



DC/FAULT ANALYSES IN SMART GRID USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Detection, isolation and fault diagnosis have become necessary steps for improving the reliability of a smart grid (SG) operation. Several methods have been developed based on Kalman filter and other. Those methods allow detecting simultaneous faults, but can't select exactly the attacked busses. In this paper, we propose an improved method for detection and insulation in real time of multiple simultaneous faults in SG. It is based on an artificial neural network (ANN). For this, a mathematical model of a multi-bus network was used for the learning of the neural network developed. At the output of the neural model, a page-Hinkly test was performed to facilitate the detection steps. This method is able to detect and isolate any simultaneous faults on each bus.

Keywords: *Artificial Neural Network (ANN), Bus, Electrical Network, Matlab-Simulink, Page-Hinkly, Smart Grid.*

1. INTRODUCTION

Since the appearance of Smart Grid networks, the need for a comprehensive security has increased. Particularly, there are new physical faults or cyber-attacks [1]. Several methods have been developed, using Kalman filters, which are able to ensure the detection, isolation and diagnosis of one or more faults, attacks targeting data [9] [2] [3]. In [2] the type of attack is a fault injection in a DC electrical network.

In scientific research a lot of methods have been proposed to overcome the problems resulting from fault existence. Among these methods, are: Dedicated Observer Scheme (DOS) [15], and Generalized Observer Scheme (GOS) [16], used for faults detection and isolation [9]. Both methods are based on Kalman filter bank [6].

In [6] and [5] a method was developed for the faults detection in a double-feed AC generator. In [9] GOS was used for fault detection in Smart Grid, it is used with a chi-square detector capable of deciding whether or not the fault is present [16].

In [4] and [6], DOS has been proposed while in [6] fault detection in turbine generator has been presented. The latter method is capable to detect simultaneous faults using a technique that separately generates all residues. In [13] an ANN has been presented for a load predict in Smart Grid.

For SG, the proposed methods for detection and diagnosis of faults are developed in [9], [10] and [11]. Iterative Observer Scheme (IOS) has been proposed in [9], based on the Kalman filter and a chi-square detector [16]. GOS is able to detect a single fault or attack at the same time, but IOS is capable of detecting several attacks simultaneously [9]. In [10] a method based on "Computational Data Driven" was proposed and applied to an IEEE-39 bus system. In [11] a "Machine Learning" has been designed to detect false injected data stealth in SG too.

Collecting the various previously mentioned methods, we propose in this paper an artificial neural network to observe and supervise in real-time a Smart Grid system. A test page-Hinkly was suggested after the generation of residues to facilitate the detection step. A DOS property [15] was also used for the generation of residues. This method can detect and isolate faults on each bus of an n-bus network.

The paper is organized as follows, in section II, we will present the model for a DC multi bus system. to facilitate the calculation, we have used a 9-bus network.

In Section III of this part, we will explain the proposed method using ANN and Page-Hinkly testing. In section IV we will present the simulation

results obtained by Matlab. Section V will conclude this work in.

$$\theta_{t+1} = \theta_t + w_t \tag{5}$$

2. SYSTEM MODEL

For DC power transmission between consumers and producers, lines are used with large impedances [11]. The relation of the power transmitted between two points i and j is given by [9]:

$$P_{ij} = \frac{V_i V_j}{X_{ij}} \sin(\theta_i - \theta_j) \tag{1}$$

With : P_{ij} the transmitted active power of i to bus j, V_i and V_j are the voltage amplitudes, θ_j is the phase angle of bus j, and X_{ij} is the reactance between bus i and j, in this case X_{ij} is the resistance.

In DC mode, we always assume that the difference $\theta_i - \theta_j$ between two buses is small, and that the amplitudes of voltages on the bus are close to unity [18], [11]. Then we can get the following equation which linearly links the power and the phase angle. this equation is important to simplify the study:

$$P_{ij} = \frac{\theta_i - \theta_j}{X_{ij}} \tag{2}$$

Concerning the system state estimation, and with $\theta = [\theta_1, \theta_2, \dots, \theta_n]^T$ it is necessary to find a reference bus, for this we need only to estimate $n-1$ states [9].

By using m measured active power as one can get:

$$z = P(\theta) + e \tag{3}$$

With : $z = [z_1, z_2, \dots, z_m]^T$ the m active power measurements transmitted in the lines, $P(\theta)$ the non-linear relation between the measurements and the phase angles (state vector). $e = [e_1, e_2, \dots, e_m]^T$ is the Gaussian noise measurements vector.

