TRANSMISSION LINE HEALTH PREDICTION SYSTEM IN HVDC AND HVAC LINES

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Abstract - *This presents the study of various configurations in HVDC transmission, converter topologies, and its control analysis. The HVDC system configuration and converter topologies play significant roles in terms of economy, efficiency, and reliability in operation together with existing AC transmission networks. Due to the absence of DC circuit breakers in 2-terminal HVDC transmission, any normal and abnormal disturbances are taken care of by its control arrangement. The rectifier and inverters converting stations are crucial parts of DC transmission system provided with current control (CC), voltage control. As the world is evolving very fast the electrical energy necessity to assist the development also peaks up and the systems have to enlarge. This has led to the mutual connection of all types of power systems all over the world. The rising rate of industrialization all over the world makes a huge demand for the consumption of electrical energy. More requirements for electrical energy have led to the search of more efficient methods of electrical energy transmission at higher power and voltage levels. High voltage AC (HVAC) used across the world tends to be fussy over longer distances and it creates various environment issues. Therefore, HVDC use is been propound*.

Key Words: *HVDC, HVAC, Fault Location, Random forest, ANN.,*

1. INTRODUCTION

Three-phase PWM VSR systems have gradually gained popularity in the fields of motor drivers, uninterruptible power supply (UPS), renewable energy systems, and other energy conversion technologies (Yang et al., 2016; Li and Yang, 2017; Bueno and Pomilio, 2018; Zhang et al., 2021). However, the majority of renewable energy equipment is constructed in mountainous or isolated regions distant from the shore since the likelihood of sensor failures is relatively high in these environments (Bidadfar et al., 2021). When a failure develops in one of the crucial sensors for the control system, the entire apparatus may malfunction or operate ineffectively (Peng et al., 2018). Therefore, it is crucial to accurately diagnose sensor faults in three-phase PWM VSR systems in order to guarantee the overall system's dependability.

Hard faults and soft faults are two categories of sensor defects that may be separated based on fault severity (Huang and Tan, 2008; Li et al., 2011; Darvishi et al., 2021). Damage to sensor components, electrical system short circuits, or open circuits are the main causes of hard failures, and the measured value will fluctuate significantly as a result. Sensor component ageing is referred to as a soft defect. Soft faults do not do as much damage as hard faults, but prolonged use will decrease system efficiency and hasten system ageing (Fravolini et al., 2019). For instance, the closed-loop feedback control will be affected, the control performance will be reduced, the ageing of other equipment will be accelerated, and even safety incidents may result if the fault output signals of the current sensors are utilised as the input signals of the control system. Monitoring early soft fault characteristics allows for the early detection of possible risks, prompt repair, protection of other medical equipment, and assurance of the stability of the entire system. To increase system dependability, a reliable and efficient fault diagnostic approach is therefore especially necessary for sensor defects; it would also be preferable if the fault sites could be identified.

Data-driven and model-based strategies can be used for sensor fault detection and diagnosis (SFDD) (Reppa et al., 2015; Lee et al., 2021). Model-based approaches are typically simple to include into control systems, but they also require the establishment of sophisticated thresholds, making them more challenging to use in other domains, particularly for nonlinear systems where fault models are more challenging to construct (Kou et al., 2020; Wang et al., 2020). Without the need to comprehend the fault mathematical model pertaining to the sensor systems, data-driven approaches can just employ historical data to create a black-box model and apply a mature black-box classifier to achieve fault diagnosis and placement (Li F. et al., 2021; Shi et al., 2008). Consequently, the data-driven methodologies are independent of mathematical models and have drawn the interest of several academics (Ojo et al., 2021). For battery energy storage systems, Lee et al. (2021) developed a convolutional neural network (CNN)-based FDD approach to identify and categorise erroneous battery sensor data. Long short-term memory recurrent neural network (LSTM-RNN)-based thermal defect diagnostics for lithium-ion batteries was developed by Ojo et al. in 2021. This approach is simple to apply and does not need attention to the intricate mathematical modelling and battery physics parameters. A hypergrid and statistical analysis-based FDD technique was put out by Chen et al. (2021a) to help locate sensor defects in wireless sensor networks. A distributed SFDD framework was created by Jana et al. (2021), and a fuzzy deep neural network (FDNN) was used to detect and classify the sensor errors. An interval-valued data-driven approach developed by Hajer and Okba (2020) was implemented to identify and pinpoint sensor defects in chemical industrial areas. For micro-electromechanical system (MEMS) inertial sensors, Gao et al. (2020) suggested a CNN-based FDD approach, in which the time-domain properties of temperature-related sensor errors were employed to train the data-driven FDD classifier. Haldimann et al. (2020) created a unique approach to detect the fault sensors and suggested a disentangled RNN and residual analysis-based SFDD method. An NN-based fault estimate approach was put out by Chen et al. in 2021b and can produce an accurate assessment of sensor defects. An LSTM-based CSFDD approach was put out by Li L. et al. in 2021, and it can anticipate acceleration responses from observed data by automatically learning data characteristics. In light of the prior explanation, several fields have successfully diagnosed sensor faults using data-driven methodologies. The historical fault data under both normal and fault modes may be gathered via the simulation tools, and data-driven approaches can efficiently set up the nonlinear model between input characteristics and fault modes. To increase the fault diagnostic accuracy of the whole diagnosis system, however, the study on fault data extraction is crucial.

We have gained a lot of knowledge from the wonderful work that many academics have done in the area of sensor malfunction identification. Although the artificial neural network (ANN) is a well-liked supervised learning technique, over-fitting can damage both the capacity to generalise and the outcomes of diagnostic tests. The CSFDD classifier is therefore trained using the random forest (RF) method, which is difficult to over-fit due to the inclusion of two randomnesses (random samples, random features) (Roy et al., 2020; Fezai et al., 2021). The RF CSFDD classifier is proposed to be trained using the present fault texture characteristics, which can increase the feature diversity and diagnostic precision. Hard faults can result in significant damage, and the transition from mild faults to hard faults often takes a long period. Soft defects may thus be identified and treated quickly, allowing for timely maintenance of the equipment and the prevention of severe failures.

