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Fault Detection of HVDC Transformer Windings using Impedance Protection

Master's thesis in Sustainable Electric Power Engineeing and Electromobility

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Abstract

Power transformers play a key role in high voltage direct current (HVDC) systems to overcome the limitations of conventional AC transmission and are expensive and fundamental components in power systems. Transformer winding faults are among the most frequent issues in transformers. Since winding faults are inherently aggravated, transformer winding short circuits need to be detected at an early stage. The existing transformer protection methods encounter difficulties in detecting winding faults in transformers. This study investigates and develops a reliable method for transformer winding fault detection based on impedance protection by calculating the winding impedance utilizing the terminal voltage and current measurements, and comparing the impedance values under fault conditions with their steady-state condition values. A three-phase transformer was modelled in PSCAD simulation software using three multi-winding single-phase transformers to model internal faults. Turn-to-turn faults were simulated for different fault locations, and analyzed impedance values of each scenario using a conventional impedance protection method and Machine Learning algorithms (ML) i.e. Support Vector Machine (SVM), Decision Tree and Artificial Neural Networks (ANNS) to detect and classify the winding faults and identify their locations. The fault studies were conducted on a symmetric monopolar Voltage Source Converter (VSC) based HVDC system. The terminal voltage and current measurements were utilized to derive impedance values for each fault condition. The obtained voltage, current, and impedance measurements were fed to train the developed Machine Learning algorithm Models. A higher accuracy is obtained by optimizing the ML model parameters in fault detection, classification, and fault location detection.

Keywords: VSC-HVDC, 3-phase Transformer, Internal Winding Fault Detection, Impedance Protection, Artificial Neural Network

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Sewwandi S M Meegodage, Gothenburg, August 2025

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ANN	Artificial Neural Network
FP	False Positive
FN	False Negative
HVDC	High Voltage Direct Current
IGBT	Insulated Gate Bipolar Transistor
LM	Levenberg-Marquardt
LCC	Line-Commutated Converter
MLP	Multilayer Perceptron
MAE	Mean Absolute Error
MSE	Mean Squared Error
SVM	Support Vector Machine
TP	True Positive
TN	True Negative
VSC	Voltage Source Converter

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Introduction

1.1 Background

High Voltage Direct Current (HVDC) systems is a blooming technology in modern power systems due to their capability of transmitting power with lower losses, greater stability, and better controllability. The capability of transmitting high-capacity power via long distances and allowing interconnections between asynchronous systems are some of the advantages of HVDC systems [1]. Power transformers play a key role in HVDC systems and expensive and essential component in power systems. Power transformers step up and step down the voltage to create compatibility for HVDC converters, minimizing transmission losses and allowing safe operation at the distribution level. The power system's ability to withstand high stress levels is improved by power transformers since it is providing galvanic isolation between AC and DC side [2]. The operation and performance of the power transformer is vital to reliability and stability in today's modern power systems.

1.2 Problem Statement

Winding faults are usually caused by overheating, insulation layer failures, and high mechanical stress [4]. These are among the most common causes of transformer failure based on components (Figure 1.1). Winding short circuits are aggravated in nature and will be spread through the winding. Therefore, winding short circuits needs to be detected at early stages to prevent the damage to the transformer and the power system it supports. To ensure the stable operation of the power grid, several proper protection schemes against the certain fault conditions are implemented in transformers. i.e. differential protection, over current protection, harmonic restraint, buchholz relay etc.

However, detecting winding faults in the early stages is difficult with these existing transformer protection methods. An advanced protection method need to be implemented to detect these faults [5]. An impedance based protection algorithm can be adapted to detect and isolate transformer internal faults. In impedance-based protection scheme, the impedance values that are derived from voltage and current measurements are compared in both fault and non-fault conditions to detect the faults. This approach can be ideal solution for detect internal faults in transformer due to it's lower dependency on the external factors.

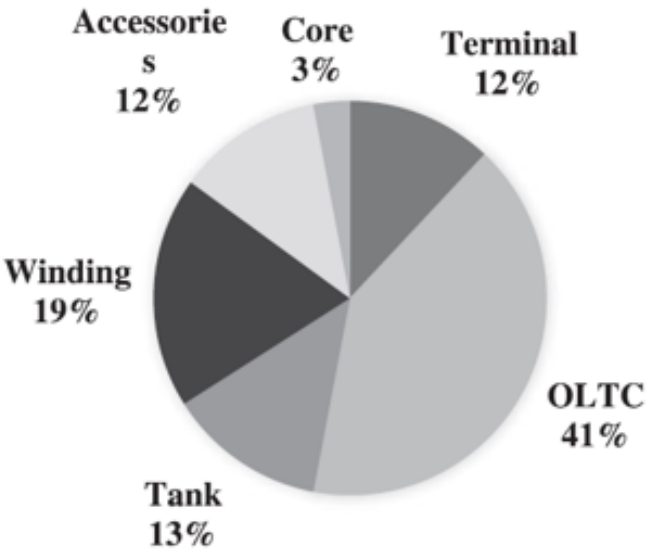

Figure 1.1: Transformer Failures based on components (CIGRE survey)[3]

1.3 Objectives

The main objective of this thesis is to investigate and develop a reliable protection scheme for transformer winding faults based on the impedance protection method. This thesis will simulate an HVDC transformer model in PSCAD/EMTDC, estimate transformer winding impedance under normal and fault conditions utilizing transformer's terminal voltage and current measurements. This study focuses on developing a setting philosophy for impedance protection to improve the reliability and accuracy of fault detection in transformer windings using modern machine learning algorithms and conventional impedance protection method. The challenges associated with detecting winding faults at early stages can be addressed with this study. Potentially this thesis will lead to mitigate possible damages to power transformers due to winding short circuits and facilitate stability of the power system.

1.4 Scope and Limitations

The internal faults in HVDC transformers caused by several characteristics even so the scope of this thesis is limited to study and analyze the winding short circuit failures. Winding faults are one of the most significant types of internal transformer faults and they can be very destructive to the transformer. In this thesis, the focus is on detecting and locating turn-to-turn winding faults in the transformer and excludes other transformer faults such as core faults, bushing faults, external system faults, and variations of transformer configurations to allow for lesser pointed focus.

Further, this thesis is focus limited to the impedance protection method, which is based on calculating impedance from terminal voltage and currents. The impedance method was chosen because it has potential to identify winding internal abnormal

conditions where conventional protection options do not work well [6]. Even though differential protection, frequency domain studies, and traveling wave methods can be utilized to identify the winding faults, those were excluded from the scope of this thesis. By focusing on a single fault mechanism (winding faults) and a single fault detection method (impedance protection), this thesis will provide further insight to reliability in impedance based protection.

1.5 Thesis Structure

This thesis is composed of five chapters.

- Chapter 1 - An overview of the research background, statement of the problem, objectives, scope, and importance of the research.

- Chapter 2 - Theoretical background of the research (HVDC systems and operation, transformer operation and faults, impedance protection, and machine learning algorithms used in the study)

- Chapter 3 - Research methodology (Modeling of transformer faults in PSCAD, the data acquisition, and then the machine learning models created for detecting, classifying, and identifying faults)

- Chapter 4 - Results of simulations and the evaluation of the models, and analyzes the proposed protection scheme.

- Chapter 5 - Discussion and conclusion of the study and recommendations for future work.

2

Theory

2.1 High Voltage Direct Current (HVDC) Systems

The conventional high voltage alternative current (HVAC) systems have higher power losses in longer transmissions. High voltage direct current (HVDC) systems are effective in longer transmission due to the lower losses and better controllability [7]. In modern power sytems, HVDC systems are emerging as it supports interconnection of asynchronous power networks, integration of remote renewable energy to power grids and is resistant to reactive power losses and carry more power per conductor with its undirectional power flow nature.[8] [9].

In HVDC technology, the electrical power is transmitting between stations with the utilization of converter stations. The converter station in sending end will convert the power from AC to DC and transmitted through DC transmission lines through longer distances. The converter station in the receiving end receives the power in Dc and convert back to AC. The operational flexibility and efficiency is higher in this two conversion procedure. [8] [9]

There are two main categories of HVDC technologies in use [1] [10]:

- **Line-Commutated Converter (LCC) systems** - In these systems the converter technology is implemented with use of thyristors. The main drawback of these systems is necessity of robust AC grid for reliable commutation. With robust AC grid, the performance of LCC system is high in bulk power transmission.
- **Voltage Source Converter (VSC) systems** - VSC technology is based on IGBTs. They are self-commutating systems with independent and dynamic control of active and reactive power. Those perform well on weak or island grids, such as offshore wind farms and remote island connections [11].

HVDC technology is blooming in modern power grids since it reduces the need of wide right-of-way corridors, supports integration of renewable energy sources to power grid efficiently and improve the stability of the power grid.

2.1.1 Voltage Source Converters (VSC)

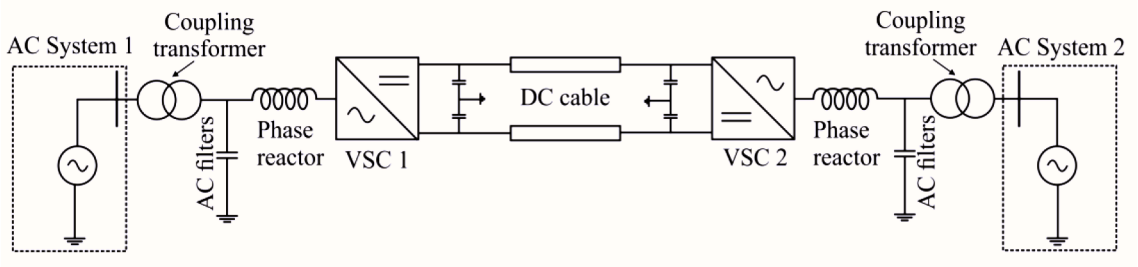

Figure 2.1: Voltage Source Converter(VSC) based two terminal HVDC system [12]

VSC technology is the emerging technology in HVDC technology in modern power systems and it plays a key role role. Unlike LCCs, which need the natural zero crossing of AC voltage for commutation, VSCs are self-commutated and operated at a very high switching frequency with the help of switching devices known as Insulated-gate Bipolar Transistors (IGBTs) or Bi-mode Insulated Gate Transistor (BIGTs). These features allow the voltage or current to be controlled fast and precisely, which is the utmost need for voltage regulation, frequency stabilization, or black start capability.[1] [11]

Key characteristics of VSC [1] [11]:

- **Control of active and reactive power independently:** VSCs are able to supply or consume reactive power on their own without the help of an external device, such as capacitors or synchronous compensators for voltage control.