Using the Jacobean matrix:

$$H = \frac{\delta P(\theta)}{\delta \theta} \Big|_{\theta=0}$$

We can write equation (3) as follows [9], [11]:

$$z = H \theta + e \tag{4}$$

And we can now write the state equation of the system by:

With: θ_{t+1} the state vector in the moment $t+1$, and w_t is the noise process.

Therefore, we find a relation in (4) linking the measured power and phase angles.

3. PROPOSED ANALYSIS

3.1. Artificial Neural Network:

From the model developed in (4), we can create a ANN (artificial neural network), able to observe in real time the SG system.

Figure (1) shows a single model of a neuron, with its activation function and its weight. However, figure (2) shows a multilayer neural network.

For each layer there are several neurons and their corresponding weight.

We used in our context a multilayer network whose regression and error histogram have been shown in figure.6 and figure.7 respectively.

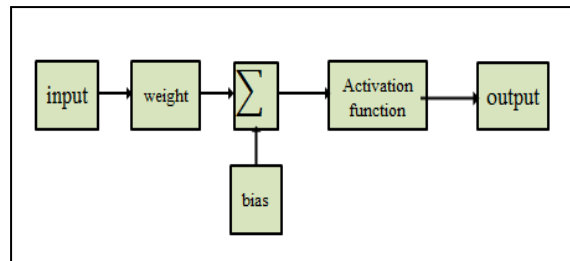


Figure 1: Neuron model of back propagation algorithm

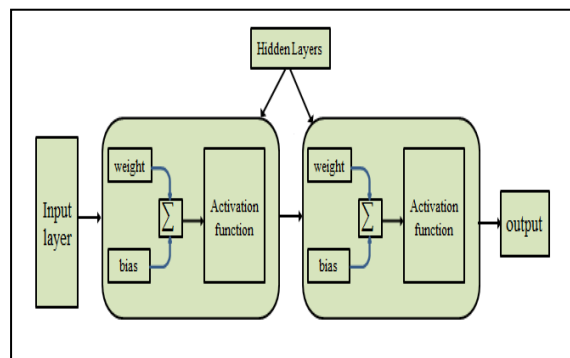


Figure 2: Architecture of multi-layer feed-forward network

In this paper, after the selection of the ANN structure, show in Figure 3 below reveals the operating principle of this proposed method:

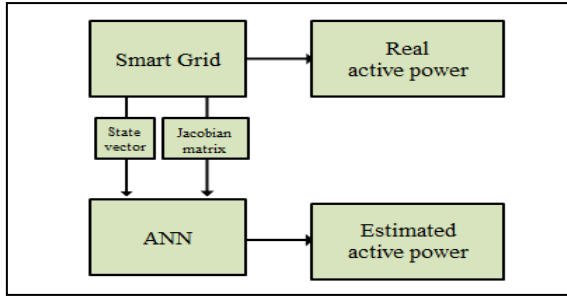


Figure 3. The Structure Of Analysis Proposed For Estimating Our Model

3.2. Page-Hinkly:

The Page-Hinkley Test was chosen with the aim of evaluating the error due to its low computational burden, simplicity, and anti-noise robustness.

- Residue generation: the residuals are the difference between the desired output and estimated output.

For this proposition, the i th residue is only sensitive to the i output bus.

If $|r_i| \geq \theta$ so the bus i is failed. with $|r_i|$ the absolute value of residue and θ the proposed threshold.

- Faults detection: after the generation of residues and if there is a fault, the value of corresponding residue will suddenly exceed the threshold at that moment and the evaluator based on Page-Hinkly takes the value of the unit, otherwise it remains at zero.

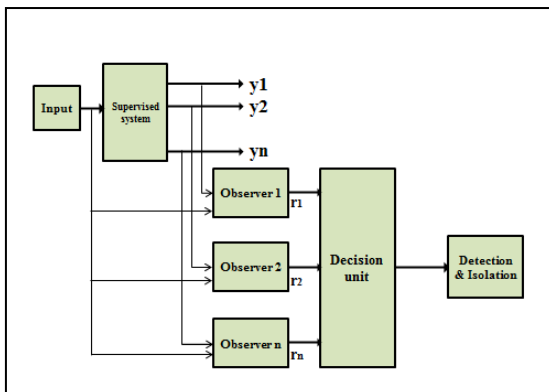


Figure 4: Structure of Dedicated Observer Scheme

also generating the matrix H [9], [17], [9], in order to simulate and test the reliability of our model.

