A Review on Automated Estimation of Fault Location in HVDC Transmission Systems Using AI and ML Techniques

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Abstract **— AI, Machine Learning (ML) and Deep Learning (DL) techniques are transforming various domains of life. One such domain in power generation and transmission, which is being made more efficient and robust against faults using AI, ML and DL techniques. 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 has been done previously towards finding accurate result. In this paper presents a comprehensive survey on the existing work done in the domain of machine learning assisted fault location in HVDC systems. Machine Learning and Deep Learning models such as the SVM, CNN, LSTM, ARIMA etc. have been analyzed with their salient features, advantages and limitation. This review is expected to enable deciding**

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), HVDC, Fault Location, Regression Analysis, Mean Absolute Error (MAE), Accuracy.

I. INTRODUCTION

AI and Machine Learning based modes are being used extensively to optimize the performance of power transmission systems. Transmission system plays the vital role in connecting generation station to load. It has the responsibility to supply continuous power from one and two other. Any type of damage to transmission line will lead to an interruption in power supply but in the present era of power system deregulation providing good power quality with continuous supply is main its main priority of all electric utility companies. Hence for this reason focus should be paid in the field of system protection and a proper planning is expected to deal with any unwanted situation. While AC transmission systems are the most commonly used, due to high losses, DC transmission becomes much more economical a higher distances. However, fault location is more challenging as is important to avoid detection switches and relays in-between for fault estimation as they need DC/AC conversion resulting in more losses and degradation in power quality [1]

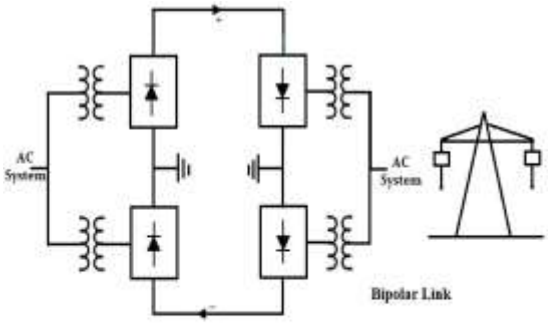

Fig.1 Bipolar HVDC Link

Figure 1 shows the DC link. Relay and circuit breakers play key part in preventing system during any fault condition. Faults are responsible for creating system malfunctioning and their immediate diagnosis is expected is expected to increase reliability [2]. Capacitor banks are used because they help in balancing reactive power in transmission line thus helping in increasing line loadability, reducing line losses and increase in system stability [4].

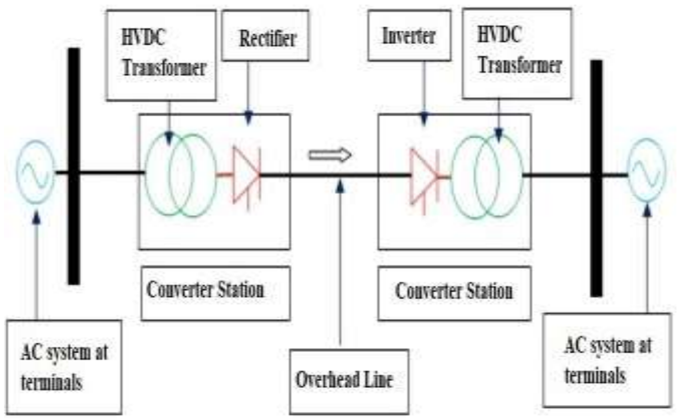

Fig.2 HVDC system model

Figure 2 shows the HVDC system model. Normally distance relays are used for locating fault. The working of distance relay is based upon the measured value of impedance between fault point and relay location (that is ratio of voltage and current between these two points). Now this should be giving accurate results, but due to the presence of series capacitor banks for compensation problem will somehow tarnish the accuracy of relay [3].

a. Neural Networks

Neural Networks are computing systems or technique that mimic the learning processes of the brain to discover the relations between the variables of a system. They process input data information to learn and obtain knowledge for forecasting or classifying patterns etc. type of work. ANN consists of number of simple processing elements called neurons. All information processing is done within this neuron only. A network of connected artificial neurons can be designed, and a learning algorithm can be applied to train it [5]. Signals (Input data) are passed between neurons over connection links and Each connection link has an associated weight, which in a neural network, multiplies the signal transmitted. The weights represent information being used by the network to solve a problem. Then the weighted sum is operated upon by an activation function (usually nonlinear), and output data are conveyed to other neurons. The weights are continuously altered while training to improve accuracy and generalize abilities.