- **Modular construction:** In VSC systems, modular multi level converters (MMC) are utilized which enables the scalability of the converter station and provide improved redundancy.

- **Bidirectional power flow:** VSC systems enables the ability to change the direction of power flow without changing the polarity of the DC voltage. This capability leads to high flexibility in power systems.

- **Operation under weak grid conditions:** VSC technology enables the power system's ability to operate in islanded mode or low short circuit levels since its commutation is independent of grid condition.

VSC technology is improved rapidly with more complex interface capabilities. This paved path to improved smart grid functionalities and improved power system stability.

2.2 HVDC - Transformers

In HVDC systems, a dedicated transformer is used to connect AC side of the power system with converter units and those can be considered as crucial components [13]. The key usages of power transformers in HVDC systems are:

- Voltage transformation: The desired voltage level at converter station is induced with use of tap changers.
- Electrical isolation: Transformers provide galvanic isolation between AC and DC systems. This characteristic provide safety against faults in both systems while blocking the intense fault propagation.
- Impedance adjustment: The impedance of the transformer can be adjusted in manufacturing step to an acceptable level such that impedance losses are reduced. Therefore, the system's performance will be maximized.

In HVDC systems, converter transformers need to have unique insulation systems defer from AC transformers and heavy construction due to its high probability of experiencing non standard stresses with harmonics and high-frequency switching which will cause premature aging and failure [13] [14].

2.2.1 Transformer faults and protection schemes

Transformers are intricate and expensive, vulnerable to many fault types while they are in service. Faults can be classified as internal and external faults: [15] [16]

1. Internal faults originate from within the tank of the transformer, which include:
    - Turn-to-turn faults present in the transformer as a consequence of insulation failures occur between the adjacent turns of same winding. Due to generation of localized heat, these faults may lead to rapid thermal damage.
    - Turn-to-ground faults occur when insulation fails on the transformer due to insulation degrading between the winding and metallic grounded components such as the core or tank.
    - Inter-winding faults take place as a result of insulation failure between two different windings and cause unwanted current flow in windings which may lead to imbalance in the system.
2. External faults in transformer are the faults which appear outside the transformer and impact the transformer's performance i.e. faults on the transmission lines. The effects of external faults are typically overcurrent, which are mostly resolved by the line protection scheme.

The protection against the above mentioned faults is essential in power transformers. The few of traditional protection methods in transformers are as mentioned below[17] [18] [19]. These protection schemes must operate quickly to detect and isolate faults originated internally in or on the transformer to avoid catastrophic failures in the system.

- Differential protection: In this protection method, the current entering and leaving the transformer is measured. When the difference of in and out current exceeds defined threshold, faulty condition is detected. This method struggles to detect faults with low magnitudes.

- Over-current protection: These protection schemes are simple and low cost. Detect the faults when current through the transformer terminals crosses the defined threshold. Drawbacks of these protection scheme are less sensitivity and selectivity.

- Impedance-based protection: Enhanced fault discrimination that utilizes the variation of apparent impedance under fault conditions.

HVDC transformers operate in complex environment and to improve the sensitivity and reliability of fault detection, an advanced protection schemes need to be implemented.

2.3 Impedance Protection

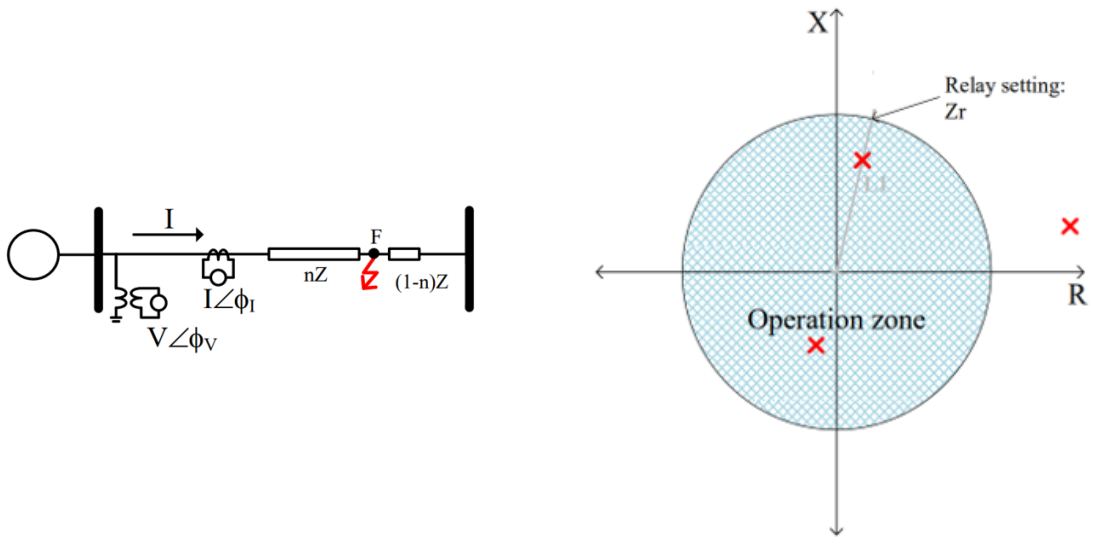

Figure 2.2: Impedance Protection method for transmission lines [20]

Impedance protection is a basic protection principle that is commonly used in power

systems, particularly for the protection of transmission lines. This method can be utilized based location of electrical fault occurrence when the fault significantly impacts the apparent impedance measured from the protection relay [20] [21].

2.3.1 Impedance Protection in Transmission Lines

In a transmission line the voltage and current at a given point (normally at the protective relay location) is evaluated continually. During normal operation the ratio of voltage to current observed by the protective relay (the apparent impedance) is equal to the line impedance to the point of measurement. The apparent impedanceZ_a can be calculated as:

$$Z_a = \frac{V_r}{I_r} \tag{2.1}$$

In the event of a fault occur on the line (phase-to-ground or phase-to-phase short circuit) the fault will raise the current and drop the voltage. Therefore the resultant apparent impedance value will be lower than the normal line impedance.

The impedance seen from the protection relay decreases relative to the normal operation of the line when the fault is clear of the rest of the line as viewed from the the relay location or if not in zone of the relay. Alternatively, it is possible to have a fault that is either, internal to a zone of protection or even between zones, however at least the fault can be indicated that it is situated somewhere in its calculated area of protection. In transmission line protection based on impedance, line will be divided in to different zones of protection from the location of protection relay with different reach settings and time settings.

- Zone 1: Instantaneous Protection (example 80% of the line length).
- Zone 2: Backup protection with a small delay (covers remaining line and a portion of the next more proximal line).
- Zone 3: Backup for remote zones with a longer time delay

The relay logic utilized compares the measured impedance to predetermined threshold (often the apparent impedance is enabled to be plotted on an R-X diagram or similar). If the measured impedance falls within the characteristic of the zone of protection e.g. a circle or a polygon in the R-X plane), and the fault has not been cleared, the relay will trip and send a signal to the breaker to operate and isolate the line [20].

2.3.2 Impedance Protection for Transformer Winding Faults Detection

The same principle of change in impedance during fault conditions can be applied to transformer winding protection. Transformer windings are traditionally protected with differential and overcurrent protection, but impedance based protection may

be a viable option, especially for internal faults that are often difficult to detect [22].

The transformer in normal operating conditions has stable and predictable levels of impedance. During internal fault conditions, the characteristics of impedance can change dramatically (for example, short-circuits of the transformer windings or ground faults). Internal faults in a transformer can be detected by comparing real-time impedance values to the known impedance of a healthy operating state. Impedance protection is useful for detecting incipient faults and high resistance faults, which may not result in sufficient fault currents to detect mechanisms involved in differential protection.

Benefits of utilizing Impedance Logic for transformer protection:

- Sensitivity to internal faults: Particularly beneficial for the reliable detection of high-resistance or incipient faults.
- Localizes faults: The variation of impedance value can be observed according to the location of the fault along the winding.
- No dependency on differential current thresholds: More effective in recognizing fault currents

2.4 Machine Learning Algorithms

2.4.1 Machine Learning for Power System Protection

Machine Learning (ML) enables to create systems which have ability to make decisions by identifying the patterns in the training data set. There has been a growing interest in applying ML methods in the power systems field, since a lot of data is produced by monitoring and control devices. In protection systems and fault detection applications, ML models can learn from past data, or simulated data, to identify faults types, location of faults and predict system behavior in real-time[23].

Machine Learning algorithms can model complex, nonlinear relationships between system variables (e.g., impedance, current, voltage) unlike rule-based logic in protection schemes, or threshold based schemes. This means that they could adapt to new operating conditions or to model weather/ambient conditions, managed to interact with noisy data and data that may not always be complete. ML can be useful in fault detection in complicated systems such as HVDC where a significant variation in fault signature can be observed. This variations challenge the traditional protection schemes.

In this research study, machine learning methods are used to present both classification and regression models that attempt to achieve the following tasks:

- Classification: Identify whether a fault occurs and if so, what type of fault it is (which phase is faulted).

- Regression: Compute the fault location along the faulted winding, described as a % of the winding length from a reference point.

2.4.2 Classification Models

Classification, involves predicting a finite label (or class) for each input data point, when only a, binary or multi-class outcome is needed according to the task (e.g., determining if the power system is in a faulty state or a healthy state)[23] [24] [25].

2.4.2.1 Support Vector Machine (SVM)

SVM is a supervised and robust learning algorithm used for the supervised learning, linear and non-linear classification tasks. SVM works by finding a 'best' hyperplane that separates data points of two or more classes in a high-dimensional feature space [25] [26] [27].

Linear vs Nonlinear Kernels: When using SVM on nonlinear classification problems, it can also be extended using kernel functions, by utilizing kernel functions (e.g., Radial Basis Function -RBF) and polynomial kernels.

Maximizing Margin: A hyperplane will be defined in this method to separate data within class A and B. All hyperplanes will maximize the margin (width) separating between A and B. Maximizing the margin will increase generalization and decrease the possibility of misclassifications.

SVM can be used to classify operational condition of the transformer i.e. healthy or faulty with analyzing the given electrical quantities and trained data.