A variable load between value [Min and Max] was generated to create a learning base for the ANN. A Page-Hinkly test model was realized under Matlab-Simulink.

After the generation of residues, the page-Hinkly test uses a threshold for testing the faults' absence or presence. If a residue exceeds the threshold (positive or negative) the detector is set to 1. Otherwise, the detector stays at 0. In figures (8) and (9) below, we will present only the step of the residues' evaluation.

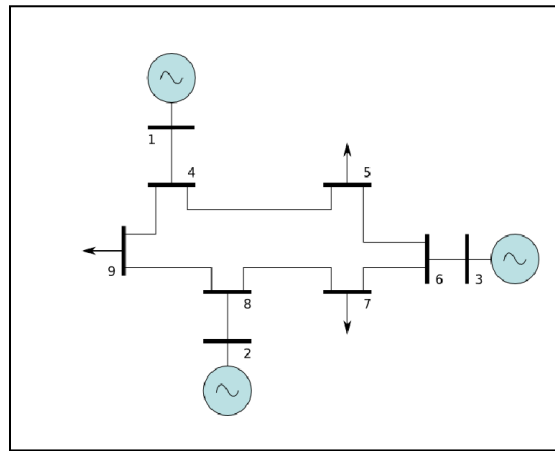


Figure 5 : System IEEE-9 bus

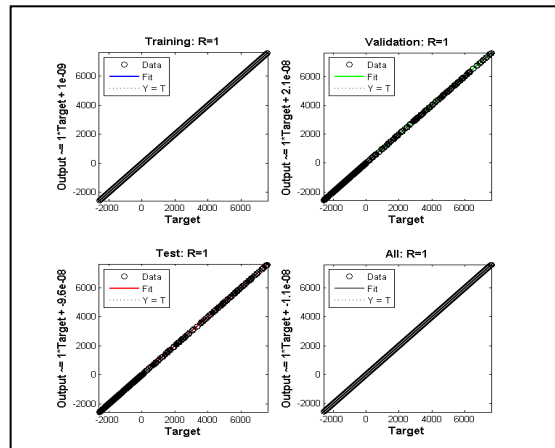


Figure 6 : The ANN Regression During Learning

4. SIMULATION AND RESULTS

Matlab toolbox was used to create and to make learning ANN. Matpower was used for solving and analyzing an IEEE 9-bus system (Figure 5), and

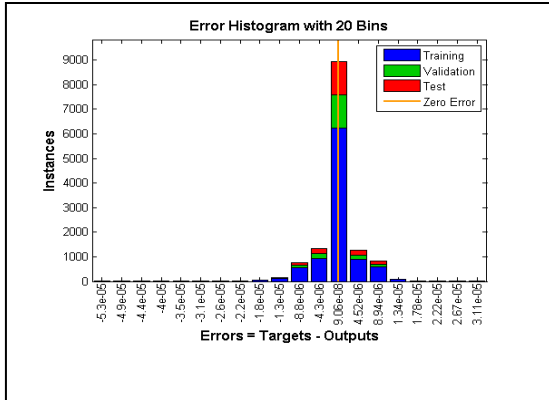


Figure 7 : Error Histogram

TABLE 1 : Fault Injection Times For Each Bus(non-simultaneous)

Bus number	Time starter(sec)
1	1.5
2	0.7
3	1
4	0.9
5	1.2
6	1.7
7	1
8	1
9	1.5

4.1. Faults In Different Instants (Non-Simultaneous Faults):

The attacks' instants are different, using Table1 this time; each bus is attacked in different times Figure (8).

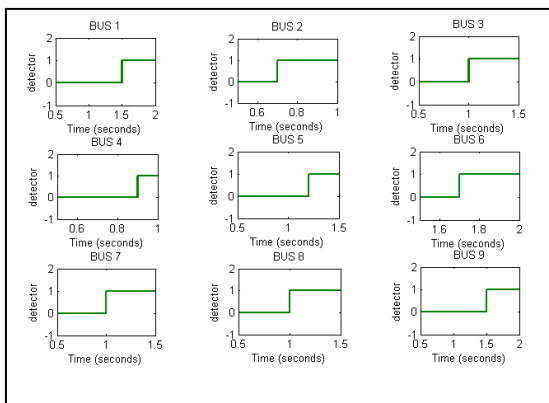


Figure 8: Display faults injected on the bus using the moment shown in Table 1. The detector can detect and isolated each faults. The residues with this bus will change their default values at injection timing, then the decision unit shows and stays 1 at that point.