2. RENEWABLE SOURCES INTEGRATION CHALLENGES

Transmission of large amounts of energy from renewable sources or traditional generators must be accomplished at the high voltage level to minimize losses. As described in [3], greater voltage for the same amount of delivered power reduces the current and, in turn, the loss over the line for both direct current (DC) and alternating current (AC) transmission. Therefore, HVDC is more efficient since there is less energy wasted, and DC eliminates reactive power, so only active power is flowing in a DC line [22]. When transferring electricity, a direct current (DC) line uses two wires, one to carry the negative charge (or "-") and the other to carry the positive charge (or "+"). Alternating current transmission uses a three-wire AC line (or three phases). Therefore, HVDC would call for fewer conductors and a smaller right-of-way, leading to fewer land uses and cheaper conductor equipment.

HVDC is mostly used to transport power over the sea, where overhead lines are not practical, and to connect offshore wind farms to onshore substations. For that reason alone, HVDC has a significant benefit over HVAC.

In the AC situation, the cable is carrying both the load current and the capacitive current because of the AC cables' significant capacitance, which limits the power carried via the cable. A DC cable, on the other hand, solely transmits load current to do away with capacitive current, which justifies the use of HVDC undersea cables for power transmission over the sea [23]. Unlike HVAC, which suffers from inductive voltage loss, HVDC doesn't have this problem.

Since DC voltage is constant throughout the process, HVDC conductors may transport more power than their HVAC counterparts. On the other hand, AC switches between two different frequencies at regular intervals. Because of this, the root mean square (RMS) is the accepted norm in alternating current (AC), despite the fact that it represents only around 75% of AC's peak voltage [22].

3. STABILITY AND FAULT ANALYSIS

In this article, we will examine the significance of system stability in the electric power system and the causes of system instability. In a safe and reliable working electrical system, system stability is the most important factor. Major blackouts can occur in systems due to power system faults. Maintaining system stability is of paramount importance in this setting. We also discuss high voltage direct current (HVDC) and how it contributes to the reliability of the alternating current (AC) system. We also introduce failure analysis in the AC system with HVDC attached and explore the implications of the problem on both the AC system and HVDC independently. This section concludes with a discussion of why pinpointing a line's exact point of failure is so crucial.

3.1 STABILITY

"system stability" is a condition in which competing forces are in a state of balance [24]. The stability of an electric power system is measured by how well it can return to its original state of operation after being subjected to a perturbing physical force. Since the loads, generator yields, topology, and other crucial operating characteristics are always shifting, the power system architecture is a highly nonlinear system. An upsetting impact may be slight or significant, depending on the circumstances. An unstable electric power system [25] may be the result of voltage fluctuations or recurrence variance affecting the linked power system. Lightning strikes, extreme temperatures, faulty wiring, vandalism, trees falling on transmission lines, plane crashes, too much demand, and car accidents are only some of the additional threats to the reliability of the electricity grid. Faults in the system relate to these instances of instability.

When a malfunction occurs, the engine loses synchronism, a fundamental requirement for a power system, if the regular repetition of swaying matches to the repeated wavering of the generators.

High voltage direct current (HVDC) transmission systems employ the coordinate flow with a more common alternating current (AC) system to transmit electrical power [26]. High voltage direct current lines are used as connectors in AC transmission systems due to their reliability, security, and cost-effectiveness. Terminating circuits of the thermistors put in the two rectifiers and inverters make it much simpler to regulate current on the HVDC side. The AC side is where the switching and breaker actions take place (CB).

HVDC essentially enables control transfer between asynchronous AC transmission systems. An HVDC link can help stabilise a system against the disruptive effects of rapid power changes [27] because power flows can be flexibly controlled at the staging point between the source and the load. In addition, 24 HVDC enables the trading of intensity across systems operating at different frequencies, which improves the robustness and economy of any electric system.

Given its ability to lessen system instability and increase security, HVDC systems may be more cost-effective for transmission work and operations over greater distances. HVDC avoids the massive fluxes needed to charge and discharge the link capacitance during each cycle, making it ideal for underwater power lines. This is why most modern electrical power systems benefit from high-voltage direct current.

3.2 LOCATION OF FAULT

In any electric system, but especially those with very lengthy transmission lines, pinpointing the exact site of the defect is essential for fixing the problem. If a fire breaks out because of a problem, lives may be lost, property would be destroyed, and the electricity grid would be wiped out. In addition, interruptions in power supply might occur in several areas beyond the fault spot in the transmission and circulation arrangement [29]. Estimates of system voltages and flows must be made under fault conditions, with protective devices ready to detect and mitigate faults' potentially disastrous effects. Faults are easier to correct and their related costs are lessened when their precise locations are known.

Engineers working on electric systems need to put system stability first, therefore they should give serious thought to all of the aforementioned precautions before committing to a final design and installation. Faults may be extremely dangerous to human life and have a devastating effect on the economy. Therefore, a reliable and safe system is crucial.

4. RESEARCH METHODOLOGY

4.1 INTRODUCTION TO NEURAL NETWORKS

Artificial neural networks (ANNs) may be defined as "a group of simple neurons coupled together in biologically inspired topologies and arranged in a hierarchical structure" [39]. Feed-forward ANNs, also known as perceptrons, have the following structure shown by Fig 1. Each successive layer contains Ni more neurons, all of which receive input from cells in the layer below them. All of the stimulation information is delivered into the input layer. A single non-linear action on its inputs is all it takes for a basic neuron to generate an output [40]. Each neuron is assigned a weight, and training an ANN entails fine-tuning those weights such that they are optimal for the data in the training set. Adjusting the weights of the nodes in an artificial neural network allows it to learn from its inputs and outputs the desired result. In order to train the neural network, we require a set of data called the training data set. The capacity to extrapolate benefits from this in a new light [39]. The importance of parallel computing in ANN cannot be overstated. Therefore, it can generate the proper output for any input, even if such input was not provided to the ANN during training. Synthesizing the algorithm for the adaptive learning process was another difficulty in developing ANN-based applications.