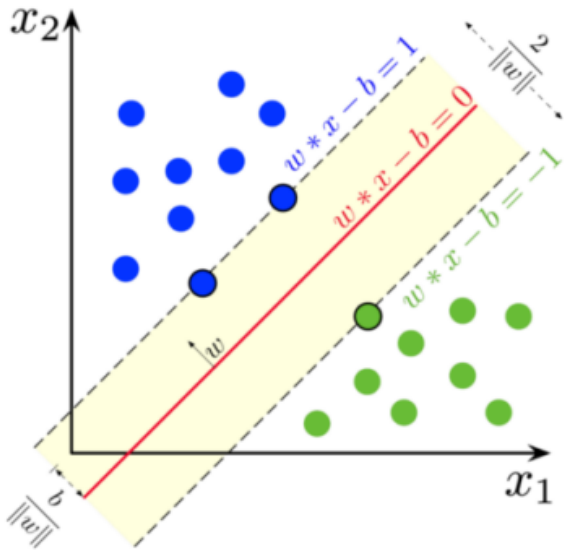

Figure 2.3: Support Vector Machine (SVM)[27]

2.4.2.2 Decision Tree

Decision Tree can be utilized to classify the conditions of transformers and this ML algorithm represented with tree -like model. Each internal node in this model involves a test on attribute(feature) and branch represents the results which leads to leaf in tree which is label of the test data (class) [26] [28] [29].

Splitting Criteria: Common metrics used to determine which feature and threshold attribute of a data set should be split in the construction of the data tree include Gini Index, Entropy, and Information Gain.

One of the main benefits of using Decision Trees is the ability to easily interpret the output, which makes them advantageous for realtime applications as well as for engineering analysis.

In this study, decision tree can be used to detect winding faults in transformer. Decision tree model can be trained with impedance signals and decision tree will split the given test data set based on the thresholds.

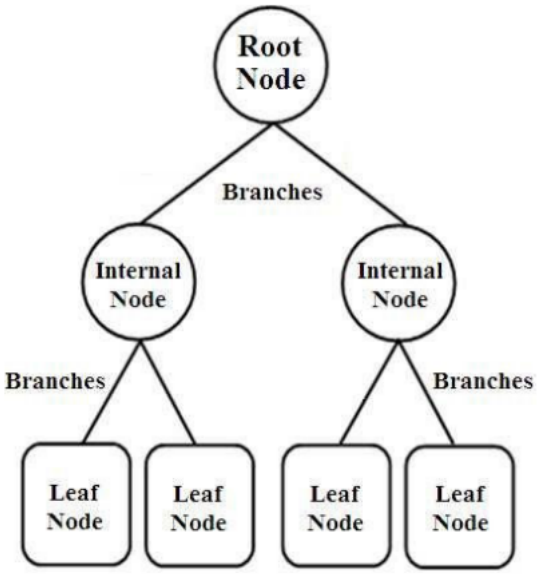

Figure 2.4: Decision Tree [29]

2.4.2.3 Artificial Neural Networks (ANNs) for Classification

Artificial Neural Networks(ANNs) are used for classification of complex data sets. This ML algorithm inspired by the human brain. In an Ann, input layer, series of hidden layers and a output layer can be observed. Each neuron takes each input, applies a weighted sum and an activation function, and uses supervised learning to recognize complex patterns [30] [31].

In this study, Multilayer Perceptron (MLP) was utilized which consists of an input layer, hidden layers, and output layer(s). ReLU, sigmoid, and softmax are some of the activation functions that can be used for ANNs. They are used to create non-linearity and to provide an alternative for multi-class output.

The most common learning algorithm used in ANNs is backpropagation, this algorithm is typically executed using methods for optimization (gradient descent). The purpose of using backpropagation is to adjust the network weights in order to minimize the classification error [32].

ANNs offer excellent support for identifying subtle fault occurrences in conditions in which one knows there was a fault in degrees of difficulty.

2.4.3 Regression Models

In Regression models,the target variables are predicted with statistical techniques based on the trained data. These can be categorized into linear and non-linear models. Linear regression assumes a direct, proportional relationship between the input and output variables, making it simple and easy to interpret. Non-linear regression models i.e. polynomial or machine learning based methods provide more flexibility in complex relationships.The primary goal of regression is to identify the best-fitting model that minimizes prediction errors, often evaluated using metrics like Mean Squared Error (MSE) or R-squared. Regression models predict continuous output values making them suitable for estimating where the fault is along the length of a transformer's winding [33].

2.4.3.1 Artificial Neural Networks(ANNs):

ANNs can be easily adapted for use with a regression model by adopting a linear activation function as the activation function in the output layer, and changing the loss function to one that was suitable for continuous (e.g. Mean Squared Error) data. The input for this analysis is comprised of the impedance, voltage, and current for the faults extracted from the simulations.And the output will be continuous estimate to identify the location of the fault (e.g., 25 % of the winding from neutral end).The model must be trained on numerous fault locations and types, so that it is capable of estimating the fault location under the different operating conditions. Figure 2.5 shows typical arrangement of a ANN which can be used for this study [30] [31] [34].

Levenberg–Marquardt (LM) Algorithm

The Levenberg-Marquardt algorithm is a second order optimization algorithm that unifies the methodologies of gradient descent and Gauss-Newton methods in the pursuit of estimating the location of fault in the transformer winding, via a minimization of the error function applicable for nonlinear regression problems [35] [36]

[37]. LM converges faster than the normal direction of gradient descent method, especially for small and medium networks.LM is able to adjust its update step based on the curvature of the error surface. This attributes more reliability and stability to LM even when working with complex and nonlinear problems. In this study, LM is used to train the regression ANN model to locate the fault location in the transformer winding using the voltage from the impedance and voltage patterns.

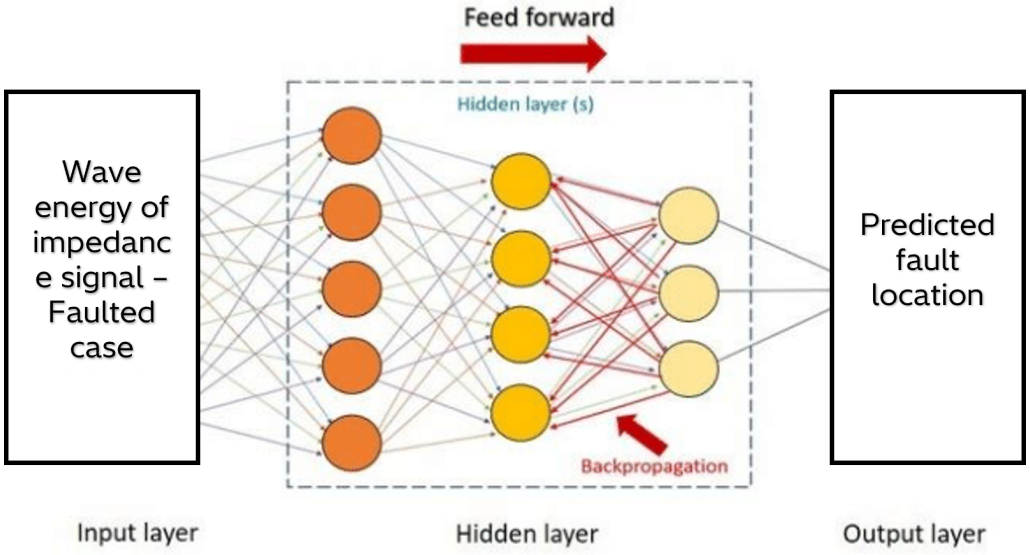

Figure 2.5: Typical ANN regression model

2.4.4 Utilized Evaluation Metrics in this Study

The performance, robustness and reliability of machine learning models needs to be evaluated for each study. Evaluation metrics can be utilized for this concern. Evaluation metrics will depend on the type of prediction task (classification - categorical output, regression - continuous output). In power system protection, classification (fault or none fault, fault types) and regression tasks (fault location) are equally important to ensure safety and sustainability of the system [38].

2.4.4.1 Classification Metrics

Classification is a type of prediction that focuses on mapping data inputs to outputs in discrete, pre-defined enumerated categories (such as fault type, healthy state). The following metrics can be evaluated to understand how well the model truly classifies such conditions[38] [39] [40].

- **Confusion Matrix**
  A confusion matrix is a matrix that is tabular, and summarizes prediction results showing number of true positives and true negatives by class. For example, a confusion matrix for a binary classification (fault or no-fault) can break the input stream into the following classes:

True positive (TP): the model accurately predicted cases with fault

True negative (TN): the model accurately predicted cases with no-fault

False positive (FP): the model inaccurately predicted cases with fault,and give no-fault.

False negative (FN):the model inaccurately predicted cases with no-fault,and give fault.

The confusion matrix for multiclass classification (ex. fault type) is simply an aggregate of these classes.

- **Accuracy**

  Accuracy is a measure of the overall level of correctness of a model, and is calculated as the proportion of correctly predicted cases to the entirety of predicted cases.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

  In imbalanced datasets with rare fault conditions, accuracy can be misleading as it can be higher even though some faults are missed.

- **Precision**
  Precision is the ratio between total predicted positive cases and correctly predicted positive cases.

$$\text{Precision} = \frac{TP}{TP + FP}$$

  High precision indicates that the ML model produce few false alarms. If the protection action is costly, false alarms cause burden to the system. Therefore, precision is important to analyze.

- **Recall**
  Recall is the ratio between all actual positive cases and the correctly predicted positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

  Recall provides statistical data about model's ability to predict faults correctly. High call implies that few actual faults missing in fault predictions. In real-world systems, it needs to identify most of the faults to provide better protection.

- **F1 Score**
  F1 score is the harmonic mean of precision and recall. When both false positives and false negatives are critical in the system, F1 score provide measures

to evaluate the performance of ML algorithm.

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

2.4.4.2 Regression Metrics

Regression evaluation metrics are used when the model predicts a continuing value such as fault location along the transformer windings[41] [42] [43].

- Mean Absolute Error (MAE)
  MAE is the average of absolute differences between predicted and actual values.It expresses the average prediction error directly in the same units as the output (e.g., % or m of winding length).

  $$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

  where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of samples.
- Mean Squared Error (MSE)
  MSE is derived from difference between predicted and actual values. This evaluation value can be used to identify the larger errors in predictions and mitigate them.

  $$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- R-squared (R^2) Score

  The R-squared score is the proportion of variance in the dependent variable that can be explained by the independent variables.

  $$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

  where $\bar{y}$ is the mean of the actual values y_i

  Interpretation:
  - $R^2 = 1$: Perfect prediction.
  - $R^2 = 0$: Model performs no better than the mean.
  - Negative R^2: Model performs worse than the mean.

3
Methods

3.1 Overview

Chapter 3 describes the methodology utilized to model winding faults in an HVDC transformer using PSCAD/EMTDC and the methodology adopted for fault detection, classification, and fault location identification using MATLAB. The fault analysis approach implemented in this thesis can be divided into four categories based on their aspects of fault analysis.

- Fault detection based on impedance protection
- Fault detection using machine learning (ML) algorithms
- Fault classification using machine learning (ML) algorithms
- Fault location identification using Artificial Neural Network (ANN)

An overview of the research methodology flow can be represented as shown in figure 3.1. The following sections consist of detailed descriptions of the method for each approach.

