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Detection of Faults on STATCOM Compensated AC Transmission Line by ANN

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***Abstract*— This paper presents an algorithm for the detection of faults on transmission line compensated with Static Synchronous Compensator (STATCOM) using on Artificial Neural Network (ANN) technique. A feed-forward ANN has been developed for the detection of faults. Data was generated by simulating a 400 kV, 50Hz, 200 km transmission line with STATCOM connected at the midpoint in PSCAD/EMTDC. Back-propagation algorithm has been used. RMS values of line voltages and currents have been used as inputs to the ANN. The ANN was trained at 0 degree and tested at 90 degree. Fault was accurately detected at 5ms delay.**

***Index Terms*— Artificial Neural Network, Static Synchronous Compensator (STATCOM), Transmission Line Protection.**

I. INTRODUCTION

In the recent past, particularly the last few decades, the world has seen a rapid growth in the power grid system which in turn has resulted in the installation of new transmission and distribution lines on a large scale basis. Any disproportionate flow of current in a power system is designated as a fault in that particular power system. Apart from technical reasons, some faults are known to occur due to natural reason and hence cannot be prevented easily. This gives rise to the necessity of having very well-coordinated protection systems to detect any abnormal flow of current in the power system. The identification of anomalies should be done easily by this detection system added with its accurate position in the power system. The Faults are mended usually by the fault occurrence detector while separating the section of fault from the remaining power system.

Therefore, detection, classification, and locations are among few of the important challenges for undisturbed supply of power. The various types of faults namely transient, persistent, symmetric or asymmetric faults all are having their own sense of distinctly unique of detection process. Due to the lack of insulation, the faults are more occurring in high voltage transmission lines than in distribution lines which possess insulation around the cables. There are multiple reasons for occurrence of faults on a transmission lines, such as contact with a tree or bird or any animal contact. The transmissions lines are altered due to natural occurring also like, thunderstorm or lightning. Also the surface area out in the open contact with free air should be minimum. Due to the extra longitivity of transmission lines, the major portion of research done in the field of contact or any other natural reason concentrates on the protection of faults in the transmission line. This is because of the fact that transmission lines are very long and it can take anything from just a few minutes to several hours to check the lines for fault.

Some last years have been used with intelligent based methods for fault detection and locations to the technological advancements in this field. The three most important and effective techniques based on artificial intelligence that has been most commonly taken use of are:

1. Expert System Techniques
2. Artificial Neural Networks
3. Fuzzy Logic Systems

The ANN compensated with STATCOM has been used rigorously for fault detection on transmission lines. The ANN need not require the positions of faults unlike other artificial intelligence based methods.

II .SIMULATION

A transmission line of 400 KV, 200 km has been simulated in PSCAD/EMTDC. The transmission line is compensated with STATCOM at the midpoint by means of a breaker. The line is subjected to three phase fault at two locations (mid-point and remote end) with two values of fault inception angles (0 degree and 90 degree). Figure 2 shows the simulation diagram of the system. System consist of one generator of 400kV located on one side of the STATCOM compensated transmission line along three phase fault module used to simulate faults at various positions on transmission line. The line has been modeled using distributed parameters so that it more accurately describes a very long transmission line.

The transmission line (line 1 and line 2) is 200km and the three phase module is used to simulate fault at varying locations along the transmission line. The values of the three-phase rms voltages and currents are measured and modified accordingly and are ultimately fed into the neural network as inputs. The neural network toolbox has been used to generate the entire set of training data for the neural network in both fault and non-fault cases.

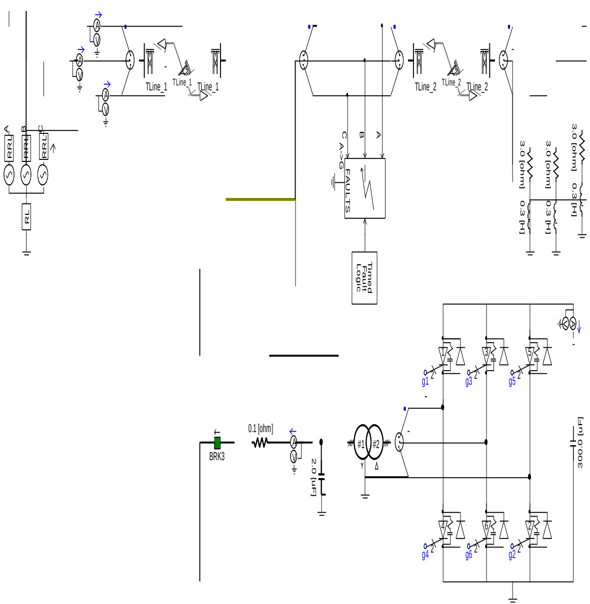


Figure 1: Simulation in PSCAD

III. GENERATION OF DATA

Data has been generated at the relay location to be used as input to the ANN for training and testing. Six inputs are used. Hence six signals have been generated to obtain the data for training and testing.