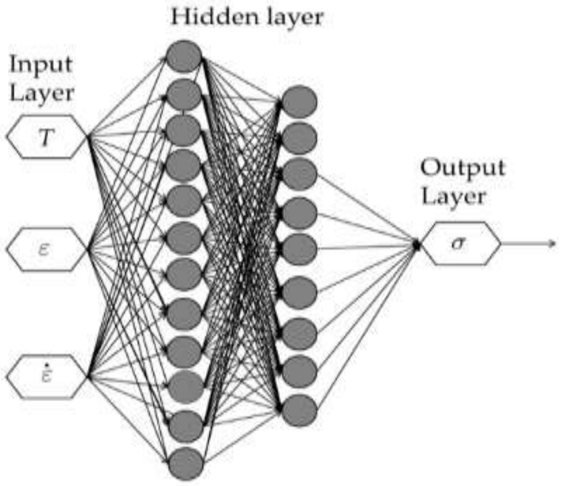

Fig.3 The Neural Network Model

The neural network which contains multiple hidden layers and is used for extremely complex pattern recognition problems. 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 [6]:

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

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. The mathematical model for a neural networks is depicted in figure 1.

b. Neural Network Training and Testing

In this stage we will feed input data to input layer of present designed model and target is fitted to output layer. It is this stage in which model is prepared and value of weights are optimized for better performance according to input and target data samples.

At this stage, the second part of dataset is used. Although only inputs are provided to already trained neural network and output is calculated from neural networks. These is then compared to original target fault distance to observe the closeness between the two. The training phase typically culminates in the convergence of the cost function of the neural network. While solving with this algorithm, the Hessian matrix and the gradient can be calculated by following relations [7],

$$g = \frac{\partial E(x,w)}{\partial x} = \left[\frac{\partial E}{\partial w_1} \quad \frac{\partial E}{\partial w_2} \quad \cdots \quad \frac{\partial E}{\partial w_N}\right]^T \qquad (2)$$

$$W_{k+1} = W_k - \alpha g_k \qquad (3)$$

This downside of steepest decent algorithm can be distant by means of alternative algorithm termed Gauss-Newton algorithm. This algorithm make use of the second order derivative of error functions in its place of first order derivative in incident of error feedback. The enhancement will lie in riddling out the convergence point very swiftly. In addition, this algorithm has the property of varying its step size and direction with curvature of error. Even if the error curvature is arbitrary, it will become unsteady very speedily. In this development Jacobean matrix is establish as

$$J = \begin{bmatrix} \frac{\partial e_{1,1}}{\partial w_1} & \frac{\partial e_{1,1}}{\partial w_2} & & \frac{\partial e_{1,1}}{\partial w_N} \\ \frac{\partial e_{1,2}}{\partial w_1} & \frac{\partial e_{1,2}}{\partial w_2} & \cdots & \frac{\partial e_{1,2}}{\partial w_N} \\ \cdots & \cdots & & \cdots \\ \frac{\partial e_{1,M}}{\partial w_1} & \frac{\partial e_{1,M}}{\partial w_2} & & \frac{\partial e_{1,M}}{\partial w_N} \\ \cdots & \cdots & & \cdots \\ \frac{\partial e_{P,1}}{\partial w_1} & \frac{\partial e_{P,1}}{\partial w_2} & & \frac{\partial e_{P,1}}{\partial w_N} \\ \frac{\partial e_{P,2}}{\partial w_1} & \frac{\partial e_{P,2}}{\partial w_2} & \cdots & \frac{\partial e_{P,2}}{\partial w_N} \\ \cdots & \cdots & & \cdots \\ \frac{\partial e_{P,M}}{\partial w_1} & \frac{\partial e_{P,M}}{\partial w_2} & & \frac{\partial e_{P,2}}{\partial w_N} \end{bmatrix} \qquad (4)$$

Than further, the equation of gradient vector can be further evaluated as

$$g_i = \frac{\partial E}{\partial w_i} = \frac{\partial\left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i} = \sum_{P=1}^{P}\sum_{M=1}^{M}\left(\frac{\partial e_{p,m}}{\partial w_i} e_{p.m}\right)$$
(5)

Further, the gradient vector can be evaluated as

$$g = Je \qquad (6)$$

Where matrix is formed as

$$e = \begin{bmatrix} e_{1,1} \\ e_{1,2} \\ \cdots \\ e_{1,M} \\ \cdots \\ e_{P,1} \\ e_{P,2} \\ e_{P,3} \\ \cdots \\ e_{P,M} \end{bmatrix} \qquad (7)$$

Hence, further hessian matrix can be evaluated as

$$h_{i,j} = \frac{\partial^2 E}{\partial w_i \partial w_j} = \frac{\partial^2\left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i \partial w_j} =$$
$$\sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial e_{p,m}}{\partial w_i} \frac{\partial e_{p,m}}{\partial w_j} + S_{i,j} \qquad (8)$$

The above equation of gradient descent is as described earlier is a mixture of two techniques such that it extracts the speed from gauss newton and it takes property of stability from steepest descent. In this equation coefficient, μ decides the speed and stability of system. It is multiply with β when any iteration results in an increment in error whereas it will be multiply with β whenever the vice-versa occurs.