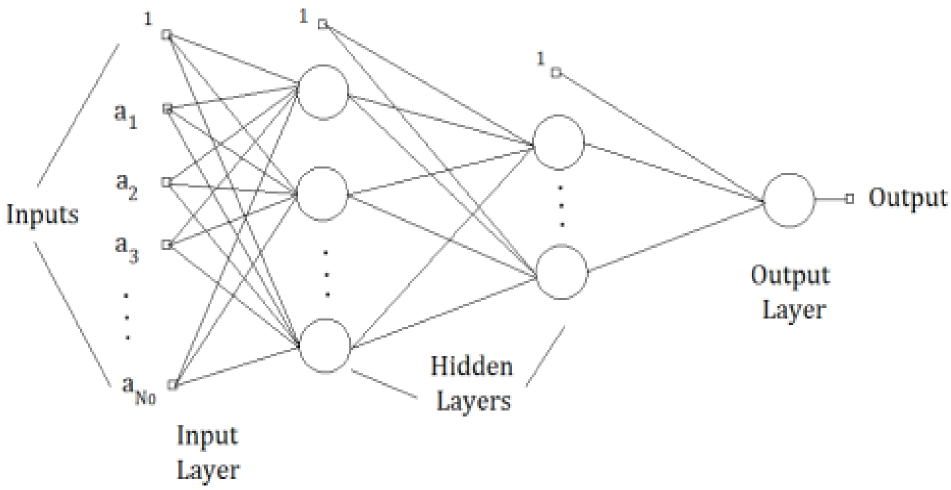

Figure 1: A basic three-layer architecture of a feed forward ANN.

Using an Artificial Neural Network (ANN) and wavelet transform as a feature extraction tool, the proposed study proposes an effective fault detection and classification technique for high voltage DC transmission lines based on bipolar Current Source Converters (CSCs). Ac sinusoidal voltage, DC voltage, and current data recorded on both poles at the rectifier terminal of the line are input to the Artificial Neural Network model in a suggested technique. When compared to other approaches, the input signals are sampled at only 1 kHz. A variety of fault circumstances, time intervals, and locations have been tested to see how the suggested technique performs. With fault detection times of less than half cycle, the ANN-based fault detector and classification method provided here is 100 percent accurate for all the fault samples that we've examined. The Deep Learning toolbox in MATLABTM is used to design and train the ANNs utilised in this thesis.

The dataset is randomly partitioned into training, test, and reference for the various networks. datasets used for testing and validation, with percentages of 70%, 15%, and 15%, respectively. To provide an objective assessment of the ANN during training, the validation dataset is employed.

Epochs are defined as the whole input training dataset being processed by the network together with the updating of the weights and biases involved. The validation dataset is sent via the network and the corresponding error is determined after each epoch. Overfitting to the training dataset can be taken into consideration and the training is terminated if the error on the validation dataset grows after each epoch. This might be viewed as a network that has been overly trained on a certain dataset and may thus be unable to accurately predict fresh input.

Every training will be distinct and provide different outcomes since the initial values of the weights and biases are created at random. Additionally, the performance of the network and its structure are directly influenced by the quantity of hidden neurons. To this degree, training is performed a good number of times for different numbers of hidden neurons, i.e. 10, 20, 30, 40, and 50, in order to preserve the best ANN. The remaining networks' hyperparameters listed in table 3.4 are set to the algorithm's default settings, with the exception of the number of hidden neurons.

The chosen input characteristics of the ANNs are impacted by this distinct procedure as well. For instance, unlike the first conventional workflow, fault distance and faulty path prediction only use the input characteristics of the phase(s) that have a defect. To this degree, the relevance of the input features for the three separate predictions is monitored to maintain the deemed most relevant ones alone, much like the old approach.

Additionally, the size of the dataset that may be used is greatly decreased when specialised ANNs are used. In fact, depending on whether fault distance group H1 or H2 they belong to, the faulty path classification ANNs may only employ 408 or 504 of the 6384 simulations that are available. Given that the size of the dataset is a crucial factor in developing reliable and accurate networks, this is a significant downside. Appendix C also lists the dimensions of the datasets utilised for each each ANN.

It is crucial to note that the faulty phase(s) must be anticipated first in the prediction process, followed by the fault distance and then the faulted route, as each forecast relies on the outcome of the other, as illustrated in (Fig. 3.19b). Naturally, it should be noted that this tactic may potentially result in correlation inaccuracies. For instance, using the incorrect ANN for faulty path classification would result from a fault distance prediction error that was too great. Path correlation error is the term used to describe this phenomena. Similar to how incorrect faulty phase prediction will inevitably result in error correlation due to the remainder of the ANNs' utilisation of incorrect input information The chosen input characteristics of the ANNs are impacted by this distinct procedure as well. For instance, unlike the first conventional workflow, fault distance and faulty path prediction only use the input characteristics of the phase(s) that have a defect. To this degree, the relevance of the input features for the three separate predictions is monitored to maintain the deemed most relevant ones alone, much like the old approach.

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4.2 RANDOM FOREST ALGORITHM

Finding the fault's location is the algorithm's main objective, particularly in multi-branch distribution systems. Finding the branch (lateral or section) where the failure took place is crucial before moving on. The position of the fault is approximated after locating the problematic area.The three-phase current-voltage statistics that were received are shown in this figure as went through a wavelet transform to learn more about the fault that occurred and how to extract features. Fault section identification and fault location estimate are performed after acquiring the best characteristics.

