INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 7, July 2026 | ISSN: 2456-4184 | IJNRD.ORG

A Deep Learning Based Approach for Accurate Estimation of Faults in HVDC Transmission Systems

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Abstract: Machine Learning and Deep Learning are being continuously used in different walks of life. One such domain is the optimization of the power transmission sector. With a continuous escalation in demand of power, the power 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. These systems requires a quick restoration after faults occur, in order to re-establish 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. Data is collected for a bi-polar transmission line 814 km long developed on PSCAD/EMTDC software based on CIGRÉ benchmark guidelines. Faults at 1km each is simulated to train a deep neural network model to correlated the values of voltages and currents with the location of the fault. The data division is done in the ratio of 70:30 for training and testing the machine learning model. The error is computed in terms of the mean absolute percentage error (MAPE) which is clearly shown to outperform existing research in the domain.

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

I. Introduction

Machine Learning and Deep Learning and transforming the energy sector which needs to fulfil ever increasing demands.. Fault location can play a vital role in achieving this aim [1]. 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 [2].

Various researches have been done previously towards finding accurate result. In this work, location detection using the mathematical neural network technique is presented [3]. 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 [4].

II. The HVDC Transmission System

HVDC stands for High Voltage Direct Current. It is generally used for bulk power transmission over long distances [5].

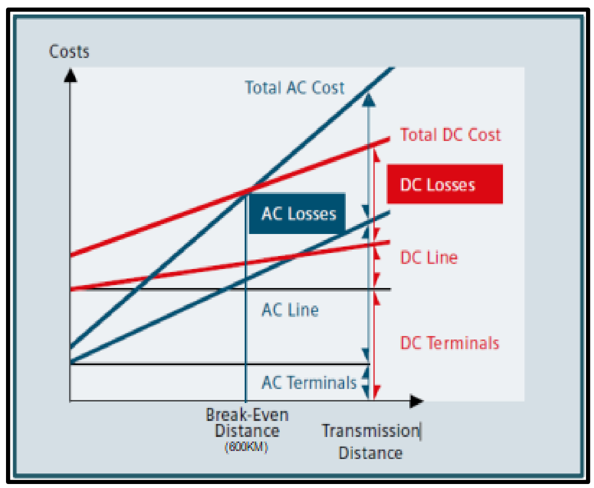


Figure 1 Cost of HVAC vs HVDC

Figure 1 presents the cost for AC and DC transmission as a function of distance. Following are some of the key points which make HVDC an effective counterpart for HVAC [6]:

1) Power Transmission capacity of HVDC is about 30%-40% more than HVAC for same width of conductor [7].

2) Transmitting DC over long distance is comparatively far much cheaper than 3 phase AC over same distance due to cheap tower and fewer conductors and low losses.
3) DC transmission has no limits over power transmitting distance because HVDC has no reactance and stability problem. Transmission Tower design of HVDC is comparatively simple.
4) Losses in HVDC over long distance is almost 30-40% less than HVAC of same voltage level because of very less corona loss and zero skin effect [8].

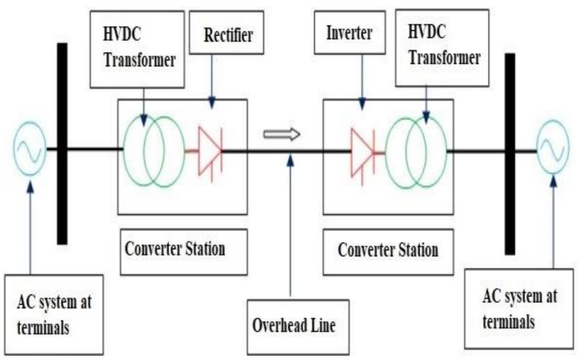


Figure 2 The HVDC System Model

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 [9].

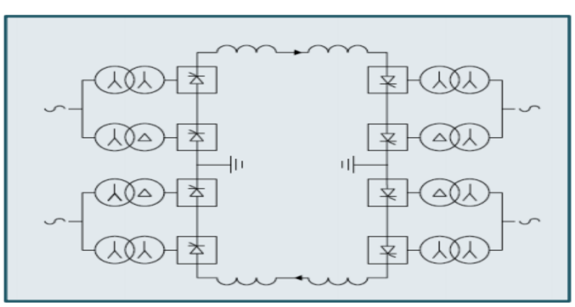


Figure 3 Schematic for Bipolar HVDC System

Figure 3 presents the schematic for the HVDC system.

