EasyChair Preprint

№ 9597

Heterogeneous Multi-ml Approach Implemented in HVDC Transmission Line

S.Faiza Nasim, Bareerah Rahman and Umme Kulsoom

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

January 20, 2023

Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Heterogeneous Multi-ml Approach Implemented in Hvdc Transmission Line

syeda faiza Nasim (sfaizaadnan@gmail.com)
NED University of Engineering and Technology
Bareeha Rehman
NED University of Engineering and Technology
Umme Kulsoom
NED University of Engineering and Technology

Research Article

Keywords: HVDC transmission,DC voltage ML models and fault classification

Posted Date: September 19th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-2070067/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

HETEROGENEOUS MULTI-ML APPROACH IMPLEMENTED IN HVDC TRANSMISSION LINE

S.Faiza Nasim*, Bareerah Rahman [2] and Umme Kulsoom [3]

[1] *COMPUTER SCIENCE AND INFORMATION TECHNOLOGY, NED University, PAKISTAN*
[2] *COMPUTER SCIENCE AND INFORMATION TECHNOLOGY, NED University, PAKISTAN*
[3] *COMPUTER SCIENCE AND INFORMATION TECHNOLOGY, PAF-KIET University, PAKISTAN*

*Corresponding author(s). E-mail(s): sfaizaadnan@gmail.com;
Contributing authors: bareerah1998@gmail.com; kulsoomshah9@gmail.com;
†These authors contributed equally to this work.

ABSTRACT

The research article describes a system of machine architecture for protection of transmission lines of HVDC, in which multiple models of ML (KNN and SVM) are employed for fault classification and recognition. The K-Nearest Neighbor classifier is intended to serve two functions. It detects the type of fault as well which serves as a backup module for the starting unit's doubtful fault declaration. From a single-end single measurement, a feature vector consisting of standard deviations gradients and of DC and harmonic current, DC voltage, and correlation coefficients is retrieved. By simulating different states that are non-fault and fault states on a data set having training and test cases are obtained. The ML algorithm is trained in MATLAB and evaluated on a total of 2220 severe instances. The acquired results demonstrated the efficacy of the suggested method in detecting and distinguishing between various internal and external/pseudo problems.In this paper we will discuss how the ANN model Simulink in the MATLAB is used for researching, collecting, and evaluating 456 data sets.

KEYWORDS: HVDC transmission,DC voltage ML models and fault classification.

I. INTRODUCTION

The study examines "fault detection in HVDC transmission lines," which is one of the key applications of machine learning in the field of electrical engineering. Due to developments in power electronics technology, two forms of High voltage DC transmission lines based on various types of converters have been produced in the preceding few decades as a solution for difficult difficulties like offshore transmission and long-distance. Every transmission system, like all other electrical systems, has to be protected. Some AC-specific safeguards have previously been proposed for modification to DC-specific safeguards. A statistical examination of China's HVDC transmission system revealed that line protection zone failures were responsible for 36.8 percent of the 114 valve group outages. Similar incidents, in which the fault detection methods fail to fulfill security requirements or rely on protective capability, result in hazardous hardware damage or an unexpected trip, as well as a power loss for consumers. As a result, a dependable protection technique can reduce incorrect fault detections, resulting in a reduction in total power outage. [2]

The proposed first approach includes two machine learning methods: a binary SVM as a starter unit on the other hand classification is done by using KNN classifier. Through the proposed system design, this innovative combination of two separate machine learning models is a fresh start and contribution to machine learning to give solutions for power system challenges. [3]

The second solution is to use ANN to detect transmission line faults. Because it is a programming approach capable of solving problems (linear or nonlinear), artificial neural networks (ANN) may be used efficiently for defect classification and detection. They are generally recognised and employed in the issue of fault categorization and detection because there are several transmission line configurations available. There are multiple approaches for quickly and reliably simulating the network with various power system circumstances. [5]