TABLE 2 : Same Fault Injection Times For Each Bus (Simultaneous Faults)

Bus number	Time starter (sec)
1	1.5
2	1.5
3	1.5
4	1.5
5	1.5
6	1.5
7	1.5
8	1.5
9	1.5

4.2. Faults At The Same Time (Simultaneous):

This time using the same injection time fault Table2 to test the possibility and the power of this detector if all buses are under simultaneous attack and at the time of injection (Figure 9).

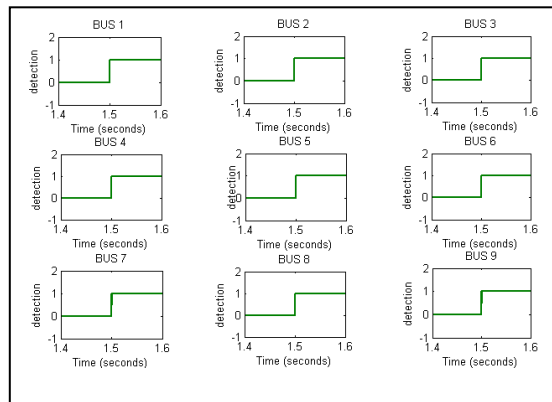


Figure 9: injected fault display on all buses at the same time 1.5 seconds, the detector can detect and isolated each fault, all residues corresponding to these buses will change their values at that moment, so the decision unit shows and stays 1 at that point..

4.3. Comparison:

Figure 10 shows the detection used in IOS method developed in [9].

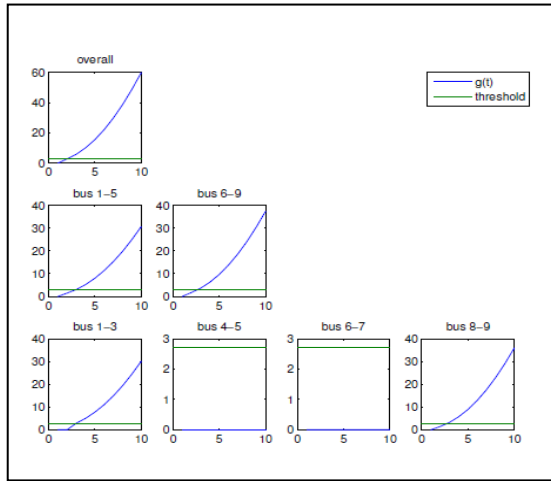


Figure 10 : Detection Of Faults Injected In Bus 2 And 8, Using IOS In [9].

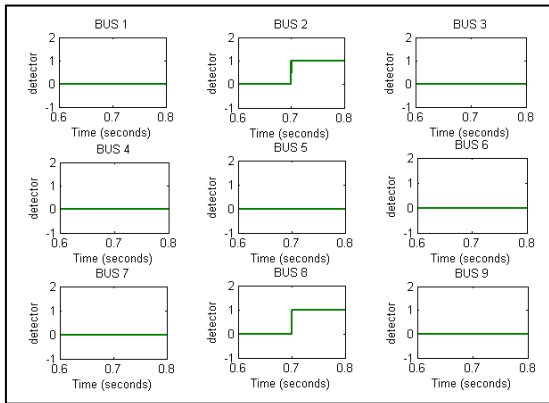


Figure 11: Detection Of Faults Injected In Bus 2 And 8, Using Our Proposition In This Paper.

We can notice that our proposal can detect and isolate faults injected to each bus, and accurately determine the damaged bus. While in IOS we can say that there is a fault between 1-3 bus and another between 8- 9, but this latter method cannot accurately determine the damaged bus.

5. CONCLUSION

A fault detection system based on ANN and Page-Hinkly was proposed in this paper which is able to detect and isolate faults on each bus in DC power grid. It thus provides an accurate observation in real time on all buses in the Smart Grid.

This method uses intelligence, reliability and efficiency of ANN to supervise in real time an SG with any number of buses.

This method can be used to develop a complete system of faults diagnosis of smart grid.

In the future work, we plan to explore the possibilities of using the developed method to AC power grid.

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