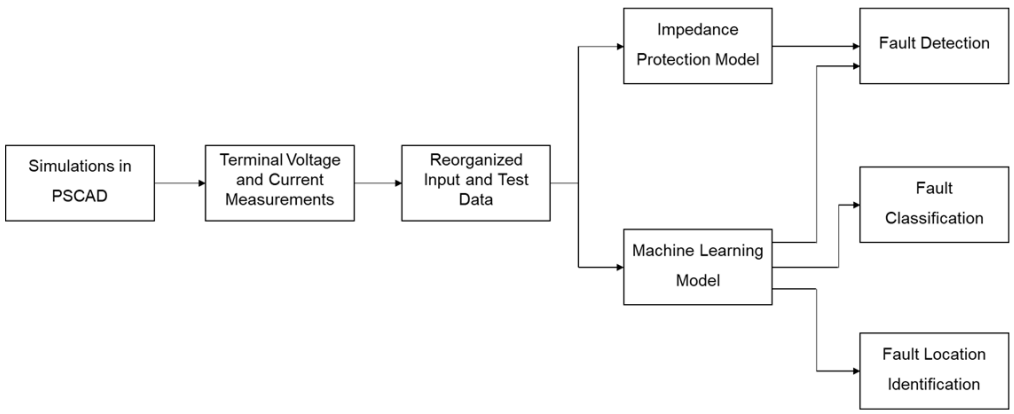

Figure 3.1: Overview of the research methodology flow

3.2 System Modelling in PSCAD

In this study, a symmetric monopolar VSC-HVDC system as shown in figure 3.2 was modeled in PSCAD. Here the three-phase transformers in VSC-HVDC systems were modeled using three user-defined single-phase transformers. All analyzes were conducted on the basis of the terminal voltage and current measurements of the primary side of the faulty HVDC transformer, which were extracted from PSCAD simulations. This symmetric monopolar VSC-HVDC system consist of two VSC based HVDC systems with following specifications.

Specifications	VSC1	VSC2
Voltage input AC Peak	420 kV	420 kV
Nominal Frequency	60 Hz	50 Hz
Transmission line DC voltage	±200 kV	±200 kV

Table 3.1: Specifications of VSC-HVDC systems

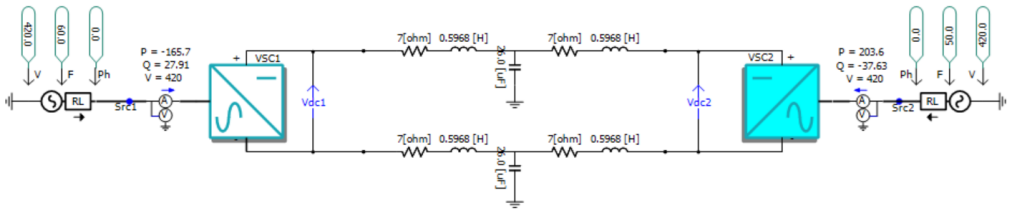

Figure 3.2: Symmetric monopolar VSC-HVDC system

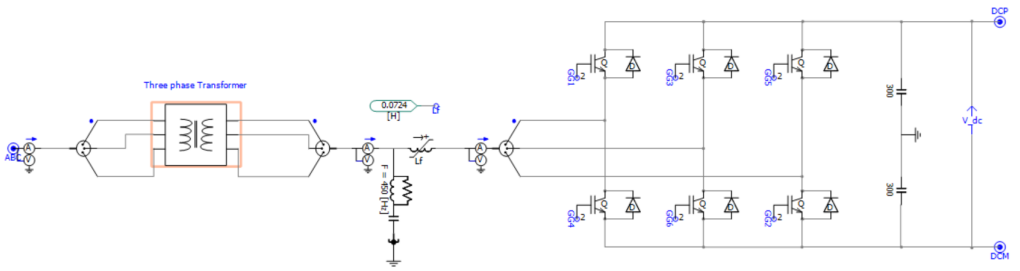

Figure 3.3: VSC1 - HVDC system

3.2.1 Transformer Modeling for Internal Fault Studies

In this study, the internal winding structure of the HVDC transformer was replicated by modeling user-defined multi-winding transformers in PSCAD software to simulate internal winding faults [44]. An effective fault detection and location identification technique can be developed with an accurate simulation of transformer internal faults.

Internal faults in the primary winding of the HVDC transformer in VSC1 were the main focus of this research study. The three-phase transformer in VSC1 is modeled using three user-defined single-phase transformers, and the three-phase transformer in VSC2 is modeled with three two-winding single-phase transformers. To replicate the actual winding structure of the transformer, the primary winding is split into three sub-coils to simulate different fault scenarios by adjusting the position (i.e., the number of shorted turns) of the applied fault. The division of the winding into subcoils will have an impact on the electrical properties of the transformer. Therefore, the transformer inductance and resistance matrices need to be adjusted accordingly. Ultimately, changes in these electrical characteristics affect the simulated voltage and current responses during each fault scenario. The specifications of the three-phase transformer are presented in the below table 3.2.

MVA rating	1500 MVA
Voltage rating	420kV /230kV
Winding connection	Y/Y
Turns ratio of faulted single-phase transformer	1050/575

Table 3.2: Specifications of Three-phase transformer in VSC1-HVDC system

3.2.1.1 Turn-to-Turn Fault Modeling

Turn-to-turn faults occur due to insulation failure between adjacent turns, and those are among the major internal faults. These faults create a localized short circuit within the faulty winding.

This can be represented by splitting the primary winding of the shorted phase into three sub coils and short circuiting a sub coil. The induced magnetic flux and the transformer impedance affected by this circulating fault current in sub coil. Then the impedance matrix of the transformer is modified accordingly to reflect the fault condition. As a result of that, variations in terminal current and voltage measurements can be detected. Inductance matrix for a four-winding single-phase transformer can represented as following;

$$[L] = \begin{pmatrix} L_1 & M_{12} & M_{13} & M_{14} \\ M_{21} & L_2 & M_{23} & M_{24} \\ M_{31} & M_{32} & L_3 & M_{34} \\ M_{41} & M_{42} & M_{43} & L_4 \end{pmatrix} \tag{3.1}$$

Here, windings 1, 2, 3 represent the primary winding of the single-phase transformer, and winding 4 represents the secondary winding of the transformer.

The new self-inductances, mutual inductances and new resistances of the transformer winding can be defined using the number of turns in each winding by equations 3.2-3.10 [44].

$$L_1 = \left(\frac{n_1}{n_p}\right)^2 L_p \tag{3.2}$$

$$L_2 = \left(\frac{n_2}{n_p}\right)^2 L_p \tag{3.3}$$

$$L_3 = \left(\frac{n_3}{n_p}\right)^2 L_p \tag{3.4}$$

$$M_{12} = \left(\frac{n_1 n_2}{n_p^2}\right) L_p \tag{3.5}$$

$$M_{13} = \left(\frac{n_1 n_3}{n_p^2}\right) L_p \tag{3.6}$$

$$M_{23} = \left(\frac{n_2 n_3}{n_p^2}\right) L_p \tag{3.7}$$

$$R_1 = \left(\frac{n_1}{n_p}\right) R \tag{3.8}$$

$$R_2 = \left(\frac{n_2}{n_p}\right) R \tag{3.9}$$

$$R_3 = \left(\frac{n_3}{n_p}\right) R \tag{3.10}$$

Here,

- n_1 — number of turns in sub-coil '1'
- n_2 — number of turns in sub-coil '2' (faulted segment)
- n_2 — number of turns in sub-coil '3'
- n_p — Total number of turns in primary winding
- L_p — Self-inductance of the primary winding
- R — Resistance of the primary winding

In PSCAD, user-defined transformers were created by defining an impedance matrix using the transformer segment in the script section as shown in figure 3.4. All values assigned in the impedance matrix were defined in the computational segment in the script section using above equations.

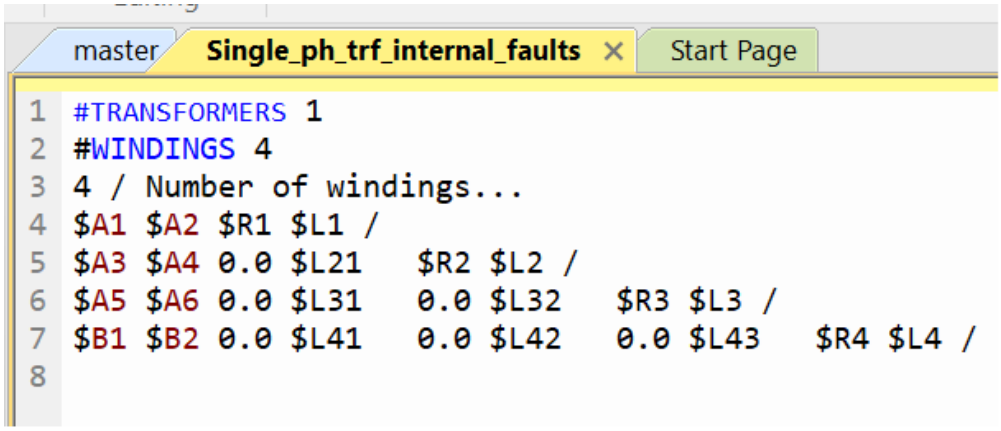

Figure 3.4: Transformer Segment in PSCAD

3.3 Fault Scenarios

In this study, the main focus was to simulate internal winding faults in each phase, and to observe the system response to identify the faults and analyze them. To simulate a turn-to-turn fault in a phase, four winding single-phase transformer was connected to faulty phase while two winding single-phase transformers were connected to non-faulty phases. Accordingly, turn-to-turn fault was simulated in phase A as shown in figure 3.5.

For each fault scenario, faults were introduced at 1 seconds with duration of 30 miliseconds in a 3 seconds simulation run with 4kHz sampling rate. Faults were given using Timed fault logic block in PSCAD. Each fault scenario (turn-to-turn fault in phase A, phase B and phase C) was created with a varying number of faulted turns from 0.5% to 99.5% of the total number of turns in primary winding. Here, fault location is defined with number of shorted turns in the primary winding of the transformer. 25% of the primary winding length is short-circuited means 263 turns in primary winding are short circuited out of total 1050 turns. In this study, faults were applied to the system with different fault resistance values. For each phase, turn-to-turn faults were created with fault resistances of 0.01 ohms, 0.05 ohms , 0.1 ohms, 0.5 ohms, 1 ohms and 5 ohms. All the simulations were done in PSCAD using batch simulation theory with aid of python scripts. The terminal RMS current and RMS voltage measurements were extracted from the simulations for each fault case scenario and processed using MATLAB to analyze the impedance data variations. For non-faulted scenarios, different load conditions also considered to have dynamic dataset. For this study, a 10 miliseconds data sampling window was utilized which captures the data for each 10 milliseconds and compare that value with the prior sampling window.

