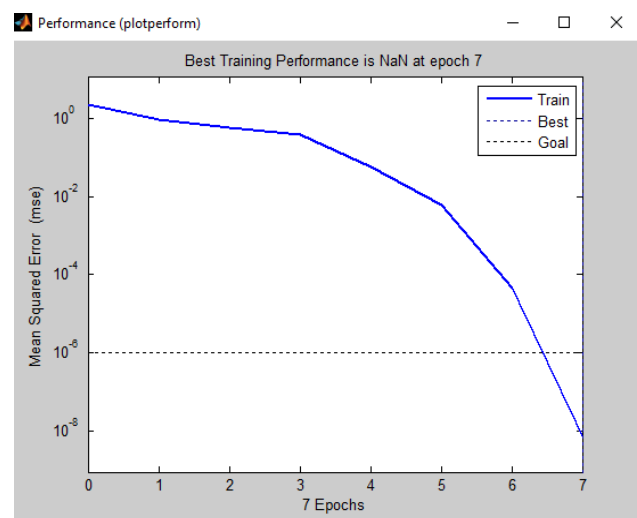


Figure 6: Training performance.

The Table II shows the results of the training performed in the neural network for each type of failure, the number of times that each training took to reach the solution, the time in seconds and the mean square error for each situation.

Table II. - Failure Summary.

Failure Summary Table			
Classification	Epochs	Time (s)	Error
Failure 1	3	17	0,025
Failure 2	6	42	0,066
Failure 3	7	4	0,088
Failure 4	17	38	0,023
Failure 5	4	8	0,045

4 Discussions

The focus of this article was on the reclosing of an electricity distribution network as soon as possible, considering that there was a failure in a certain part of the model.

According to [9], the solution of the problem of reestablishment of Electric Energy Distribution Systems (EEDS) is important. About this, several works have been developed as: Comprehensive Search Methods [10]; Automation Logics; Intelligent Systems [11], [12], [7].

Among the researches, it was observed that the researchers used many techniques of artificial intelligence to solve this type of problem, but little research was done using ANN for self-recovery, which motivated the choice of the technique.

In this way, it was possible to obtain the currents of each section through the power flow realized in the OpenDSS, and with this information to realize the classification of the types of failures through an ANN. This is similar to what [12] has researched.

The way the problem was solved was innovative with respect to time, within the parameters stipulated by the National Electric Energy Agency (NEEA), that is, the recovery of the network took less than 3 minutes.

In Table II it can be noted that the time to perform the ANN training was adequate to what NEEA establishes.

The time in excess of that established can be explored in the treatment of other variables, such as in the communication between the automation and the keys.

5 Conclusion

Through the DSS, the IEEE 123 nodes test feeder network was selected. Some adaptations were made, including keys that were disabled in the default configuration, which enabled them to be fed, in order to increase the reliability of the system.

For the study, these secondary feeds are capable of supplying the entire system's needs, given the new reality, since a defective part is isolated and will no longer participate in the total system load.

Another important point is how the failures were selected, the same by sectors, classifying them in five, that is, any failure within that region will provide the same switching solution to isolate it, although there may be alternative power sources through the faults.

No simultaneous faults were considered, but the method can be applied in other systems to solve other faults in electricity distribution networks.

Thus, it is necessary to perform other experiments, to confirm the efficiency of the method in real time and make known this new technique.

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