Some of the significant elements include the network type, network design (which contains the learning algorithm parameters, number of neurons, activation functions, number of layers, termination criteria, and so on). For exact fault detection and classification, different characteristics such as post and pre fault currents and voltages of the relevant 3 phases in steady state are required. The post and pre fault voltages and currents levels of the corresponding three phases are extremely different and are regulated by the type of fault. As a result, the fault classification approach necessitated the use of a neural network to assess the kind of fault based on patterns of voltages and currents before and after the fault created from values recorded from a 3 phase transmission line of an electrical power system at one terminal. The NN is built on a total of six inputs, which are the currents and voltage of the three phases. These six inputs are used to train the neural network. The NN contains four outputs in total, which are 3 phases ground, A, B, and C of a 3 phase transmission line. [1]

II. RESEARCH METHODOLOGY:

With a sampling frequency of 20 kHz, a voltage is simulated. Measurements are taken after the DC side filters on the rectifier side. At typical operating conditions, 2kA is the extreme current passing across the transmission link. The transmission line's frequency dependent model is used. Some of the processing techniques we have discussed in our work are:

A. Suitable feature vector for fault identification

When compared to outward faults, internal faults cause dramatic variations in current and voltage. Furthermore, the sign of gradients may distinguish backward and forward faults, making it an effective characteristic for determining fault severity and direction. It is worth mentioning that appropriately determining the length of the sample window can help to evade protection system failures since the indicated gradient is computed using a predetermined sampling window. Beside current and voltage gradients, it is clear that exterior faults induce less harmonic current distortion than interior faults. This is because smooth reactors are present on both ends of the line, in which the reactors function as low-pass filters. and the low impedance provided by DC side filters which is route for current harmonics. Input impedance of external and internal faults reveals that harmonic current of high-frequency generated by external faults encounters a greater impedance route (nearly 60 times) than internal faults. The low impedance route may also be seen as local minimums created by the DC filters at frequencies 1800,1200,600 Hz. As a result, the existence of harmonic current of high frequency may be used to discriminate between external and internal defects. [4]

B. Suitable feature vector for fault classifications

Types of faults are mainly of two types. Line to line faults and ground faults. The main three faults are Positive to negative (PN), Negative to ground (NG), and Positive to ground (PG) faults. Because the negative and positive poles are electromagnetically coupled, the traveling wave signal generated by the defect may be recognised on the strong pole as well. To address this issue, the transformation matrix of phase mode is utilised for voltage and current decoupling of the negative and positive pole. The transformation matrix of phase mode can be written as:

$$\begin{bmatrix} M_{1\pm} \\ M_{0\pm} \end{bmatrix} = \frac{\sqrt{2}}{2} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} C_{\pm} \\ C_{\mp} \end{bmatrix}$$

M1 = Aerial mode

M0 = Zero mode

C = Fault component

C. PROPOSED ALGORITHM

Among the several techniques, the SVM classifier is recommended for the starter unit. The gradients of harmonic current and pole voltage current are calculated using a six-sample window. The SDs of harmonic current and pole current are calculated concurrently. When the SVM starter unit identifies defects in the protection zone, this KNN classifier is activated by shifting its output from 0 to 1. The trigger signal then instantly stimulates the KNN classifier, and another window of six samples starts calculating the fault currents of zero mode and aerial modes, as well as the corresponding correlation coefficient. The KNN classifier inputs are the SDs of harmonic current, fault current and the correlation coefficients of negative and positive poles. The KNN module predicts the kind of failure based on the learned data. A pseudo- fault is an additional fault to the remaining three types of faults (positive-negative, and aground faults) as shown in Figure 1, here pseudo-fault which comprises disturbances that might be mistaken for true problems are shown. Using different approaches of ML and revision, this approach results in a more trustworthy and safe protection mechanism. In this example, the KNN classifier adjusts for the starting unit's likely faults and improves overall accuracy. [3]