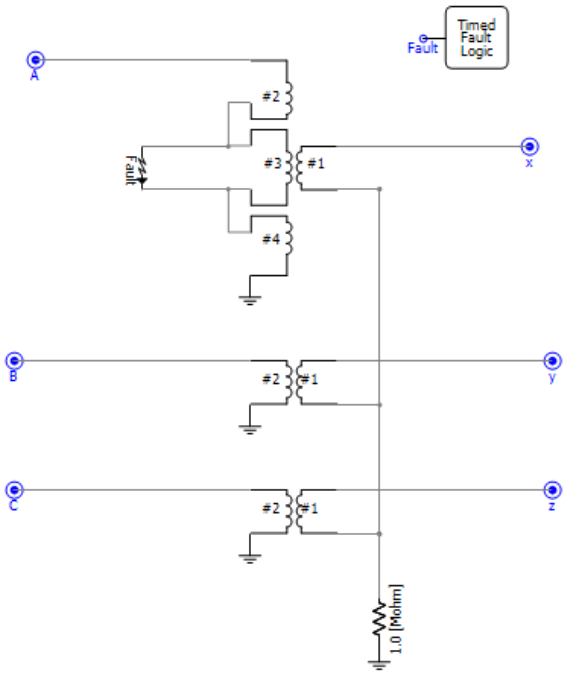

Figure 3.5: Turn to turn fault Modelling - HVDC

3.4 Data Acquisition

The extracted terminal RMS voltage and RMS current measurements of primary winding were rearranged to obtain the impedance measurements using equation for each time step. Since data was captured for 3s with 4kHz sampling rate each RMS voltage, current and impedance measurement consists of 12000 data entries. Prior to feed these raw data into fault detection, classification and location identification models, data should be reorganized to ensure that it is structured in meaningful and analytically useful format.

For the impedance protection model, the raw input data was reorganized by considering the average value of the impedance signal over a time span of 10ms before and after the fault. The average value (Zavg) of an impedance signal $x(t)$ can be defined by equation 3.11.

$$\text{Zavg} = \frac{1}{t}\int_0^t x(t)\,dt \tag{3.11}$$

The resistance (R) and reactance (X) values are derived from the average impedance signal for each 10 milliseconds to analyze the faulty and non-faulty conditions using the impedance protection model. With average values, the model can clearly identify the difference between the resistance and reactance values before and during the

faults.

Detection, classification, and location identification of faults using machine learning algorithms was carried out based on the wave energies of the terminal voltage and current signals. The wave energy of the voltage and current signals was taken to capture the differences in signal intensity.

The wave energy(v_e) for a voltage signal $v(t)$ and the wave energy(i_e) for a current

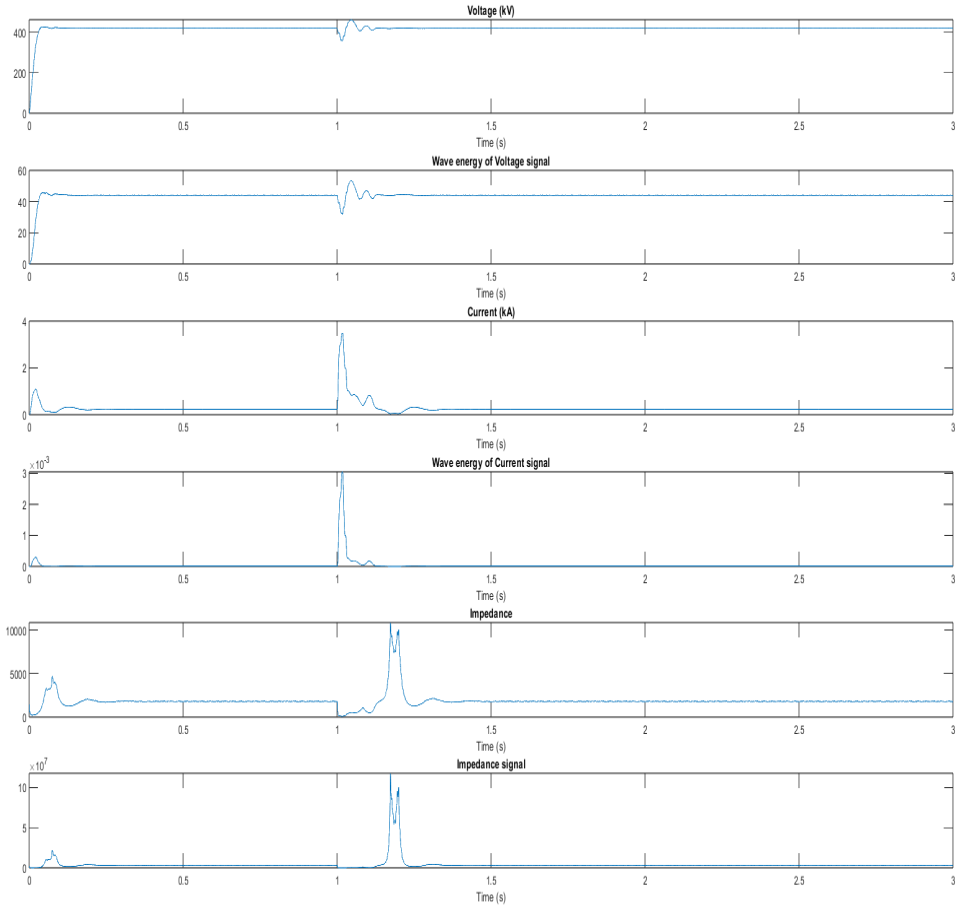

Figure 3.6: Wave Energy of signals

signal $i(t)$ can be approximated by equation 3.12 and equation 3.13 respectively.

$$v_e = \int v^2(t)\, dt \tag{3.12}$$

$$i_e = \int i^2(t)\, dt \tag{3.13}$$

The impedance signal (Z_e) can be determined on the basis of these wave energies of the terminal voltage and current signals accordingly.

$$Z_e = \frac{v_e}{i_e} \tag{3.14}$$

Figure 3.6 shows the terminal voltage and current response of the primary side of the VSC1 transformer when 25% of the total turns (263 turns) were shorted-circuited in Phase B for 10ms and the impedance signal considered for the fault analysis based on the wave energies of the terminal voltage and current response. Instead of directly using impedance values of the transformer winding, an impedance signal was derived based on the wave energies of the voltage and current signal to feed more meaningful and accurate data set to the machine learning models. The derived impedance signal is shown figure 3.6. Machine learning algorithms can accurately identify the changes in the impedance signal during fault conditions with this kind of signal. The impedance signal value is approximately zero before and after the fault conditions, and during the fault, a comparatively higher value is obtained by the impedance signal. Therefore, the machine learning model can capture the differences accurately and predict the results.

3.5 Impedance Protection Method for Fault Detection

In this study, winding faults were detected based on a method similar to the impedance protection method in transmission lines. In transmission lines, different zones of protection are defined for impedance protection according to the relay and breaker arrangement. Due to restrictions on the physical structure of transformer windings, one zone of protection can be defined in transformer winding protection related to impedance protection. During a fault, a significant change in the winding impedance can be observed, and this difference in impedance before and during the fault can be used to define the protection zone for the transformer. With the measurements of terminal current and voltage, the deviations in the average resistance and reactance values can be determined.More meaningful and accurate inputs can be provide to the model by taking average values.

To define the circular protection zone (zone 1), several fault and non fault scenarios were considered. Internal winding faults were created in each phase A, B, and C with 0.5% to 99.5% of shorted turns on the primary side and captured the terminal voltage and current response. For different load conditions, the non-fault scenario is simulated in PSCAD and the terminal voltage and current responses are obtained. In this method, a 10% safety margin was defined to accommodate measurement noise and uncertainties. Consequently, the setting for zone 1 protection was determined. For a given mixed fault and non-fault test data set, fault detection was predicted by checking whether the impedance values fell inside or outside the protection zone. The accuracy, precision, recall, and F1 score metrics for the method were then calculated.

3.6 Machine Learning Algorithms for Fault Analysis

In this approach, transformer winding faults were detected, classified, and the fault location was identified using several machine learning algorithms. Fault detection was performed using several classification models such as SVM, Decision Tree, and ANN. In this approach, several ANNs are used for fault analysis. The accuracy of fault location identification was increased by having separate ANNs for each phase fault scenario. Figure 3.7 shows the flow chart of the proposed multi ANN approach for fault analysis in two terminal HVDC network.

Terminal voltage and current measurements for fault in each phase A, B, and C were obtained from PSCAD and wave energies of the voltage and current signal were calculated accordingly to have meaningful dataset for the machine learning algorithms. An impedance signal is derived from those voltage and current measurements and initial ANN, SVM, and DT were trained with several fault case scenarios. These machine learning algorithms were used to determined the faulty and non-faulty cases for a given test dataset.Using second ANN, SVM, and DT, the faulted cases are classified as Phase A faulted, Phase B faulted or Phase C faulted. After determining which Phase is faulted, the fault location of the winding is determined using the final ANN which is specifically determined the fault location for each phase. In this case, only the ANN for faulted phase is activated and ANNs for other two phases are disabled.

The configurations and hyper parameters of each machine learning algorithm used for fault analysis can be described as follows;

3.6.1 Fault Detection and Classification

The configurations hyper parameters of each classification model SVM, Decision Tree and ANN used in this study are shown in following sections.

SVM

- Kernel: RBF
- $C = 1.0$
- $\gamma =$ scale

Decision Tree

- Criterion: Gini
- Max depth: 5

ANN Classifier

- Architecture: [4776 (input), 20, 4, 1 (output)]
- Activation: ReLU (hidden), Sigmoid (output)

- Loss: Binary Cross-Entropy
- Optimizer: LM
- Learning rate: 0.001
- Epochs: 500

Model evaluation was performed using confusion matrices and standard evaluation metrics.

3.6.2 Fault Location Identification

Fault localization was addressed using separate ANN regression models for each phase. The models was trained to estimate the percentage of faulted winding turns in each phase. The specific configurations used for fault location identification can be described as follows.

ANN Regression Model

- Architecture: [597 (input), 20, 4, 1 (output)]
- Activation: ReLU (hidden), Linear (output)
- Loss: MSE
- Optimizer: LM, Learning rate: 0.001
- Epochs: 500

Performance evaluation was performed using Mean Squared Error (MSE) and Coefficient of Determination (R^2).