5. RESULTS AND DISCUSSION

SIMULINK MODEL

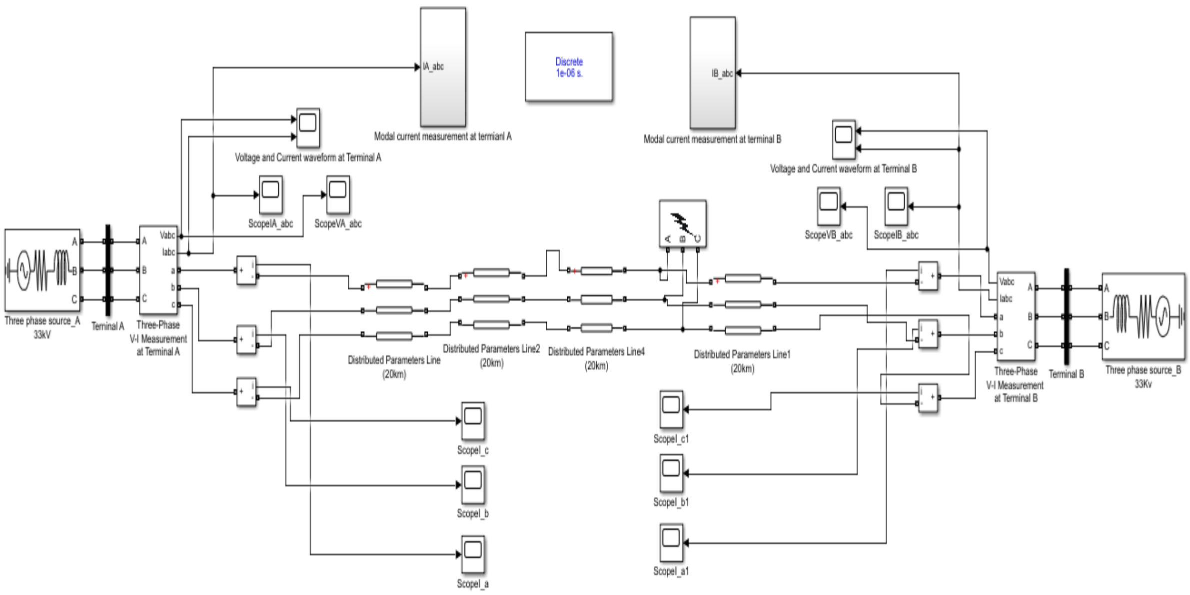


Figure 2: Simulink Model

A) RESULTS AT TERMINAL A

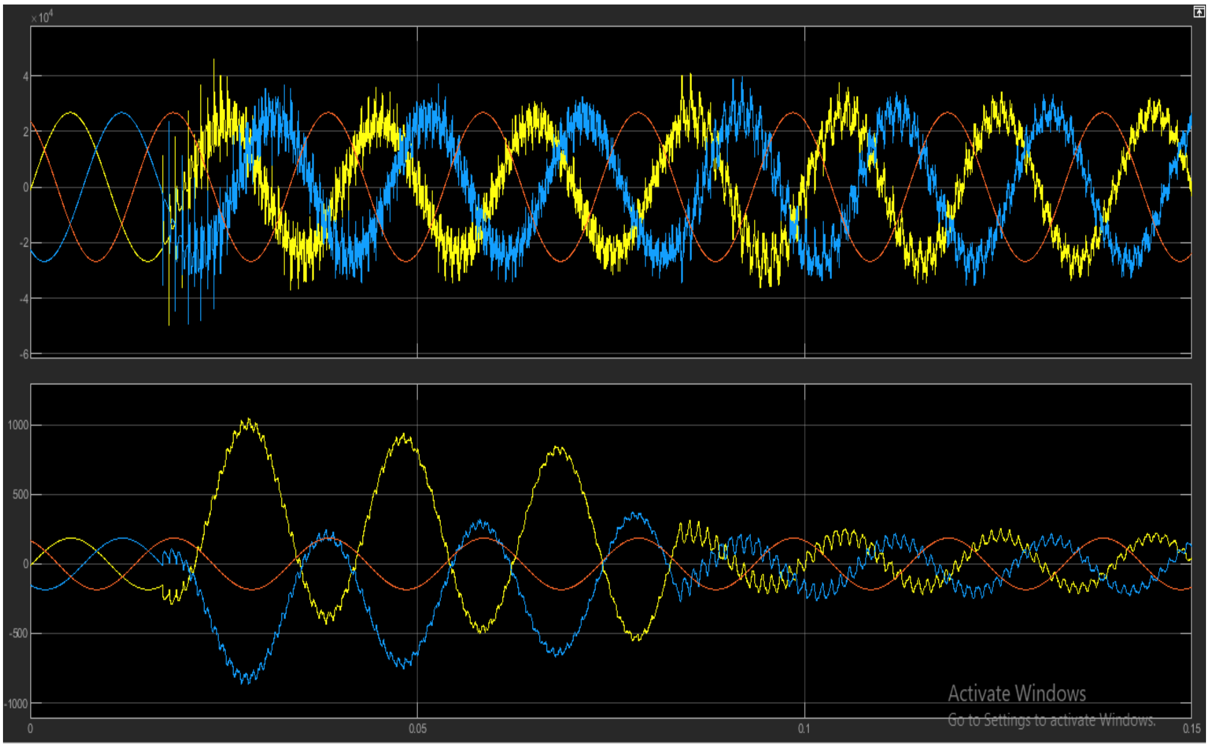
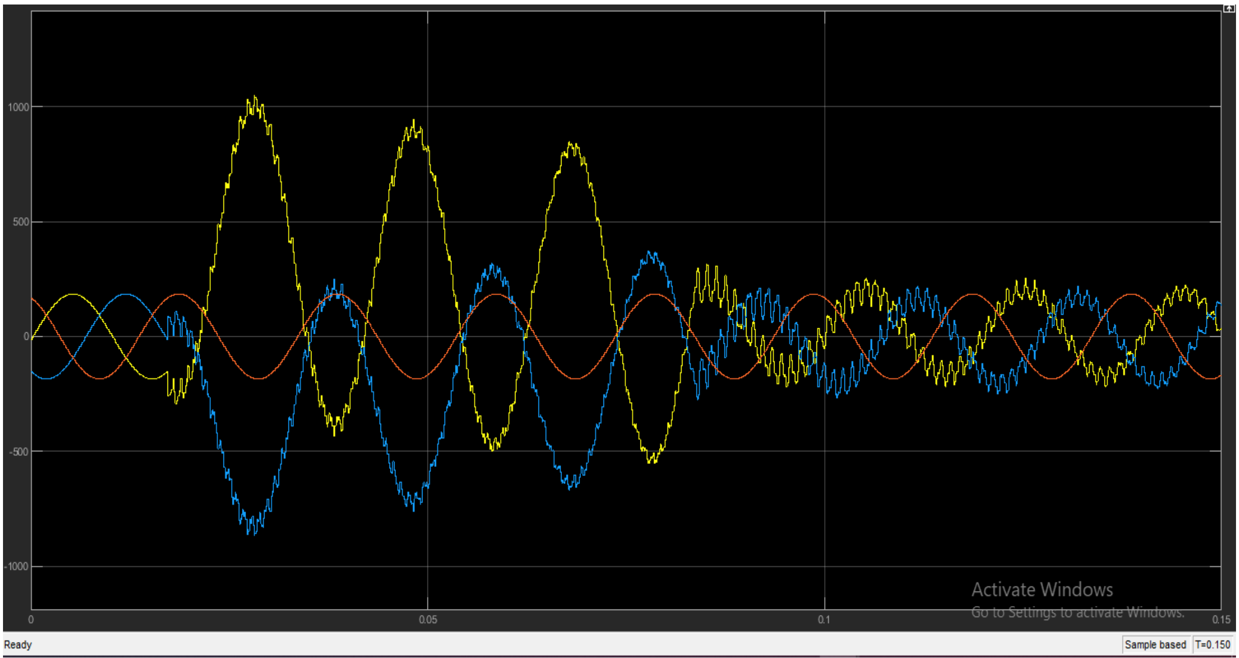
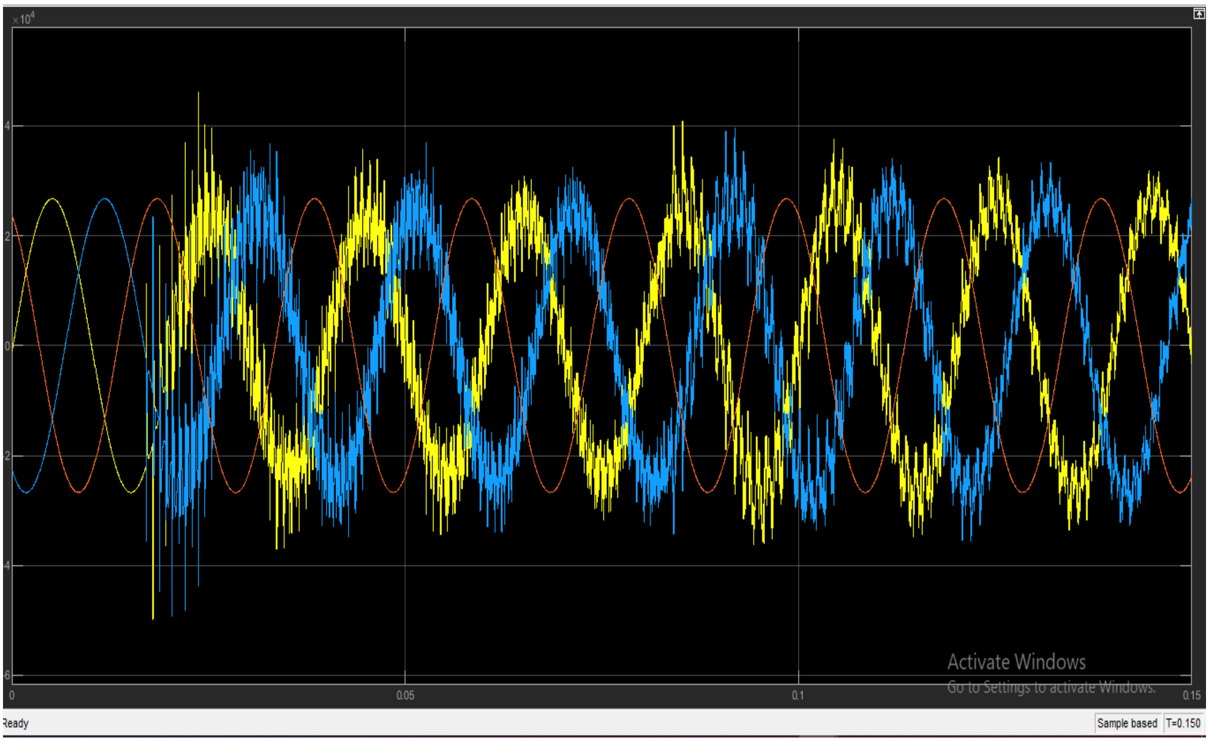