II. PREVIOUS WORK

This section highlights the previous work done in the domain:

a. Previous Work

Rohani et al. [8] proposed a fault location method consists of three major sections. In the first section, HH transform is applied to extract new features from current signal. In the second part, ANFIS uses the extracted features to estimate the fault location in transmission lines. Learning algorithm determines the accuracy and efficiency of each machine-learning algorithm. In the third section of the developed system, enhanced version of particle swarm optimization (PSO) algorithm named chaotic dynamic weight PSO (CDWPSO) algorithm is implemented as learning algorithm to train the ANFIS. The developed fault detection and location system was tested on a VSC-HVDC system with 250 km length and the obtained results using MATLAB simulations have shown that combination of new features, and CDWPSO-based ANFIS has high accuracy in fault detection and location in VSC-HVDC systems. High fault location accuracy, robust performance of neuro-fuzzy system, optimal training of ANFIS, extraction of novel effective features from current signal and fault location only with six features are the main contribution of the developed system.

Keshri et al. [9] proposed support vector machine (SVM) based classification approach for Fault estimation in HVDC transmission system. SVM based method is comparatively a novel method that is based on computational as well as theory of statistical learning. Along with the input space vector is made into a dot product of high dimension that is called a feature space in SVM theory. Therefore, the optimal hyper-plane has to be consider greater ability of classification in the feature space. Thus the optimal hyper-plane is to be determined by exploring the theory of optimization, and the critical information providing via the theory of statistical learning. Therefore, SVM approach has got the ability to counter a large featured space vector. So that the proposed approach has ability to assist in the area of fault classification as there is no restriction on the number of features.

Somsundaran Vasanath et al. [10] have proposed a technique for the estimate of the location of the faults in HHDC lines by the dint of the artificial neural network model after the design of the system on PS-CAD based model. It was shown that the system has a better power quality compared to the ac counterpart with lesser losses, however the fault location was much more daunting due to the long continuity of the t-line. The system uses a 200km T-Line with the performance to be the mean square error. The paper shows that the proposed system attains a mean square error of 20.5886km.

Jenifer Mariam et al. [11] have presented a method of detecting fault location of ±500 kV HVDC transmission system using artificial neural network (ANN). Author has modelled and simulated ± 500 kV bipolar HVDC transmission line over PSCAD/EMTDC software. Author has proposed a model developed using ANN in MATLAB environment, trained and tested using one sided voltage and current magnitude of HVDC transmission line for various fault location. Author has simulated HVDC line model for LG fault at distance of every 2 kilometer of transmission and noted the data corresponding to that. From this model has observed a result with an accuracy of 2-kilometer distance. Model is developed for a HVDC bipolar transmission line of ±500 kV and 936 KM.

Sunil Singh et al. [12] have developed a fault location estimation technique for a 300 km, 400 kV transmission line. Author has performed fault analysis at various location of this transmission line in MATLAB environment and the data obtained during simulation at various fault location is stored. This data is than transformed using wavelet analysis for the sole purpose of feature extraction which than can be supplied to ANN for prediction of fault location. After obtaining results from ANN, author came to conclusion DWT and ANN model together are very efficient in predicting exact location of fault with very high accuracy.

Ankita Nag et al. [13] have proposed an ANN based protective scheme for the hybrid transmission system both overhead and underground. Author has discussed various advantages of AI has over primitive location detecting techniques like one based on phasor based method which usually utilizes fundamental component of signal and other is traveling wave based method which works on the basis of value of reflected wales. Author has developed and simulated15 kilometer, 132 kV, 50 hz transmission line with 3-kilometer underground cable and 12-kilometer overhead lines for a LG fault. After training and testing author came to conclusion that the output is very accurate compare to other techniques.

Qingqing Yang et al. [14] have developed a model for DC microgrid fault detection and fault location using artificial neural network. The DC microgrid is modeled in PSCAD/EMTDC to simulate various faults. Author has discussed the importance of microgrid for present day power system in which penetration of renewable energy is increasing day by day leading to more unpredicted grid behavior and hence making control strategies more complicated. A total of 40 neurons are taken in input layer consisting of 20-20 data from both sending end and receiving end of dc microgrid. Author has obtained results from trained model with an accuracy of one percent error which is very accurate considering distance.