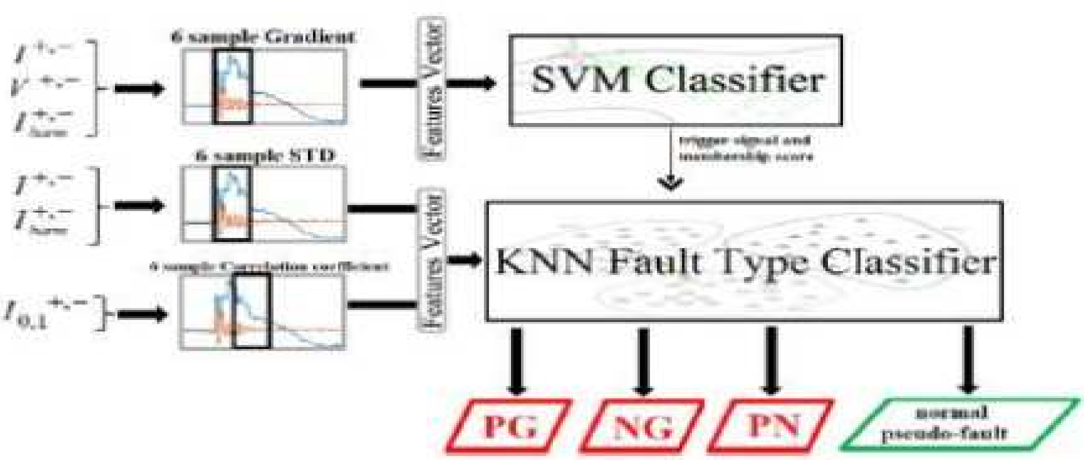

Figure 1.KNN Fault Type Classifier

III EVALUATION METRICS

Confusion matrices and accuracy were used to determine the efficiency of the algorithm. SVM Confusion matrix for training as shown here in Figure 2 [3]

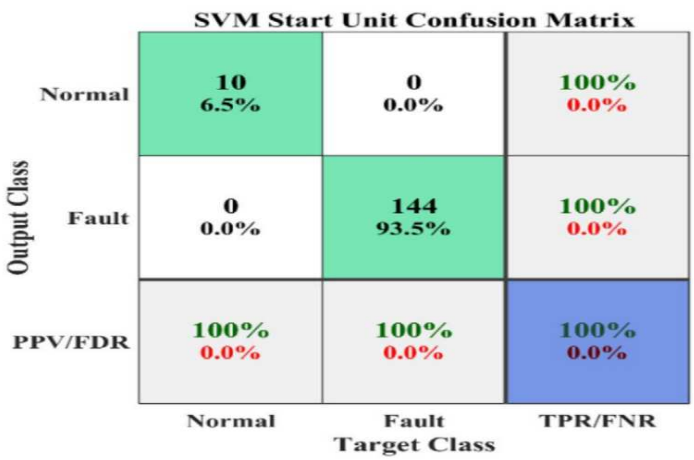

Figure 2. SVM Smart Unit Matrix

Confusion matrix for KNN model is shown here in Figure 3.(results are training validation data set)

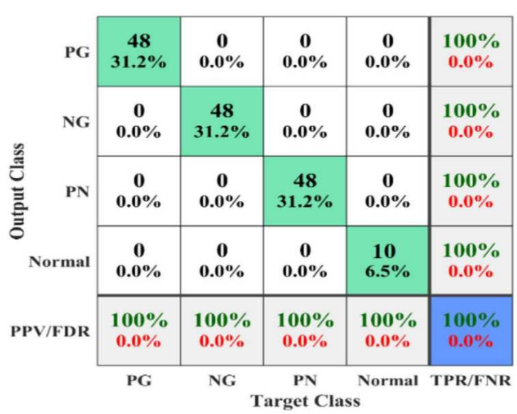

Figure 3.KNN model Matrix

Confusion matrix for total protection of algorithms (results of test case) is shown below in Figure 4:

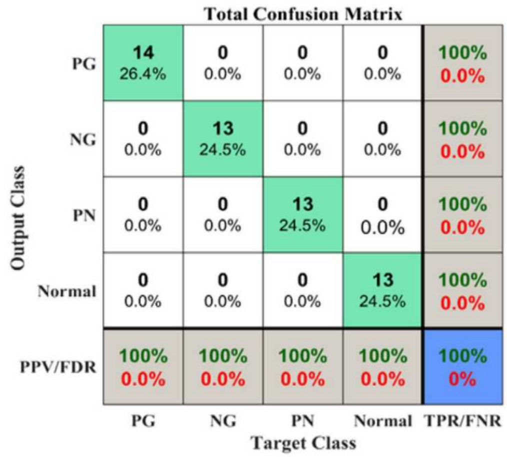

Figure 4.Protection Algorithm

Going through different research papers that utilize different algorithms to solve this particular problem related to fault detection in HVDC transmission lines, it is evident enough that a heterogeneous technique to solve this problem is far better than using any specific algorithm. This problem can be solved using decision trees. SVM, KNN, ANN, and linear discrimination.