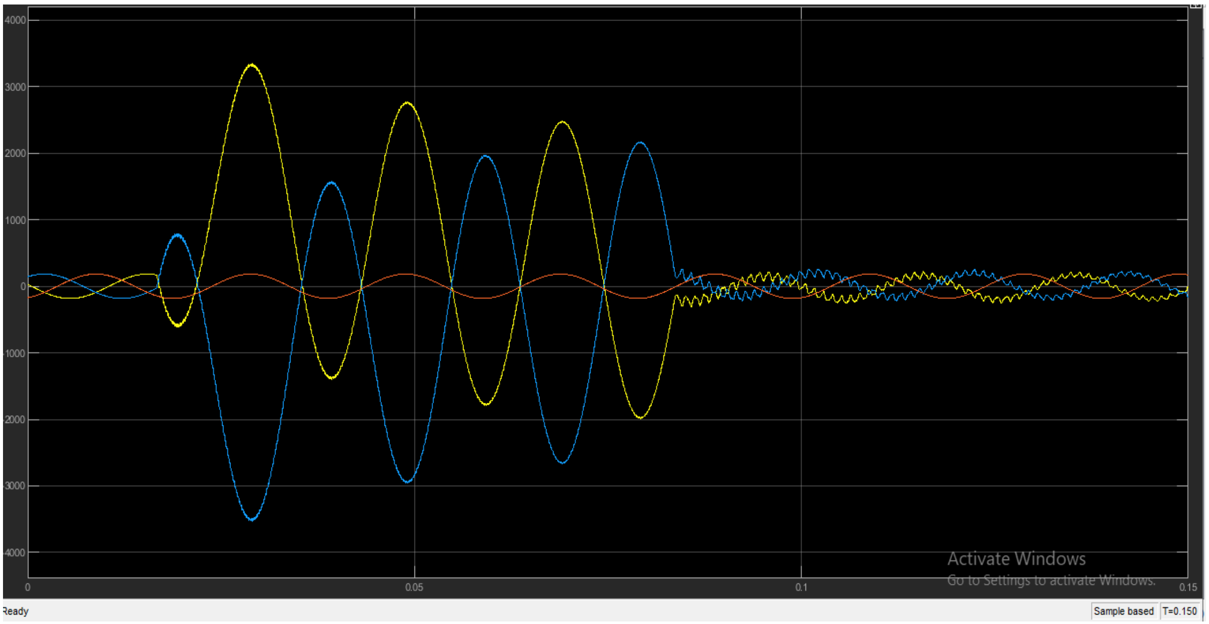
Figure 3 (a): Current and voltage graph at terminal A