Nabamita Roy et al. [15] have presented a technique for detecting fault, classifying it had then forecasting fault location. Various techniques author has used in this work is s-transform and wavelet transform for feature extraction purpose. Values of this features is used for both classification and locating fault in this work. Author has concluded that above following techniques includes BPNN techniques has developed a model which has great speed of computation and very high accuracy. Author has utilized value of current and voltage parameter values for solving about problem and obtained error of maximum value of 4.35 percent.

Liang Yuansheng et al. [16] have discuss a noble algorithm to detect fault location. Author has performed a mix of travelling wave theory and Bergeron times domain fault location method. The value of voltage and current from both sides is taken as input parameters. In this study a self-adopted filter is also utilized which has ultimately improved performance of the algorithm. After the simulation and performing all tests related to fault at different location, author came to conclusion that this method is efficient for faults location detection for unsynchronized two end measurements on HVDC lines.

Pu Liu et al. [17] have presented an excellent HVDC transmission system model which comprise of all components including transformer, converters, filters, reactor, transmission tower and transmission line. The model is designed and simulator in PSCAD/EMTDC software. This study is done on the benchmark model for ± 500 kV HVDC system that is CIGRE benchmark. On simulating it is concluded that this CIGRE benchmark model can accurately simulate HVDC transmission system accurately for ±500 kV DC transmission line and that this model can be used for any further research related to high voltage dc transmission system.

S. F. Alwash et al. [18] have developed an algorithm for identification of all shunt type fault location. This work mainly presented a scheme where author has used impedance method for fault location. This method is tested for IEEE 34 bus distribution system designed and simulated in PSCAD/EMTDC software. In the study author has computed a method which has capability to identify faults location irrespective of type of shunt fault. In this work while designing model for fault location estimation for both distributed generation and capacitive effect of lines are considered.

Jae-Do Park et al. [19] have proposed a DC microgrid system's fault location technique is proposed. This study describes a technique which includes a ring type bus. This work describes the importance of dc in not only transmission system but evenly in distribution system. In this work author has used intelligent electronic devices for the controlling and monitoring all nodes. The author has successfully implemented proposed algorithm/technique both in hardware and simulation experimentally.

Farshad et al. [20] proposed a method for fault locating in HVDC transmission lines which only uses the voltage signal measured at one of the line terminals. The postfault voltage signal, in a relatively short-time window, is considered and the corresponding fault location is estimated based on the similarity of the captured voltage signal to existing patterns. In this approach, the Pearson correlation coefficient is used to measure the similarity. Despite simplicity and low complexity of the proposed fault-location method, it does not suffer from the technical problems which are associated with the traveling-wave-based methods, such as the difficulty of identifying traveling wavefronts or the strong dependency of accuracy on the sampling frequency. Numerous training and test patterns are obtained by simulating various fault types in a long overhead HVDC transmission line under different fault location, fault resistance, and prefault current values. The accuracy of the proposed fault-location method is verified using these patterns.

Abedini et al. [21] showed that series capacitors (SCs) are installed on long transmission lines to reduce the inductive reactance of lines. This makes it appear electrically shorter and increases the power transfer capability. Series capacitors and their associated over-voltage protection devices (typically Metal Oxide Varistors (MOVs), and/or air gaps) create several problems for protection relays and fault locators including voltage and/or current inversion, sub-harmonic oscillations, transients caused by the air-gap flashover and sudden changes in the operating reach. In this paper, an accurate fault location algorithm for series compensated power transmission lines is presented.. A simple power system containing a compensated transmission line is simulated on PSCAD/EMTDC software and fault location algorithm is implemented on MATLAB environment using wavelet transformer.

M Ramesh et al. [22] have presented an overview of various intelligent techniques for detecting fault in HVDC. In study author has discussed drawbacks of primitive fault detection techniques in HVDC. Then author has provided an overview to various artificial intelligent techniques in view to identify fault of HVDC transmission system. The study concluded that the rule based linear fuzzy logic controller can be used to achieve the desired fault detection of the HVDC link. This controller has a benefit that they don't require a mathematical model to estimate control input under disturbance conditions.

Sun et al. [23] showed that VSC-HVDC is a kind of HVDC technology which based on voltage source converter and turn-off devices. Its poor over voltage/current capacity are prone to failure. Based on the established VSC-HVDC system simulation model, the DC voltage waveforms under various fault conditions are achieved, and then the character of system fault is decided according to the amplitude fluctuation range of DC voltage. Moreover, in full consideration of influence of transmission power, the wavelet analysis method is adopted to extract the feature of faulty signal, and combined with artificial neural network the system fault is identified. Simulation results show that this method can diagnose and identify VSC-HVDC fault effectively, and the accuracy is not impacted by transmission power.