The remaining algorithms accuracy of different papers are discussed here in Table 1.

Algorithm	**Accuracy**
Medium trees	73.4%
Linear decision tress	87.40%
Svm	83.60%
Fine KNN	89.90%
ANN	77.84%
Linear discrimination	42.70%

Table 1. Algorithm Accuracy table

IV. DISCUSSIONS AND CONCLUSION

This research offers a ML based security system for High voltage DC transmission lines composed of two distinct ML modules. As a starter module, an SVM model is used because requires minimum period to categorize the query sample of a feature vector which is 6D comprising the gradients of harmonic current, DC voltage DC current of positive and negative poles.Analyzing above results it is clearly evident that rather using any one algorithm, different algorithm can be used so that accuracy increases. The two outputs are then fed into a KNN classifier for 4 class, which is in charge of classification of fault type and serves as a backup unit for the start-up unit when the posterior probability of query samples is low. The acquired findings support the algorithm's speed and accuracy, with a maximum detection time of 4.2 ms. The proposed algorithm's great performance is due to the use of well-separated characteristics as feature vector elements, which provide a clear separation among non-fault and fault classes. A heterogeneous ensemble learning strategy also produces a model that is more effective than a specific ML approach.

The given method makes no direct use of threshold values, and the classification and detection procedure is determined by the similarity of standard deviations and gradients among query samples' signals and training examples. [3] Also there are some different techniques in different papers that use one algorithm but are not giving better results than this heterogeneous algorithm.

- **ACKNOWLEDGMENT**

Finally, it is a real pleasure for me to acknowledge the contributions of my amazing partners Umme Kulsoom who's working with at PAF-KIET as a Lecturer as well as Bareeha Rehman my student who is enrolled in Ned Univeroty CIS department, both of them gave up there time and read every version of this paper.This paper and the research behind it would not have been possible without their extraordinary support .

Non-funded This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

[1] Ben Hessine, M., & Ben Saber, S. (2014). Accurate Fault Classifier and Locator for EHV Transmission Lines Based on Artificial Neural Networks. *Mathematical Problems In Engineering*, *2014*, 1-19. doi: 10.1155/2014/240565

[2] GANGWAR, A., & Gafoor Shaik, A. (2022). Fault Detection, Location in Hybrid Distribution Network Using Machine Learning Algorithm. *SSRN Electronic Journal*. doi: 10.2139/ssrn.4170512

[3] Ghashghaei, S., & Akhbari, M. (2021). Fault detection and classification of an HVDC transmission line using a heterogeneous multi‐machine learning algorithm. *IET Generation, Transmission &Amp; Distribution*, *15*(16), 2319-2332. doi: 10.1049/gtd2.12180

[4] Jamil, M., Sharma, S., & Singh, R. (2015). Fault detection and classification in electrical power transmission systems using artificial neural networks. *Springerplus*, *4*(1). doi: 10.1186/s40064-015-1080-x

[5] Liu, J., Tai, N., Fan, C., & Huang, W. (2015). Protection scheme for high‐voltage direct‐ current transmission lines based on transient AC current. *IET Generation, Transmission &Amp; Distribution*, *9*(16), 2633-2643. doi: 10.1049/iet-gtd.2015.0792

[6] Wang, Q., Yu, Y., Ahmed, H., Darwish, M., & Nandi, A. (2020). Fault Detection and Classification in MMC-HVDC Systems Using Learning Methods. *Sensors*, *20*(16), 4438. doi: 10.3390/s2016443