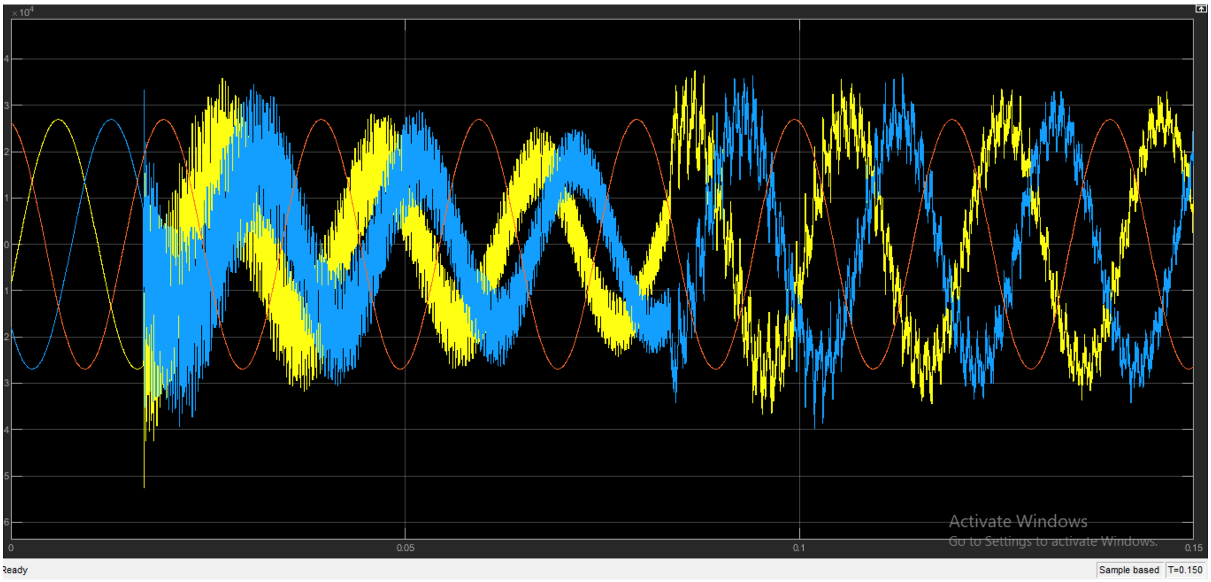
b) Current Source at Terminal A



c) Voltage source At A

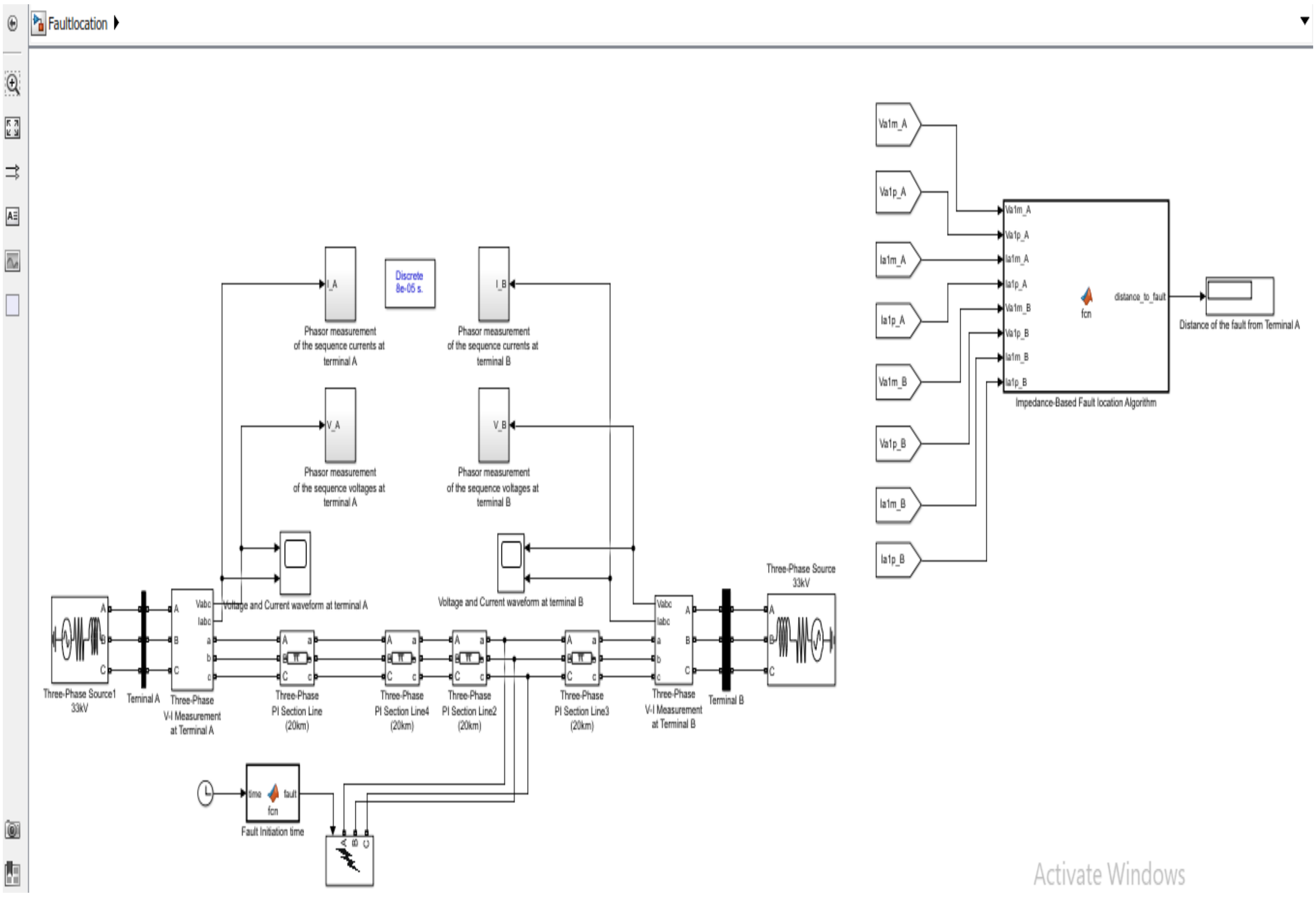


d) Current Source At Terminal B

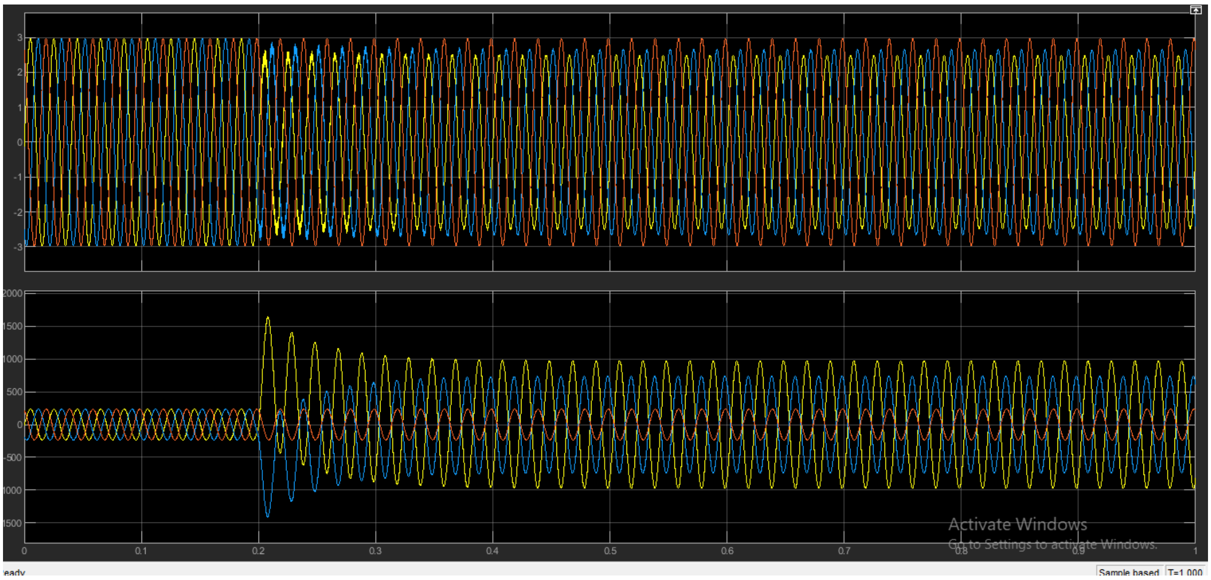


e) Voltage Source at B

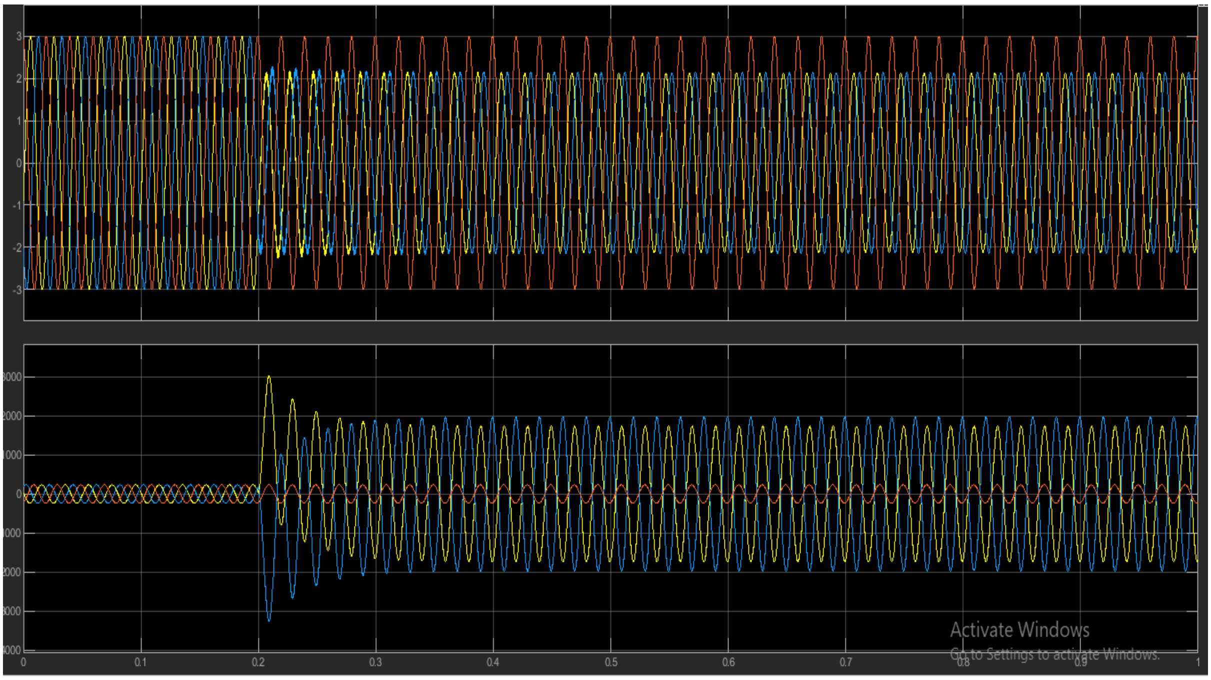
B) FAULT LOCATION



Based on the above simulink diagram the fault location is calculated by placed the fault between the phase A and