Saravanan et al. [24] proposed fault classification & fault location techniques for parallel overhead transmission lines. Fault location is carried out by measuring the distributed line model of faulted line parameters. Different system faults such as LG, LLG and LLLG on a protected transmission line should be detected, classified & located rapidly in order to bring the system to the normal state. A novel application of neural network approach with three variance of feed forward neural networks such as the one with Back propagation algorithm (BPN), Radial basis function (RBF) network and Cascaded correlation feed forward network (CFBPN) is proposed for the protection of double circuit transmission line has been demonstrated in this work. The proposed method uses line current values to learn the hidden relationship in the input patterns. Using the proposed approach, fault detection, classification, location and faulted phase selection could be achieved. An improved performance is experienced once the neural network is trained sufficiently and suitably, thus performing correctly when faced with varied system parameters and conditions. Results of performance studies show that the proposed neural network-based modules outperform the performance of conventional fault selection algorithms. Among the ANN modules, result of RBF network is found to be better than the other two networks in terms of accuracy.

EisaBashier M. et al. [25] showed that in power system are always exposed to abnormal conditions, which are the reason for the damage of transmission line and other electrical equipment's of power system. These abnormalities are termed as faults. These faults are required to be detected and classified for better performance of transmission line. In this paper author has presented a Back-Propagation technique of Artificial Neural Network as an alternative for transmission line fault detection, classification and isolation. Author has performed the study by using MATLAB software and Neuroshell 2 software.RMS value of phase current and phase voltage as input to neural network.

Ning et al. [26] proposed a novel fault location algorithm based on variant travelling wave speed for HVDC (High Voltage Direct Current) transmission line. The algorithm effectively reduces the large fault locating errors, caused by adopting consistent wave speeds, under off-design conditions. Firstly, it is illustrated how travelling wave speed varies with fault distance, and then how the variant speed effect fault locating accuracy is analyzed. At last, the new algorithm is proposed to guarantee the accuracy at any fault distance. The validity of the algorithm is verified by the relevant simulation results in EMTDC.

Ibrahim et al. [27] proposed an approach for the protection of transmission lines with flexible AC transmission systems based on artificial neural networks using the total least square estimation of signal parameters via rotational invariance technique. The required features for the proposed algorithm are extracted from the measured transient currents and voltages waveforms using the total least square estimation of signal parameters via rotational invariance technique. Since these transient waveforms are considered as a summation of damped sinusoids, the total least square estimation of signal parameters via rotational invariance technique is used to estimate different signal parameters, mainly damping factors, frequencies, and amplitudes of different modes contained in the signal. Those features are employed for fault detection and faulted phase selection using artificial neural networks. Two types of flexible AC transmission system compensated transmission lines, namely the thyristor-controlled series capacitor and static synchronous compensator, are considered. System simulation and test results indicate the feasibility of using neural networks with the total least square estimation of signal parameters via rotational invariance technique in the fault detection, classification, and faulted phase selection of flexible AC transmission system compensated transmission lines.

JialeSuonan et al. [28] have presented a novel method of locating fault which can outperform commonly used travelling wave technique. The proposed technique is performed in time domain and is simulated using EMTDC software. This paper has utilized Bergeron model of HVDC transmission line to check performance of proposed fault location method. This algorithm was built on a distributed parameter model and thus can be directly implemented in the domain based on current and voltage of both ends of transmission line.

Abdollahi et al. [29] proposed a comparative study of the performance of Fourier transform and wavelet transform based methods combined with Neural Network (NN) for location estimation of faults on high voltage transmission lines is presented. A new location method is proposed for decreasing training time and dimensions of NN. The proposed algorithms are based on Fourier transform analysis of fundamental frequency of current and voltage signals in the event of a short circuit on a transmission line. Similar analysis is performed on transient current and voltage signals using multi-resolution Daubchies-9 wavelet transform, and comparative characteristics of the two methods are discussed.

Kouraichi et al. [30] proposed that deep learning (DL) has emerged as a powerful tool, capable of extracting latent features from raw, high-dimensional data and offering robust, automated fault analysis. This paper analyzes recent progress in DL-based fault diagnosis for transmission lines, with a focus on key neural architectures including convolutional neural networks (CNNs), recurrent networks (LSTM/GRU), attention mechanisms, and generative models. Major research challenges such as limited labeled data, rare fault type detection, model robustness, and real-time deployment constraints are critically analyzed. Furthermore, authors explore novel directions including self-supervised learning, transfer learning, edge deployment, and privacy-preserving federated learning tailored to smart grid ecosystems.