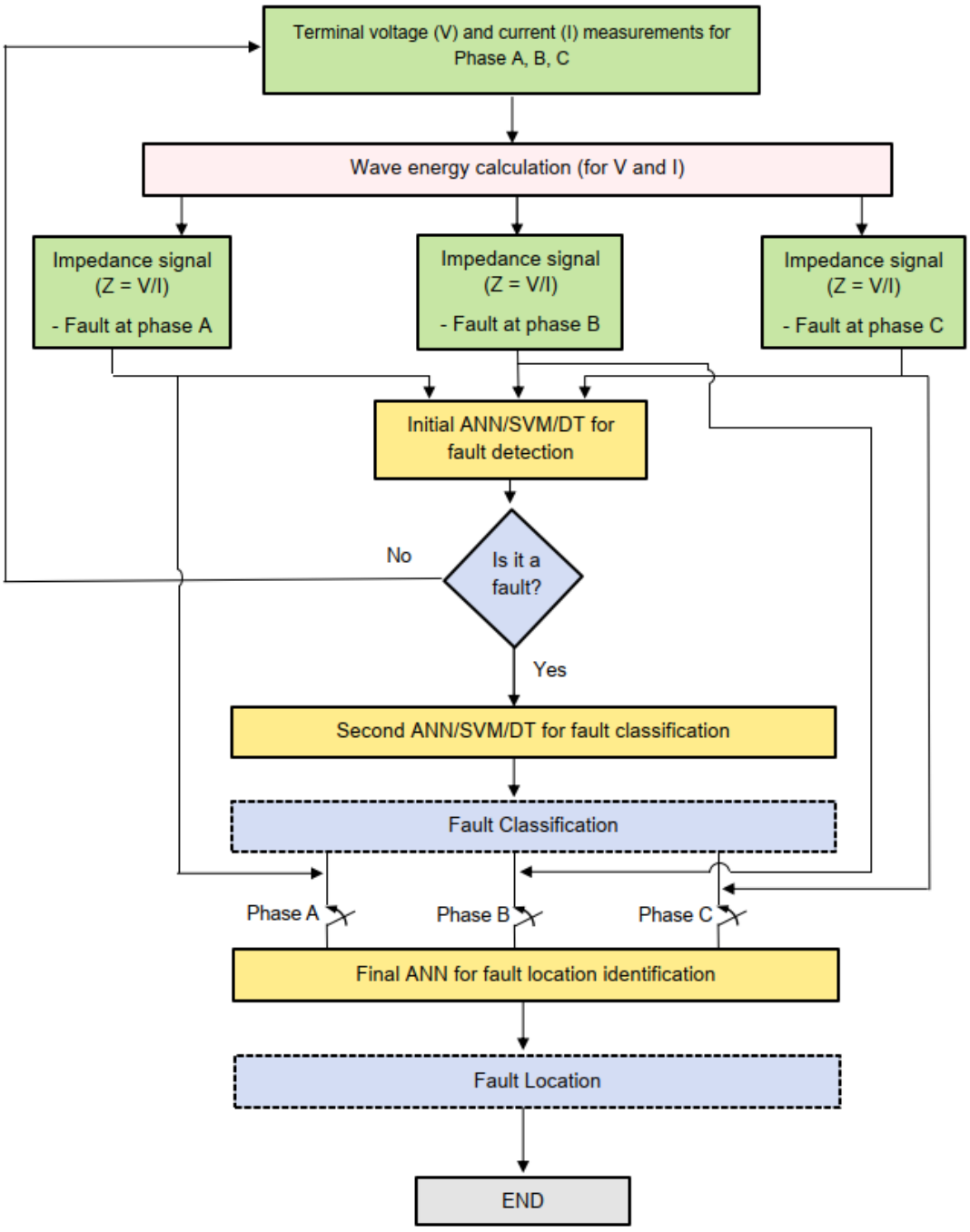

Figure 3.7: Methodology - ANN fault detection, classification and fault location identification

4

Results

Chapter 4 consists the evaluation of results for fault detection, classification, and fault location identification. Moreover, the system's dynamic response to several internal winding faults is highlighted here. This chapter represents the evaluation of results of fault detection, classification, and location identification technologies. Furthermore, this chapter emphasizes the dynamic response of VSC based HVDC system to several internal winding faults.

4.1 VSC based HVDC system response to winding faults

To analyze how the HVDC system would respond to internal transformer faults, several time-domain simulations were conducted in PSCAD. The simulations focused on capturing the voltage and current transients to identify appropriate fault signatures.

This study examines how the severity of internal winding faults affects a transformer's dynamic performance and the impedance values used in fault analysis. To identify the response of the system, simulations were carried out for three fault cases—15%, 60%, and 80% of turns shorted in winding 3 to represent different levels of degradation. A clear basis to analyze the performance of impedance based fault analysis at different fault severities is provided by these results.

For each case, voltage and current on the primary side were measured to calculate the apparent impedance. As shown in Figure 4.1, with a 15% fault (158 turns shorted), voltage and current remained close to nominal condition, and the impedance showed only a small drop from the healthy value. This is expected, since the small number of shorted turns causes only a minor disturbance in the magnetic flux linkage.

As shown in Figure 4.2 and Figure 4.3 respectively, when the fault deepened to 60% (630 turns) and 80% (840 turns), there were corresponding larger voltage drops and increases in current, which led to a substantial drop in impedance, since the increased level of fault presented the least impedance path in the winding. This non-linear impedance reduced continues to reflect the fact that as the fault severity level rises, the problems with the transformer's ability to maintain healthy voltage while limiting fault current are deteriorating.

The combined changes in voltage and current clearly demonstrate that impedance-

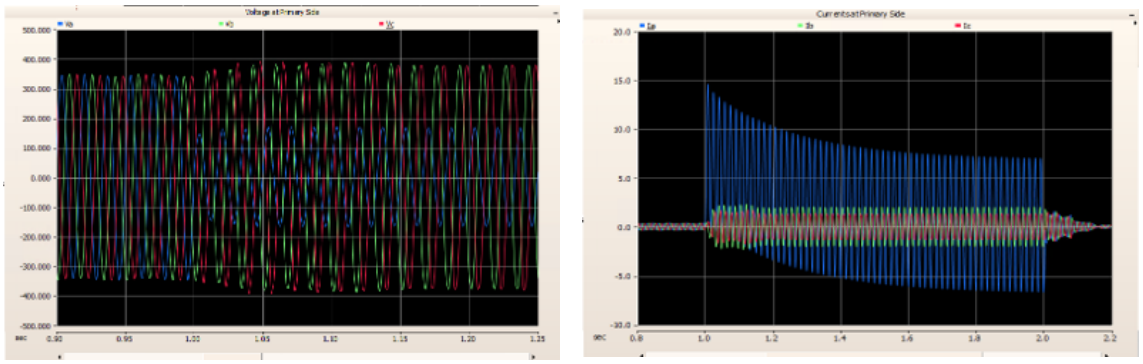

Figure 4.1: Voltage and Current response for 15% turns shorted (TT)

based protection can detect winding faults effectively, with impedance changes closely tracking fault severity. However, for stable operation, relay settings must be properly adjusted to avoid false tripping during temporary or transient conditions.

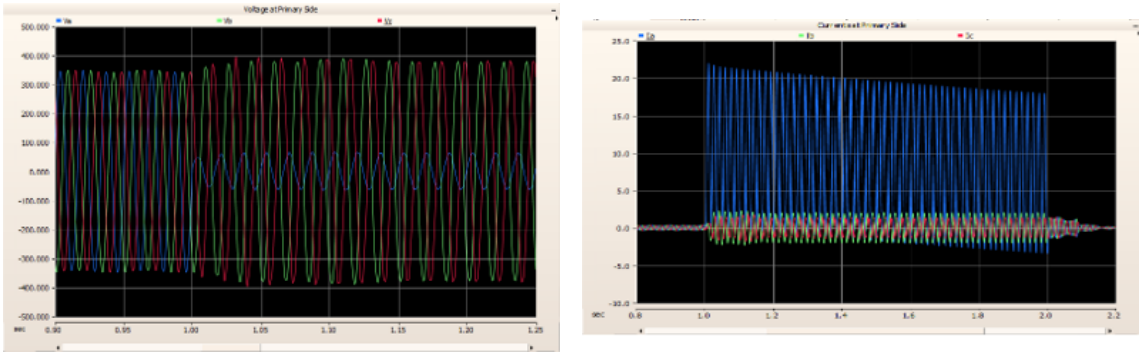

Figure 4.2: Voltage and Current response for 60% turns shorted (TT)

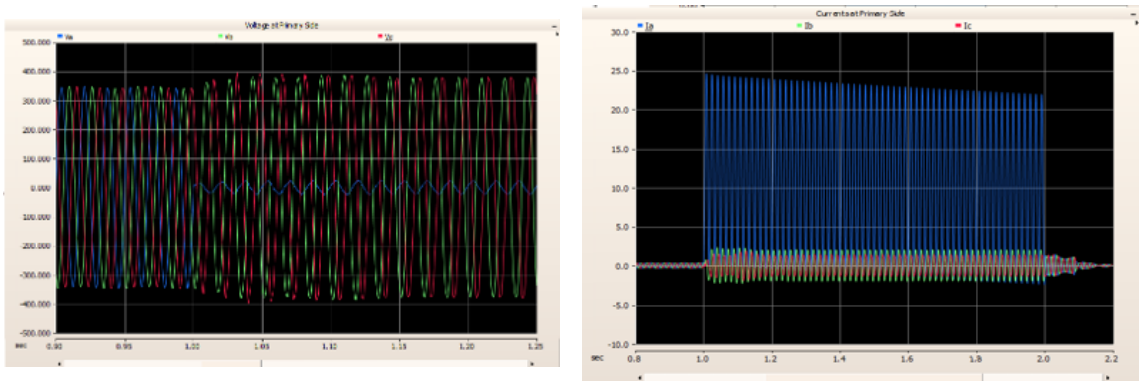

Figure 4.3: Voltage and Current response for 80% turns shorted (TT)

4.2 Results of Fault Detection using Impedance Protection Method

This section consists of the results of an impedance-based protection method for the detection of internal faults in VSC-HVDC systems. The method was investigated for its ability to identify turn-to-turn faults. Additionally, the analysis considers the robustness of the impedance protection method against the change in loading levels and fault severity, examining its performance in accuracy of fault detection and the ability to discriminate between faulty and normal conditions.