B , By changing the line length of the transmission line the fault location will change accordingly with reference to A. The fault location time is set at 0.2 sec, so in the current and voltage graph , it shows changes from time 0.2 seconds.



f) Voltage and current wave form at point A



g) Voltage and current at point B

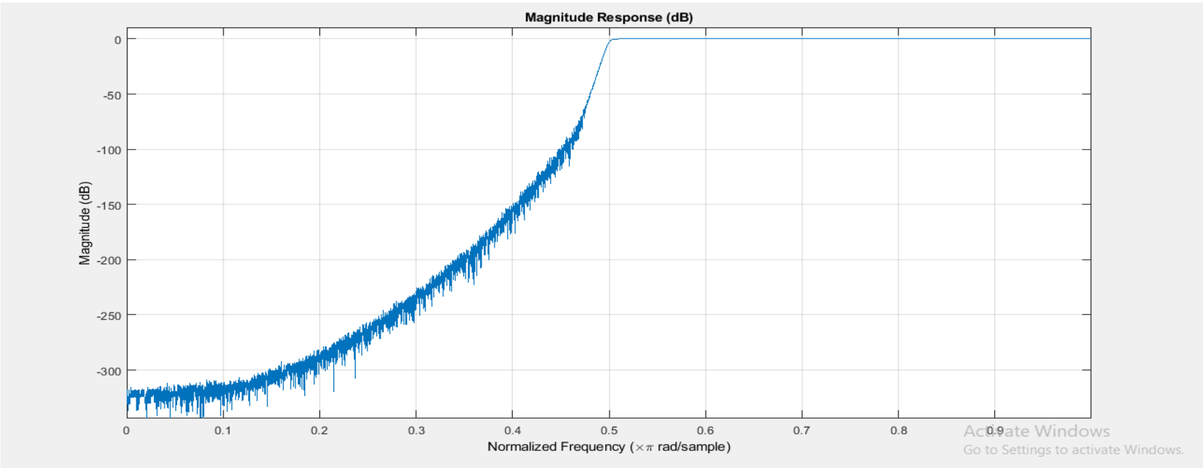
Table 1: Fault location from point A by changing

