Abstract—Recent developments in high voltage direct current (HVDC) transmission have had a positive impact on the research community. HVDC transmission offers superior power quality and low transmission loss, however, the fault location and clearance technology is not as mature as its AC counterpart. This paper aims to propose a fault location technique on a 200 km two-terminal VSC-HVDC system using wavelet transform (WT) and artificial neural networks (ANN). The HVDC system is modeled in PSCAD and the results are treated with WT and ANN using MATLAB. The fault of concern in this paper is pole-to-pole fault. The simulation is repeated by varying fault resistance and location along 200 km to test the influence of these two parameters on the proposed fault location method. The result demonstrates reasonably high reliability in predicting the fault location with low error.

Index Terms—HVDC system, VSC-HVDC, Wavelet analysis, Neural networks, PSCAD, MATLAB.

I. INTRODUCTION

AC transmission has limited transmission capacity and distance constraints. Besides that, two asynchronous AC networks cannot be connected directly. To overcome these disadvantages, there has been discussion to use HVDC as an alternative. HVDC is used in bulk power transmission to minimize losses and to improve power quality and load flow control. Compared to the conventional HVDC system, voltage source converter (VSC) based HVDC systems offers the advantages such that the reactive power can be controlled independently without the need for reactive power compensation as in the classical HVDC link. Improvement in power electronics have contributed immensely to the development of VSC based-HVDC system, eg. its high power application insulated-gate bipolar transistor (IGBT) is used in the converters to convert AC into DC and vice-versa.

The fault location technology in HVDC system is in its adolescent stage. Numerous fault location technique in AC system has been reviewed in [1]. The fault distance can be calculated based on voltage and current phasor estimation [2]. The method proposed by Novosel et. al [3] uses a lumped parameter model to represent all impedance behind the fault, applicable for short transmission lines. These information, however, is not available to HVDC system. Due to the absence of nominal frequency, it is impossible to compute the impedance merely based on the voltage and the current. In addition, the impedance-based method is considered to be slow by the standard of VSC-HVDC system [4] as the lack of line inductance causes the DC fault to penetrate the network extremely fast. The fault analysis in [5]–[7] shows that pole-to-pole fault can result in a fault current that rises to its peak faster than AC fault and load change. For these reasons, HVDC system needs to take on a different approach.

A technique for fault location using transient fault signals in hybrid HVDC systems, based on terminal recorded data, is proposed by Hassan [8]. It involves the modification of Rogowski coil, measuring surge times over a wide spectrum of currents, without saturating, and offers significant advantages over transformers [9]. Takagi et. al [10] developed a new fault locator, which determines reactance in a fault line, using single terminal voltage and current data, obtained using a microprocessor. The algorithm is able to automatically correct load flow, fault resistance, and dissymmetry errors in the transmission line. However, the fault locater is able to perform satisfactorily only for single faults in the transmission line, and is unable to determine multi-fault locations simultaneously. Most of the fault location methods are based on traveling wave [11]. However, they require the detection of the wave arrival time with high degree of precision, making them difficult to be implemented. The problem is addressed by Song et. al’s method [12], in which the natural frequency is used as a criterion to locate fault.

This paper is aimed to simulate, study and create a machine learning based algorithm to predict faults in the two terminal HVDC link. The two-terminal HVDC system is modeled and pole-to-pole faults are simulated in PSCAD. The fault result is reinterpreted in time-frequency domain using wavelet transform (WT). With the wavelet coefficient of the fault current signal as input data, an Artificial Neural Network (ANN) is developed using MATLAB to predict the fault location over the transmission line. The paper is organized as follows. Section II presents the background of two-terminal HVDC system modeling in PSCAD. The concepts of WT and ANN are briefly introduced in Section III and IV, respectively. Section V presents the result of ANN processing the fault signal. Finally, conclusion is given in Section VI.

II. WAVELET ANALYSIS OF FAULT SIGNAL

Similar to Fourier analysis, wavelet analysis is used to represent the function in frequency domain. Unlike Fourier analysis of signals which are localized only in frequency domain, the wavelet analysis is able to extract the signal information in
both time and frequency domain, thereby allowing to track the change in the frequency components over time. Thus, wavelet analysis is useful in analyzing the functions with discontinuity or abrupt change [13].

MATLAB is used to perform the wavelet analysis, with a variety of functions that a WT can perform: signal denoising and data compression are of primary importance with respect to the paper, the rise time of the fault current is a finer parameter than the entire fault signal [13].

Fig. 1 shows the result of a fault current signal being treated with WT. The first plot is the fault signal generated from a simple simulation. When a signal is processed with WT, the smoothed coefficient (XA) and the detailed coefficient (XD) are plotted and the first peak of XD coefficient is taken as an input to the neural network. In this case, each simulation contains 6002 data points in the time domain. Using the scale of 4, the signal is downsampled by \(2^4\), approximately yielding 359 data points as a result. The spike observed in the plot of XD suggests that there is high frequency component in the fault signal at that particular time. From the plot of XA, it can be seen that the signal resembles the original one implying successful reconstruction.

### III. Artificial Neural Network

Artificial Neural Networks (ANN) are identical to a cluster of neurons in a human brain. The neural networks communicate with each other in order to arrive at a decision. Networks in ‘Neural Networks’ refer to linkage between neurons from different layers, the higher the intricacy of the problem, the higher is the requirement for number of hidden layers. Fig. 2 shows a flow diagram of the steps associated with the data prediction using ANN, which involves 3 layers consisting of 2 input nodes, 13 hidden nodes and 1 output node.