III. Fault Estimation Using Neural Networks

The goal of this study is to develop a model using machine learning tool to locate fault in bipolar HVDC system. Also, it is desirable from model to perform about duty quickly and effectively and precisely. The first stage of a deep learning-based HVDC fault estimation framework is the acquisition of electrical signals. Measurements such as DC voltage, DC current, and travelling-wave components can be collected from both ends of the transmission line

This study is also carried out carried out to check the effectiveness of neural network in solving our present fault location detection problem for HVDC transmission line. ANN is utilized in excellent property to recognize patterns in non-linearity, it's robustness and its quick operation. The main objectives of the proposed work are [10]:

- Designing a base model for HDDC on PSCAD.
- Generating faults on the T-Line and collecting voltage and current values for **Generator and Load sides.**
- Designing a mathematical neural network model and training it with the data variables for generator and load side (**Voltage and Current Values)**
- Testing the model and computing mean square error (**MSE)** and Accuracy.
- Obtaining lower error and higher accuracy compared to existing systems [11].

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 [12]:

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

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.

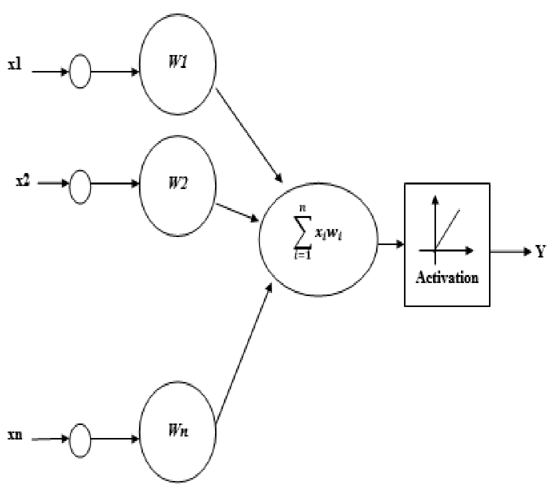
The mathematical model for a neural networks is depicted in figure 4.

Figure 4 Mathematical Equivalent of Neural Network

The ANN which contains multiple hidden layers and is used for extremely complex pattern recognition problems. The HVDC system would be designed in Power Systems CAD Softtware (PSCAD). PSCAD (Power Systems Computer Aided Design) is a versatile simulation tool for Studying Power system transients [13]. Manitoba HVDC Research Centre has developed this software by the intension of creating a tool which is specifically dedicated toward power system simulation with instantaneous results.It is also known as PSCAD/EMTDC. The GUI of PSCAD significantly increases the power and efficiency of simulation. It allows the user to schematically build a circuit, run a simulation, analyze the results, and manage the data in an entirely unified graphical environment. This tool provides flexibility to simulate model ranging from nanoseconds to seconds. PSCAD finds wide application in planning, operation, design and commissioning [14].

Previous research papers indicate that the following parameters can be analyzed to estimate faults in HVDC systems [15]:

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
7. Distance of fault from Generator (Dependent Variable)



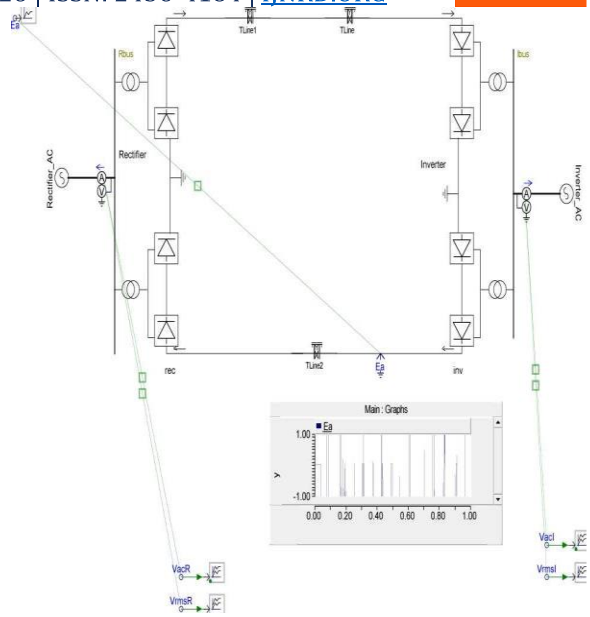


Figure 5 The PSCAD Model for HVDC

It is necessary to train the neural network is such a way that it attains convergence in less number of iterations [16].