Distance (Line length km)	Fault location from point A	Relative error
25	20.83	0.1668
75	62.45	0.167
125	104.1	0.1672
250	208.3	0.166
300	249.9	0.167

375	312.4	0.1669
425	354.1	0.166
475	395.7	0.166

length between A and B

From the above table the line length of the transmission line is changed from 25 km to 475 km respectively and the location of the fault changed with respect to the line length , but the relatives error between all the location remains almost same



h) Frequency graph

C) RANDOM FOREST

One ensemble method is the random forest F=t1,t2,tt,tt, which consists of a set of unrelated and autonomous decision trees. Model F can achieve a reliable generalization with the help of these uncorrelated trees since they introduce a little of unpredictability into the decision trees. Bagging, a technique that combines bootstrapping and aggregation, is used to get these broad conclusions. Input feature space including voltage (v), phase angle (), current I and frequency (f) are part of a training set S=Xm,Ymm(M=1), where XRD (f). The fault location and fault time are both included inside Y, a multidimensional continuous space with the dimensions YRD′. Bootstrap is a subset St of the full training set S, where each instance is randomly picked from the distribution with or without replacement, and M is the number of samples. The number of instances in the final bootstrap data is the same as in the original data set S; however, about one-third of the samples are duplicated and approximately one-third of the instances are eliminated. To generate bootstraps for each tree, the input data is processed via several iterations. After training and testing on bootstrap data, the aggregated value of all the individual trees' predictions is calculated.

Four experimental scenarios were considered for the evaluation of the RFR model performance. The proposed model was assessed based on the accuracy metric in experiment , which is the ratio of the correctly classified fault location cases over the total number of cases. The accuracy metric can be expressed as

Accuracy= (TP+TN)/(TP+TN+FP+FN)

where TP denotes a positive result, TN a negative one, FP a false positive, and FN a false negative. The confusion matrix provided us with these values. An further set of tests looked at how well the model estimated how long a failure would last. Due to the continuous nature of this feature, different performance measurements, such as mean absolute error (MAE) and mean squared error (MSE), were used. The Mean Absolute Error (MAE) is calculated by averaging the squared deviations between the observed and expected fault times.

MAE= 1/n ∑i=1n| (y^−y) |

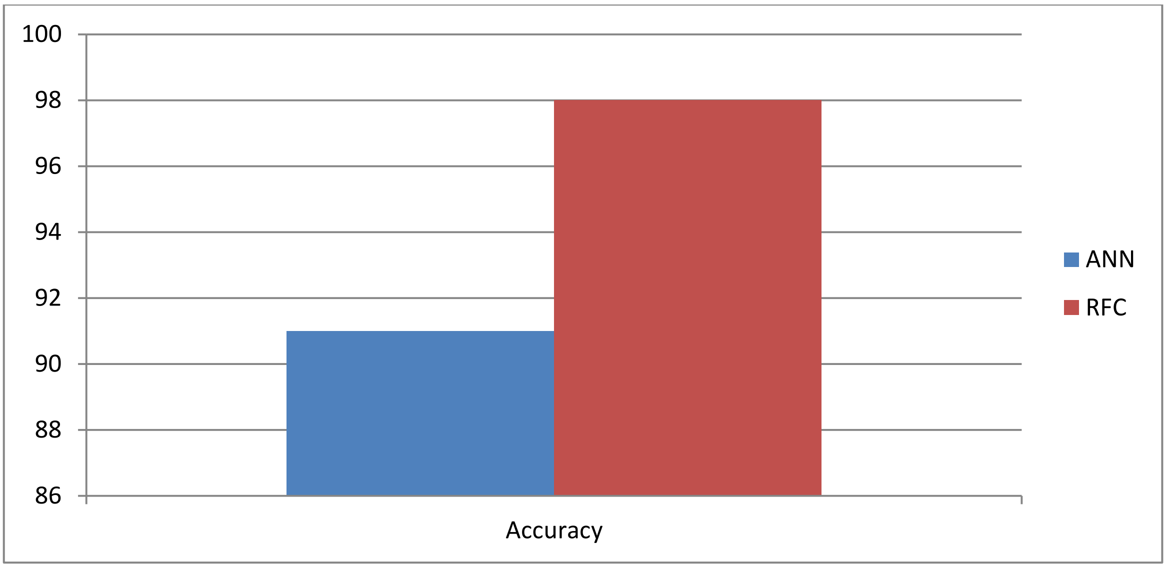
The number of cases, n, the actual fault duration, y, and the expected fault duration, y. By averaging the squared discrepancies between the actual fault time and the projected one, MSE penalises for severe inaccuracies while maintaining the advantages of MAE

MSE=1n∑i=1n(y^−y)²

By comparing the two algorithms ANN and Random Forest Classification on the basis of fault between the two terminals A and B, The results of the two algorithms are compared as mentioned in table and graph

Table 2: Algorithm Comparison

	PERFORMANCE METRICES	
	ANN	**RFC**
ACCURACY	91	94
SENSITIVITY	98	98
PRECISION	95	98
RECALL	95	98



6 CONCLUSIONS

The HVDC transmission is perpetually developed and widely used in renewable power applications, so it has a wide outlook. This research presents the study and analysis of HVDC transmission system at the time of DC transmission pole to pole short circuit fault and pole to ground faults. DC pole to pole fault is choose to be analysed because it is observed as one of the most dangerous faults in any transmission system. The fault characteristics has been studied starting from the instant of fault moment and until it reaches its steady state condition. It is seen that during this type of faults the system configuration changes in time. A HVDC transmission system has been simulated by using MATLAB Simulink and the system has been tested in normal and fault conditions.

This technique uses the ratio of instantaneous energies to pinpoint the defect. The method is unaffected by the resistance of the fault transition thanks to the ratio. This approach is based on detecting the electrical amount information at both ends of the DC line to obtains the problem location. It is unaffected by the synchronous clock since it does not depend on measurement time.

It is determined that the approach is straightforward and simple to execute, and that it is both accurate and resilient in its ability to pinpoint problems on DC power lines. As a result, the findings of this research have some bearing on the problem of fault localization in DC lines. From the above techniques it is clear that RFC is more accurate than ANN and other algorithms.

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