Minh et al. [31] proposed a novel method to classify and localize faults in power transmission line using machine learning algorithms. The IEEE 9 Bus is simulated in MATLAB Simulink and faults are generated with various conditions including fault types, load level, fault resistance, and fault location. More than 300 thousand fault datasets are created for both classifying and localizing tasks. Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), XGBoost, and Artificial Neural Network (ANN) are used for fault classification while Convolutional Neural Network (CNN), Long-Short Term Memory (LSTM) and combined CNN-LSTM models are used for fault localization.

b. Performance Metrics

The parameters which can be used to evaluate the performance of the ANN design are given by:

1. Mean Absolute Error (MAE)
2. Mean Absolute Percentage Error (MAPE)
3. Mean square Error (MSE)

The above mentioned errors are mathematically expressed as:

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |Y_t - \hat{Y}_t| \quad \textbf{(9)}$$

Or

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |e_t| \quad \textbf{(10)}$$

$$MAPE = \frac{100}{N}\sum_{t=1}^{N} \frac{|Y_t - \hat{Y}_t|}{V_t} \quad \textbf{(11)}$$

$$MSE = \frac{1}{N}\sum_{t=1}^{N} {e_t}^2 \quad \textbf{(12)}$$

Here,
N denotes the number of samples in prediction.
Y is the predicted value of the variable.
$\hat{Y}_t$ is the actual value of the variable.
e is the error value in each prediction.

The accuracy is generally computed as:

$$Accuracy = 100 - error(\%) \quad \textbf{(13)}$$

Low values of the error metrics are desirable for the estimation of faults. Moreover, to increase the feasibility of any system, the system complexity should be as low as possible. The metrics

for the evaluation is generally the iterations needed to convergence of the system.

A comparison of commonly used techniques and their associated advantages and limitations based on the study of existing literature is cited in table 1.

S.No.	Technique	Advantages	Limitations
1	Fuzzy Logic	Vessel center lines clearly enhanced with labelled Fuzzy training.	Saturation of performance after which adding training data doesn't improve performance.
2	SVM (Support Vector Machine)	Simple implementation on the basis of Hyperplane	Performance Saturation
3	Transform Domain analysis such as S-Transform, DWT.	Data features in higher resolution	Higher Complexity in transform domain.
4	Long Short Term Memory (LSTM)	Recent averages considered and forget gate making lower complexity.	Prone to overfitting.
5	Convolution Neural Network (CNN)	Features directly extracted through convolution operation.	Prone to overfitting and vanishing gradient.
6	Ensemble methods	Suitable for both low and high resolution analysis	Relatively higher computational complexity.
7	ANFIS	Combines advantages of both ANN and Fuzzy Logic	Relative high computational complexity with increasing features and performance saturation for less number of features.
8	SVR (Support Vector Regression)	Low computational complexity.	Relatively low accuracy owing to lesser number of features extracted.
9	ARIMA	Relatively high accuracy.	Not applicable for large datasets without pre-processing
10	Directional Multiscale Line Detectors	Robust multi-variate classifier.	Relatively low accuracy
11	Deep-learning-based approach	Relatively high accuracy with low and high level features extracted through hidden layers of Deep Neural Network.	Relatively high computational complexity.
12	Naïve Bayes Classifier	Probabilistic approach robust for overlapping features.	Background enhancement and noise removal not explored.

Table 1. Comparative Analysis of Common Machine Learning Algorithms

III. CONCLUSION

It can be concluded from the previous work that the AI and ML models are transforming various real world challenges such as power transmission. However, faults in power systems lead 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. This paper presents a comprehensive review of state of the art ML and Deep Learning models with goal of developing a model which can render high fault detection accuracy in locating faults in HVDC systems, thereby helps in improving the system performance.

REFRENCES

[1] V. Psaras, A. Emhemed, G. Adam and G. Burt, "Review and Evaluation of the State of the Art of DC Fault Detection for HVDC Grids," 2018 53rd International Universities Power Engineering Conference (UPEC), 2018, pp. 1-6, doi: 10.1109/UPEC.2018.8541961.

[2] T. -C. Peng, D. Tzelepis, A. Dysko and I. Glesk, "Assessment of fault location techniques in voltage source converter based HVDC systems," 2017 IEEE Texas Power and Energy Conference (TPEC), 2017, pp. 1-6, doi: 10.1109/TPEC.2017.7868270.

