Locating Faults on HVDC Transmission Systems Using Neural Network Model

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Abstract: The HVDC system is a viable option, particularly for long-distance transmission. Electrical transmission systems are susceptible to short circuit problems, resulting in excessive current that can ultimately damage the system's equipment. Consequently, the system necessitates prompt repair to reinstate power transmission and ensure system safety. Therefore, the aim of this study is to create a model that can accurately determine the fault's position. The objective of the effort is to develop a model that yields precise findings while also being collectively optimal. A bipolar transmission line, measuring 814 km in length, operates at 700 kV and has the capacity to transmit 1500 MW of electricity, constructed using PSCAD/EMTDC software in accordance with CIGRÉ benchmark requirements. The constructed model is subsequently simulated for a short circuit defect with an ON resistance of 0.01 Ω and an OFF resistance of 1.0 x 10^6 Ω, altering the fault location along the transmission line at 1 km intervals. The collected data was processed for feature extraction. Data from both terminals of the transmission line is utilized for the training and evaluation of deep neural network models. The assessment of the suggested system was conducted based on the mean squared error and the accuracy of fault estimation. The suggested system demonstrates superior performance compared to current baseline methods.

Keywords: Neural Network, Fault Location, HVDC, PSCAD, 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.

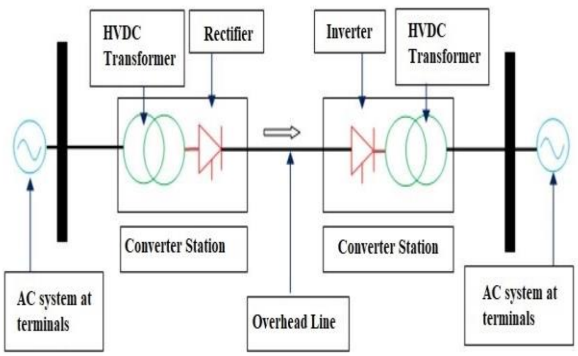


Figure 1 The HVDC System Model

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:

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

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:

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

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.

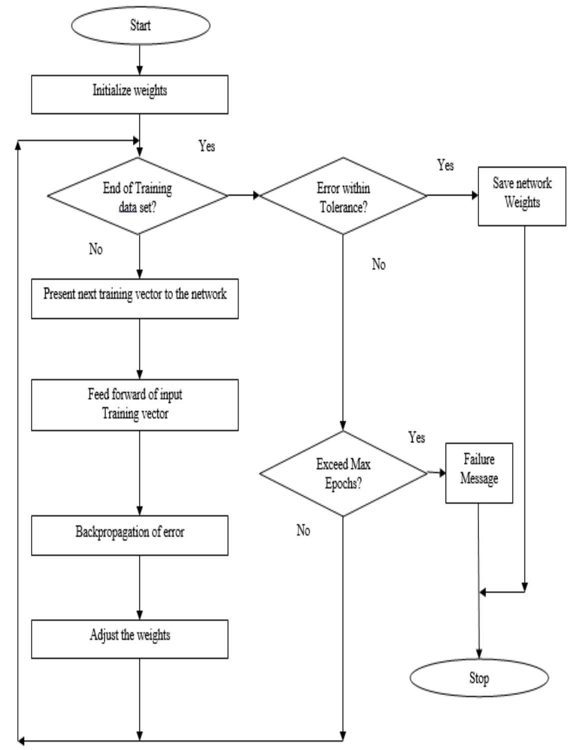


Figure 2 Flowchart of Back Propagation in ANN

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).

$error = p - a$ (3)

Mathematically,

$g = \frac{\partial e}{\partial w}$ (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:

$w_{k+1} = w_k - \left[J_k J_k^T + \mu I\right]^{-1} J_k^T e_k$ (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 2^{nd} 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,

$g = \frac{\partial e}{\partial w}$ (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.

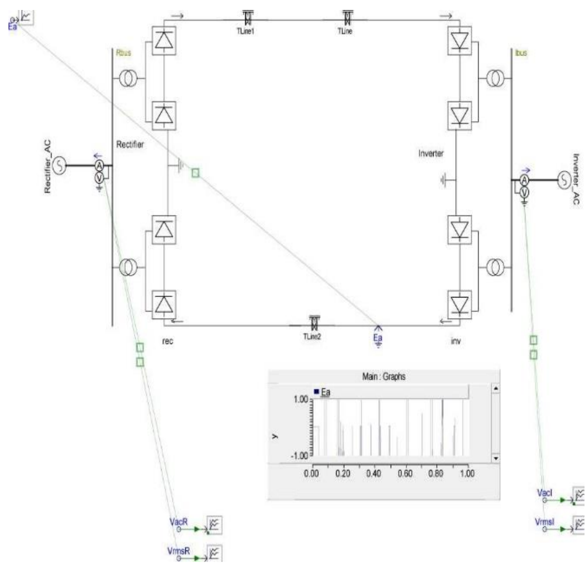


Figure 3 The PSCAD Model for HVDC

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.

