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Design of a Data Driven Model for Automated Fault Detection in HVDC Transmission Systems

Rajesh Nayma[1], Dr. Saurabh Gupta[2], Dr. Devendra Sharma[3]

Abstract: With a continuous escalation in demand of power, the Indian Electrical system is in constant demand for long transmission lines to fulfill its requirement due to extremely distributed demand and generation location. Advanced HVDC system is one such possibility that finds its utility, especially during long-distance transmission. Such electrical transmission systems are prone to short circuit faults, which subsequently leads to a large current, which will eventually harm or damage the system's equipment. Thus, the system requires a quick restoration in order to reestablish power transmission and assure system safety. Hence, the objective of this work is to develop a model, which can precisely assess the location of the fault. The work intends to cultivate a model, which will not only provide accurate results but is also collectively optimal. A Bi-polar transmission line 814 km long and operates at 700 kV, with the ability to transfer 1500 MW of power, developed on PSCAD/EMTDC software based on CIGRÉ benchmark guidelines. The designed model is further simulated for short circuit fault with fault ON resistance of 0.01 Ω and fault OFF resistance of 1.0 x 10^6 Ω with varying fault location along transmission line at an interval of 1 km. The acquired data collected and processed for feature extraction. Data from both the ends of the transmission line is used for training and testing of deep neural network models. The evaluation of the proposed system has been done based on the mean squared error and accuracy of fault estimation. It is shown that the proposed system outperforms contemporary baseline approaches.

Keywords: HVDC, Fault Location, Machine Learning, Deep Learning, Mean Squared Error, Accuracy.

1.Introduction

In the present era of deregulation and competition, demand from every energy supplier is to have good continuity, dependability and reliability. Fault location can play a vital role in achieving this aim. As uninterrupted power supply is the prime demand by all consumers. However, faults in power system will leads to the interruption in power supply and it will make system vulnerable towards system outrage/collapsing and will lead to damage various electrical peripheral of switch gear/ electrical equipment. Hence all faults are required to be detected and clear as soon as possible to restart power supply to consumer. Having accuracy knowledge of fault

location will come very handy in reducing system outrage time and they're by improving continuity and reliability of system.Various researches have been done previously towards finding accurate result. In this work, location detection using the mathematical neural network technique is presented. The goal of the work is to prepare a model which can somehow manage to give accurate fault location on HVDC line thus helps in improving the system performance. The proposed work is designed with a motivation to achieve higher accuracy of detection compared to existing work.

2.The HVDC Transmission System

HVDC stands for High Voltage Direct Current. It is generally used for bulk power transmission over long distances. Typically, the cost incurred in ac transmission becomes more compared to dc transmission in case the transmission distance is greater than 700km, which typically is considered the point of break-even. While the initial set up cost and equipment cost for the dc transmission system is grater compared to the ac counterpart, but the transmission losses account for a staggeringly large compensation cost in case of ac transmission which make dc transmission cheaper for larger distances.

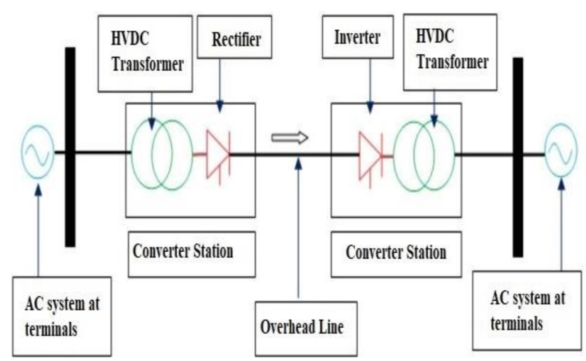

Figure 1 The HVDC System Model

Traditionally, in HVDC transmission (500kV-600kV) the losses accounts for almost about two -three times less than its counterpart HVAC for same amount of power leading to the savings of a large amount of power which can be utilized for the far remote areas of our country where still continue supply electricity is a big challenge due to shortage of electricity.

3. Fault Estimation Using Neural Networks

Typically, the most common fault type encountered in dc transmission is the line to ground (LG) fault. As the fault occurs, it has been found that the occurrence of fault impacts the following parameters.