[3] P. C. Fernandes, H. Naomira Gomes Venzi Gonçalves, K. Melo e Silva and F. Vigolvino Lopes, "Two-Terminal Modal Traveling Wave-Based Fault Location Method for HVDC Systems," 2018 Workshop on Communication Networks and Power Systems (WCNPS), 2018, pp. 1-4, doi: 10.1109/WCNPS.2018.8604378.

[4] L. Yang, F. Chen, M. Xue, Y. Li, S. Chen and L. Zou, "A Novel Fault Location Method for HVDC Transmission Lines," 2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia), 2019, pp. 341-346, doi: 10.1109/GTDAsia.2019.8715936.

[5] S. Naik and E. Koley, "Fault Detection and Classification scheme using KNN for AC/HVDC Transmission Lines," 2019 International Conference on Communication and Electronics Systems (ICCES), 2019, pp. 1131-1135, doi: 10.1109/ICCES45898.2019.9002230.

[6] M. Ashouri, F. F. da Silva and C. L. Bak, "On the Application of Modal Transient Analysis for Online Fault Localization in HVDC Cable Bundles," in IEEE Transactions on Power Delivery, vol. 35, no. 3, pp. 1365-1378, June 2020, doi: 10.1109/TPWRD.2019.2942016.

[7] J. O. A. Torres and R. C. d. Santos, "New Method Based on Wavelet Transform and ANN for Multiterminal HVDC System Protection," 2019 IEEE Milan PowerTech, 2019, pp. 1-6, doi: 10.1109/PTC.2019.8810587.

[8] R. Rohani and A. Koochaki, "A Hybrid Method Based on Optimized Neuro-Fuzzy System and Effective Features for Fault Location in VSC-HVDC Systems," in IEEE Access, vol. 8, pp. 70861-70869, 2020. DOI 10.1109/ACCESS.2020.2986919.

[9] J. P. Keshri and H. Tiwari, "Fault Classification in VSC-HVDC Transmission System using Machine Learning Approach," 2019 8th International Conference on Power Systems (ICPS), 2019, pp. 1-6. DOI doi: 10.1109/ICPS48983.2019.9067699.

[10] Somsundar Vasanth, Yew Ming Yeap, Abhisek Ukil, "Fault Location Estimation for VSC-HVDC System Using Artificial Neural Network",IEEE Explore: 2018. DOI doi: 10.1109/TENCON.2016.7848050.

[11] Jenifer Mariam Johnson and Anamika Yadav, "Fault Location Estimation in HVDC transmission line using ANN" First International Conference on Information and Communication Technology for Intelligent Systems: Volume 1, Smart Innovation, Systems and Technologies, Volume 50, pp 205-211, Springer, 2016. DOI https://doi.org/10.1007/978-3-319-30933-0_22

[12] Sunil Singh, D. N. Vishwakarma, "ANN and Wavelet Entropy based Approach for Fault Location in Series Compensated Lines",International Conference on

Microelectronics, Computing and Communications (MicroCom), 2016.
DOI: 10.1109/MicroCom.2016.7522557

[13] Ankita Nag and Anamika Yadav, “Fault Classification using Artificial Neural Network in Combined Underground Cable and Overhead Line”, 1st IEEE International Conference on Power Electronics. Intelligent Control and Energy Systems (ICPEICES-2016), 2016.
DOI: 10.1109/ICPEICES.2016.7853664

[14] Qingqing Yang, Jianwei Li, Simon Le Blond, Cheng Wang, “Artificial Neural Network Based Fault Detection and Fault Location in the DC Microgrid”, Energy Procedia,Volume 103, pp 129 – 134, ScienceDirect, 2016.
DOI: https://doi.org/10.1016/j.egypro.2016.11.261

[15] Nabamita Roy &Kesab Bhattacharya, “Detection, Classification, and Estimation of Fault Location on an Overhead Transmission Line Using S-transform and Neural Network”, Electric Power Components and Systems, Volume 43(4), pp 461–472, Taylor & Francis, 2015.
DOI: http://dx.doi.org/10.1080/15325008.2014.986776

[16] Liang Yuansheng, Wang Gang, and Li Haifeng, “Time-Domain Fault-Location Method on HVDC Transmission Lines Under Unsynchronized Two-End Measurement and Uncertain Line Parameters”, IEEE Transactions on Power Delivery 1,Volume 30, Issue 3, pp 1031 – 1038, 2015.
DOI: 10.1109/TPWRD.2014.2335748