The proposed fault location method in this paper feeds the XD coefficients generated from wavelet analysis to the ANN as the inputs. In the case of two-terminal system, the XD coefficients of line currents \(I_{dc\_12} \& I_{dc\_21}\) are of interest and necessary for the ANN to learn the fault features. The algorithm developed to estimate the fault location in the HVDC line uses train-br (Bayesian regularization) and 640 training epochs, the ANN is commenced with 80% of the data to be test data. It is in this stage where the ANN is given the two inputs and the corresponding fault location obtained from the simulation. In this stage, the ANN strives to establish a trend between the given inputs and the corresponding outputs.

After the training stage, the remaining 20% of the data is used to test the ANN. In this stage, the generated output from the logic of the ANN is compared to the actual output obtained from the simulation. The disparity in the actual values to the predicted values is computed as an error vector.

### IV. Modeling and Simulation

A two-terminal HVDC system, as depicted in Fig. 3 is modeled with the technical specifications as indicated in Table I. A typical HVDC transmission system consists of an AC source, a filter, transformer, converters and DC transmission link.

Pole-to-pole faults are simulated on the aforementioned 200 km transmission line based on the parameters specified in Table I, the fault location is kept constant and the fault resistance is varied from 0.01 \(\Omega\) to 100 \(\Omega\), the corresponding currents \(I_{dc\_12}\) and \(I_{dc\_21}\) are plotted and the database is created using the values obtained in the simulation. The simulation is performed on 13 different fault locations ranging from 25 km to 175 km in steps of 12.5 km, this diverse range of data enables the ANN to learn and understand the dataset [14] and
analyze the trends developed with increasing fault resistance or fault location.

V. RESULT AND DISCUSSION

The ANN is implemented to estimate the fault location in the 200 km HVDC transmission line. Various statistical parameters are used to measure the compatibility of ANN. Table I summarizes the statistical error parameters obtained from the ANN.

As observed from Table II,

- The Mean Squared Error ($MSE$) is found to be 20.5886 $km^2$.
- The Root Mean Squared Error ($RMSE$) is found to be 4.5375 $km$ which indicates that on an average there is a 4.5375 $km$ difference between the actual data and the predicted data.
- The Mean Absolute Error ($MAE$) is found to be 2.7544 $km$ which indicates that on an absolute scale there is an error of 2.7544 $km$ predicted by the ANN.
- The Mean Forecast Error ($MFE$) is found to be 0.0037, this value indicates that the ANN is over forecasting with a factor of 0.0037.
- The correlation coefficient ($R$) is found to be 0.99532 and it indicates a good fit of prescribed values to the actual values.
- The coefficient of determination ($R^2$) is found to be 0.9906 and it also indicates a liner fit of the predicted values to the actual values.

Fig. 4 shows the regression plot after running the ANN. $R$ as mentioned above is the correlation coefficient, $R$ value of 1 indicates perfect correlation. In this case, $R$ value is found to be 0.99532 indicating that the predicted values are in good fit with respect to the actual values.

Fig. 5 shows the deviation of the predicted values from the actual values, the x-axis indicates the number of simulations performed and the y-axis indicates the fault location in km. It can be observed that the ANN predicts with a higher accuracy in the middle of the transmission line and it predicts at a lower accuracy towards the sending end and the receiving end of the transmission line.

A. Comparative Analysis on identifying fault location at a constant fault resistance

The aim of this section is to compare and analyze the accuracy of the fault location technique for different fault resistances and to identify the fault resistance at which the ANN is highly efficient. The fault resistance is held constant and the fault location is identified using the ANN. Fig. 6 shows

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**TABLE I**

Technical specifications of the simulated model.

<table>
<thead>
<tr>
<th>System parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated capacity</td>
<td>1200 MVA</td>
</tr>
<tr>
<td>Rated AC voltage</td>
<td>230 kV</td>
</tr>
<tr>
<td>Rated DC voltage</td>
<td>640 kV</td>
</tr>
<tr>
<td>Length of transmission</td>
<td>200 km</td>
</tr>
<tr>
<td>Steady state frequency</td>
<td>60 Hz</td>
</tr>
<tr>
<td>Transformer ratio</td>
<td>230/370 kV</td>
</tr>
<tr>
<td>Switching frequency</td>
<td>1980 Hz</td>
</tr>
<tr>
<td>DC capacitance</td>
<td>5000 $\mu$F</td>
</tr>
</tbody>
</table>

**TABLE II**

Statistical error parameters.

<table>
<thead>
<tr>
<th>Error</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>20.5886</td>
</tr>
<tr>
<td>RMSE</td>
<td>4.5375</td>
</tr>
<tr>
<td>MAE</td>
<td>2.7544</td>
</tr>
<tr>
<td>MFE</td>
<td>0.0037</td>
</tr>
<tr>
<td>$R$</td>
<td>0.99532</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9906</td>
</tr>
</tbody>
</table>
a plot of correlation coefficient of finding fault location at a given fault resistance.

It can be observed that the ANN has a high correlation coefficient $R$ at lower fault resistances, this can be attributed to the fact that the data set used to train the ANN has fault location values corresponding to the lower fault location case.

VI. CONCLUSION

In this paper the VSC-based HVDC system has been examined. The two terminal VSC-based HVDC system is built in PSCAD, in which the DC faults are simulated and the corresponding fault currents are recorded. The experiment is repeated for various values of fault resistances at various fault locations along the 200 km transmission line.

The DC fault current data is processed with wavelet analysis to generate the detailed coefficient, which is then used as input to artificial neural network (ANN) to learn the fault pattern.

It is found that the ANN is able to locate the DC fault with relatively high accuracy, as proven by high correlation coefficient and low error. The study can be further extended to multi-terminal network in which the influence of other terminals can complicate the fault location. Reliability of the suggested model can be verified by performing similar analysis under different model parameters.

REFERENCES