1. Rectifier side AC Voltage
2. Rectifier side AC Current
3. Rectifier side DC Voltage
4. Inverter side AC current
5. Inverter side AC Voltage
6. Inverter side DC Voltage

Thus the generator side rectifier voltages and currents are impacted by the occurrence of faults. Similarly, the inverter side voltages and currents are also impacted by faults.
Although no transmission of power takes place once the fault has occurred, but just prior to the fault occurs, the instantaneous values of voltages and currents at the rectifier and inverter are affected. It is noteworthy, that the distance at which the fault occurs governs the values of the instantaneous values of rectifier and inverter voltages and currents. Typically, the distance of fault from Generator is considered to be the dependent variable

4.Methodology

The methodology proposed in this paper can be thought of as a sequential implementation of the following steps:

1. Design a standard CIGRE HVDC model on a simulation platform (PSCAD) in this case.
2. Generate faults at regular intervals of 1km each along the line. It is to be noted that 15km from both generator and load sides need to be left out for avoiding ambiguity in faults on the transmission line or the generator/load itself.
3. Tabulate the values of the rectifier and inverter voltages and currents for the various distances of the faults occurring on the transmission line.
4. Design a back propagation based neural network for pattern recognition.
5. Train the neural network with the voltages and currents as dependent variables and the distance of the fault as the independent variable.
6. Use 70% of the data for training and 30% of the data for testing. The bifurcation should be made randomly.
7. Compute performance metrics such as mean squared error and number of iterations to convergence.

A sequential description of the methods adopted in described subsequently.

Artificial Neural Networks (ANN) are one of the most effective techniques for time series or regression problems. The output of the neural networks is given by:

$$y = f\left(\sum_{i=1}^{n} x_i w_i + \varphi\right) \qquad (1)$$

Here,
y is the output
x are the inputs
w are the weights
φ is the bias
f stands for the activation function
The commonly logic or activation functions used are the sigmoid, log sigmoid, tangent-sigmoid, rectified linear (ReLu), step or hard-limiting function etc..In the previous approaches, there are several techniques and mechanisms to train a neural network out of which one of the most effective techniques is the back propagation based approach. The flowchart of back propagation is depicted in figure 4. The benefit of the back-propagation based approach is the use of the feedback mechanism from the out of the neural network to the input of the neural network thereby affecting the training in each iteration with the error of the previous iteration. This helps the neural network not only in finding patterns in large and complex data sets but also learn from its own errors. Mathematically, it is given by:

$$Y_k = f(X, e_{k-1}) \qquad (2)$$

Here,
Y is the output of kth iteration
X is the input to the kth iteration
e_{k-1} is the error of the (k-1)st iteration
f stands for a function of.

The flowchart of the back propagation algorithm is depicted in figure 4.

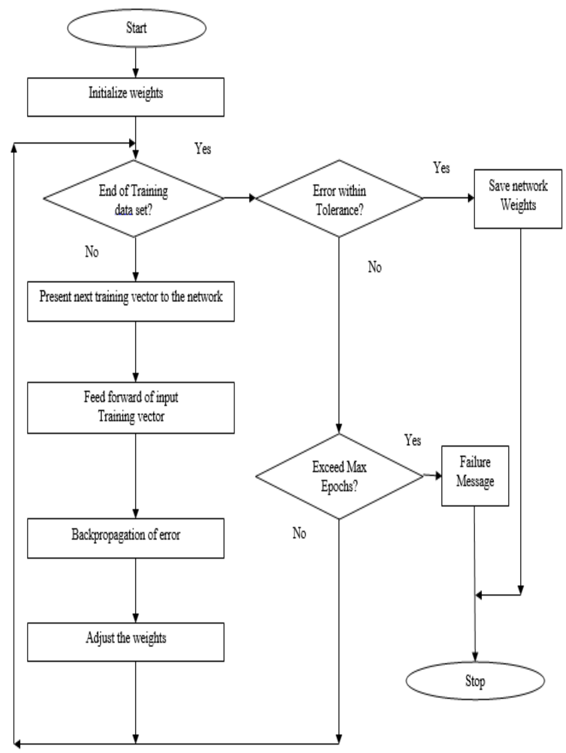

Figure 2 Flowchart of Back Propagation in ANN

The salient take away from the back propagation flowchart are:

1. Initially the training is started with random weights.
2. The weights are updated with each iteration as the fault data is fed to the network.
3. The error in each iteration becomes an exogenous input to the network which in turn impacts the weights in each subsequent iteration.
4. The training vector is fed and training is continued till one of the two conditions are fulfilled:
   A) Cost function (MSE) stabilizes.
   B) Maximum iterations are exhausted (1000).
5. Once any of the above conditions are satisfied, the training is terminated and the performance metrics can be computed.