The multi-meter block is used to measure the voltage and current samples at the terminal A B and C. The transmission line (line 1 and line 2 together) is 200 km long and the three-phase fault simulator is used to simulate symmetrical fault at varying locations along the transmission line with different fault inception Angle and location of fault. Six different values of I_a, I_b, I_c, V_a, V_b, V_c are measured.

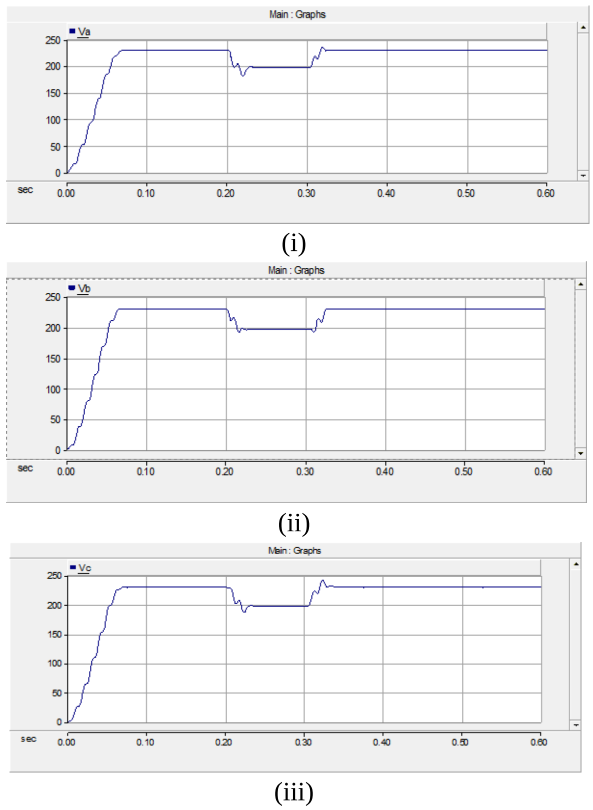
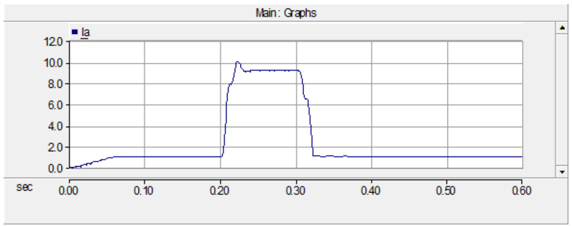
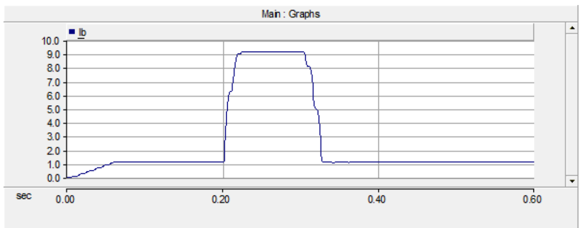


Figure 2: RMS values of line voltages



(i)



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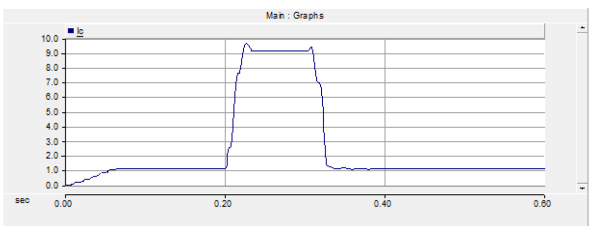

(iii)

Figure 3: RMS values of line currents

IV. TRAINING AND TESTING OF ANN

The goal of this work is to propose an integrated method to perform each of these tasks using artificial neural networks. A back-propagation based neural network has been used for the purpose of fault detection.

Although the basic concept behind relays remains the same, the digital technology has had a significant influence on the way relays operate and have offered several improvements over traditional electromechanical relays.

In fault detection phase, the network takes in six inputs at a time, which are the rms voltages and currents for all the three phases for symmetrical fault and also no-fault case.. The output of the neural network is just a yes or a no (1 or 0) depending on whether or not a fault has been detected.

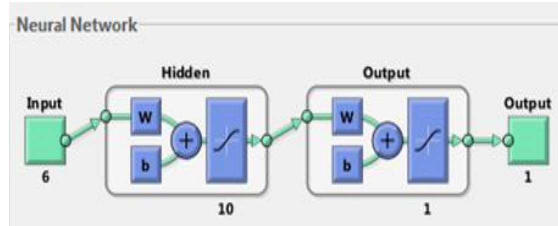

Figure 4: ANN Configuration

A. Results in Training

The output of the neural network is a yes or a no (1 or 0) depending on whether or not a fault has been detected. In training the inputs are three phase rms voltages, currents, used with different fault inception angles with varying fault location (10, 50 km).