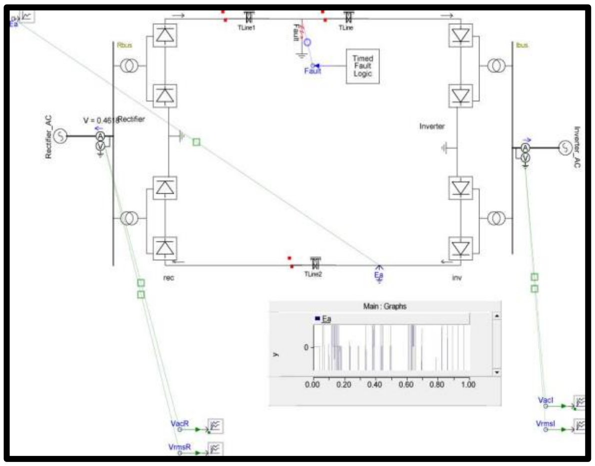
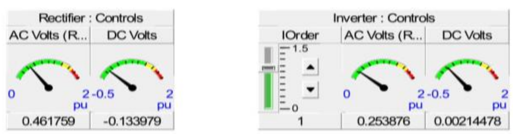


Figure 4 T-Line Section with LG Fault



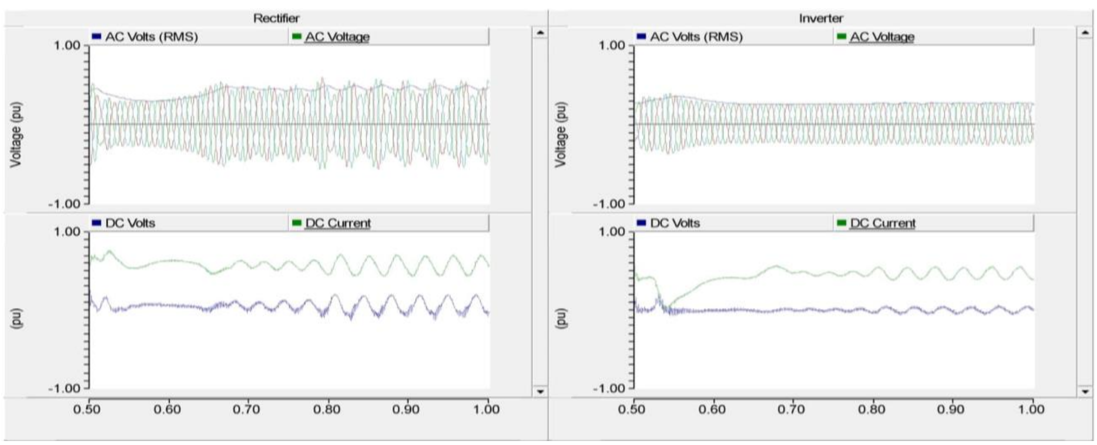


Figure 5 Rectifier and Inverter Voltages and Currents for the LG fault condition

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.

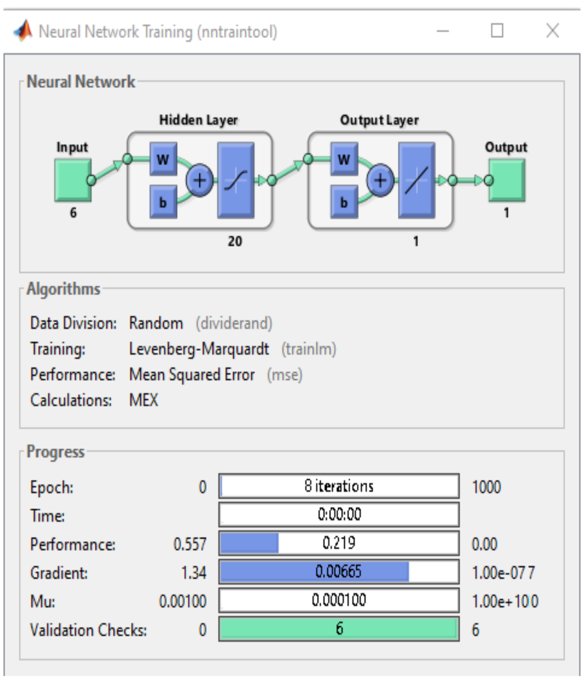


Figure 6 Designed Neural Network Model on MATLAB for fault estimation

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

The conclusions drawn from the above discussions indicate that the neural network model-based suggested system can identify defects in high voltage DC transmission lines. Using PSCAD, we have measured currents and voltages on the rectifier and inverter sides under fault and non-fault scenarios, and we have used a neural network trained using gradient descent to examine the relationships between these variables. Table 1 shows that the method achieves a very low mean absolute percentage error of around 1km kilometers while locating faults in DC transmission lines.

A notable benefit of the system's architecture is its ability to detect line failures with a reasonable degree of precision. In addition, the suggested algorithm's iterations have a moderate impact on both space and temporal complexity. This means that the suggested method has the potential to be a

useful automated tool for HVDC systems' automatic and precise fault estimation mechanisms.

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