[17] Pu Liu, Renfei Che, Yijing Xu, Hong Zhang, “Detailed Modeling and Simulation of ±500kV HVDC Transmission System Using PSCAD/EMTDC”, IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), 2015.
DOI: 10.1109/APPEEC.2015.7446227

[18] S. F. Alwash, V. K. Ramachandaramurthy, and N. Mithulananthan, “Fault Location Scheme for Power Distribution System with Distributed Generation”, IEEE Transactions on Power Delivery,Volume 30, Issue 3,pp 1187 – 1195, 2014.
DOI: 10.1109/TPWRD.2014.2372045

[19] Jae-Do Park, Jared Candelaria, Liuyan Ma, and Kyle Dunn, “DC Ring-Bus Microgrid Fault Protection and Identification of Fault Location”, IEEE Transactions On Power Delivery, Volume 28, Issue 4,pp 2574 – 2584, 2013.
DOI: 10.1109/TPWRD.2013.2267750

[20] M. Farshad and J. Sadeh, "A Novel Fault-Location Method for HVDC Transmission Lines Based on Similarity Measure of Voltage Signals," in IEEE Transactions on Power Delivery, vol. 28, no. 4, pp. 2483-2490, Oct. 2013, doi: 10.1109/TPWRD.2013.2272436.

[21] M. Abedini, A. Hasani, A. H. Hajbabaie and V. Khaligh, "A new traveling wave fault location algorithm in series compensated transmission line," 2013 21st Iranian Conference on Electrical Engineering (ICEE), 2013, pp. 1-6, doi: 10.1109/IranianCEE.2013.6599888.

[22] M Ramesh, A. Jaya Laxmi, “Fault Identification in HVDC using Artificial Intelligence – Recent Trends and Perspective”, International Conference on Power, Signals, Controls and Computation, IEEE,2012.
DOI: 10.1109/EPSCICON.2012.6175256

[23] X. Sun, X. Tong and J. Yin, "Fault Diagnosis for VSC-HVDC Using Wavelet Transform," 2012 Asia-Pacific Power and Energy Engineering Conference, 2012, pp. 1-4, doi: 10.1109/APPEEC.2012.6307632.

[24] N. Saravanan and A. Rathinam, "A Comparitive Study on ANN Based Fault Location and Classification Technique for Double Circuit Transmission Line," 2012 Fourth International Conference on Computational Intelligence and Communication Networks, 2012, pp. 824-830, doi: 10.1109/CICN.2012.15.

[25] EisaBashier M. Tayeb,Orner AI Aziz AlRhirn, “Transmission Line Faults Detection, Classification and Location using Artificial Neural Network”,International Conference & Utility Exhibition on Power and Energy Systems: Issues and Prospects for Asia (ICUE), IEEE,2012.
DOI: 10.1109/ICUEPES.2011.6497761

[26] Z. Yi-ning, L. Yong-hao, X. Min and C. Ze-xiang, "A novel algorithm for HVDC line fault location based on variant travelling wave speed," 2011 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT), 2011, pp. 1459-1463, doi: 10.1109/DRPT.2011.5994126.

[27] AM Ibrahim, MI Marei, SF Mekhamer, “An Artificial Neural Network Based Protection Approach Using Total Least Square Estimation of Signal Parameters via the Rotational Invariance Technique for Flexible AC Transmission System Compensated Transmission Lines”, Electrical Power Components and Systems, Taylor and Francis, 2011, vol.39., no.1., pp-64-79.

[28] JialeSuonan, Shuping Gao, Guobing Song, Zaibin Jiao, and Xiaoning Kang,“A Novel Fault-Location Methodfor HVDC Transmission Lines”, IEEE Transactions on Power Delivery, Volume 25, Issue 2, pp 1203 – 1209, 2010.
DOI: 10.1109/TPWRD.2009.2033078.

[29] A. Abdollahi and S. Seyedtabaii, "Transmission line fault location estimation by Fourier & wavelet transforms using ANN," 2010 4th International Power Engineering and Optimization Conference (PEOCO), 2010, pp. 573-578, doi: 10.1109/PEOCO.2010.5559253.

[30] M. Kouraichi, M. Mansouri, M. Trabelsi, A. M'Halla, A. S. Abdel-Khalik and A. Sakly, "Deep Learning for Fault Diagnosis in Power Transmission Lines: Current Trends, Limitations, and Future Directions," in IEEE Access, vol. 13, pp. 192105-192142, 2025, DOI: 10.1109/ACCESS.2025.3628908.

[31] N. Minh, NT Khiem, VH Giang, "Fault classification and localization in power transmission line based on machine learning and combined CNN-LSTM models", Energy Reports, Elsevier 2024, vol. 12, pp. 5610-5622.