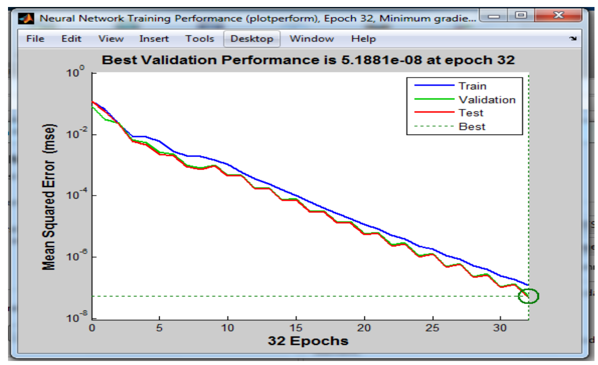

Figure 5 Mean-square error performance of the network with a delay of 5 ms

From the figure 5 training performance plots, it is to be noted that very satisfactory training performance has been achieved by the neural network with the 6-10-1 configuration. The overall MSE of the trained neural network is way below the value of 0.01 and is actually 5.1881e.8 by the end of the training process. Hence this has been chosen as the ideal ANN for the purpose of fault detection.

The other means of testing is by confusion matrix which is shown in Fig 6. The diagonal cells in green indicate the number of cases that have been classified correctly by the neural network and the off diagonal cells which are in red indicate the number of cases that have been wrongly classified by the ANN. The last cell in blue in each of the matrices indicates the total percentage of cases that have been classified correctly in green and the vice-versa in red.

Figure 6 shows the confusion matrix which tells the accuracy of 100% of fault detection with 5 ms delay.

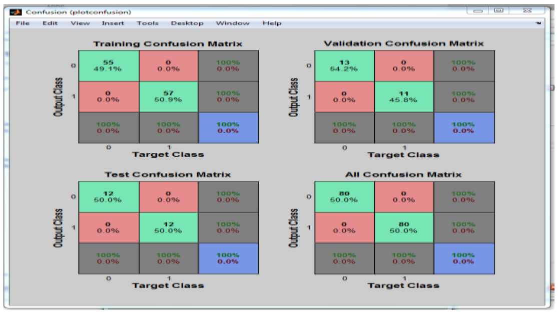

Figure 6 Confusion matrix with 5 Samples delay

B. Results in Testing

Once the neural network has been trained, its performance has been tested by different factors. There are same testing data sets except for different fault inception angles (90 degree).

Figure 7 shows the confusion matrix which tells the accuracy of 98.8% of fault detection without any delay.

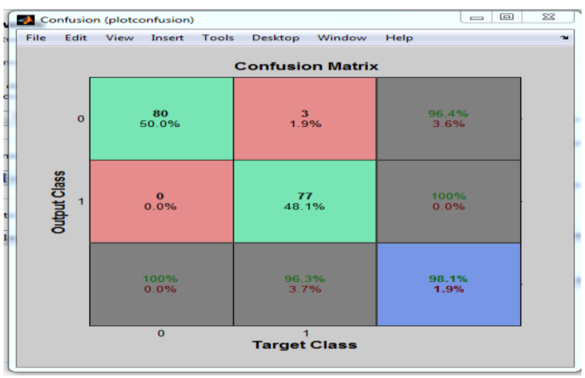

Figure 7 Confusion matrix without any delay

V. CONCLUSION

This work has focussed on a new viable and feasible method involved in the detection of faults at different points in the circuit and also the fault inception angles on transmission lines reinforced with STATCOM. The various techniques involved make use of rms of the phase voltages as well as phase currents. For over 100 km length transmission line (400KV/50 Hz) the simulation was done in PSCAD/EMTDC. The resulting data was used in the testing and training of ANN. Simulation of three phase faults on PSCAD/EMTDC has been carried out in the work.

The resulting demonstration of the working of back propagation (BP) neural network architecture has displayed highly satisfying results. The study of neural network as viable alternative method to identify faults on STATCOM compensated transmission line. The employment of the rms phase voltages and currents as inputs to the neural network system were achieved 1KHz was the sampling frequency adopted for the sampling voltage and current waveform.

The MATLAB software is used in combination with PSCAD/EMTDC software to obtain the simulation of whole power transmission line model and obtaining the training data set. There has been extensive use of the Artificial Neural toolbox to evaluate the performance of networks. Maximum relay operating time is $1/4^{th}$ of a cycle for the fault detection in obtaining the 100 % accuracy which provide the convergence/operating time for the relay to make a trip decision.

It can be provided further extension to tabulate the faults and point out the faulted phase. Also this work can be extended to other categories of transmission lines which include lines with FACT devices double circuit lines and series compensated lines.

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