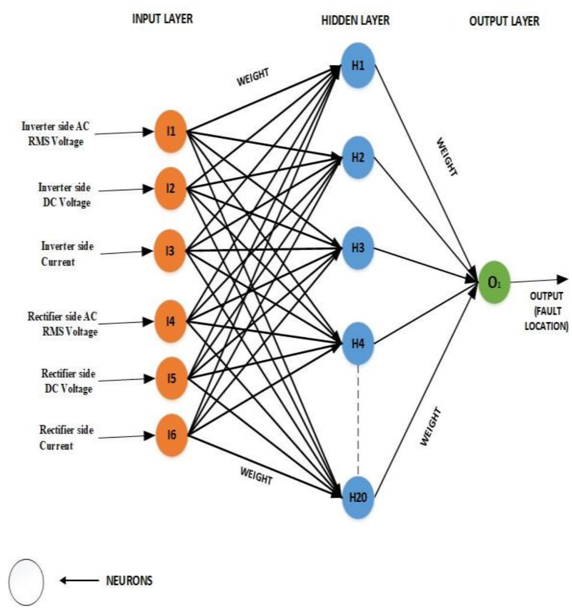


Figure 6 The Neural Network Model

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 [17]. The flowchart of back propagation is depicted in figure 7.

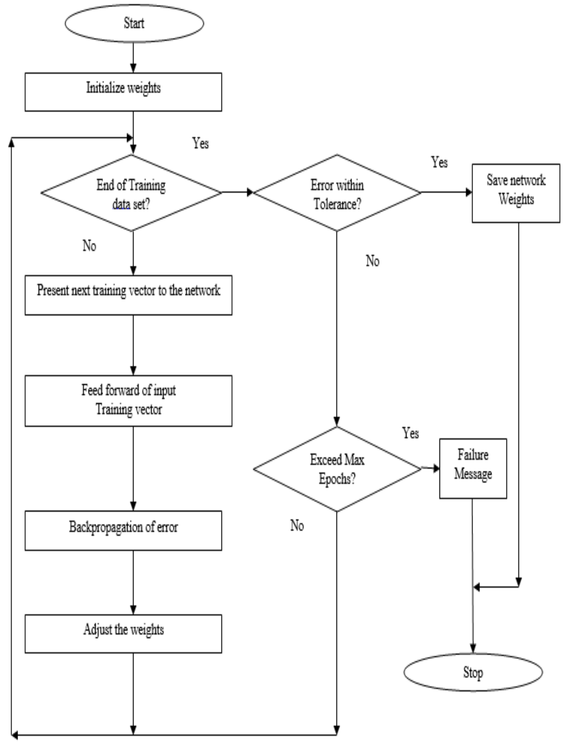


Figure 7 Back Propagation in Deep Nets

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 [18]. 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 [19]:

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

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 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 [21],

$$g = \frac{\partial e}{\partial w} \quad (3)$$

Here,
g is the gradient
e is the error
w is the weight
Since the weight varies as a function of iterations (n), clearly gradient is also a function of the iteration number (n)

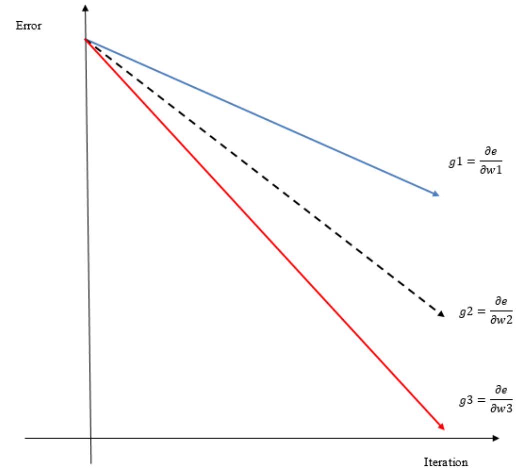


Figure 8 Gradient Descent

IV. Simulation Results

The system has been designed for the faulty and non-faulty conditions. The system parameters have been taken as the voltages and currents tabulated as a function as of the distance of the fault 'd'. The dataset has been obtained from:
https://www.kaggle.com/datasets/ziya07/power-system-faults-dataset
The system has bene simulated on MATLAB with N-Net and Deep Learning libraries.

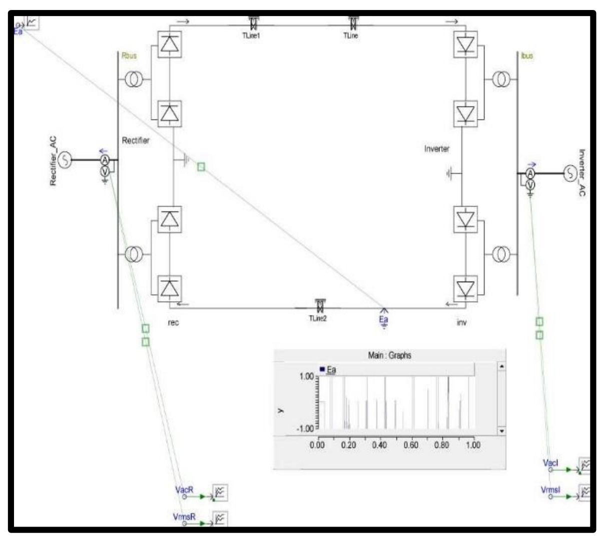


Figure 8 HVDC transmission line model for fault estimation

Figure 9 Designed Neural Network Model on MATLAB for fault estimation

The network architecture is 6-30-30-20-20-10-1.
The 6 neurons present in the input indicate the 6 independent variables and the 1 neuron in the output indicates the 1 variable (distance to be estimated at the output)