The back propagation training rule can be stated mathematically as;

The rate at which the error falls is one of the most critical factors in training a gradient descent based neural network. The rate of error decrease in generally designated by a negative quantity and is mathematically represented by the gradient (g).

$$error = p - a \quad (3)$$

Mathematically,

$$g = \frac{\partial e}{\partial w} \quad (4)$$

Here,
p is predicted value
a is actual value
g is the gradient
e is the error
w is the weight

The training rule for gradient descent is given by:

$$w_{k+1} = w_k - \left[J_k J_k^T + \mu I\right]^{-1} J_k^T e_k \quad (5)$$

Here,
k is present iteration
k+1 is next iteration
w_k is weight of present iteration k
w_{k+1} is weight of next iteration (k+1)
e_k is error of present iteration
J_k is the Jacobian Matrix which contains 2nd order derivatives of errors w.r.t. weights i.e. $\frac{\partial^2 e}{\partial_w^2}$
J_k^T is the transpose of the Jacobian Matrix
I is an identity matrix
μ is the step size or combination co-efficient which is the amount by which the weight changes in each iteration

The rate at which the error falls is one of the most critical factors in training a back propagation based neural network. The rate of error decrease in generally designated by a negative quantity and is mathematically represented by the gradient (g). Mathematically,

$$g = \frac{\partial e}{\partial w} \quad (6)$$

Here,
g is the gradient
e is the error
w is the weight

The HVDC system would be designed in Power Systems CAD Softtware (PSCAD). This tool provides flexibility to simulate model ranging from nanoseconds to seconds. PSCAD finds wide application in planning, operation, design and commissioning.

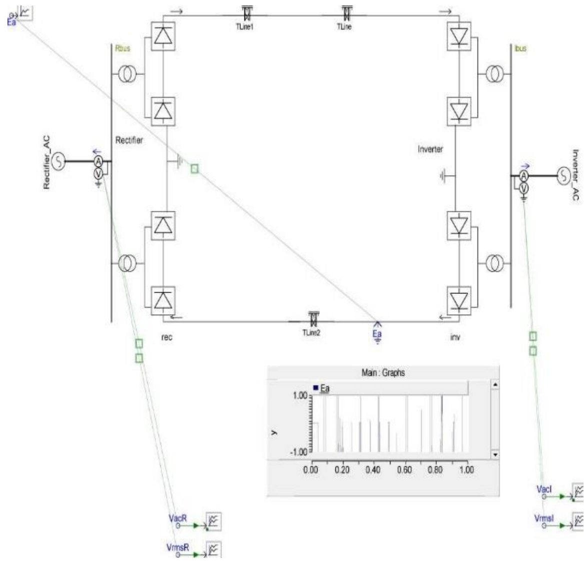

Figure 3 The PSCAD Model for HVDC

It is necessary to train the neural network is such a way that it attains convergence in less number of iterations.

Figure 6 Feeding neural network with training parameters. Since the weight varies as a function of iterations (n), clearly gradient is also a function of the iteration number (n)

5.Simulation Results

The details of the PSCAD model are depicted in figures 4 and 5.