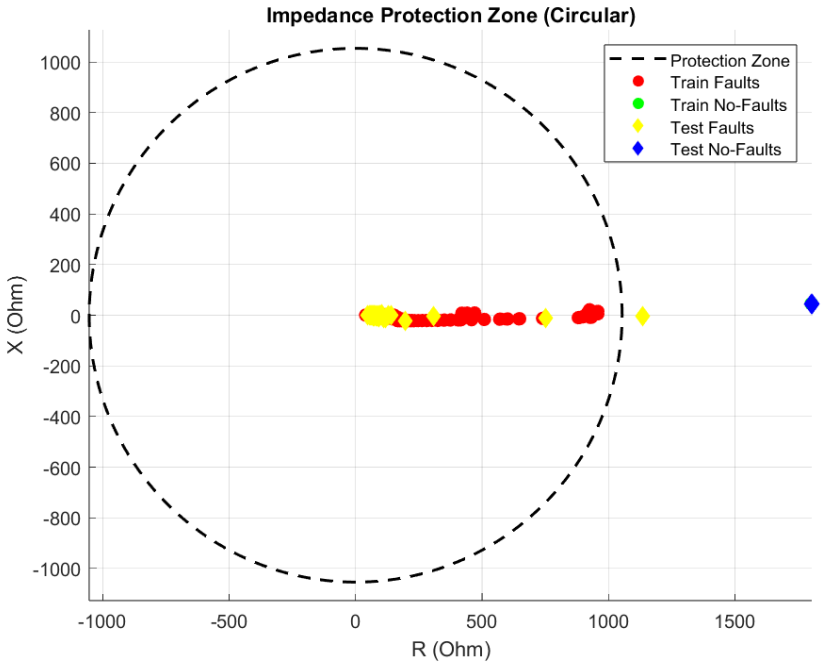

Figure 4.4: R-X Diagram for HVDC system (TT)

The impedance protection method was first tested on the VSC-HVDC under nominal load conditions for turn-to-turn faults. Figure 4.4 shows the obtained R-X diagram for the impedance protection method. The protection zone was determined to be 1053.9 ohm according to the behavior of the system. Figure 4.5 represent the confusion matrix observed for this method. Here, class 0 indicates No fault condition and class 1 indicates faulted case. This method achieved 98.33% testing accuracy, almost perfectly classifying the fault and healthy states. The performance of this method evaluated using some key performance indicators. Precision, recall, and F1 score were recorded as 1.00, 0.98, and 0.99, respectively, with no false classification of healthy states, and one missed fault detections for a given test data set of 60 data with mixed fault and non-fault cases. This means that this impedance protection scheme is effective when deployed to detect turn-to-turn faults in the HVDC system. Furthermore, the high degree of fault detection performance indicates that alerting of the faulted state was possible. Therefore, the impedance protection method would be an excellent first line of defense against internal winding faults in real-world ap-

plications of VSC-HVDC.

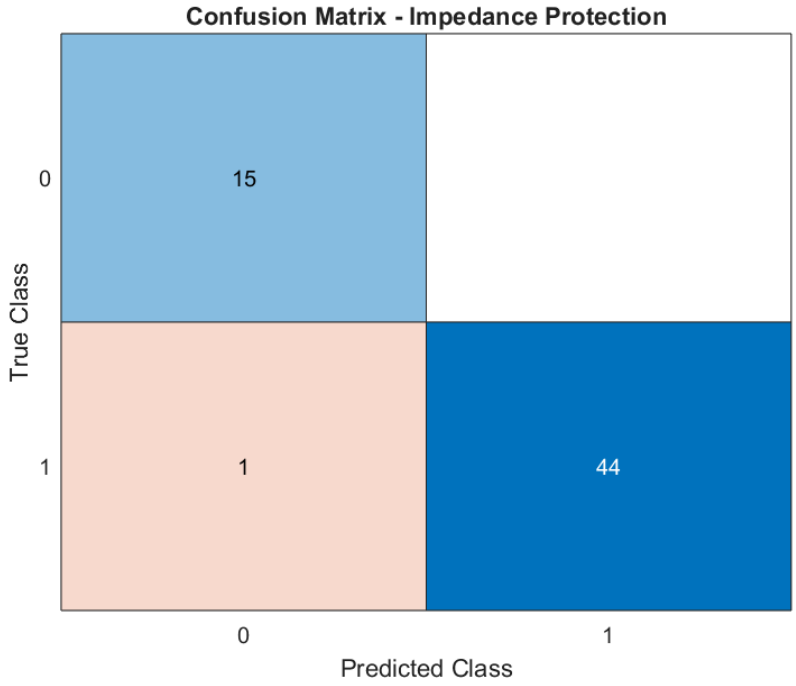

Figure 4.5: Confusion matrix for impedance protection method

4.3 Results of Fault Detection And Classification using ML Algorithms

This study employs machine learning techniques, including Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN), to detect internal faults based on variations in system voltage and current and classify the fault whether it caused by Phase A, B, or C. The models are trained to recognize the distinct signatures associated with different fault types and severities. Evaluation is based on metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive assessment of each model's effectiveness.

The classification ability of three models, SVM, Decision Tree, and ANN, was compared. The confusion matrices and evaluation matrices obtained for each method is described below and in confusion matrix, class 0 represnts No fault, class 1 represents Phase A fault, Class 2 represents Phase B fault, and Class 3 represents Phase C fault. the confusion matrix obtained from Decision Tree(DT) Method is shown in Figure 4.6. In this method, 93.33% of test accuracy was achieved for fault detection and classification. All the non faulted and faulted cases were predicted correctly as fault and non-fault. However, 4 faulted cases were classified in false phases.The maximum tree depth was 5.

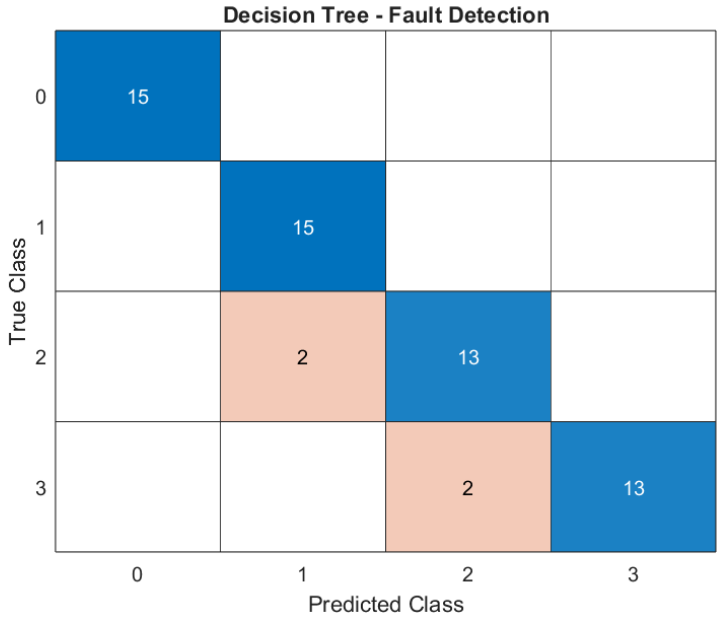

Figure 4.6: Confusion matrix for Decision Tree Method

Figure 4.7 shows the confusion matrix attained for the Support Vector Machine(SVM) method. 96.67% of test accuracy was achieved for this method while detecting all non fault and fault cases correctly. In this method 1 Phase A fault, classified as Phase B fault and 1 Phase B fault classified as Phase A. Phase C fault cases were classified correctly. DT and SVM method mainly implemented in this thesis to compare the accuracy and performance of ANN with them. The SVM, being strong when it comes to handling the high-dimensional feature spaces, achieves perfect classification and strictly separates the faulty from the healthy signatures. The decision tree model also performed well, possibly due to the unique and interpretive patterns in voltage and current waveforms produced under fault conditions.

The proposed ANN method for fault detection and classification provided confusion matrix as shown in Figure 4.8. In this method, 90% test accuracy was achieved for given test data set of 60 data. This performance is also attested by the reported precision, recall, and F1 score, which yielded 0.87, 1.00, and 0.93, respectively. The confusion matrix shows that the model could differentiate between healthy and unhealthy conditions accurately. Six fault cases were classified as other Phases that caused a reduction in accuracy of the model. Mostly ANN was unable to differentiate between Phase B and Phase C faults.

In HVDC systems, where undetectable errors can cause significant system damage and false alarms can cause unwanted service outages. Therefore, need of fault detection and classification is essential.