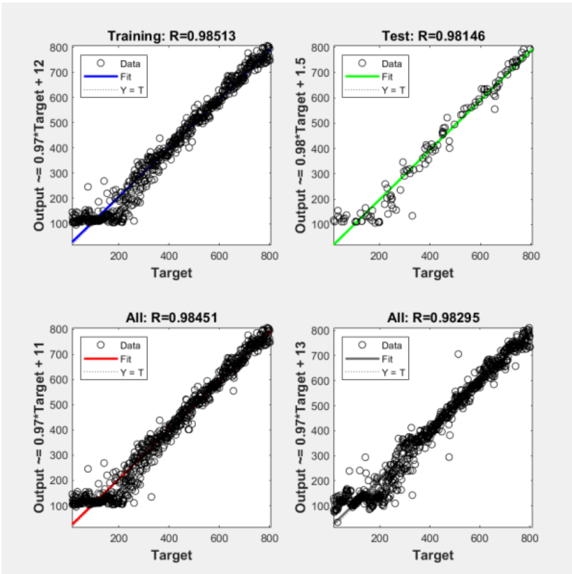


Figure 10 Regression Values.

Figure 10 presents the overall regression to be 0.98.

Table 1 HVDC Error Analysis

Actual Distance	Estimated Distance	Error
159	160.5	1.56
302	301.3	-0.62
346	344.3	-1.67
458	455.6	-2.31
576	576.8	0.84
684	684.0	0.01
727	727.6	0.67

Table 1 presents some samples of the errors in fault estimation. The regularization based back propagation training algorithm is given by [21]:

$$w_{k+1} = w_k - \left[J_k J_k^T + \mu' I\right]^{-1} J_k^T e_k \quad (4)$$

Here,

K is the iteration number

w_{k+1} is weight of next iteration,

w_k is weight of present iteration

J_k is the Jacobian Matrix and is given by the terms $J_k = \frac{\partial^2 e}{\partial w^2}$ i.e. the second order rate of change of errors with respect to weights

J_k^T is Transpose of Jacobian Matrix

e_k is error of Present Iteration

I is an identity matrix, with all diagonal elements equal to 1 and other elements 0

$\mu' = \mu \mathbf{R}$ is the effective step size with regularization

R is the regularization factor

The different between the actual and forecasted fault distances has been used to compute the mean absolute percentage error as:

$$MAPE = \frac{1}{K} \sum_1^K \left| d_i - \hat{d}_i \right| \quad (5)$$

Here,
MAPE represents mean absolute percentage error.
d_i represents the actual distance of fault from the generator
$\hat{d}_i$ represents the predicted distance of fault from generator.

The values of the cost function or MSE at the convergence is 5.9, rendering an average error of 2.4, when computed as the MAPE of the model renders a value of (2.42/816)*100%=0.3% (approx.)

Table 2. Comparison with Existing Work in the Domain

S.No.	Author	Approach	Result Obtained
1.	Swetapadma et al. [17]	Wavelet transform with feed forward networks.	Fault estimation error of 1%
2.	Elgamasy et al. [18]	Feed Forward Network with 4 hidden layers	Regression of 0.99877 and MAPE of 2.39%
3.	Zhang et al. [19]	RNN trained with V,I and distance features.	MAPE of 0.41% obtained.
4.	Mishra et al. [20]	Scattering wavelet transform and LSTM	MAPE of 3.7148% obtained.
5.	**Proposed method**	**DWT with Regularization Based Deep Neural Network**	**MAPE of 0.3% and regression of 0.98%**

VI. Conclusion

Deep learning provides an effective framework for analyzing complex and nonlinear relationships within HVDC fault data. Unlike conventional machine learning techniques, deep neural networks can automatically learn hierarchical representations from large volumes of voltage and current measurements. A deep learning-based fault estimation system can receive sampled signals from the HVDC transmission line and process them to determine whether a fault has occurred. The model can subsequently classify the fault type and estimate its location. This integrated approach can improve the speed and accuracy of HVDC protection systems while reducing dependence on manually engineered signal features. 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 2 that the proposed approach clearly outperforms existing work in the domain in terms of the prediction MAPE making the system much more accurate.

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