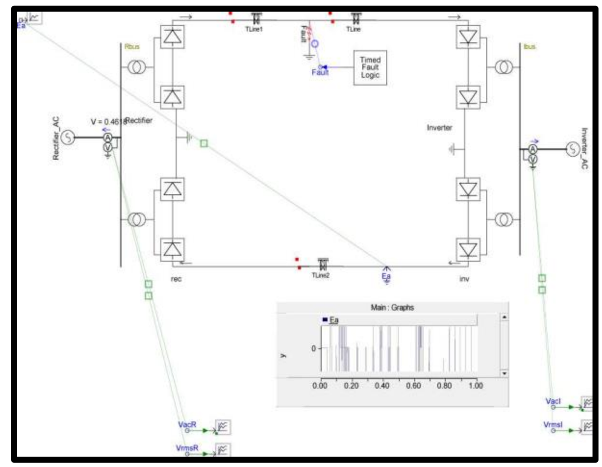

Figure 4 T-Line Section with LG Fault

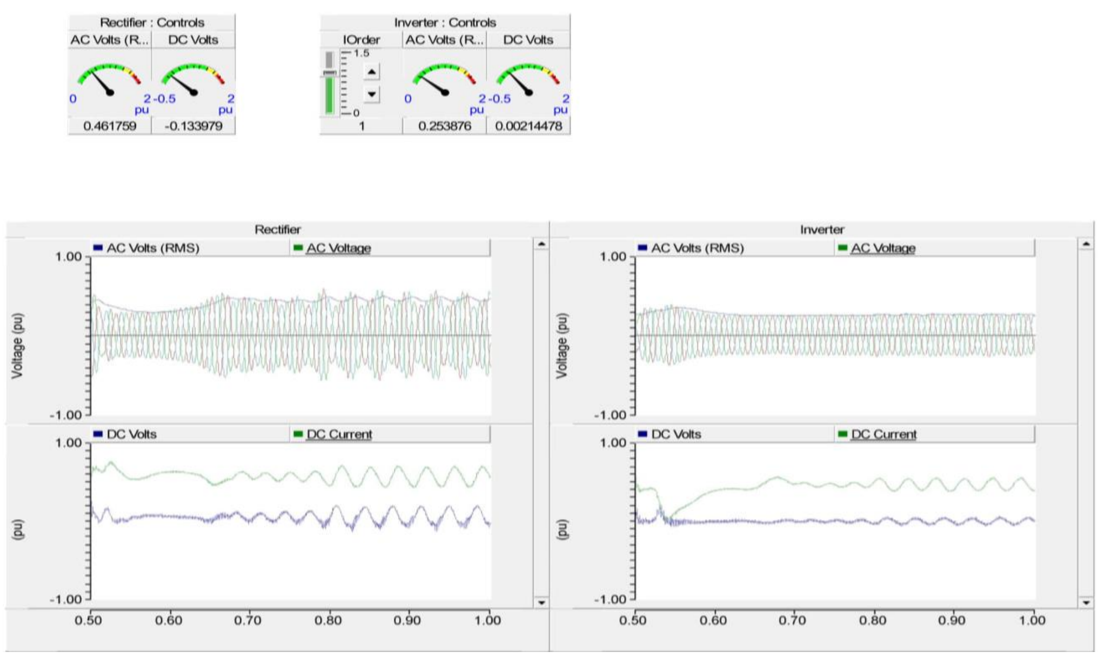

Figure 5 Rectifier and Inverter Voltages and Currents for the LG fault condition

Table 1. Data generated after generation of faults on the T-Line.

distance from rectifier side(in KM)	rectifier side dc voltage	rectifier side ac voltage	rectifier AC current	inverter side dc voltage	inverter side AC voltage	inverter AC current
784	-0.153431	0.482629	-0.0114851	0.0024935	0.255724	0.0201792
785	0.0239929	0.48439	-0.013506	-0.0104698	0.254981	0.0199629
786	0.0522543	0.478397	-0.0138247	-0.0107615	0.255333	0.0200645
787	-0.113336	0.469223	-0.011613	-0.00488431	0.255068	0.020443
788	-0.119555	0.471921	-0.0114958	-0.00285127	0.255178	0.0204267
789	-0.00546305	0.438314	-0.0150871	0.0102227	0.255622	0.0212443

The values generated through the simulation of the transmission line with faults at every kilometre has been depicted in table 1. There are a total of 6 variables which are dependent on the distance of the fault from the generator side. Subsequently the fault data is fed to the neural network that is designed on MATLAB for pattern recognition.

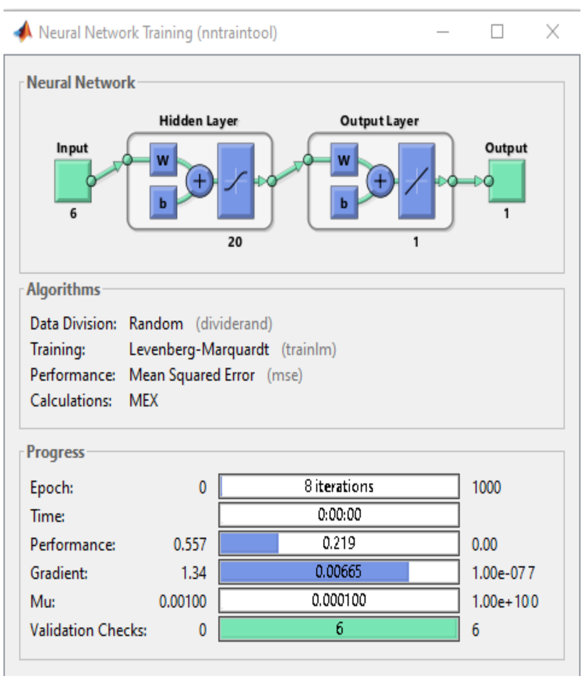

Figure 6 Designed Neural Network Model on MATLAB for fault estimation

The summary of the results are depicted in table 2, which are used to evaluate the performance of the proposed system.

Table 2. Summary of parameters

S.No.	Parameter	Value
1	T-Line Length	816km
2	ANN structure	6-20-1
3	ANN Topology	Back Propagation
4	MSE	0.219
5	Mean error	.467
6	Regression	.9816

It can be observed that the proposed system attains a very small mean error of only .467km. The accuracy can be attributed to the use of the back propagation algorithm employed in the work and the multitude of variables dependent on the distance of the fault.

6.Conclusion and future work

It can be concluded from the previous discussions that the proposed system is capable of detecting faults in high voltage DC transmission lines based on the neural network model. The rectifier and inverter side voltages and currents for both fault and non-fault conditions have been generated on PSCAD and the correlation among the variables has been analyzed by the gradient descent trained neural network. It can be observed from table 1 that the system attains a mean absolute percentage error of just 1.1 km which is extremely less for a DC transmission line fault location.

The conspicuous advantage of the designed system is the fact that the proposed system is able to identify faults on the line with relatively high accuracy. Moreover, the iterations are moderate rendering to moderate space and time complexity for the proposed algorithm. Thus the proposed approach can serve as an effective automated tool for automated and accurate fault estimation mechanism for HVDC systems.

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