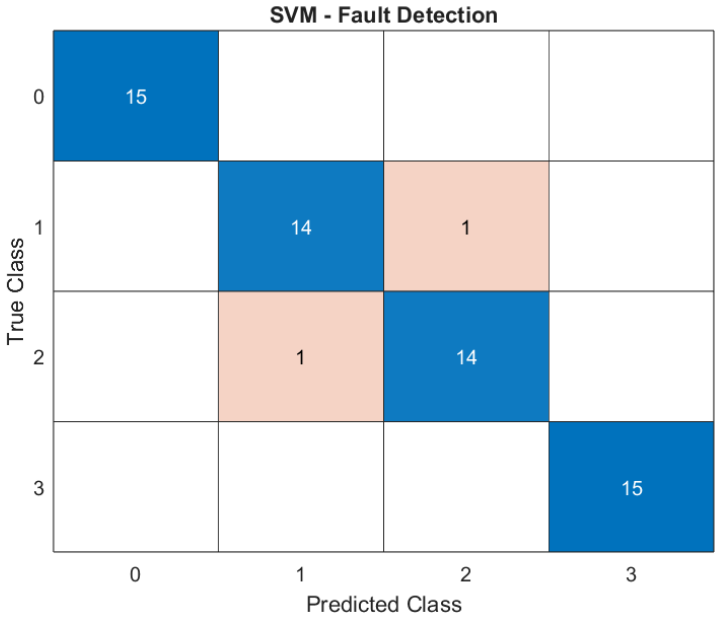

Figure 4.7: Confusion matrix for SVM Method

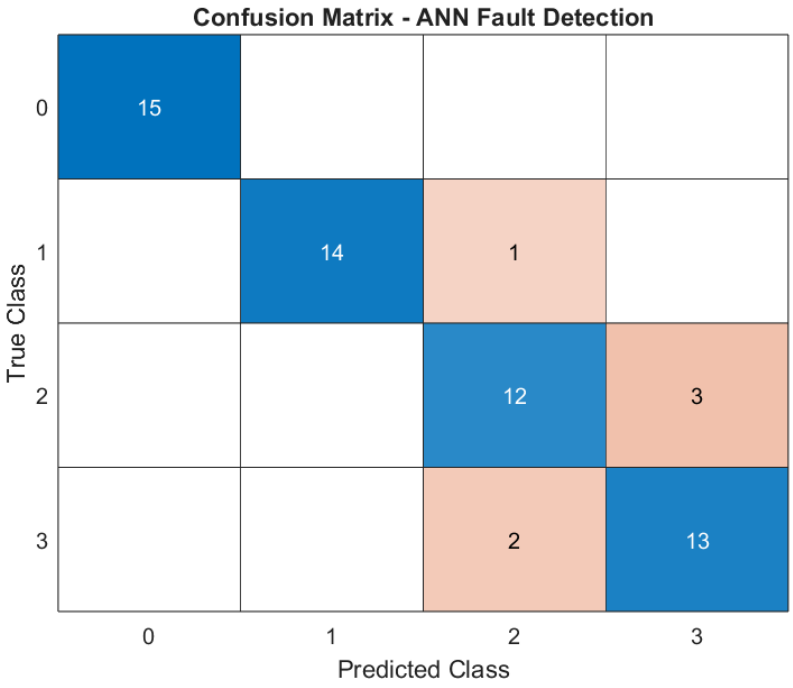

Figure 4.8: Confusion matrix for ANN Method

4.4 Results of Fault Location Identification using ANN

Fault location identification is an essential power system reliability and protection enhancement, particularly in VSC-HVDC. This study focuses on identifying the location of turn-to-turn faults using an Artificial Neural Network (ANN) regression model. The model's accuracy was evaluated using Mean Squared Error (MSE), and the coefficient of determination (R^2 value). These measures how well the predictions match the actual fault locations. Three separate ANNs were used for each phase to identify the correct fault location. Using separate ANN for each phase improved the accuracy of the whole ANN model. Figure 4.9, Figure 4.10, and Figure 4.11 represents the coefficients of determination for each ANN for Phase A, Phase B, and Phase C respectively.

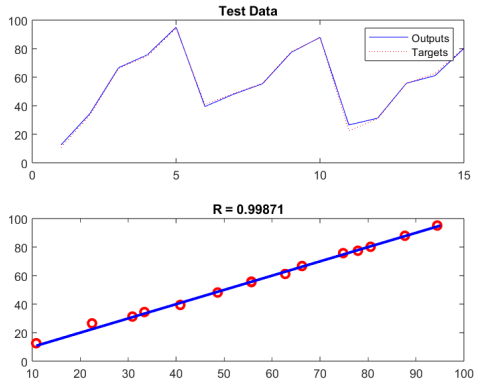

Figure 4.9: R^2 for ANN - Phase A

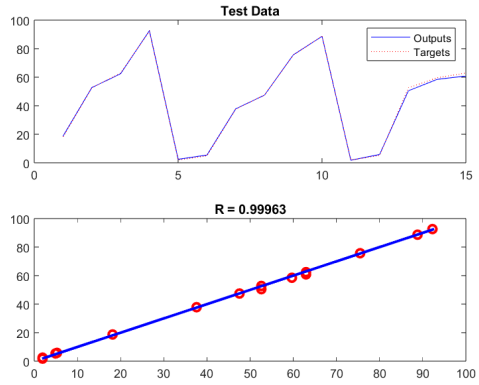

Figure 4.10: R^2 for ANN - Phase B

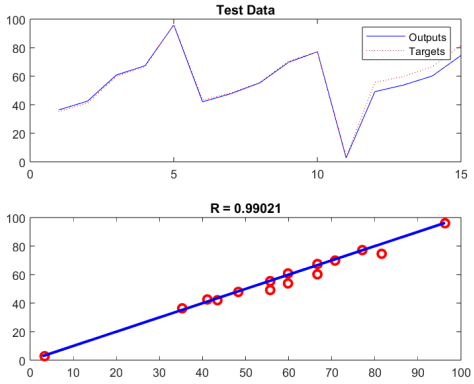

Figure 4.11: R^2 for ANN - Phase C

The ANN model for Phase A, Phase B, and Phase C achieved a mean squared error (MSE) of 1.859, 0.7961, and 11.817 respectively along with a high R^2 value close to 1, indicating a high level of precision in locating the fault within the transformer winding. The average percentage error for each fault location identification

in Phase A, Phase B and Phase C were obtained as 3.39%, 4.81%, and 4.78% respectively. This low error suggests that the ANN model effectively captured the relationship between system responses—likely voltage and current variations—and the exact location of the internal winding fault. The predictability and accuracy make this approach highly suitable for real-time fault localization in HVDC protection schemes, especially given the complexity and high sensitivity of such systems.

The obtained results for test data set which consists of 45 fault cases for fault detection, classification and fault location identification can be summarized as shown in table 4.1.

Actual Value				Predicted Value		
Fault Resistance	Fault/ Non-Fault	Faulty Phase	Location	Fault/ Non-Fault	Faulty Phase	Location
0.05	F	A	10.82	F	A	12.61
	F	A	33.38	F	A	34.48
	F	A	66.24	F	A	66.72
	F	A	74.82	F	A	75.77
	F	B	94.43	F	B	95.10
	F	B	18.14	F	C	18.76
	F	B	52.60	F	B	52.77
	F	B	62.95	F	B	62.44
	F	B	92.24	F	B	92.63
	F	C	35.29	F	C	36.39
	F	C	41.12	F	C	42.59
	F	C	59.84	F	C	60.84
	F	C	66.67	F	C	67.43
	F	C	96.29	F	B	96.02
0.5	F	A	40.86	F	A	39.46
	F	A	48.64	F	A	48.16
	F	A	55.68	F	A	55.44
	F	A	77.89	F	A	77.45
	F	A	87.69	F	A	87.96
	F	B	1.92	F	B	2.49
	F	B	4.93	F	B	5.47
	F	B	37.59	F	C	37.86
	F	B	47.54	F	C	47.46
	F	B	75.49	F	B	75.70
	F	B	88.78	F	B	88.70
	F	C	43.47	F	C	42.08
	F	C	48.31	F	C	47.86
	F	C	55.71	F	C	55.40
	F	C	70.77	F	C	69.85
	F	C	77.09	F	C	77.18
5	F	A	22.46	F	A	26.53
	F	A	30.88	F	A	31.31
	F	A	55.68	F	A	55.79
	F	A	62.74	F	A	61.16
	F	A	80.54	F	A	80.24
	F	B	1.92	F	B	1.83
	F	B	5.25	F	B	5.85
	F	B	52.60	F	B	50.52
	F	B	59.68	F	B	58.53
	F	B	62.95	F	B	60.87
	F	C	3.36	F	B	2.83
	F	C	55.71	F	C	49.20
	F	C	59.84	F	C	53.86
	F	C	66.67	F	C	60.20
	F	C	81.58	F	C	74.59

Table 4.1: Summary of results for test data

5

Conclusion

5.1 Discussion

The results obtained from this study provide valuable insights into the performance of intelligent models for internal fault analysis in VSC-HVDC systems. The use of machine learning techniques—Support Vector Machine (SVM), Decision Tree, and Artificial Neural Network (ANN)—enabled accurate and reliable fault detection and classification, while the ANN model was further utilized for precise fault location identification.The impedance-based protection method is highly efficient with 98.33% test accuracy and no false trips under normal operating conditions. Due to the dependency on highly tuned relay settings,this method can result in false alarms during transient disturbances with improper configurations.

Across all scenarios, fault detection and classification models achieved more than 90% accuracy in classifying turn-to-turn faults. SVM achieving the highest performance at 96.67%, demonstrating strong capability in separating healthy and faulty signatures. This remarkable performance highlights the effectiveness of data-driven approaches in identifying the presence of internal transformer faults. Each of the three models successfully learned the patterns in voltage and current responses associated with different fault conditions, confirming that even relatively simple algorithms like Decision Trees (Test accuracy of 93.33%), can be powerful when well-trained on quality data. However, the ANN model remains preferred for further tasks even it displayed slightly lower accuracy in classification due to its superior generalization capabilities and scalability.

For the fault location identification in the HVDC system, the ANNs achieved low average percentage errors for turn-to-turn faults, along with a high R^2 value, indicating a strong correlation between the predicted and actual fault locations. These results demonstrate that the ANN was highly effective in modeling the complex non-linear dynamics of transformer windings under internal fault conditions. The slightly higher error for Phase C suggests that further model refinement or additional feature inputs could improve phase-specific accuracy. Overall, the combination of high detection accuracy, reliable classification, and precise localization underscores the suitability of ANN-based approaches for advanced HVDC fault analysis.

These results suggest that integrated protection framework provide greatest reliability for fault analysis in practical complex power system. Impedance based detection

can provide the initial fault identification while machine learning algorithms improve the quality of fault analysis by accurately classifying the fault type and identifying the fault location. This kind of hybrid approach will provide high reliability in fault mitigation with identifying undetected faults which could damage transformers.

5.2 Conclusion

This study demonstrated a reliable method of detection and localization of transformer internal winding faults in HVDC systems through the integration of the principles of impedance-based protection and intelligent classification. Winding impedance from measurements of the terminal voltage and currents for different fault conditions allowed the simulation and analysis of turn-to-turn faults.

The use of machine learning models—Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees—allowed for reliable fault detection and classification. Of the three, the SVM and Decision Tree models performed with high accuracy and low computational complexity, whereas the ANN, once optimized, showed strong performance in both fault detection,classification and fault location identification, providing a data-driven alternative to conventional protection methods. This capability is especially valuable for identifying challenging faults, such as those located near the neutral point, where traditional protection may fail.

Furthermore, the analysis based upon impedance yielded the useful physical insight that a practicable decision boundary is possible to represent in the R-X plane for fault and no-fault conditions. Such impedance protection scheme improves fault discrimination, particularly for problematic conditions like faults close to the point of neutrality.

Overall, the proposed hybrid method shows strong potential for integration into advanced protection schemes in HVDC applications, improving fault sensitivity and minimizing the risk of misoperation in critical transformer components. And it offers a practical pathway toward more resilient and intelligent protection systems for modern power networks.

5.3 Suggestions and Future Work

This study has demonstrated the potential of impedance-based protection combined with machine learning to effectively detect transformer winding faults in HVDC systems. However, future research can expand the scope by incorporating other types of internal and external transformer faults to evaluate the broader applicability of the proposed method. Additionally, implementing real-time hardware-in-the-loop (HIL) testing or deploying the developed protection algorithm in an actual HVDC system would validate its practical performance. Exploring hybrid models that combine impedance methods with differential protection or traveling wave-based approaches may further improve fault detection accuracy under complex fault scenarios. Fi-

nally, enhancing the machine learning models with larger, more diverse datasets and online learning capabilities can help adapt the system to varying operational conditions and transformer aging effects, leading to a more robust and adaptive protection strategy.

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